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PhD Thesis

Acoustic Event Detection and Classification

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Моїй сім'ї,

Abstract

The human activity that takes place in meeting-rooms or class-rooms is reflected in a rich variety of acoustic events, either produced by the human body or by objects handled by humans, so the determination of both the identity of sounds and their position in time may help to detect and describe that human activity. Additionally, detection of sounds other than speech may be useful to enhance the robustness of speech technologies like automatic speech recognition.

Automatic detection and classification of acoustic events is the objective of this thesis work. It aims at processing the acoustic signals collected by distant microphones in meeting-room or classroom environments to convert them into symbolic descriptions corresponding to a listener's perception of the different sound events that are present in the signals and their sources.

First of all, the task of acoustic event classification is faced using Support Vector Machine (SVM) classifiers, which are motivated by the scarcity of training data. A confusion-matrix-based variable-feature-set clustering scheme is developed for the multiclass recognition problem, and tested on the gathered database. With it, a higher classification rate than the GMM-based technique is obtained, arriving to a large relative average error reduction with respect to the best result from the conventional binary tree scheme. Moreover, several ways to extend SVMs to sequence processing are compared, in an attempt to avoid the drawback of SVMs when dealing with audio data, i.e. their restriction to work with fixed-length vectors, observing that the dynamic time warping kernels work well for sounds that show a temporal structure. Furthermore, concepts and tools from the fuzzy theory are used to investigate, first, the importance of and degree of interaction among features, and second, ways to fuse the outputs of several classification systems. The developed AEC systems are tested also by participating in several international evaluations from 2004 to 2006, and the results are reported.

The second main contribution of this thesis work is the development of systems for detection of acoustic events. The detection problem is more complex since it includes both classification and determination of the time intervals where the sound takes place. Two system versions are developed and tested on the datasets of the two CLEAR international evaluation campaigns in 2006 and 2007. Two kinds of databases are used: two databases of isolated acoustic events, and a database of interactive seminars containing a significant number of acoustic events of interest. Our developed systems, which consist of SVM-based classification within a sliding window plus post-processing, were the only submissions not using HMMs, and each of them obtained competitive results in the corresponding evaluation.

Speech activity detection was also pursued in this thesis since, in fact, it is a –especially important – particular case of acoustic event detection. An enhanced SVM training approach for the speech activity detection task is developed, mainly to cope with the problem of dataset reduction. The resulting SVM-based system is tested with several NIST Rich Transcription (RT) evaluation datasets, and it shows better scores than our GMM-based system, which ranked among the best systems in the RT06 evaluation.

Finally, it is worth mentioning a few side outcomes from this thesis work. As it has been carried out in the framework of the CHIL EU project, the author has been responsible for the organization of the above mentioned international evaluations in acoustic event classification and detection, taking a leading role in the specification of acoustic event classes, databases, and evaluation protocols, and, especially, in the proposal and implementation of the various metrics that have been used. Moreover, the detection systems have been implemented in the UPC's smart-room and work in real time for purposes of testing and demonstration.

Resum

L'activitat humana que té lloc en sales de reunions o aules d'ensenyament es veu reflectida en una rica varietat d'events acústics, ja siguin produïts pel cos humà o per objectes que les persones manegen. Per això, la determinació de la identitat dels sons i de la seva posició temporal pot ajudar a detectar i a descriure l'activitat humana que té lloc en la sala. A més a més, la detecció de sons diferents de la veu pot ajudar a millorar la robustes de tecnologies de la parla com el reconeixement automàtica a condicions de treball adverses.

L'objectiu d'aquesta tesi és la detecció i classificació automàtica d'events acústics. Es tracta de processar els senyals acústics recollits per micròfons distants en sales de reunions o aules per tal de convertir-los en descripcions simbòliques que es corresponguin amb la percepció que un oient tindria dels diversos events sonors continguts en els senyals i de les seves fonts.

En primer lloc, s'encara la tasca de classificació automàtica d'events acústics amb classificadors de màquines de vectors suport (Support Vector Machines (SVM)), elecció motivada per l'escassetat de dades d'entrenament. Per al problema de reconeixement multiclasse es desenvolupa un esquema d'agrupament automàtic amb conjunt de característiques variable i basat en matrius de confusió. Realitzant proves amb la base de dades recollida, aquest classificador obté uns millors resultats que la tècnica basada en models de barreges de Gaussianes (Gaussian Mixture Models (GMM)), i aconsegueix una reducció relativa de l'error mitjà elevada en comparació amb el millor resultat obtingut amb l'esquema convencional basat en arbre binari.

Continuant amb el problema de classificació, es comparen unes quantes maneres alternatives d'estendre els SVM al processament de seqüències, en un intent d'evitar l'inconvenient de treballar amb vectors de longitud fixa que presenten els SVM quan han de tractar dades d'àudio. En aquestes proves s'observa que els nuclis de deformació temporal dinàmica funcionen bé amb sons que presenten una estructura temporal. A més a més, s'usen conceptes i eines manllevats de la teoria de lògica difusa per investigar, d'una banda, la importància de cada una de les característiques i el grau d'interacció entre elles, i d'altra banda, tot cercant l'augment de la taxa de classificació, s'investiga la fusió de les sortides de diversos sistemes de classificació. Els sistemes de classificació d'events acústics desenvolupats s'han testejat també mitjançant la participació en unes quantes avaluacions d'àmbit internacional, entre els anys 2004 i 2006.

La segona principal contribució d'aquest treball de tesi consisteix en el desenvolupament de sistemes de detecció d'events acústics. El problema de la detecció és més complex, ja que inclou tant la classificació dels sons com la determinació dels intervals temporals on tenen lloc. Es desenvolupen

dues versions del sistema i es proven amb els conjunts de dades de les dues campanyes d'avaluació internacional CLEAR que van tenir lloc els anys 2006 i 2007, fent-se servir dos tipus de bases de dades: dues bases d'events acústics aïllats, i una base d'enregistraments de seminaris interactius, les quals contenen un nombre relativament elevat d'ocurrències dels events acústics especificats. Els sistemes desenvolupats, que consisteixen en l'ús de classificadors basats en SVM que operen dins d'una finestra lliscant més un post-processament, van ser els únics presentats a les avaluacions esmentades que no es basaven en models de Markov ocults (Hidden Markov Models) i cada un d'ells va obtenir resultats competitius en la corresponent avaluació.

La detecció d'activitat oral és un altre dels objectius d'aquest treball de tesi, pel fet de ser un cas particular de detecció d'events acústics especialment important. Es desenvolupa una tècnica de millora de l'entrenament dels SVM per fer front a la necessitat de reducció de l'enorme conjunt de dades existents. El sistema resultant, basat en SVM, és testejat amb uns quants conjunts de dades de l'avaluació NIST RT (Rich Transcription), on mostra puntuacions millors que les del sistema basat en GMM, malgrat que aquest darrer va quedar entre els primers en l'avaluació NIST RT de 2006.

Per acabar, val la pena esmentar alguns resultats col·laterals d'aquest treball de tesi. Com que s'ha dut a terme en l'entorn del projecte europeu CHIL, l'autor ha estat responsable de l'organització de les avaluacions internacionals de classificació i detecció d'events acústics abans esmentades, liderant l'especificació de les classes d'events, les bases de dades, els protocols d'avaluació i, especialment, proposant i implementant les diverses mètriques utilitzades. A més a més, els sistemes de detecció s'han implementat en la sala intel·ligent de la UPC, on funcionen en temps real a efectes de test i demostració.

Thanks to…

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Contents

List of Acronyms

AE(s)	Acoustic Event(s)
AEC	Acoustic Event Classification
AED	Acoustic Event Detection
ANN(s)	Artificial Neural Network(s)
ASL	Acoustic Source Localization
ASR	Automatic Speech Recognition
CASA	Computational Auditory Scene Analysis
BIC	Bayesian Information Criteria
CHIL	Computer in the Human Interaction Loop
CLEAR	Classification of Event, Activities, and Relationships
CV	Cross Validation
DAG	Directed Acyclic Graphs
DFT	Discrete Fourier Transform
DP	Decision Profile
DT(s)	Decision Tree(s)
DTW	Dynamic Time Warping
EM	Expectation-Maximization
ERM	Empirical Risk Minimization
FBE	Filter Bank Energies
FF(BE)	Frequency Filtered (Band Energies)
FFT	Fast Fourier Transform
FI	Fuzzy Integral
FM(s)	Fuzzy Measure(s)
GMM(s)	Gaussian Mixture Model(s)
GUI	Graphic User Interface
HMM(s)	Hidden Markov Model(s)
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
LPC	Linear Prediction Coefficients
MFCC	Mel-Frequency Cepstral Coefficients
NIST	National Institute of Standards and Technology
PCA	Principal Component Analysis
PSVM	Proximal Support Vector Machines
RBF	Radial Basis Function
RT	Rich Transcription
SAD	Speech Activity Detection
SNR	Signal-to-Noise Ratio
SRM	Structural Risk Minimization
SV(s)	Support Vector(s)
SVM(s)	Support Vector Machine(s)
VC	Vapnik-Chervonenkis dimension
VQ	Vector Quantization
WAM	Weighted Arithmetical Mean

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Chapter 1. Introduction

1.1 Thesis Overview and Motivation

Activity detection and description is a key functionality of perceptually aware interfaces working in collaborative human communication environments like meeting-rooms or classrooms. In the context of person-machine communication, computers involved in human communication activities have to be designed to have minimal possible awareness from the users. Consequently, there is a need of perceptual user interfaces which, besides being multimodal and robust, use unobtrusive sensors. One example of new challenging multimodal research efforts is the development of smart-rooms. A smart-room is a closed space equipped with multiple microphones and cameras, and several functionalities, which are designed to assist and complement human activities. In the case of the audio processing, some of the technologies that may be involved are speech activity detection, automatic speech recognition, speaker identification and verification, and speaker localization.

Indeed, speech usually is the most informative acoustic event, but other kind of sounds may also carry useful information. Since in such types of environments the human activity is reflected in a rich variety of acoustic events, either produced by the human body or by objects handled by humans, detection and classification of acoustic events may help to detect and describe human activity. For example: clapping or laughing inside a speech, a strong yawn in the middle of a lecture, a chair moving or door slam when the meeting has just started. Additionally, the robustness of automatic speech recognition systems may be increased if such non-speech acoustic events are previously detected and identified.

The main goal of this thesis work is detection and classification of meeting-room acoustic events, namely Acoustic Event Detection/Classification (AED/C). AED/C is a recent discipline belonging to the area of computational auditory scene analysis [WB06] that consists of processing acoustic signals and converting them into symbolic descriptions corresponding to a listener's perception of the different sound events that are present in the signals and their sources.

1.2 Thesis Objectives

The primary objective of this PhD thesis is the development of systems for acoustic event detection and classification. As required in any pattern recognition task, the thesis work focuses on algorithms for both feature extraction and classification. The developed systems are tested through the participation in international evaluations in the framework of the project Computers in the Human Interaction Loop (CHIL). A secondary objective of the thesis is to design and implement a system of acoustic event detection that provides in real time semantic content to specific services defined in CHIL.

Investigation of different types of features is an important point of any classification system. The relevance of conventional sets of features that are widely used in speech processing applications will be addressed. Several basic feature sets will be compared and investigated to find the most appropriate set of features. Apart from the features used in speech processing, there exist a number of features that have a more perceptually-oriented profile. The usefulness of the perceptual features will be investigated in terms of individual feature importance and degree of interaction.

A large part of the work has to be concerned with the problem of acoustic event classification (AEC), since detection also requires classification. Due to the problem of scarcity of data in the available corpus, the development of classification algorithms that can tackle this problem is crucial and necessary. Recently, the Support Vector Machine (SVM) paradigm has proved highly successful in a number of classification tasks. As a classifier that discriminates the data by creating boundaries between classes rather than estimating class conditional densities, it may need considerably less data to perform accurate classification. For this reason the SVM classifier is initially chosen in this thesis as the main classification technique, and it is compared to Gaussian mixture models in a series of tests. As the developed algorithm may benefit from using the temporal evolution of the acoustic events, several techniques for sequential processing will be compared. The thesis will also explore the combination of several information sources in order to capture the interdependencies among them.

Applications in real meeting-room environments require facing the acoustic event detection (AED) problem. For that purpose, it is necessary to produce a database with a sufficient number of acoustic events of interest. The database can be used as a training material and as a testing material to evaluate the algorithm performance for AED. Besides, participation in the international evaluation campaigns is a good way for evaluating and comparing the various approaches submitted by the participants. Indeed, those evaluations have to be organized and coordinated, and appropriate metrics and evaluation tools for AED have to be developed. Moreover, the AED systems will be implemented in the UPC's smart-room and work in real time for purposes of testing and demonstration.

1.3 Thesis Outline

The thesis is organized as follows. Chapter 2 presents state of the art in the area of general audio recognition, discussing the schemes for sound organization, presenting a literature review from the application point of view, and reporting the features, classification and detection techniques that have been used so far for acoustic event detection and classification.

Chapter 3 reports the work done in the area of acoustic event classification and presents the a novel SVM-based classification technique. Moreover, several advanced classification techniques are compared in that chapter including those SVM-based techniques which can model the time dynamics of sounds. Importance and interaction of various perceptual features are investigated in the framework of fusion several information sources using fuzzy theory and concepts.

Chapter 5 describes a few new systems for acoustic event detection developed in this thesis. Results, obtained with the above-mentioned systems of AEC and AED in several international evaluations, are reported in Chapter 6.

Chapter 7 considers the particular problem of speech activity detection and the way SVM classifier is applied to this problem. Results obtained with the international evaluation datasets are reported and compared with the previously developed detectors.

The activities on AED, which were carried out in the UPC's smart-room, are described in Chapter 8: database recordings, implementation of the AED system in real time, development of demos.

Chapter 9 concludes the work. The main achievements are summarised in this chapter. Several promising future directions are highlighted.

Chapter 2. State of the Art

2.1 Chapter Overview

In this chapter the current state of the art in the area of Acoustic Event Detection and Classification (AED/C) is presented.

The remaining sections of this chapter are organized as follows. In Section 2.2 the schemes for sound organization are discussed. Section 2.3 presents a literature review from the application point of view, while Sections 2.4, 2.5, and 2.6 discuss features, classification and detection techniques that have been used so far for AED/C.

2.2 Sounds Taxonomy

The research on sound classification has usually been carried out so far for a limited number of classes, like speech/music [PRO02] [MP04] [And04], music/song [Ger03a], or music/speech/other, where "other" is any kind of environmental sounds [LZJ02]. In the last years, however, the interest in AED/C has been significantly increased. The area of AED/C can be structured by different semantic levels. It can be the classification of events specific to a certain environment, classification of sounds specific to a given activity, generic sound classification, etc. In all the cases, there exist a large number of sounds and it is necessary to limit the number of classes considered. That is the reason why authors usually try to provide a sound taxonomy. The development of the sound taxonomy helps to better understand the data domain [Ger03b], and increase the accuracy and speed of classification [Cow04]. One example of a general sound taxonomy has been first presented in [Ger03b] and can be seen in Figure 2.2.1. It divides sounds firstly into hearable and non-hearable. Then the hearable part is further divided into noise, natural sound, artificial sounds, speech and music. An example of a standard taxonomy suitable for text-based query applications, such as WWW search engines, or any processing tool that uses text fields, was used in [Cas02] and it is presented in Figure 2.2.2. It is less general than the previous one as it is fitted to a given task. A sound taxonomy scheme for environmental sound classification can be found in [Cow04]. Because of the uncountable number of classes for a general environment, the author has proposed the taxonomy based on the physical states of sounding objects (solid, liquid, gas) and the possible interaction of objects (solid-solid, solid-liquid, etc). A scheme proposed in [AN00] has been based on the nature of sound sources. Firstly, the sources are divided into continuous and changing. Semantic classes appear at the next level.

Clearly, the conception of sound taxonomy is subjective and it strongly depends on the chosen classification domain. In the framework of the CHIL project [CHI] it has been decided that for the chosen meeting-room environment it is reasonable to have an acoustic sound taxonomy for general sound description and a semantic sound taxonomy for a specific task. The proposed acoustic scheme is shown in Figure 2.2.3. Actually, almost any type of sounds can be referred to one of the proposed groups according to its acoustical property. On the contrary, the semantic scheme that is presented in Figure 2.2.4 is very specific to the CHIL meeting-room scenario. Additionally, with two sound taxonomies (acoustic and semantic) it is possible to cope with situations when the produced event does not match any semantic label but can be identified acoustically.

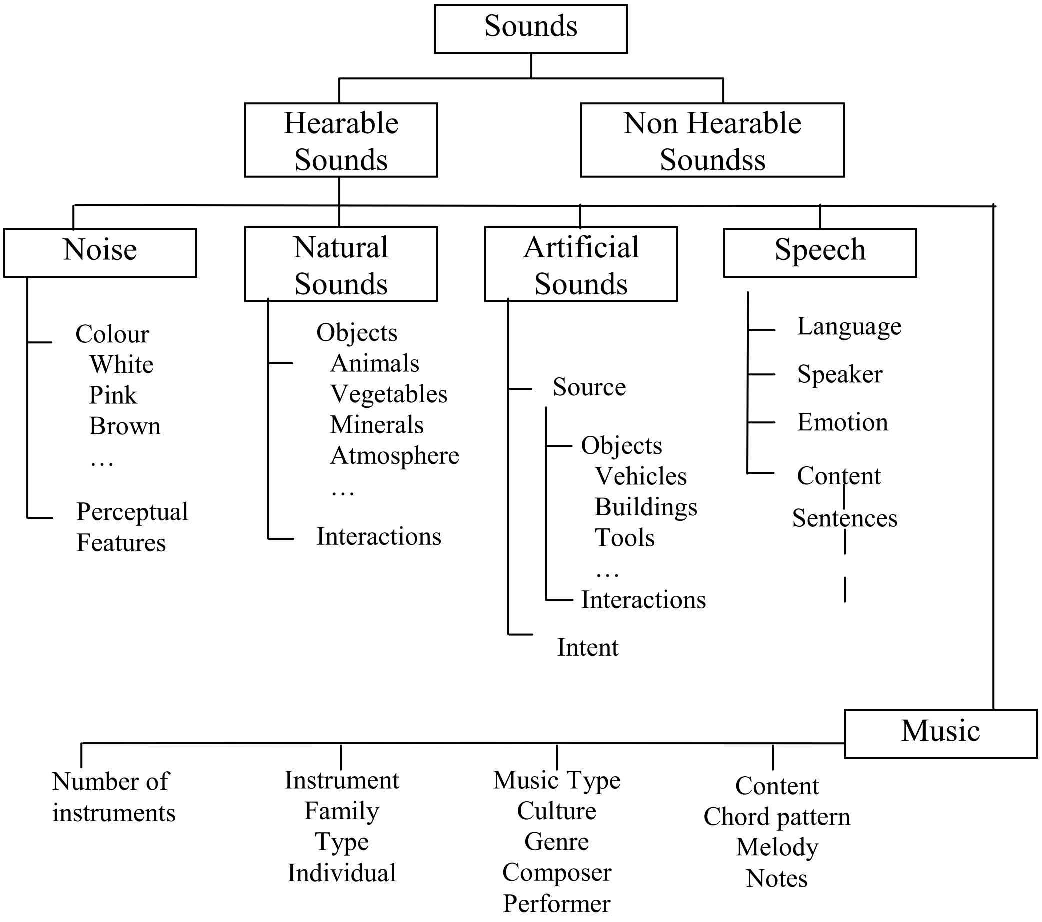


Figure 2.2.1. Sound taxonomy proposed in [Ger03b]

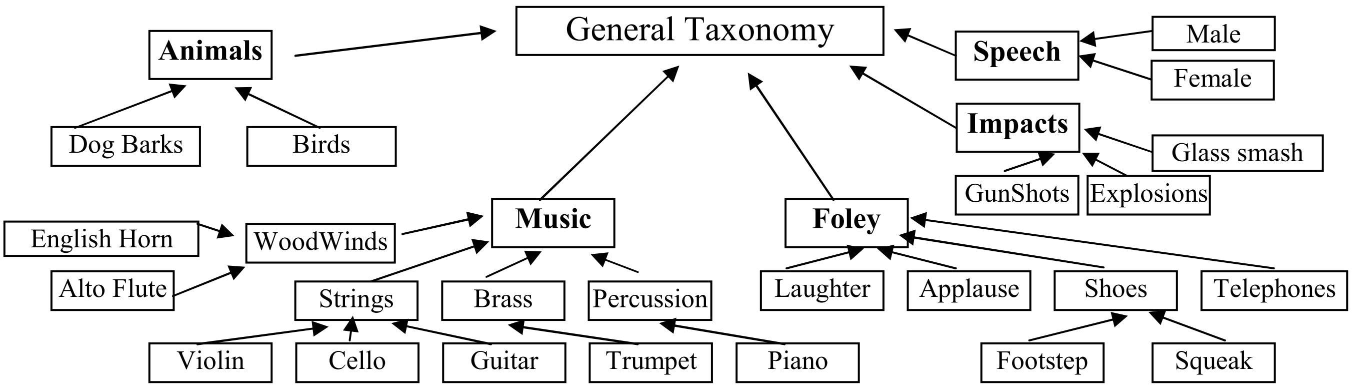


Figure 2.2.2. Sound taxonomy proposed in [Cas02]

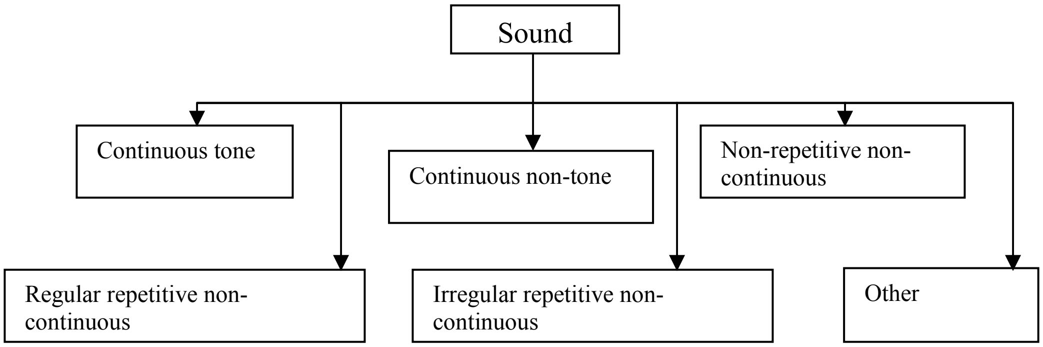

Sound
Continuous tone
Continuous non-tone
Non-repetitive non-continuous
Regular repetitive non-continuous
Irregular repetitive non-continuous
Other

Figure 2.2.3. CHIL acoustic sound taxonomy

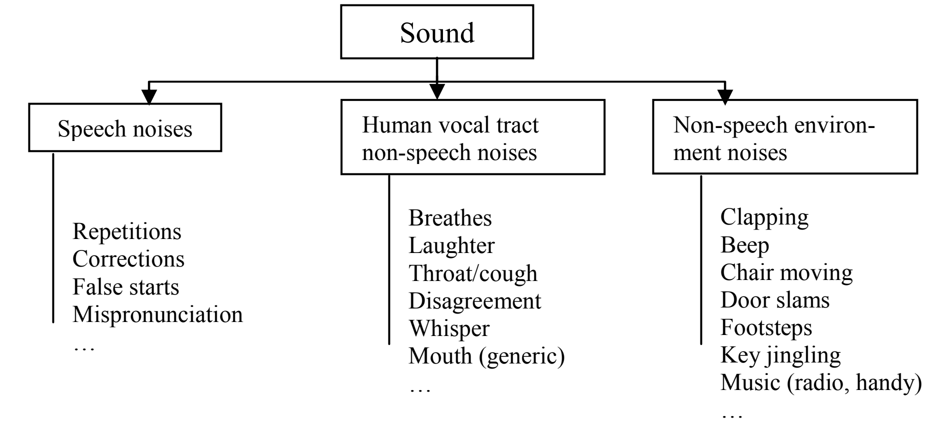


Figure 2.2.4. CHIL meeting-room semantic sound taxonomy

2.3 Applications of Audio Recognition

2.3.1 Audio indexing and retrieval

A lot of applications of audio recognition are related to audio indexing and retrieval. In [Sla02a], the authors have considered the problem of animal sound classification for the purposes of semantic-audio retrieval. The semantic and acoustic spaces are clustered and the probability linkage between the resulting models is established. The acoustic clustering has been done using Mel-Frequency Cepstral Coefficients (MFCC) [RJ93] and an agglomerative clustering algorithm with Gaussian Mixture models (GMM) [RJ93] to represent each cluster. The same authors proposed another solution for the same domain task in [Sla02b]. In that paper, mixture-of-probability experts have been used to learn the association between acoustic and semantic spaces. A similar approach for sounds retrieval made according to their nature (changing vs. continuous) is implemented in [AN00].

The system for content-based classification, search, and retrieval of audio has been proposed in [WBK+96]. It was one of the earliest in the domain of audio classification, and it has been patented as a “Muscle Fish” system. The authors have discussed how several perceptual features fit to the task of sound classification and retrieval. The classification itself was based on the Euclidian distance between feature vectors that consisted of mean, variance and autocorrelation coefficient at a small lag over the features computed by frame analysis. The investigation of feature importance was also performed. Several practical applications for similar systems were given as examples.

In [GL03], the similar task with the same database has been more efficiently solved by using a binary tree scheme with Support Vector Machine (SVM) [DHS00] as a node. Retrieval has been done based on the distance-from-boundary conception. An improvement in comparison to the previous work has been obtained with concatenation of cepstral and perceptual features and SVM classification.

In [APA05], the authors have applied two classification techniques (SVM and GMM) to audio indexing. They have performed a discrimination of “speech” and “music” in radio programs and a discrimination of environmental sounds (“laughter” and “applause”) in TV broadcasts.

In [CLH05], the unsupervised approach for discovering and categorizing semantic content in a composite audio stream has been developed. Firstly, the authors have performed spectral clustering in order to discover natural semantic sound clusters in the analyzed data stream. The auditory scenes are categorized then in terms of the extracted audio elements.

2.3.2 Audio recognition for a given environment

Recently, a huge interest has arisen in the area of detecting and classifying sounds which are specific to a given environment. Such environments can be lectures or meeting rooms, clinics or hospitals, sport stadiums or natural parks, kitchens or coffer shops, etc. In [KE04], the authors have considered the detection of “laughter” in meetings with SVM. In their experiments, MFCC features outperform the proposed spatial features and modulation spectrum features. No significant gain in the performance has been reported from combination of the examined features. Also the first six cepstral coefficients have been reported to provide the most information for classification.

In [KE03], the detection of an emphasis for the purpose of characterization of meeting recordings has been proposed. The approach uses only pitch information to identify the utterances of interest.

Apart from the meeting environments, sound classification is performed in environments related to the medicine. In [BHM+04], authors have used a classification system to analyze the sound of drills in the context of spine surgery. To facilitate the work of surgeon maintain the same accuracy, the system gives information about the density of the bones using the results of the sound analysis. Several features like zero crossing rate, median frequency, sub-band energies, as well as MFCC and pitch have been used with Artificial Neural Networks (ANN) [DHS00], SVM and Hidden Markov Models (HMM) [RJ93] classifiers.

A smart audio sensor for a telemonitoring system in telemedicine has been developed in [VIB+03a]. That sensor is equipped with microphones in order to detect a sound event (an abnormal noise or a call for help). Comparison of Linear Prediction Coefficients (LPC), MFCC along with their combination with time-derivatives and some perceptual features has been considered. The same authors have proposed the technique based on transient models and wavelet coefficient tree to classify the sounds for clinic telesurvey purposes in [VIS04]. The paper discusses the sound analysis of patient activity, psychology and possible stress situations. Among other classification models, GMM has been chosen as the least complex one. Bayesian Information Criteria (BIC) has been used to find the optimal number of Gaussians. In [VIB+03b], the classification of sounds in different Signal-to-Noise Ratios (SNR) for the medical telemonitoring has been investigated.

Baseball, golf and soccer games have been viewed a unified framework for sport highlight extraction in [XRD+03]. The authors have compared MPEG-7 spectral vectors and MFCC features. MPEG-7 feature extraction mainly consists of a Normalized Audio Spectrum Envelope (NASE), basis decomposition algorithm (e.g. Singular Value Decomposition or Independent Component

Analysis (ICA) [DHS00]), and a spectrum basis projection, obtained by multiplying the NASE with a set of extracted basis functions. HMMs with entropy prior and maximum likelihood training algorithms have been used as classifiers. The authors have obtained promising results using chosen pre- and post-processing techniques and exploiting general sports knowledge.

In [HMS05], the authors report an experiment with an acoustic surveillance system comprised of a computer and microphone situated in a typical office environment. The system continuously analyzes the acoustic activity at the recording site, and using a set of low-level acoustic features the system is able to separate all interesting events in an unsupervised manner.

The work presented in [CER05] deals with audio events detection in noisy homeland environments for a homeland security. The performance of a GMM-based shot detection system was improved by considering the hierarchical approach.

The acoustic event recognition for four different environments - kitchen, workshop (maintenance), office and outdoors – has been applied in [SLP+03]. The paper discusses a prototype of a sound recognition system focused on an ultra low power hardware implementation in a button-like miniature form. The implementation and evaluation of the final version of the prototype are performed in [SLT04]. In those papers, the authors have used FFT features and compared a k-nearest centre classifier with a k-nearest neighbour classifier. To preserve the low energy consume of the proposed technique, while maintaining high accuracy, several feature combinations as well as feature selection and feature relevance extraction algorithms have been tested. The paper also discusses the trade-off between computational cost and recognition rate, analyses the signal intensity for two microphones recognition system, and estimates the complexity of different parts of the whole system.

Recognition of sounds related to the bathroom environment has been done in [JJK+05]. The system is designed to recognize and classify different activities of daily living occurring within a bathroom based on sound. It uses an HMM classifier and MFCC features. Preliminary results showed high average accuracy.

In [RD06], the authors have defined the conception of the background and the foreground sounds. It is done by tracking the generative process that consists of detecting and adapting to changes in the underlying generative process. The proposed approach for the adaptive background modelling was applied to detection of suspicious sounds in an elevator environment.

In [SKI07], an unsupervised algorithm for audio segmentation is proposed and applied to the database of meeting-room isolated acoustic events produced in the CHIL project (see Appendix A).

It is compared to the BIC algorithm and the better results are obtained. The algorithm is based on a modification of the Expectation-Maximization algorithm.

In [Luk04], the authors have considered human activity detection in public places mainly by concentrating on coffee shop activity detection. The main priority of the final system has been defined as a real time or close-to-real time functionality for the activity detection module, and dealing with both single speaker acoustic events and a whole auditory scene. A wide range of features and two distinct classifiers (k-nearest neighbours and GMM) have been compared. The research done on auditory scene analysis has been reported as probably the most interesting and the most valuable for the project.

2.3.3 Recognition of generic sounds

The group of works presented in this subsection deals with detection and classification of generic sounds that are not related to any specific environment. In [Ell01], the author compare two different approaches to alarm sound detection and classification, namely: ANN and a technique specifically designed to exploit the structure of alarm sounds and minimize the influence of background noise. The usefulness of a set of general characteristics in different types of noises has been investigated on a collected small database of alarm sounds.

The commercial removal system for personal video recorders has been considered in [GMR+04]. In the paper, the authors have applied k-means clustering to assign a chosen audio segment with commercial or program label. Unlike other existing systems, they make no assumption about program content resulting to the content-adaptive method.

Bird species sound recognition has been performed in [Har03]. The authors have investigated recognition of a limited set of bird species by comparing sinusoidal representations of isolated syllables assuming that a large number of songbird syllables can be approximated as amplitude-and-frequency-varying brief sinusoidal pulses.

Jingle detection and classification has been done in [PO04]. A sequence of spectral vectors is used to represent each key jingle event. Some heuristic classification procedures are then applied to the obtained event “signature”.

In [NNM+03] the authors have tackled the problem of classifying many types of isolated environmental sounds that had been collected in an anechoic room, the RWCP (Real World Computing Partnership) sound scene database [NHA+00]. Along with finding the identity of the tested sounds, their main goal was to improve the robustness of an ASR system, so they have used HMMs and worked in the context of speech recognition.

In [CS02], the authors have compared the performance of speech recognition techniques applied to the task of non-speech environmental sound recognition. The Learning Vector Quantization (LVQ) and ANN have been used. The same authors in [CS03] have presented the results of a comparative study of several classification techniques, which are typically used in speech/speaker recognition and musical instrument recognition, applied to the environmental sound identification. They have found also that conventional "winners" in the speech/speaker recognition are either not suitable or performs not so good as other techniques in the environment sound recognition.

This work in [AMK06] presents a hierarchical approach of audio based event detection for surveillance. A given audio frame is firstly classified as vocal or non-vocal, and then further classified as normal and excited. The approach is based on a GMM classifier and LPC features.

In [Cow04], a system of non-speech environmental sound classification for autonomous surveillance has been discussed. Features based on a wavelet transformation and MFCC features performed the best.

The comparison of MFCC and Mpeg7 features as well as analysis of the latter has been done in [KBS04]. The authors have evaluated also three approaches of feature selection (feature space reduction): Principal Component Analysis (PCA) [DHS00], ICA, and non-negative matrix factorization. The features are fed to a continuous HMM classifier. From analysis of efficiency, it is concluded that MFCC features yield better performance in comparison with MPEG-7 features in the general sound recognition under some practical constraints. Nevertheless, the best results have been obtained with PCA applied to Mpeg7 features. The same authors in [KMS04] have compared one-level and hierarchical classification strategies based on a HMM and ICA-pre-processed Mpeg7 features. The best results have been obtained by "hierarchical structure with hints" that implies the usage of some auxiliary information about the task domain.

In [RAS04], a comparison of MFCC and proposed Noise-Robust Auditory Features (NRAF) has been done for a four class audio classification problem. Motivated by the fact that MFCCs do not perform so well in the presence of noise, a viable alternative in the form of NRAF was proposed. GMMs have been used for classification. The proposed alternative has been also conditioned by a need to have a low-power autonomous classification system.

A multi-class audio classification system has been proposed in [HKS05]. The authors have created SOLAR: Sound Object Localization and Retrieval in Complex Audio Environments system based on frequency band energy based features (band-width, peaks, loudness, etc) and AdaBoost for boosting several decision trees. Due to the diversity of sounds, the cascade of classifier is reported to recover special types of errors made in previous classification steps.

In [SN07], the authors have focused on the problem of discriminating between machine-generated and natural noise sources. A bio-inspired tensor representation of audio that models the processing at the primary auditory cortex is used for feature extraction. Comparing with MFCC features, better performance has been obtained using the cortical representation.

2.3.4 Classification of acoustic environments

On the contrary to the above-mentioned works where authors recognize sounds specific to a chosen environment, the authors in [EL04] have investigated the problem of recognizing environments specific to a set of sounds. They have performed personal audio archiving using environment as a clustering criteria. The author have tried to facilitate user's access to the requested information by segmenting the audio stream into 16 environment classes like "street", "restaurant", "class", "library", "campus", etc. Spectral clustering of a feature set consisting of bark-scaled frequency energies and spectral entropy has been performed.

An HMM-based classification of different listening environments, like speech in quiet, speech in traffic, and speech in babble, for the purposes of hearing aids has been presented in [Nor04]. The work also investigates the robustness of the classification at a variety of SNR. In [Buc02], the work for hearing aids deals with the problems of how to increase the performance of automatic and robust classification of five types of sounds by using the information of the detected acoustic environments.

In [MSM03] [SMR05] the authors have proposed an approach of rapid recognition of an environmental noise, minimizing the computation cost by usage of adaptive learning and easy training based on HMMs. The system can rapidly recognize 12 types of environments by classifying 3-second segments.

An HMM-based system for classification of 24 everyday audio contexts (street, road, nature, market, etc) has been proposed in [EPT+06]. In that work, computational efficiency of the developed recognition methods have been evaluated. In comparison with a human ability, the proposed system has obtained comparative results. Slight increase in recognition accuracy has been obtained by using PCA or ICA transformation applied to MFCC features.

2.4 Types of Features

Lots of works on audio recognition have been devoted to the feature extraction block. Good features simplify the design of a classifier whereas features with little discriminating power can hardly be compensated with any classifier. A long list of features has been investigated, ranging from standard ASR features to new application-driven perceptual features.

As ASR features are well-known, they have been very popular in audio recognition tasks. MFCC features have been used in a number of works [Sla02a] [Sla02b] [CLH05] [NNM+03] [Cow04] [APA05].

Nevertheless, in many cases the best performance may be obtained by concatenation of perceptual and conventional ASR features as it has been done in [GL03] [BHM+04] [CER05].

Comparison of MPEG-7 spectral vectors and MFCC features has been done in [KBS04] and [XRD+03]. **In** [RAS04] the authors have tested MFCC features and proposed new noise-robust auditory features. Wavelet dispersion feature vectors have been used in [KZD02]. The comparison of LPC, MFCC, and their combination with time-derivatives and some perceptual features has been done in [VIB+03a].

The content of the perceptual set of feature differs from application to application. Here we mention some of the perceptual features that can be found in the literature:

- *Distance to voicing* [BBW+03] is an estimation of the voicing level profile of the waveform. Regions above a given threshold are marked as voices. The distance to voicing is defined as the distance between the current frame and the closest voiced frame. A distance of zero indicates that the frame is a voiced frame. A large distance hints that the frame is probably a non-speech since human speech typically does not contain long segments with no voicing.
- *Frame energy* [BBW+03] [SPP99] [ZK01] [GL03] is a total energy of a current frame.
- *The silence ratio* [GL03] is the number of silent frames divided by total number of frames.
- *The pitched ratio* [GL03] is the number of pitched frames divided by total number of frames.
- *Spectral tilt* [BBW+03] is defined as a ratio of high- to low-frequency energies. Fricatives typically display a larger spectral tilt than steady-state noises such as car noise.
- *Sub-band energies* [SPP99] [GL03] the log FBE of some number of chosen subbands.

- *Zero-crossing rate* ([SPP99] [Ger03b]) is defined as the number of zero crossing in a frame.
- *High zero-crossing rate ratio* (HZCRR) [LZJ02] is defined as a ratio of the number of frames whose *ZCR* is above 1.5 fold average zero-crossing rate in one-second window.
- *Low Short-Time Energy Ratio* [LZJ02] is defined as a ratio of the number of frames whose *STE* are less than 0.5 times of average short time energy in a one-second.
- *Spectrum Flux* [LZJ02] [LLZ03] is defined as a (squared) difference of the spectra between two adjacent frames.
- *Band Periodicity* [LZJ02] [LLZ03] is defined as the periodicity of each sub-band derived by sub-band correlation analysis.
- *Noise Frame Ratio* [LZJ02] is defined as a ratio of noise frames in a given audio clip.
- *Fundamental frequency* [GL03] [ZK01] is the lowest frequency in a harmonic series.
- *Spectral centroid* [LZJ02] is a centroid of the (linear) spectrum. It is a measure of the spectral “brightness”.
- *Spectral roll-off* [LZJ02] is the 95th percentile of the spectral energy distribution. It is a measure of the “skewness” of the spectral shape.
- *Spectral bandwidth* [LZJ02] is a measure of spreading of the spectrum around the spectral centroid.
- *Modulation spectrum* [KE04] [SA02] is characterization of the time-varying behaviour of the signal.

Because of a large number of possible features several works have studied feature selection techniques. In [SLP+03] [SLT04] a selection of FFT features has been carried out based on relevance estimation algorithms. Three approaches of feature selection (feature space reduction), namely PCA, ICA, and non-negative matrix factorization, have been evaluated in [KBS04] [EPT+06].

2.5 Audio Classification Algorithms

Any recognition task requires a classification. The task of classification is to provide a label for an unseen input pattern. However, as it was mentioned in the previous subsection, a poor feature processing can hardly be compensated by a good classification.

One of the very first works on audio classification has used a minimum distance classification model - simple distance-based classifier with the Euclidian distance between extracted features [WBK+96]. The minimum distance classifiers choose a class according to the closest training sample. Little more complex algorithms pick k-nearest neighbours to an unknown input and then choose the class that is most often picked. In that case classification gets very complex with a lot of training data, as one must measure a distance to all training samples. Performing clustering and storing only centres of the clusters (class prototypes) can improve computational efficiency. Mentioned algorithms and related optimization steps for audio classification have been reviewed in [SLP+03] [SLT04] [Luk04] [GMR+04].

A rule-based classification algorithm that initially also relies on good feature extraction has been used in [PO04]. In that work several task-specific features have been proposed with a set of heuristic classification rules.

Among other classification paradigms a way to classify audio data is to use already developed and well-tested speech recognition algorithms. In ASR usually GMMs or HMMs are used. They are well suited to work with time series data, may use information included in the temporal evolution of an audio signal. A lot of audio recognition works have exploited the mentioned techniques. GMMs have been used in [Sla02a] [Sla02b] [AN00] [VIB+03a] [VIS04] [VIB+03b] [Luk04] [RAS04] and HMMs in [BHM+04] [XRD+03] [KE04] [NHA+00] [KMS04] [Nor04] [MSM03] [SMR05].

In [CS03] the comparison of ASR techniques for the task of the environmental sound recognition has been performed. The conclusion was that conventional ASR techniques are not that suited for the general task of audio recognition. Instead of using generative classification models like GMM, discriminative classification models have been used in a number of works, like ANN in [BHM+04] [Ell01] [KZD02], VQ in [CS02], decision trees in [HKS05], SVM in [GL03] [KE04] [BHM+04] [LLZ03] [APA05].

2.6 Audio Detection Algorithms

It is necessary to mention that detection is only involved in those tasks that deal with continuous audio and not with events that have been already extracted. Indeed, the audio detection can be performed in two different ways. The first one consists of detection of a sound endpoints and then classification of the end-pointed segment. Hereafter we refer to it as *detection-and-classification*. The second one detects by classifying the consecutive audio segments. We refer to it as *detection-by-classification*.

2.6.1 Detection-by-classification

Most papers give preference to the detection-by-classification due to its natural simplicity. In that way, the detection task converts to the classification task. The problem consists of the choice of a window length. The detection itself is carried on by assigning a segment with a label given by the classification when applied to that segment (Figure 2.6.1). The number of works that use this strategy is by far larger than the number of works that perform detection and then classification. Clearly, the window length is an arbitrary value. For “laughter” detection it may be one second [KE04] [APA05], for “music” a window of several seconds may be chosen [KZD02]. Depending on the task domain, the length of a segment usually goes from half a second up to several minutes [KE04] [BHM+04] [SLP+03] [SLT04] [NHA+00] [And04] [Ell01] [KZD02] [GMR+04] [DL04] [HKS05].

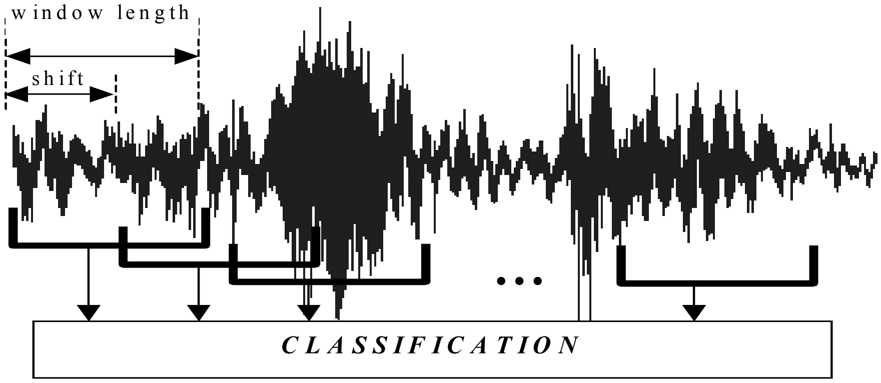


Figure 2.6.1. Detection-by-classification

Although the scheme can be soundly applied only to signals where the main part is stationary this type of detection has been successfully applied to impulse-like sounds in [Ell01] and [HKS05].

Consequently, knowledge of task domain may have a great impact upon the accuracy of chosen detection scheme. The choice of the length and the shift of the sliding window becomes very important. Moreover, a kind of a compromise between temporal resolutions of the decision-making and implied computational cost has to be found. The influence of the window length on the classification results has been reviewed in [KBS04] and the reasons for the chosen detection strategy have been investigated in [HKS05].

An important aspect of the detection-by-classification strategy is the application of some post-processing techniques. As even an appropriate window length and shift cannot naturally satisfy all acoustical requirements of a signal, a certain smoothing of results is necessary. Under the assumption that it is improbable that sound types change suddenly or frequently in an arbitrary way, a smoothing of the final segmentation of an audio sequence can be applied. For instance, the sequence labelled as "Music-Music-Speech-Music-Music" may be smoothed to "all-Music" sequence. The rules usually are highly heuristic. Smoothing applied to silence /speech /music /environment segmentation in [LZJ02] can serve as an example.

Another aspect in the detection-by-classification strategy is a usage of a classifier that has its own segmentation algorithm inside. As an example, HMMs borrowed from speech/speaker recognition sphere has been successfully used in [XRD+03] [Nor04] [KMS04] [KBS04]. The difference with above-mentioned methods is that it has no constant window length for decision-making as it classifies by accumulating probabilities. In that case the limitation of the technique is that HMM accurate modelling requires relatively large amount of data.

2.6.2 Detection-and-classification

An interesting strategy appears to be detection and then classification of the segment bounded by detection algorithm. It should be noted that resulting temporal segmentation does not try to interpret the data but in case the classes under review consist of both stationary and impulse-like sounds both affected by background noise the detection algorithms become quite challenging.

Thus, in [Pfe01] the approach based upon exploration of relative silences has been proposed. A relative silence has been considered as a pause between important foreground sounds. However, the approach has been mainly designed for spoken words extraction. As an example a reporter speech on the background crowd noise was considered.

A large number of papers in detection-and-classification deal with metric-based detection techniques. In that sense segmentation refers to the process of breaking audio into time segments based on what could be called "texture" of sound [TC99]. A sliding window goes through the signal and a certain similarity measure between adjacent regions is calculated and compared to the chosen threshold. This way no classification decision is made, instead, a segment boundary is claimed to be detected when the metric value exceeds the threshold. As a similarity measure distance measures such as Euclidian distance [WBK+96] [PO04], Mahalanobis distance [TC99], Kullback-Leibler [CTK+03], Bhattacharyya [PCC01] have been used. An important issue is the usage of the self-adapting threshold and other heuristics. For instance, in [TC99] the peaks of the derivative of Mahalanobis distance correspond to texture changes and are used to automatically determine segmentation boundaries; or in [PO04] only candidates that have a value less than half of the mean of the values in the window are considered. The distance-based methods have some advantages and disadvantages. Low computational cost and real time processing possibility from one side and difficult choice of a threshold and a relatively long window required from the other side. Moreover to apply some of the distance-based similarity measure the assumption that the features follow some distribution (usually Gaussian) is done.

To overcome some of the above-mentioned disadvantages, similarity measures that are not based on distances have been used in [VIB+03b] [VIB+03a]. In those papers, the authors have used two metrics: cross-correlation and energy spline interpolation. In the first one, maximum value of cross-correlation has been taken as a measure of similarity between two adjacent windows. For the energy prediction-based method, ten previous values of energy have been used to predict the next one using spline interpolation. The authors have investigated the behaviour of the detection techniques in artificial and real environmental noises with different SNR.

On the other hand the model-based algorithms like BIC do not need any threshold and can be applied directly to audio streams [CW03] [CW04] [EL04]. However they also have disadvantages as a relatively high computational cost and a need for long windows that is bearable for stationary sounds and not suitable for impulse-like sounds. For the latter, the technique based on median-filter is proposed in [DBA+00]. The signal energy is estimated for every successive time block. Then, the obtained energy sequence is median-filtered, and the output of the filter is subtracted from the energy resulting in a new sequence which being normalized emphasizes the relevant energy pulses.

A very interesting method for detection of both stationary and impulse-like sounds has been proposed in [VIB+03b] where six techniques for sound detection have been compared. The discrete wavelet transform has been applied to extract high order wavelet coefficients that are reported to detect impulsive sounds almost clearly. The method is shown to outperform two methods based on median-filtering, simple energy-variance-based method, and the cross-correlation and spline interpolation for energy prediction methods for different noises with several SNR conditions tested. The above-mentioned method has been modified in [VIS04] [VIS+05] where the authors have used transient models based on dyadic trees of wavelet coefficients.

2.7 Chapter Summary

In this chapter we have quickly reviewed the work done so far in the area of acoustic event classification and acoustic event detection. Firstly, the main schemes for sound semantic organization have been discussed. Also, a literature review from the application point of view has been presented, where the application domain has been subdivided into audio indexing and retrieval, sound recognition for a given environment, recognition of generic sounds, and classification of acoustic environments. Then, the features and classification techniques that have been used in the area of audio recognition have been discussed. Finally, detection techniques, subdivided into detection-by-classification and detection-and-classification, have been explained, and the relevant reported works have been presented.

Chapter 3. Basic Pattern Recognition Techniques

3.1 Chapter Overview

Three basic classification techniques are considered in this work: Support Vector Machine (SVM), Gaussian Mixture Model (GMM), and Fuzzy Integral (FI). In this section, the above-mentioned techniques will be presented.

Firstly, the basic theory of SVM will be given in Section 3.2. Specifically, the construction of SVM will be overviewed in Subsection 3.2.2. Subsection 3.2.3 will discuss the generalization properties of SVM. Finally, the main advantages and disadvantages of SVM will be highlighted in Subsection 3.2.4.

The very basics of GMM will be given in Section 3.3.

The basic theory of the FI and Fuzzy Measure (FM) that are used to fuse various information sources in the way to benefit from the interactions between them will be presented in Section 3.4.

3.2 Support Vector Machines

3.2.1 Introduction

The SVM is a discriminative model classification technique that mainly relies on two assumptions. First, transforming data into a high-dimensional space may convert complex classification problems (with complex decision surfaces) into simpler problems that can use linear discriminant functions. Second, SVMs are based on using only those training patterns that are near the decision surface assuming they provide the most useful information for classification. In this section the basic theory of SVM will be given. Firstly, the construction of an SVM classifier will be presented in Subsection 3.2.2. Subsection 3.2.3 gives the basics of Structural Risk Minimization (SRM) and its connection to the SVM classifier. The outline of the main advantages and disadvantages of SVM concludes the section in Subsection 3.2.4.

3.2.2 Construction of SVM

Let us assume a typical two-class problem in which the training patterns (vectors) $x_i \in \Re^n$ are linearly separable, as in [Bur98], where the decision surface used to classify a pattern as belonging to one of the two classes is the hyperplane H_0 (Figure 3.2.1). If x is an arbitrary vector ($x \in \Re^n$), we define

$$f(x) = w \cdot x + b \qquad (3.2.1)$$

where $w \in \Re^n$ and $(\cdot)$ denotes the dot product. H_0 is the region of vectors x which verify the equation $f(x) = 0$ [SS02], and H_1 and H_{-1} are two hyperplanes parallel to H_0, and defined by $f(x) = 1$ and $f(x) = -1$, respectively. The distance separating the H_1 and H_{-1} hyperplanes is

$$\frac{2}{\|w\|} \qquad (3.2.2)$$

and it is called *margin*. The margin must be maximal in order to obtain a classifier that is not much adapted to the training data, i.e. with good generalization characteristics. As we will see, the decision hyperplane H_0 directly depends on vectors closest to the two parallel hyperplanes H_1 and H_2, which are called *support vectors*.

Consider a set of training data vectors $X = \{x_1, \ldots x_L\}$, $x_i \in \Re^n$, and a set of corresponding labels $Y = \{y_1, \ldots y_L\}$, $y_i \in \{1, -1\}$. We consider that the vectors are optimally separated by the

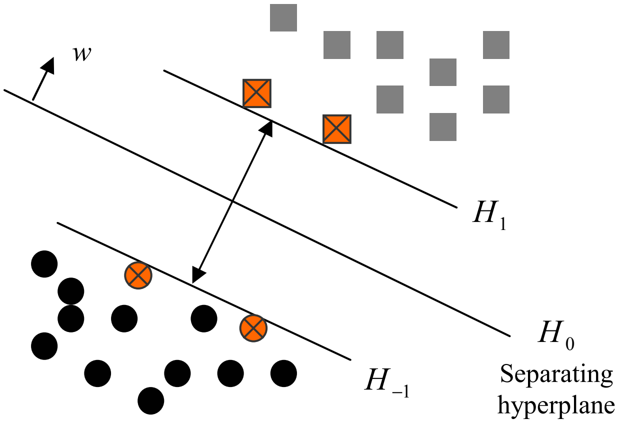


Figure 3.2.1. Two-class linear classification. The support vectors are indicated with crosses

hyperplane *H₀* if they are classified without error and the margin is maximal. In order to be correctly classified, the vectors must verify

$$f(x_i) \geq +1 \;\; for \;\; y_i = +1 \qquad (3.2.3)$$

$$f(x_i) \leq -1 \;\; for \;\; y_i = -1$$

Or, more concisely,

$$y_i f(x_i) \geq 1, \quad \forall i. \qquad (3.2.4)$$

Thus the problem of finding the SVM classifying function H_0 can be stated as follows:

$$\text{minimize } \frac{1}{2}\|w\|^2 \qquad (3.2.5)$$

$$\text{subject to } y_i f(x_i) \geq 1, \quad \forall i.$$

This is called the *primal* optimization problem [Bur98] [SS02] [MMR+01]. In order to solve it, we form the following Lagrange function

$$L(w,b) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{L} \alpha_i [y_i f(x_i) - 1] \qquad (3.2.6)$$

where the Lagrange multipliers α_i verify

$$\alpha_i \geq 0, \quad \forall i. \qquad (3.2.7)$$

The Lagrangian *L(w,b)* must be minimized with respect to *w* and *b*, so its gradient must vanish, i.e.

$$\frac{\partial}{\partial b}L(w,b)=0,\ \frac{\partial}{\partial w}L(w,b)=0 \qquad (3.2.8)$$

From the two above equations, it follows, respectively, that

$$\sum_{i=1}^{L}\alpha_i y_i = 0 \qquad (3.2.9)$$

$$\text{and } w=\sum_{i=1}^{L}\alpha_i y_i x_i \qquad (3.2.10)$$

Substituting the conditions (3.2.9) and (3.2.10) into the Lagrangian (3.2.6), we arrive at the so-called *dual* optimization problem:

$$\text{maximize } \sum_{i=1}^{L}\alpha_i - \frac{1}{2}\sum_{i=1}^{L}\sum_{j=1}^{L}\alpha_i\alpha_j y_i y_j x_i\cdot x_j \qquad (3.2.11)$$

$$\text{subject to } \sum_{i=1}^{L}\alpha_i y_i = 0 \text{ and } \alpha_i \geq 0,\ \forall i$$

The dual optimization problem is a (convex [Ber90]) quadratic programming problem that can be efficiently solved with a number of mathematical algorithms [Ber95]. In our work we use the decomposition method with conventional modifications [MMR+01].

Data observed in real conditions are frequently affected by outliers. Sometimes they are caused by noisy measurements. If the outliers are taken into account, the margin of separation decreases so the solution does not generalize so well, and the data patterns may no longer be linearly separable. To account for the presence of outliers, we can *soften* the decision boundaries by introducing a *slack* positive variable ξ_i for each training vector [SS02]. Thus, we can modify the equations (3.2.3) in the following way:

$$\underline{w}'\underline{x}_i + b \geq +1-\xi_i \quad \textit{for } y_i=+1 \qquad (3.2.12)$$

$$\underline{w}'\underline{x}_i + b \leq -1+\xi_i \quad \textit{for } y_i=-1$$

Obviously, if we take ξ_i large enough, the constraints (3.2.12) will be met for all *i*. To avoid the trivial solution of large ξ_i, we introduce a penalization cost in the objective function in (3.2.5), and thus the primal optimization formulation becomes:

$$\text{minimize } (\frac{1}{2}\|\underline{w}\|^2 + C\sum_{i=1}^{L}\xi_i) \qquad (3.2.13)$$

$$\text{subject to } y_i(\underline{w}'\underline{x}_i + b) \geq 1 - \xi_i, \ \forall i,$$

where C is a positive regularization constant which controls the degree of penalization of the slack variables $\xi_{i,}$ so that, when C increases, fewer training errors are permitted, though the generalization capacity may degrade. The resulting classifier is usually called *soft margin classifier.* If $C = \infty$, no value for ξ_i except 0 is allowed; it is the so-called *hard margin* SVM case.

The formulation (3.2.13) leads to the same dual problem as in (3.2.11) but changing the positivity constraints on α_i by the constraints $0 \leq \alpha_i \leq C$. Thus, it can be shown that the optimal solution has to fulfil the following conditions (known as Karush-Kuhn-Tucker optimality conditions) [MMR+01]:

$$\alpha_i = 0 \quad \Rightarrow \quad y_i f(x_i) \geq 1 \quad \textit{and} \quad \xi_i = 0 \qquad (3.2.14)$$

$$0 < \alpha_i < C \quad \Rightarrow \quad y_i f(x_i) = 1 \quad \textit{and} \quad \xi_i = 0 \qquad (3.2.15)$$

$$\alpha_i = C \quad \Rightarrow \quad y_i f(x_i) \leq 1 \quad \textit{and} \quad \xi_i > 0 \qquad (3.2.16)$$

The above equations reveal one of the most important features of SVM: since most patterns lie outside the margin area, their optimal α_i's are zero (equation (3.2.14)). Only those training patterns x_i which lie on the margin surface (equation (3.2.15)) or inside the margin area (equation (3.2.16)) have non-zero α_i, and they are named support vectors. Consequently, the classification problem consists of assigning to any input vector x one of the two classes according to the sign of

$$f(x) = \sum_{j=1}^{M}\alpha_j y_j x_j \cdot x + b, \qquad (3.2.17)$$

being M the number of support vectors. The fact that the support vectors are a small part of the training data set makes the SVM implementation practical for large data sets [MMR+01].

In real situations, the distribution of the data among the classes is often not uniform, so some classes are statistically under-represented with respect to other classes. To cope with this problem in the two-class SVM formulation, we can introduce different cost functions for positively- and negatively-labelled points in order to have asymmetric soft margins, so that the class with smaller data size obtains a larger margin [VCC99]. Consequently, the conventional soft margin approach can be generalized as

$$\text{minimize } (\frac{1}{2}\|\underline{w}\|^2 + C_- \sum_{i:y_i=-1} \xi_i + C_+ \sum_{i:y_i=1} \xi_i) \qquad (3.2.18)$$

$$\text{subject to } y_i(\underline{w}'\underline{x}_i + b) \geq 1 - \xi_i, \quad \forall i.$$

As the formulation (3.2.18) suggests, when C_+ increases, the number of allowed training errors from positively-labelled data decreases, but at the expenses of increasing the allowed number of training errors from the negatively-labelled data. And the opposite occurs when C_- increases.

The resulting dual problem has the same Lagrangian as in (11), but the positivity constraints on α_i now become:

$$0 \leq \alpha_i \leq C_+ \text{ for } \; y_i = +1 \qquad (3.2.19)$$

$$0 \leq \alpha_i \leq C_- \text{ for } \; y_i = -1$$

For a non-linearly separable classification problem we have first to map the data onto a higher dimensional (possibly infinite) feature space where the data are linearly separable. Accordingly, the Lagrangian of the dual optimization problem (3.2.11) must be changed to

$$\sum_{i=1}^{L} \alpha_i - \frac{1}{2} \sum_{i=1}^{L} \sum_{j=1}^{L} \alpha_i \alpha_j y_i y_j \phi(x_i) \cdot \phi(x_j) \qquad (3.2.20)$$

Notice the input vectors are involved in the expression through a kernel function

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j), \qquad (3.2.21)$$

which can be thought as a non-linear similarity measure between two datapoints. According to the Mercer's theorem [GR79], any (semi) positive definite symmetric function can be regarded as a kernel function, that is, as a dot product in some space, so we will look for (semi) positive definite symmetric functions that imply a data transformation to a new space where the classes can be linearly separated. Note that there is no need to know the mapping function ϕ explicitly, but only the kernel $K(x_i, x_j)$.

The most often used kernel functions in SVM applications are the following two:

$$\text{Radial Basis Function (RBF): } K(x_i, x_j) = e^{-|x_i - x_j|^2 / 2\sigma} \qquad (3.2.22)$$

$$\text{Polynomial: } K(x_i, x_j) = (x_i \cdot x_j)^d \qquad (3.2.23)$$

Thus, from equation (3.2.17) and the kernel concept, it follows that the two-class classification process with a SVM consists of assigning a positive/negative label to each input vector *x* through the following equation:

$$y(x) = \text{sgn}(\sum_{j=1}^{M} \alpha_j y_j K(x, x_j) + b) \tag{3.2.24}$$

being *M* the number of support vectors.

3.2.3 Generalization error and SVM

As it was said in the previous subsection the SVM problem is to find a hyperplane that separates the data. It is obvious that the problem is ill-posed as many of such hyperplanes exist. As a criterion of optimality, the hyperplane that gives the maximal margin to the nearest datapoints is chosen. Here we will shortly summarize how that maximal margin principle that is used in SVM is connected to SRM and thus to the generalization problem.

Consider a same set of training data vectors $X = \{x_1,...x_L\}$, $x_i \in \Re^n$ and a set of corresponding labels $Y = \{y_1,...y_L\}$, $y_i \in \{1,-1\}$. Further, assume that the samples are all drawn i.i.d. (independent and identically distributed) from an unknown but fixed probability distribution *P(x, y)*. If a unit loss is defined for a misclassified point, and a zero loss for a correctly-classified point, we can define the empirical risk as a measure of average absolute error (L_1 norm) on the training data:

$$R_{emp}(\theta) = \frac{1}{m} \sum_{i=1}^{m} |(f(x_i, \theta) - y_i)| \tag{3.2.25}$$

where the $f(x_i, \theta)$ is the class label predicted for the *i-th* training sample by the machine learning algorithm which may be parameterized by a set of adjustable parameters denoted by θ. It is clear that different values of θ generate different learning functions *f.* The empirical risk minimization (ERM) principle is widely used in current learning algorithms. The least squares method in the problem of regression estimation or the maximum likelihood method in the problem of density estimation are realizations of the ERM principle for specific loss functions [Vap99].

The danger for the researcher that arises from using the ERM principle is that $R_{emp}(\theta)$ can be as low as desired for the arbitrarily-chosen parameters θ of the function *f.* Let's assume a learning algorithm that can memorize all training points. Obviously, it will obtain 0% error on training data but will not *generalize* on test data. The *actual risk*, also called generalization error, which is the mean of the error rate on the unknown entire distribution *P(x, y)* can be found by integrating over the entire distribution, that is:

$$R_{actual}(\theta) = \int (f(x_i, \theta) - y_i) dP(x, y) \qquad (3.2.26)$$

Although the law of large number [SS02] states that with $m \to \infty$

$$R_{emp} \to R_{actual} \qquad (3.2.27)$$

it does not imply the optimal results in the limit of the infinite sample size as the law of large numbers is not uniform over the whole set of functions *f* that the learning machine can implement [Vap99].

Statistical learning theory or Vapnik – Chervonenkis (VC) theory shows that it is imperative to restrict the set of functions from which *f* is chosen to one that has a *capacity* suitable for the amount of training data. By capacity the authors (V.C.) mean an index or a number that measures the flexibility that a function has. For example, intuitively, a quadratic function is more flexible than a linear function; therefore it should have a higher capacity. The best-known capacity concept from VC theory is the VC dimension. It was introduced in [VC71] to measure the capacity of a hypothesis space. The *m* datapoints can be labelled in 2^m different ways as positives or negatives. It means that 2^m learning problems can be defined. If for any *i-th* problem we can find a hypothesis H_i that separates the positive examples from the negative, *H* is said to *shatter* (separate) *m* datapoints. The maximum number of datapoints that can be shattered by *H* is called the VC dimension of *H* and is

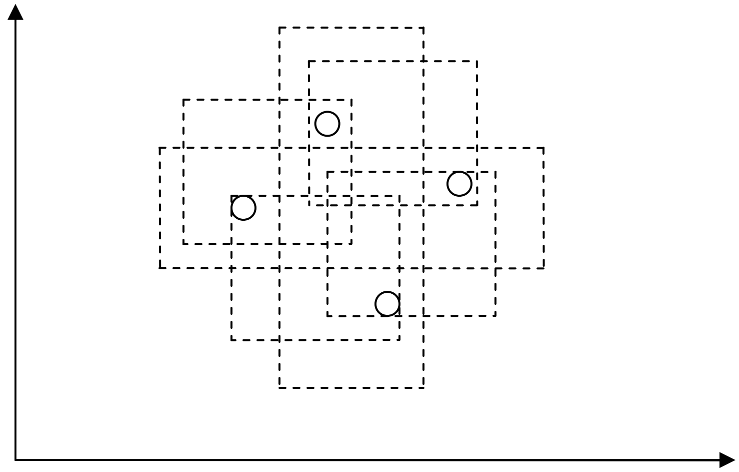


Figure 3.2.2. Four points in two dimensions shattered by axis-aligned rectangles

denoted as *h.* Consider the following example. In Figure 3.2.2 we see how four points in a two-dimensional space can be shattered by an axis-aligned rectangle for any possible labelling of the four points (the trivial cases are not plotted). Thus, the VC dimension of the hypothesis class of axis-aligned rectangles in a two-dimensional space is 4. Note that it is enough that we find a case of four points that can be shattered; it is not necessary that any four points can be shattered. For example, four points placed in a line can not be shattered by rectangles. However, for five points placed *anywhere* in two dimensions we can not find such a set of rectangles that is able to separate the positive and the negative examples for all possible labellings [Alp04].

It was shown in [Vap79] that for a whole set of functions *f* with known VC dimension *h* an upper bound for the value of actual risk given the empirical risk can be derived. For a given $\eta \in (0,1]$, with probability of at least $1-\eta$ the following bound holds:

$$R_{actual}(\theta) \le R_{emp}(\theta) + \sqrt{\frac{h(\ln(2m/h)+1) - \ln(\eta/4)}{m}} \qquad (3.2.28)$$

From [3.2.28] it comes that generalization error relates the number of examples (*m)*, the training set error ($R_{emp}(\theta)$) and the VC dimension *(h)*. The right side of the equation (3.2.28) is called structural risk (or functional risk). The expression (3.2.28) can be understood intuitively as follows. As it was said above, the ERM criterion may lead to overfitting. That is why the second term – capacity – is added. We can expect that the capacity term gets larger if we increase the VC dimension (*h)*, and in the same time the empirical error will decrease. On the other hand the capacity term gets smaller as we increase the number of training datapoints (*m)*, because the learning functions *f* get better constrained by data and in the same time empirical error will increase. Conceptually, the expression (3.2.28) is shown in Figure 3.2.3.

Recall from the previous subsection that one of the optimization criteria of SVM is to maximize the margin by minimizing its norm ||w||:

$$\Delta = \frac{2}{\|w\|} \qquad (3.2.29)$$

One can show [SS02] that the VC dimension *h* is bounded:

$$h < \frac{r^2}{\Delta^2} + 1 \qquad (3.2.30)$$

where *r* indicates the radius of the minimal sphere containing all datapoints. It is obvious from (3.2.30) that maximizing the margin we minimize the VC dimension *h* and thus the capacity term of

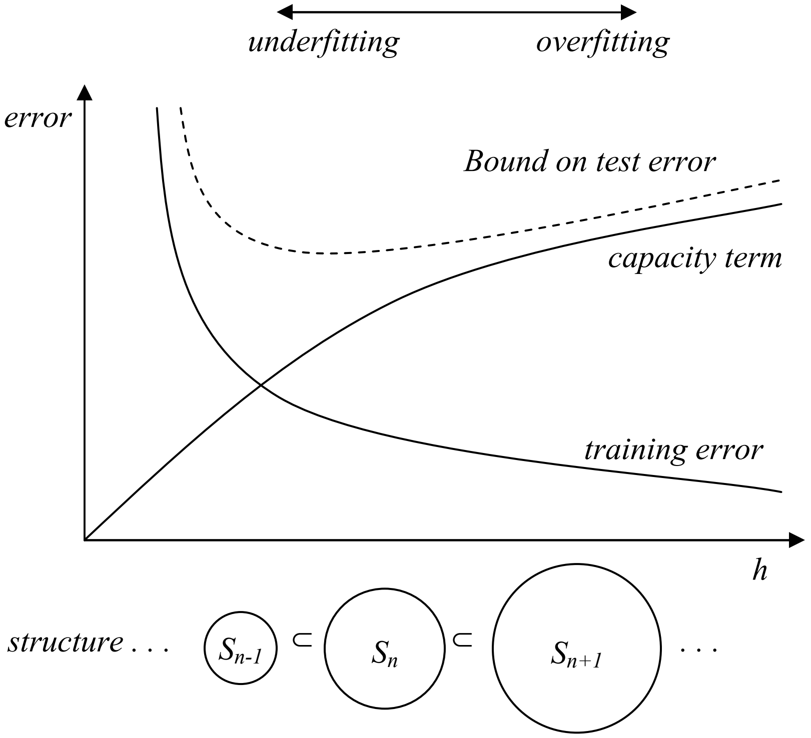


Figure 3.2.3. Graphical depiction of the SRM principle. A set of functions f are decomposed into a nested sequence of subsets S of increasing size and capacity.

the expression (3.2.28). Now the equation (3.2.5) can be reformulated as: to minimize the capacity term of the expression (3.2.28) with the restriction to correctly classify all datapoints. It justifies that the hyperplane with the largest margin of separation is the optimal hyperplane in the framework of the VC-dimension-based risk bounds [Zha01].

3.2.4 Summary on SVM

The key advantages of SVM can be outlined in the following way:

- The control on capacity is obtained by maximizing the margin inspired by SRM.
- The absence of local minima that comes from convexity [Ber90] of the quadratic optimization problem.
- The dual formulation that enables the usage of kernels. The kernel function represents a computational shortcut because we never explicitly have to evaluate the feature map in the high dimensional feature space. The number of operations required is not necessarily proportional to the number of features. The kernel defines a similarity measure between two datapoints and thus allows us to incorporate our prior knowledge of the problem.

- The sparseness of the solution. Only a small part of data is preserved.

The main disadvantages are:

- The choice of the kernel is crucial for the success of all kernel algorithms because the kernel constitutes prior knowledge that is available about a task.
- The selection of the kernel function parameters and the parameter C that controls slack variables.
- Both training and testing speed and size of the high algorithmic complexity and extensive memory requirements of the required quadratic programming in large-scale tasks.
- The disability of SVM to deal with non-static data (dynamic data, sequences)
- A lack of optimal design for multiclass SVM classifiers.

3.3 Gaussian Mixture Models

Gaussian mixture models are quite popular in speech and speaker recognition. In the design step, we have to find the probability density functions that most likely have generated the training patterns of each of the classes, assuming that they can be modelled by mixtures of Gaussians.

In the GMM, the likelihood function is defined as

$$p(x) = \sum_{i=1}^{P} w_i N(x;\mu_i,\Sigma_i) \qquad (3.3.1)$$

where P is the number of Gaussians, the weights w_i verify

$$\sum_{i=1}^{P} w_i = 1 \text{ and } w_i \geq 0, \forall i \qquad (3.3.2)$$

and $N(x;\mu,\Sigma)$ denotes the multivariate Gaussian distribution

$$N(x;\mu,\Sigma) = \frac{1}{(2\pi)^{\frac{|x|}{2}}\sqrt{|\Sigma|}} \exp\left(-\frac{1}{2}(x-\mu)^{\mathrm{T}}\Sigma^{-1}(x-\mu)\right) \qquad (3.3.3)$$

being μ the mean vector and Σ the covariance matrix (often considered diagonal). As the goal is to maximize the likelihood (ML), the parameters of the GMM ($w_i, \mu_i, \text{and}\, \Sigma_i$) are obtained via the Expectation-Maximization (EM) algorithm [RJ93]. Unlike SVM, which is a two-class classifier, GMM-based classifiers can handle an arbitrary number of classes. The GMM-ML classifier belongs to the group of generative classifiers, unlike SVM, which is a discriminative classifier. Due to this different approach, GMM generally needs a larger training set than SVM and so it is usually considered more complex [DHS00].

3.4 Fuzzy Integral and Fuzzy Measure

We are searching for a suitable fusion operator to combine a finite set of information sources $Z = \{1,...,z\}$. Let $D = \{D_1, D_2,..., D_z\}$ be a set of trained classification systems and $\Omega = \{c_1, c_2,..., c_N\}$ be a set of class labels. Each classification system takes as input a datapoint $x \in \Re^n$ and assigns it to a class label from Ω.

Alternatively, each classifier output can be formed as an *N*-dimensional vector that represents the degree of support of a classification system to each of *N* classes. It is convenient to organize the output of all classification systems in a Decision Profile (DP) [Kun04]:

$$DP(x) = \begin{bmatrix} d_{1,1}(x)... d_{1,n}(x)... d_{1,N}(x) \\ ... \\ d_{j,1}(x)... d_{j,n}(x)... d_{j,N}(x) \\ ... \\ d_{z,1}(x)... d_{z,n}(x)... d_{z,N}(x) \end{bmatrix}$$

where a row is classifier output and a column is a support of all classifiers for a class. We suppose these classifier outputs are commensurable, i.e. defined on the same measurement scale (most often they are posterior probability-like).

Let's denote *h_i*, *i=1,..,z,* the output scores of *z* classification systems for the class c_n (the supports for class c_n, i.e. a column from DP) and before defining how FI combines information sources, let's look to the conventional WAM fusion operator. A final support measure for the class c_n using WAM can be defined as:

$$M_{WAM} = \sum_{i \in Z} \mu(i) h_i \qquad (3.4.1)$$

where $\sum_{i \in Z} \mu(i) = 1$ (additive), $\mu(i) \geq 0 \; for\, all\, i \in Z$

The WAM operator combines the score of *z* competent information sources through the weights of importance expressed by $\mu(i)$. The main disadvantage of the WAM operator is that it implies preferential independence of the information sources [Mar00].

Let's denote with $\mu(i, j) = \mu(\{i, j\})$ the weight of importance corresponding to the couple of information sources *i* and *j* from Z. If μ values are not additive, i.e. $\mu(i, j) \neq [\mu(i) + \mu(j)]$ for a given couple $\{i, j\} \subseteq Z$, we must take into account some interaction among the information sources. Therefore, we can build an aggregation operator starting from the WAM, adding the term of "second order" that involves the corrective coefficients $\mu(i,j)-[\mu(i)+\mu(j)]$, then the term of "third order", etc. In this way, we arrive to the definition of the FI: assuming the sequence h_i, $i=1,..,z$, is ordered in such a way that $h_1 \le ... \le h_z$, the Choquet *fuzzy integral* [Kun03] [Gra95a] [Gra04] can be computed as

$$M_{FI}(\mu,h)=\sum_{i=1}^{z}[\mu(i,...,z)-\mu(i+1,...,z)]\ h_i \tag{3.4.2}$$

where $\mu(z+1)=\mu(ø)=0$. $\mu(S)$ can be viewed as a weight related to a subset S of the set Z of information sources. It is called *fuzzy measure* and has to meet the following conditions:

$\mu(ø)=0, \mu(Z)=1$, Boundary

$S \subseteq T \Rightarrow \mu(S) \le \mu(T)$, Monotonicity

where S, $T \subseteq Z$.

To illustrate the FI, let us consider a case of two information sources with outputs h_1 and h_2, and assume that $h_1<h_2$. Consequently, we have corrective coefficients of the second order only: $\mu(1,2)-[\mu(1)+\mu(2)]$. According to (3.4.2), FI is computed as

$$M_{FI}(\mu,h)=[\mu(1,2)-\mu(2)]\ h_1+\mu(2)\ h_2 \tag{3.4.3}$$

which, after a slight manipulation, results in

$$M_{FI}(\mu,h)=[\mu(1,2)-(\mu(2)+\mu(1))]\ h_1+\mu(1)\ h_1+\mu(2)\ h_2 \tag{3.4.4}$$

where the first term corresponds to the "second order" correction mentioned above.

For Z information sources there are a total of 2^Z FM parameters that can be arranged in a lattice with the usual ordering of real numbers [CG03]. The lattice representation shows the monotonicity of the FM and particular values involved in the FI calculation. An example of lattice representation of FM defined for 4 information sources is shown on Figure 3.4.1. The lattice consists of $Z+1$ layers with each node representing a particular subset of Z. Two nodes in adjacent layers are connected only if there are set-inclusion relationships between the two subsets of Z whose measures they represent. The red line on the Figure 3.4.1 shows the values used for the FI calculation given the following ordering of classifiers' scores: $h_1<h_4<h_2<h_3$.

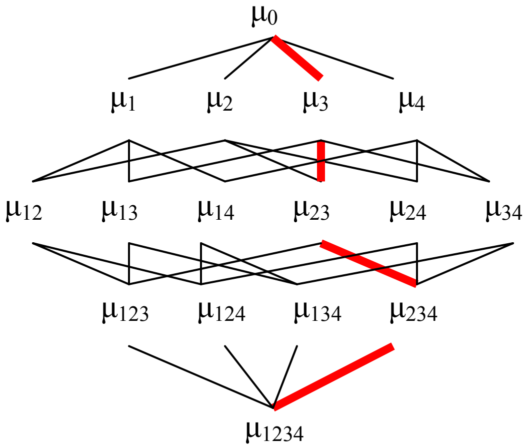


Figure 3.4.1. Lattice representation of fuzzy measure for 4 information sources.

Indeed, the large flexibility of the FI aggregation operator is due to the use of FM that can model interaction among criteria. And although the FM $\mu(i)$ provides an initial view about the importance of information source *i*, all possible subsets of *Z* that include that information source should be analysed to give a final score. For instance, we may have $\mu(i) = 0$, suggesting that element *i*, $i \notin T$, is not important; but if, at the same time, $\mu(T \cup i) >> \mu(T)$, this actually indicates *i* is an important element for the decision. For calculating the *importance* of the information source *i*, the Shapley score [Gra95a] [Mar00] is used. It is defined as:

$$\phi(\mu, i) = \sum_{T \subseteq Z \setminus i} \frac{(|Z| - |T| - 1)!|T|!}{|Z|!}[\mu(T \cup i) - \mu(T)] \qquad (3.4.5)$$

Generally, (3.4.5) calculates a weighted average value of the marginal contribution $\mu(T \cup i) - \mu(T)$ of the element *i* over all possible combinations. It can be easily shown that the information source importance sums to one.

Another interesting concept is interaction among information sources. As long as the FM is not additive, there exists some correlation among information sources. When $\mu(i, j) < \mu(i) + \mu(j)$ the information sources *i* and *j* express negative synergy and can be considered redundant. On the contrary, when $\mu(i, j) > \mu(i) + \mu(j)$, the information sources *i* and *j* are complementary and express positive synergy. For calculating the interaction indices, instead of the marginal contribution of element *i* in (3.4.5), the contribution of a pair of information sources *i* and *j* is defined as the difference between the marginal contribution of the pair and the addition of the two individual marginal contributions [Mar00], or equivalently:

$$(\Delta_{i,j}\mu)(T) = \mu(T \cup i, j) - \mu(T \cup i) - \mu(T \cup j) + \mu(T) \qquad (3.4.6)$$

and the *interaction* indices are calculated as:

$$I(\mu; i, j) = \sum_{T \subseteq Z \backslash i,j} \frac{(|Z| - |T| - 2)!|T|!}{(|Z| - 1)!} (\Delta_{i,j}\mu)(T)] \qquad (3.4.7)$$

We can see the index is positive as long as *i* and *j* are negatively correlated (complementary) and negative when *i* and *j* are positively correlated (competitive).

As was mentioned in [Mar00], FI has very good properties for aggregation: it is continuous, non-decreasing, ranges between a minimum and a maximum value, and coincides with WAM (discrete Lebesgue integral) as long as the FM is additive. Actually, it was shown in [Mar00] that the ordered weighted average, the WAM, and the partial minimum and maximum operators are all particular cases of FI with special FM. In fact, FI can be seen as a compromise between the evidence expressed by the outputs of the classification systems and the competence represented by the FM's knowledge of how the different information sources interact [Kun03].

As the FM is a generalization of a probability measure, we can calculate a measure of uncertainty associated to FM analogously to the way the entropy is computed from the probability [Mar02], that is:

$$H(\mu) = \sum_{i=1}^{z} \sum_{T \subseteq Z \backslash i} \gamma_T \, g[\mu(T \cup i) - \mu(T)] \qquad (3.4.7)$$

where $\gamma_T = (|Z| - |T| - 1)! \, |T|! \; / \; |Z|!$, $g(x) = -x \ln x$, and $0 \ln 0 = 0$ by convention.

When normalized by $\ln|Z|$, $H(\mu)$ measures the extent to which the information sources are being used in calculating the aggregation value of $M_{FI}(\mu, h)$. When that *entropy* measure is close to 1, all criteria are used almost equally; when it is close to 0, the FI concentrates almost on only one criterion [KMR02].

3.5 Chapter Summary

In this chapter the basic theory of 3 techniques, support vector machines, Gaussian mixture models, and fuzzy integral, used in the work, has been given.

Firstly, the construction of SVM classifier has been presented followed by the basic notion of the structural risk minimization theory and its connection to the SVM classifier. The main advantages and disadvantages of SVM have been mentioned and discussed.

The GMM classifier is used in the work mostly for comparison purposes. In this chapter the basis of GMM has been presented and the detailed information has been referenced.

General information on information fusion and the fundamentals of fuzzy integral and fuzzy measure theory has been also given in this chapter. The FI is used to fuse various information sources in order to capture and benefit from the information about importance and interaction among the information sources.

Chapter 4. Acoustic Events Classification

4.1 Chapter Overview

Acoustic events produced in controlled environments may carry information useful for perceptually aware interfaces. In this chapter we focus on the problem of classifying meeting-room acoustic events.

In Section 4.2, we define the features that will be used throughout the work.

Section 4.3 presents 16 types of events and gathered sound database. Then, several classifiers based on Support Vector Machines (SVM) are developed using confusion matrix based clustering schemes to deal with the multi-class problem. Also, several sets of acoustic features are defined and used in the classification tests. In the experiments, the developed SVM-based classifiers are compared with an already reported binary tree scheme and with their correlative Gaussian mixture model (GMM) classifiers.

SVM are discriminant classifiers, but they cannot easily deal with the dynamic time structure of sounds, since they are constrained to work with fixed-length vectors. Several methods that adapt SVM to sequence processing have been reported in the literature. In Section 4.4, they are reviewed and applied to the classification of the 16 types of sounds from the meeting room environment.

Fuzzy Integral (FI) is a meaningful formalism for combining classifier outputs that can capture interactions among the various sources of information. In Section 4.5, fusion of different information sources with the FI, and the associated Fuzzy Measure (FM), is applied to the problem of classifying a small set of highly confusable human non-speech sounds.

4.2 Audio Features

We use the following notation in feature definition:

$s(n)$ – signal value at the time index n;

N – frame length;

$f(i)$, $a(i)$ – frequency value at the frequency bin i and the corresponding Discrete Fourier Transform (DFT) amplitude, respectively;

$x(k)$, $y(k)$ – value of mel-scaled logarithmic filter-bank energy at the sub-band frequency index k corresponding to the current and previous frame, respectively;

The following types of frame-level acoustic features with the number of features per frame in parenthesis are investigated in this thesis:

Zero crossing rate (1). It measures the number of zero crossings of the waveform within a frame and is calculated as:

$$ZCR = \sum_{n=0}^{N-1} I\{s(n)s(n-1) < 0\} \qquad (4.2.1)$$

where the indicator function $I\{A\}$ is 1 if its argument A is true and 0 otherwise.

Short-time energy (1). Total signal energy in a frame calculated as:

$$STE = \sum_{n=0}^{N-1} s(n)s(n) \qquad (4.2.2)$$

Fundamental frequency (1). A simple cepstrum-based method was used to determine the pitch in the range [70, 500] Hz [Nol67]. When the signal is unvoiced, a zero value is used.

Sub-band log energies (4). The 4 sub-bands are equally distributed along the 20 mel-scaled FBEs (5 per sub-band). The energy of each sub-band is calculated as:

$$SBE(j) = \sum_{k=5j}^{5j+N-1} x(k) \quad \text{for } j = 0,...,3 \qquad (4.2.3)$$

where $N=5$ is the number of log FBEs per sub-band.

Sub-band log energy distribution (4). Percentage distribution of the total log frame energy among the above-defined 4 sub-bands.

Sub-band log energy correlations (4). This new type of feature is a measure of correlation of log FBEs between two adjacent frames and within each of the above defined 4 sub-bands. It is computed as the maximum absolute value of the cross-correlation function between the two sequences $x(k)$ and $y(k)$:

$$SBC(j) = \max_{d} \left[abs \left(\frac{\sum_{k=5j}^{5j+N-1} \left[(x(k) - mx(j)) \cdot (y(k-d) - my(j)) \right]}{\sqrt{\sum_{k=5j}^{5j+N-1} (x(k) - mx(j))^2} \sqrt{\sum_{k=5j}^{5j+N-1} (y(k-d) - my(j))^2}} \right) \right] \quad (4.2.4)$$

for $j = 0,...,3$

where $mx(j)$ and $my(j)$ are the means of the corresponding sub-band spectra, $d=0,1...,N-1$ are mel-scaled sub-band frequency delays, and $N=5$ is the number of log FBEs per sub-band.

Sub-band log energy time differences (4). It measures the changes of spectra in time and is calculated as difference of log energies between two adjacent frames for the above defined 4 sub-bands:

$$SBD(j) = \sum_{k=5j}^{5j+N-1} (x(k) - y(k)) \quad \text{for } j = 0,...,3 \qquad (4.2.5)$$

where $N=5$ is the number of log FBEs per sub-band.

Spectral centroid (1). The centroid is a measure of the spectral “brightness” of the spectral frame and is defined as the linear average frequency weighted by DFT amplitudes, divided by the sum of the amplitudes:

$$CE = \frac{\sum_{\forall i} f(i)\, a(i)}{\sum_{\forall i} a(i)} \qquad (4.2.6)$$

Spectral roll-off (1). It is a measure of the skewness of the spectral shape and is defined as a frequency bin f_c below which the c percentage of the spectral amplitudes is concentrated (in our case c=95):

$$\sum_{i=0}^{f_c} a(i) = \frac{c}{100} \sum_{\forall i} a(i) \qquad (4.2.7)$$

Spectral bandwidth (1). A measure of spreading of the spectrum around the spectral centroid:

$$BW = \sqrt{\frac{\sum_{\forall i} (f(i) - CE)^2 a^2(i)}{\sum_{\forall i} a^2(i)}} \qquad (4.2.8)$$

where *CE* is the *spectral centroid* of the frame.

We will call the above-mentioned features as perceptual throughout the work, since it has a more perceptually-oriented profile than the conventional features taken from ASR. The ASR features used in the work are:

Cepstral coefficients (12) - 12 mel-frequency cepstral coefficients (MFCC) are computed for each frame using 20 mel-scaled spectral bands. The zero-th cepstral coefficient was removed, but the frame energy was added to the set.

FF-based spectral parameters (13) - parameters based on filtering the frequency sequence of log FBEs (FFBE) [NHG95] [NMH01]. We have used the usual second-order filter $H(z)=z-z^{-1}$, which implies subtraction of the log FBEs of the two adjacent bands. Before filtering, the sequence of log FBEs along frequency is extended with one zero at each side. In this way, the first and last parameters actually are the energies of the second and the second last sub-bands. That is the reason why the frame energy was not used with these features.

4.3 Classification of Acoustic Events Using SVM-Based Clustering Schemes

4.3.1 Introduction

In this section we focus on acoustic events that may take place in meeting-rooms or classrooms and on the preliminary task of classifying isolated sounds. The number of sounds encountered in such environments may be large, but in this initial work we have chosen 16 different acoustic events, including speech and music, and a database has been defined for training and testing. While in [NNM+03] the authors looked at the problem from the point of view of speech recognition, applying the usual ASR strategy (cepstral features, classifier based on Hidden Markov Models (HMM) and GMM)), in our work we consider, develop and compare several feature sets and classification techniques, aiming at finding the ones which are most appropriate for the problem we are dealing with. In this way, not only the parameters that are used in speech recognition to model the short-time spectral envelope of the signals and its time derivatives are considered, but also other perceptual features which may be more fitted to non-speech sounds. Moreover, HMMs require relatively large amount of data to accurately train the models, something that is not realistic in our task, since there are not many collections of meeting recordings and the number of samples of some type of sounds that can be found in them is small.

Recently, the Support Vector Machine (SVM) paradigm has proved highly successful in a number of classification tasks. As a classifier that discriminates the data by creating boundaries between classes rather than estimating class conditional densities, it may need considerably less data to perform accurate classification. In fact, SVMs have already been used for audio classification [GL03] and segmentation [LLZ03]. In this work we use SVM classifiers and compare them with GMM classifiers.

As SVMs are binary classifiers, some type of strategy must be employed to extend them to the multi-class problem. In [GL03], the authors used the binary tree classification scheme to cope with several classes. That approach requires a relatively high number of classifiers and classification steps, and the number of classes has to be a power of 2 to get the most benefit from the technique. There are other ways of applying SVMs to the multi-class problem; see [HL02] for a comparison of different methods of multi-class SVM classification. In our work, we propose and develop several variants of a tree clustering technique. Relying on a given set of confusion matrices, that technique chooses the most discriminative partition and feature set at each step of classification, and, unlike the binary tree, works for any number of classes.

Comparative tests have been carried out using the two basic classifiers (GMM and SVM) and a number of classification schemes (binary tree and several clustering alternatives). The effects of using two different regularization parameters of the SVM classifiers to compensate data unbalance, and a confusion matrix based modification of those parameters are also investigated in this work.

The section is organized as follows. In Subsection 4.3.2 we present the database of gathered sounds. Subsection 4.3.3 describes the features and explains the construction of feature sets. The classification techniques are overviewed in Subsection 4.3.4. The experiments and a discussion of the results are presented in Subsection 4.3.5. Finally, conclusions are given in Subsection 4.3.6.

4.3.2 Database

The first problem we had to face when trying to develop a system for classifying acoustic events which take place in a meeting-room environment was the lack of data. As mentioned above, there exists a relatively large database of sounds, the RWCP sound scene database, but only a small part of the sounds included in that database can be considered as usual or at least possible in a meeting room.

The second column of Table 4.3.1 shows the sixteen categories of sounds that were chosen. As can be seen in the third column, only four of them belong to the RWCP database. The other sounds

Table 4.3.1. The sixteen acoustical events considered in our database, including number of samples and their sources (I means Internet)

	Event	Source	Number
1	Chair moving	I	12
2	Clapping	RWCP + I	100+7
3	Cough	I	47
4	Door slam	I	80
5	Keyboard	I	45
6	Laughter	I	26
7	Music	I	38
8	Paper crumple	RWCP	100
9	Paper tear	RWCP	100
10	Pen/pencil handwriting	I	30
11	Liquid pouring	I	40
12	Puncher/Stapler	RWCP	200
13	Sneeze	I	40
14	Sniffing	I	13
15	Speech	ShATR	52
16	Yawn	I	12

have been found in a large number of websites, except the speech sounds, which were taken from the ShATR Multiple Simultaneous Speaker Corpus [ShA] and include short fragments from both close-talk and omnidirectional microphones. The number of samples is 100 or larger for the sounds taken from the RWCP database, but it is much smaller for a few classes. As shown in the fourth column of Table 4.3.1, chair moving and yawn events have only 12 samples in the database. The whole database amounts 53 min of audio (942 files).

Indeed both the diversity in the number of samples per class and the small number of samples for some sounds are a challenge for the classifier. And, the fact that sounds were taken from different sources makes the task even more complicated due to the presence of several (at times even unknown) environments and recording conditions.

4.3.3 Features extraction

The signals from all the sounds in the database presented above were downsampled to 8kHz, normalized to be in the range [-1 1], and partitioned in frames using: frame length=128, overlapping of 50%, and a Hamming window. The silence portions of the signals were removed using an energy threshold.

Three basic types of acoustic feature were considered in this work. Two of them are spectrum envelope representations used in speech/speaker recognition, namely the typical MFCC plus the frame energy [RJ93], and the recently introduced FFBE [NHG95]. Like in speech recognition, they will be considered either alone or together with their first and second time derivatives (the so-called delta and delta-delta features) [RJ93]. We consider both types of features because we want to compare their discriminative capability in this application. The third type of features is a small set which includes perceptual features which are not considered in the above feature sets and may be more adequate for some kind of sounds (fundamental frequency and zero crossing rate), and also a reduced representation of the spectral envelope and its time evolution.

Thus, the acoustic features considered in this work are defined in the following way:

1. Perceptual features

- Short time signal energy
- Sub-band energies
- Spectral flux
- Zero-crossing rate
- Fundamental frequency

2. Cepstral coefficients

3. FF-based spectral parameters

The three above defined types of acoustic features were combined to build the 9 different feature sets shown in Table 4.3.2 which are considered in the experiments reported in Subsection 4.3.5. The mean and standard deviation of those features, estimated by averaging over the whole acoustic event signal, were taken for classification, thus forming one final statistical feature vector per audio event with a number of elements which doubles the length of the acoustic feature set.

Table 4.3.2. Feature sets that were used in this work, the way they were constructed from the basic acoustic features, and their size. d and dd denote first and second time derivatives, respectively, E means frame energy, and "+" means concatenation of features.

	Feature set	**Content**	**Size**
1	Perc	Perceptual features	11
2	Ceps+der	E+MFCC+d+dd	39
3	Ceps	E+MFCC	13
4	FF+der	FFBE+d+dd	39
5	FF	FF	13
6	Perc+ceps+der	"Perc"+"Ceps+der"	50
7	Perc+ceps	"Perc" + "Ceps"	24
8	Perc+FF+der	"Perc" + "FF+der"	50
9	Perc+FF	"Perc" + "FF"	24

4.3.4 Classification techniques

Two basic classification techniques are considered in this work: SVM and GMM. The former is based on decision surfaces, and the latter models data with probability distributions.

As SVM is a binary classifier, we cannot employ it directly in our acoustic event classification problem, since we have a set of 16 classes. In the literature, several methods of extending from binary classifiers to multi-class classifiers can be found: *one against all*, *one against one*, DAGSVM, ECOC,… (see [HL02] [RK04] for a comparison). In our experiments, we first use the scheme proposed in [GL03], namely a binary tree with a SVM at each node. A disadvantage of the binary tree approach is that the number of classes has to be a power of two, otherwise the tree is unbalanced and some classes are more likely to be chosen than others. The alternative that is proposed in Subsection 4.3.5 is based on a decision tree that uses a specific feature set at each node, and it is trained with a clustering technique from a given set of confusion matrices. In this way, it uses the most discriminative feature set at each step of classification and works for any number of classes. The effect of a confusion matrix based modification of the generalization parameters C_+ and C_- of the SVM classifier is also presented in Subsection 4.3.5.

4.3.5 Experiments

Several experiments were carried out to assess the classification performance of the selected feature sets and the classification systems, either based on SVM or GMM. To perform the evaluation, the acoustic event samples were randomly permuted within each class and indexed, so odd index numbers were assigned to training and even index numbers to testing. Also, 20 permutations were used in each experiment. Because of unevenness in the number of representatives of the various classes, the overall performance is computed as an average of the individual class performances.

As preliminary tests with the SVM classifier showed a superiority of the Radial Basis Function (RBF) kernel over the polynomial one, only the former was used in the evaluation. There are two main parameters (hyperparameters) that are to be specified using SVMs: σ from the RBF kernel and the regularization parameter C presented in Chapter 3. Regarding the setting of σ, 5-fold cross-validation [Bur98] was applied. After that kernel parameter is found, the whole training set is used again to generate the final classifier.

4.3.5.1 Binary tree scheme

First of all, a binary tree with a SVM at each node was applied to our acoustic event classification problem. Figure 4.3.1 illustrates how the classifier works. In our implementation, the classes in the bottom level are ordered randomly. In [GL03], each SVM was trained using C=200; in our work, we chose C=1, since this value yielded better results in the experiments, a fact that may indicate that our data are more noisy (contains more outliers) than data used in [GL03].

This SVM-based classification system was compared with a GMM classifier. The latter has one model per class and, for every test pattern, the model with maximal likelihood is chosen. Both a fixed and a variable number of Gaussians per class were tried; the best accuracy was achieved by using a variable number that depends on the amount of data per class.

Figure 4.3.2 shows results for both classifiers. The best feature set in combination with the GMM classifier was the set number 9 (Perc + FF), with recognition rate 78,9%, whereas for the SVM classifier was the set number 8 (Perc + FF + der), with 82,9% recognition rate. Note that, in our experiments, the SVM approach shows a higher performance than the GMM one across all types of feature sets.

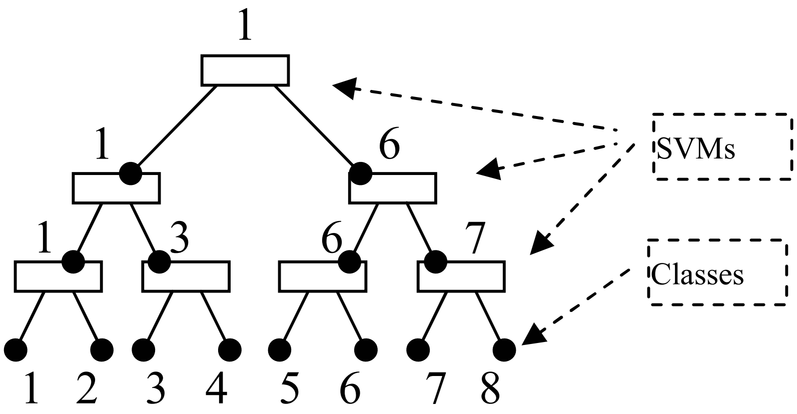


Figure 4.3.1. Binary tree structure for eight classes. Every test pattern enters each binary classifier, and the chosen class is tested in an upper level until the top of the tree is reached. The numbers 1–8 encode the classes. The figure shows a particular example, where class 1 is the class chosen by the classification scheme.

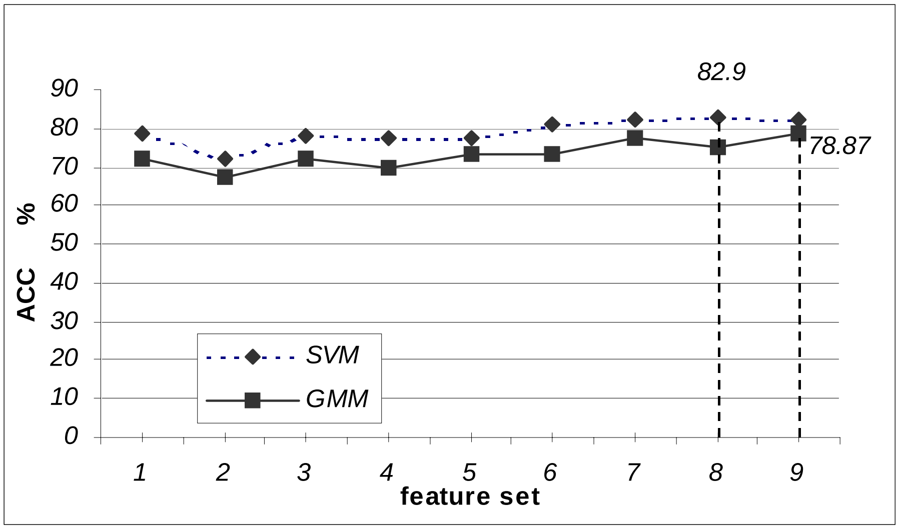


Figure 4.3.2. Percentage of classification rate for the SVM-based binary tree classifier and the GMM classifier on the defined feature sets.

4.3.5.2 Confusion matrix based clustering scheme

We have developed a tree clustering algorithm which makes use of confusion matrices, one for each feature set. They are obtained from the experiments reported in the last section, by averaging over the 20 permutations, and normalizing their elements so that each row adds up 1. Those confusion matrices are used to find the best way of splitting the classes at a given node into two clusters with the least mutual confusion. As we have a relatively small number of classes, we can perform exhaustive search and get the global minimum. For the sake of homogeneity, we use confusion matrices obtained by SVM classifiers for SVM clustering, and GMM matrices for GMM clustering.

As our database contains a large variety of sounds, the feature set that gets the largest classification rate for a given class is not necessarily the best one for a different class. This fact is illustrated in Figure 4.3.3, where the three considered classes (liquid pouring, sneezing and sniffing) show their performance peaks at different feature sets and none of the sets is the 8th, the one that yields the best overall performance. Therefore, it is reasonable to assume that the performance can improve by using a specific feature set to discriminate within each pair of classes or groups of classes.

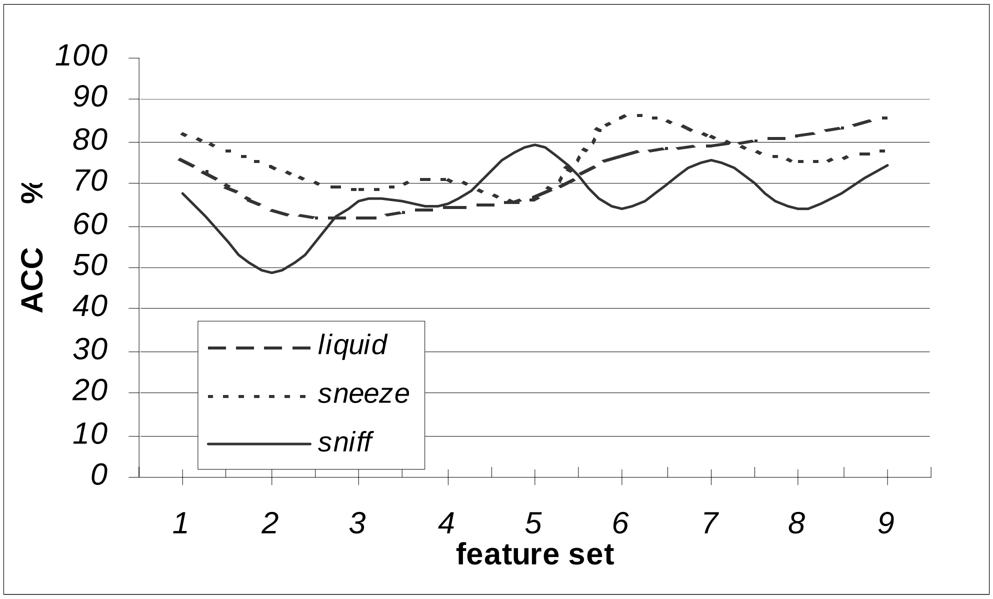


Figure 4.3.3. Dependence of performance of classifying "liquid_pouring", "sneeze" and "sniff" upon the feature sets using SVMs.

The clustering algorithm that selects a specific feature set for each tree node will be presented in the next section. The simpler case that uses the same feature set at every node is also considered in the experiments. We refer to them, respectively, as variable-feature-set and fixed-feature-set clustering schemes. In the following, we will present the former clustering algorithm since the latter is a particular case of it.

The variable-feature-set clustering algorithm

The algorithm for clustering with a variable-feature-set approach is formally described in Figure 4.3.4. At the first step, all possible combinations of grouping 16 classes into two clusters (i.e. grouping 6 and 10, 8 and 8, etc) are searched over the available 9 confusions matrices that corre-

```
1. Initialize $N$=16.

2. For $n$=1…$N$/2
   a. Determine $M$ combinations of grouping $N$ classes into two clusters $C_1$ and $C_2$ containing $n$ and $N$-$n$ classes, respectively.
   b. For $m$=1…$M$
      i. Having the $m$-th grouping combination, look up at each confusion matrix and measure how much are $C_1$ and $C_2$ confused for each feature set $k$, by computing
         $S_k^{n,m} = \frac{1}{|C_1||C_2|}\sum_{i=1}^{|C_1|}\sum_{j=1}^{|C_2|}\left(\frac{e_{ij}^k}{e_{ii}^k}+\frac{e_{ji}^k}{e_{jj}^k}\right)$
         where $e_{ij}^k$ denotes the $i,j$-th element of the $k$-th confusion matrix, and |C$_1$| and |C$_2$| are the  number of classes (cardinalities) of the two clusters.
      ii. Find the minimum confusion measure over all feature sets
         $B_{n,m} = \min_k (S_{\mathrm{k}}^{\mathrm{n,m}})$
   c. Find the minimum confusion measure over all grouping combinations for the current number of classes at each cluster
      $T_n = \min_m (\mathrm{B}_{\mathrm{n,m}})$

3. Find the minimum confusion measure over all possible numbers of classes at each cluster
   $R = \min_n (T_n)$

4. Repeat steps 2-3 for each node of growing tree, initializing $N$ with $N$-$n$ for the right branch and $N$ with $n$ for the left one, until $N$=1 is reached.
```

Figure 4.3.4. Clustering algorithm based on an exhaustive search and using a set of estimated confusion matrices.

spond to the 9 considered feature sets. For example, for the SVM clustering, we found that the 16 classes were best separated choosing the clusters C$_1$={9} and C$_2$={1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16}, and the 6th feature set. That process is carried out until we have single event clusters. Note in the expression of $S_k^{n,m}$ from Figure 4.3.4 that the confusion measures e_{ij}^k are normalized by the corresponding accuracies e_{ii}^k to cope with the dispersion of performance rates among the classes. Regarding the GMM classifier, the algorithm also groups the classes into two clusters, but in this case two models are generated at each step, one for each cluster.

The above clustering technique is intended for a relatively small number of classes, as in our acoustic event classification task. When the number of classes is large either agglomerative hierarchical clustering or divisive hierarchical clustering [Voo86] can be used if they are modified to handle several feature sets while searching; however, they do not guarantee to reach the global minimum.

Dealing with the data unbalance problem

In our experiments, we have tried several ways of alleviating the problem of having a too much different amount of training data between the two clusters at a given tree node. A straightforward way of tackling that problem which has been considered in the experiments consists of restricting the exhaustive search in Figure 4.3.4 to look for an equal number of classes at each cluster, i.e. having only the index value n=N/2 at step 2 of the algorithm. That solution is no longer optimal in terms of the tree structure, but the involved SVMs will work with more balanced data. Hereafter, we will refer to it as *restricted clustering*. Figure 4.3.5 shows the trees obtained by the normal (unrestricted) and restricted clustering algorithms in the SVM case. Note that the two trees show a very different structure, but they have the same number of nodes (N-1), that is the same number of trained SVM classifiers. Indeed, the restricted tree shows a balanced structure, whereas, as it can be observed in Figure 4.3.5, in the normal clustering case we mostly have only one class separated on each clustering step. Actually, there is only one case where there are two classes grouped in the smaller cluster, which corresponds to classes 11 and 12. We have observed that the amount of confusions between both classes is a large portion of the total error for class 11. Regarding the GMM-based techniques, since each class model is trained without using information about the other classes it is not so much influenced by the problem of data unbalance. However, we will also consider both clustering schemes for the GMM case. The resulting schemes are similar to those in Figure 4.3.5.

The alternative way of coping with data unbalance used in our experiments (already mentioned in Subsection 3.2.2) is to introduce different regularization parameters for positively- and negatively-labelled training samples. Additionally, since a measure of confusions at each tree node can be obtained as a byproduct of the clustering algorithm, we have used these estimated measures to adapt the regularization parameters. The greater the confusion is, the larger the error should be allowed during training, and so the smaller the regularization parameters should be. Consequently, we force those parameters to be inversely proportional to the confusion measures. Indeed, we have a ∞ value at the beginning for normal clustering since the confusion at this step is 0. Note from

Figure 4.3.4 that if the performance of a class for a given feature set were 0 ($e_{ii}^{k} = 0$), the value of $S_{k}^{n,m}$ would be ∞. In order to decrease the contribution of that possible zeroth performance of a class to the computation of the confusion measures of the whole cluster, we substitute zero by a small value. In our algorithm, we use 0.001.

Three different methods of using and computing the regularization parameters in the SVM-based classifiers are considered in this work, along with the baseline method that uses only a constant parameter *C*=*K*. They are defined in the following, denoting by S_n the confusion measure at the *n-th* classification step:

1) Only one regularization parameter *C* computed as

$$C = K\frac{1}{S_n}. \qquad (4.3.1)$$

2) Two different parameters C_+ and C_-, defined such that

$$C_+ = K\frac{A_-}{A_+}\ C_- = K\frac{A_+}{A_-} \qquad (4.3.2)$$

where A_+ and A_- are the number of positive and negative training samples, respectively. In this way, the training errors of the two classes contribute equally to the cost of misclassification.

3) The effect of doing both adaptations simultaneously, namely,

$$C_+ = K\frac{A_-}{A_+}\frac{1}{S_n}, \quad C_- = K\frac{A_+}{A_-}\frac{1}{S_n} \qquad (4.3.3)$$

In our tests, *K* was set to value 10 since it gave the best performance for the baseline method with constant *C*.

4.3.5.3 Results and discussion

Table 4.3.3 shows classification performance for GMM and SVM classifiers using either a variable- or a fixed-feature-set approach, and either normal (N) or restricted (R) clustering. The table also shows the standard deviation for each experiment, estimated over the 20 repetitions. The first column of results corresponds to *C*=*K*=10, and the other 3 columns correspond, respectively, to the three above-mentioned methods of computing the regularization parameters in the SVM cases. Note that SVM performs consistently better than GMM, and with SVM the highest accuracies are obtained using the third method.

The column *C*=*K* in Table 4.3.3 shows that, without any adaptation, SVM-based restricted clustering performs equally well as normal clustering (and better than the binary tree scheme). In that table, we can notice that SVM-N takes advantage of using different *C* values for each class according to the simple equation of proportionality, since the training set sizes are largely spread across classes in our database. And SVM-R does not take any advantage due presumably to the balancing average implied by the half-to-half constraint. Additionally, as we can see from Table 4.3.3, introducing prior knowledge (about confusions) with the generalization parameter *C* (method 1) does not have a positive influence on the classification performance, while introducing it along with different *C* values for positive and negative classes (method 3) leads to an improvement for both types of clustering trees. The gain in performance, however, is not much significant, so there is a need to have a more sophisticated algorithm of introducing prior knowledge about confusions in the regularization parameters. In restricted clustering we can obtain only the global minimum of error within the constraint that is why the final performance of the SVM-R technique is worse than that of the normal one (Table 4.3.3, method 3). We can also observe that normal clustering seems to perform slightly better than restricted clustering for GMM.

Notice in Table 4.3.3 how the results for SVM fixed-feature-set clustering show just a slightly worse performance with respect to the variable-feature-set ones. This can be explained in the following way. On the one hand, for fixed-feature-set clustering, the chosen feature set is the one which yielded the best results in the previous experiments with binary tree, i.e. the 8th, which includes all kind of features: perceptual, envelope representation and time derivatives. On the other hand, the SVM classifier has somehow a built-in feature selection process. In fact, as it implicitly works with features in a transformed domain, if the kernel and the hyperparameters are appropriately chosen (so that good results are obtained), its transformation may imply emphasizing those features that are crucial for a good classification. That is why for the SVM classifier no feature selection technique leads to a huge classification improvement [WMC+00]. Moreover, using real-world data, it was shown in [WMC+00] that the best feature set was the one that included all types of features. Additional evidence from our experiments is given by the fact that the difference in performance between fixed- and variable-feature-set is more noticeable for the GMM classifiers than for the SVM ones. Nevertheless, in spite of that kind of "implicit feature selection" process in SVM classifiers, and the fact that a fixed-feature-set scheme requires less computation, the variable-feature-set scheme may still be advantageous for the SVM case. In fact, apart from offering some information about the acoustical properties of the chosen classes, the variable-feature-set scheme

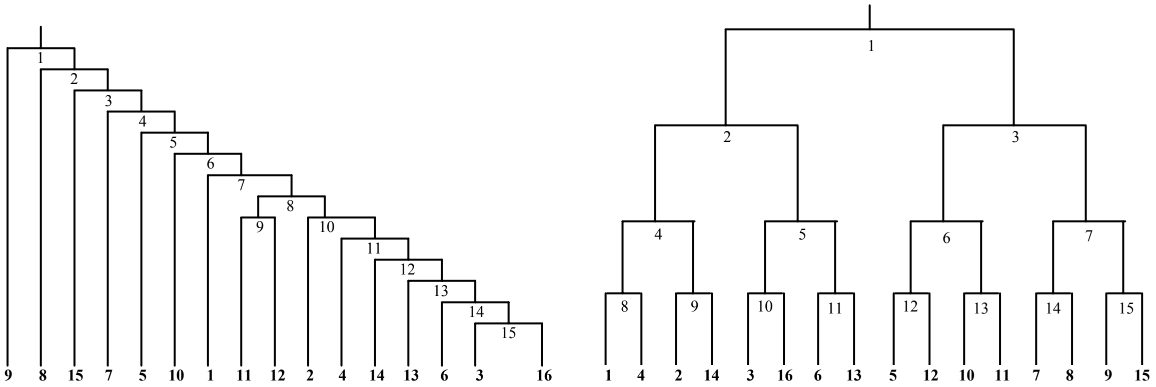


Figure 4.3.5. Normal and restricted clustering schemes for SVM classifiers

Table 4.3.3. Performances of variable-feature-set and fixed-feature-set classifiers using different adaptations of the regularization parameters for the SVM classifiers. -N and -R, denote normal and restricted clustering scheme, respectively. Standard deviations estimated over 20 repetitions are denoted with ± σ.

	C=K	**Method 1**	**Method 2**	**Method 3**
SVM-N variable	84.67 ± 2.5	84.05 ± 1.7	86.71 ± 1.4	88.29 ± 2.1
SVM-R variable	84.72 ± 2.6	84.88 ± 2.7	84.95 ± 2.2	87.20 ± 1.5
GMM-N variable		83.6 ± 2.2		
GMM-R variable		82.15 ± 2.3		
SVM-N fixed	84.6 ± 1.9	84.4 ± 1.6	86.6 ± 3.0	87.10 ± 1.8
SVM-R fixed	84.6 ± 2.7	83.8 ± 1.2	84.4 ± 2.3	87.06 ± 1.8
GMM-N fixed		81.2 ± 2.3		
GMM-R fixed		80.7 ± 2.4		

Table 4.3.4. Confusion measure S_n (multiplied by 100), best separating feature set, and percentage distribution of the classification error (for the best results in Table 4.3.3) along the 15 nodes (depicted in Figure 4.3.5 for SVM) for both normal and restricted clustering, and for the variable-features-set SVM classifier and the GMM classifier.

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
SVM-N	*Confusion*	*0*	*0.01*	*0.03*	*0.07*	*0.78*	*0.82*	*0.83*	*0.98*	3.90	1.27	1.57	2.57	8.44	**15.00**	**46.88**
	Features	*6*	*3*	*6*	*7*	*7*	*8*	*3*	*7*	5	9	5	3	6	**4**	**9**
	Error	0.78	1.97	0	0	7.65	15.42	2.19	6.30	4.47	4.38	6.64	19.63	18.93	6.23	5.39
SVM-R	*Confusion*	*0.41*	2.15	*0.04*	*0.15*	**15.74**	1.74	*0*	*0*	4.41	**46.88**	2.23	3.31	*0*	*0*	*0*
	Features	*7*	9	*7*	*8*	**6**	9	*6*	*5*	5	**4**	8	8	*3*	*1*	*1*
	Error	23.59	12.35	1.14	0.69	23.1	6.01	0.46	9.12	5.32	4.76	6.51	1.29	3.95	1.20	0.53
GMM-N	*Confusion*	*0.01*	*0.1*	*0.18*	*0.22*	*0.28*	*0.74*	1.10	1.14	2.41	3.77	3.00	7.55	**13.76**	**29.86**	**55.07**
	Features	*6*	*9*	*9*	*3*	*7*	*7*	9	5	9	4	5	7	**1**	**6**	**1**
	Error	0.07	1.00	3.46	2.91	2.19	6.55	6.89	5.94	8.33	10.63	6.11	5.28	14.61	14.60	11.42
GMM-R	*Confusion*	*0.53*	5.59	*0.10*	**15.60**	1.92	*0.58*	*0*	**12.03**	**55.07**	*0.81*	6.84	*0.77*	*0.92*	*0*	*0.1*
	Features	*9*	6	*7*	**6**	8	*3*	*1*	**1**	**1**	*5*	5	*7*	*7*	*1*	*6*
	Error	25.35	24.27	3.27	15.43	3.23	3.18	0	3.18	9.50	2.63	7.18	0.51	1.83	0.38	0.07

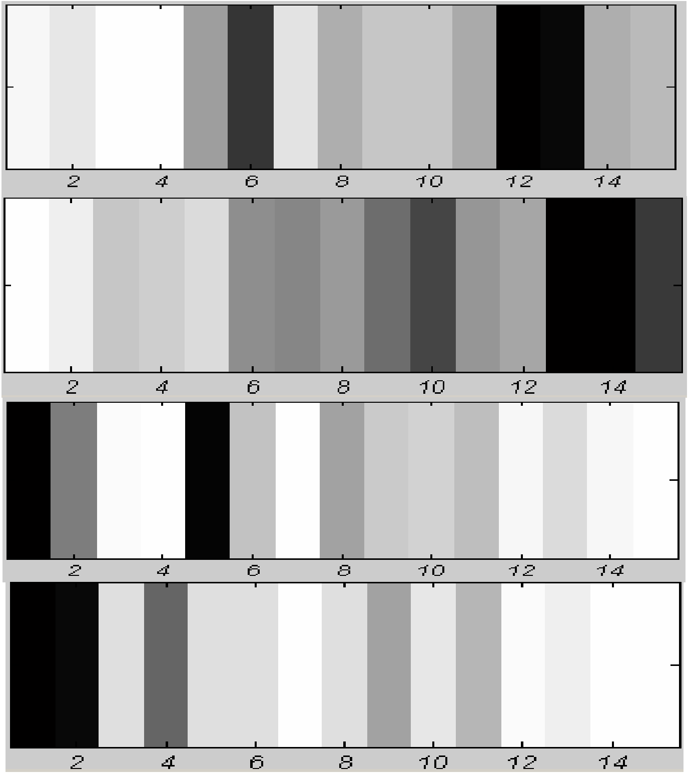


Figure 4.3.6. Distribution of the errors along the tree path for SVM-N, GMM-N, SVM-R and GMM-R. A darker cell means a larger error.

obviously shows a smaller restriction bias than that of the fixed-feature-set clustering, thus resulting in a smaller inductive bias and a presumable higher overall accuracy [LYC02].

The proposed clustering schemes (both normal and restricted) show two computational advantages in front of the binary tree classifier. First, the required number of trained SVM is *N*-1, where *N* is the number of classes, while for the binary tree (*N*-1)*N*/2 trained SVM are needed. Second, the proposed schemes involve a smaller number of classification steps, 4 for restricted clustering, and between 1 and 14, depending on the input pattern, for normal clustering in our case (see Figure 4.3.5), whereas the binary tree requires 15. However, the proposed variable-feature-set scheme has an obvious disadvantage: with our choice of feature sets (see Table 4.3.2) up to 9 feature sets can be involved in testing, 7 in our case (numbers 3 4 5 6 7 8 9).

From Table 4.3.4 we can extract some observations concerning the feature sets. Looking at bold numbers in the SVM case of Table 4.3.4, which correspond to a confusion measure larger than 10, it seems that the best separating feature sets for the most confused classes mostly are FFBE-based features (sets 4,5,8,9), while observing the italic numbers, which correspond to a confusion measure smaller than 1, it appears that the for the least confused classes the best separating feature sets are

MFCC-based (sets 2,3,6,7). This fact may indicate that the FFBE-based features are more discriminative than the MFCC features for highly overlapped data distributions, while MFCC features appear to show the best performance when there is a clearer separation between classes. However, for the most confused classes in the GMM case (see bold numbers in the GMM part of Table 4.3.4) the average best feature set is the one we have called perceptual set. This may be due to the relatively low size of that feature set, which facilitates the estimation problem.

Note in Table 4.3.4 that for normal clustering the largest errors are more located towards the end of the tree path while for restricted clustering they are towards the beginning. This effect, which is also illustrated in Figure 4.3.6, can be expected for the normal clustering technique, due to the way the clustering algorithm in Figure 4.3.4 works. Apparently, the restrictions applied by restricted clustering make the largest errors are placed at the beginning. That information can be useful to improve classification by boosting, since the most erroneous steps generally contain rare class data and boosting the SVM that deal with rare categories has been shown to improve general performance in [LYC02].

Table 4.3.5 shows the confusion matrix corresponding to the best results. The resulting classification rates for the various types of sounds are diverse due to both the acoustic nature of sounds and the unevenness of the number of samples in the database. Notice that the sounds we could name *human vocal-tract non-speech* (HVTNS) sounds (numbers 3, 6, 13, 14, and 16) account for a large relative amount of confusions, since they only are 5/16 of the total number of classes and contribute with 69.7% of the total error. The only other sound with more than 10% error is number 11. In average, the HVTNS classes have a small number of samples in the database, but there are other sounds with similar number of samples (like *chair moving*), which do not show such a high error. Furthermore, the HVTNS sounds are mainly confused among themselves (the average for the 5 classes is 73.96%). Actually, although the proposed clustering schemes are based on acoustic features, some clusters can be interpreted from a semantic point of view, that is according to their source identity; e.g. the shaded cluster in contains “cough”, “laughter”, “sneeze”, and “yawn”, sounds which belong to that HVTNS set.

Table 4.3.5. Confusion matrix corresponding to the best results (88.29 %)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**96.67**	0	0	0	0	1.67	0	0	0	0	0	0	0	0	0	1.67
2	0	**96.79**	0	0.19	0.57	0.19	0	0	0.57	0	0	0.38	1.13	0.19	0	0
3	0	0.43	**88.70**	2.61	0	5.22	0	0	0	0	0	0.43	2.61	0	0	0
4	0	0.75	0.50	**96.50**	0	0.75	0	0	0.50	0	0.50	0	0.50	0	0	0
5	0	0	0	2.27	**87.73**	3.64	0	0	0	0	2.27	3.18	0.91	0	0	0
6	0.77	0	26.92	3.85	0	**48.46**	0	0	0	9.23	0	0	10.00	0.77	0	0
7	0	0	0	0	0	0	**100**	0	0	0	0	0	0	0	0	0
8	0	0.20	0	0.40	0	0	0	**98.8**	0.20	0	0	0.2	0.20	0	0	0
9	0	0	0	0	0	0	0	0.2	**99.80**	0	0	0	0	0	0	0
10	0	0	1.33	1.33	0	3.33	0	0	0	**92.67**	0	0	1.33	0	0	0
11	0	0	0	2.00	1.50	1.00	0	2.5	0	3.50	**77.00**	10.0	2.50	0	0	0
12	0	1.30	0	0	0	0.60	0	0.2	0	0	0.10	**97.2**	0.60	0	0	0
13	0	0.50	14.50	0	0	8.00	0	0	0	0.50	2.50	0	**74**	0	0	0
14	0	5.00	5.00	0	0	0	0	0	0	6.67	0	0	6.67	**76.67**	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**100**	0
16	0	0	11.67	0	0	3.33	0	0	0	1.67	0	0	1.67	0	0	**81.67**

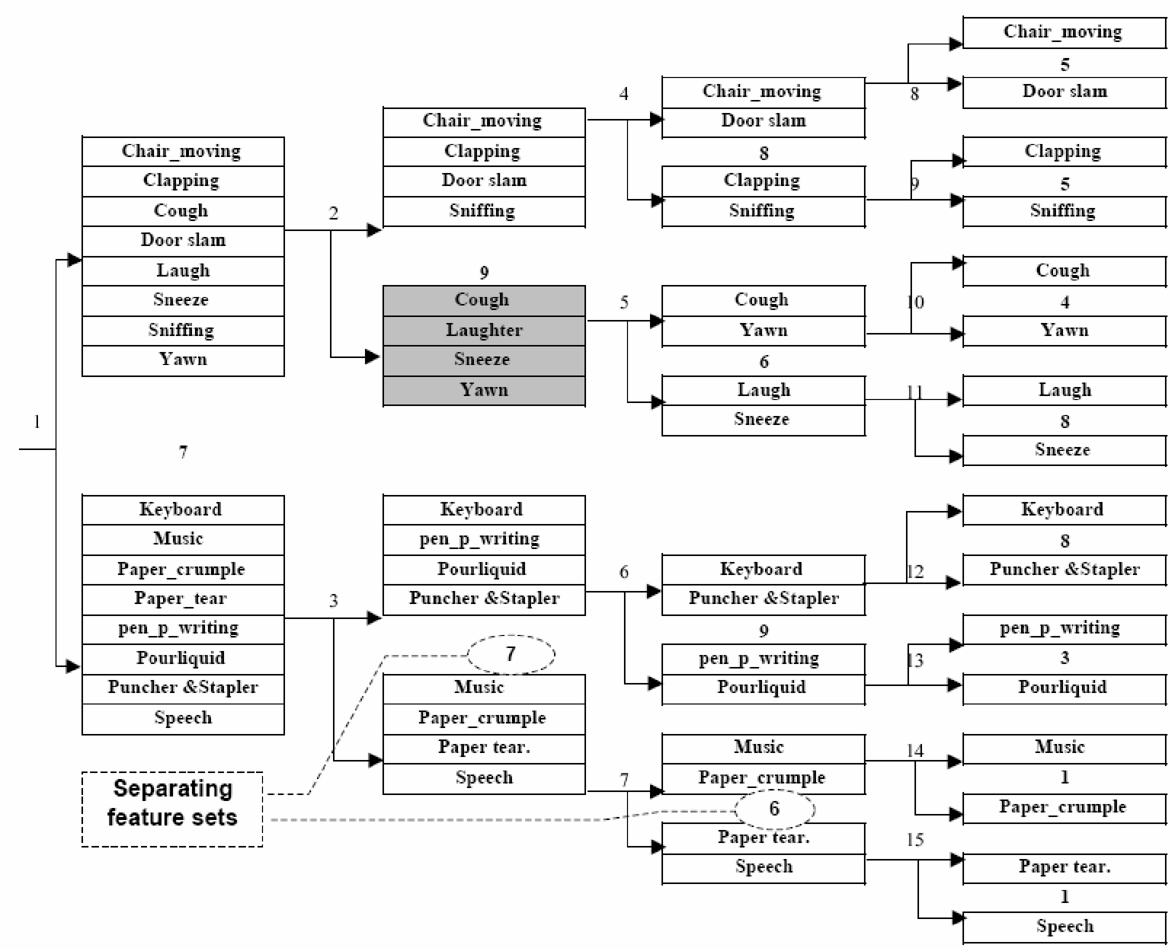


Figure 4.3.7. Restricted clustering tree based on SVM. The numbers in the nodes are the ordinal numbers of the 15 SVM classifiers, and the bold numbers between each pair of clusters denote the best separating feature sets.

4.3.6 Conclusion

The work in the section is a preliminary attempt to deal with the problem of classifying acoustic events that occur in a meeting-room environment. A preliminary small database has been defined, and several feature sets and classification techniques have been tested with it. In our tests, the SVM-based techniques show a higher classification capability than the GMM-based techniques, and the best results were consistently obtained with a confusion matrix based variable-feature-set clustering scheme, arriving with SVM to a 88.29 % classification rate, which implies a 31.5% relative average error reduction with respect to the best result from the conventional binary tree scheme. That good performance is mostly attributable to the presented clustering technique, and to the fact that SVM provides the user with the ability to introduce knowledge about data unbalance and class confusions.

4.4 Comparison of Sequence Discriminant Support Vector Machines for Acoustic Event Classification

4.4.1 Introduction

A drawback of SVMs when dealing with audio data is their restriction to work with fixed-length vectors. Both in the kernel evaluation and in the simple input space dot product, the units under processing are vectors of constant size. However, when working with audio signals, although each signal frame is converted into a feature vector of a given size, the whole acoustic event is represented by a sequence of feature vectors, which shows variable length. In order to apply a SVM to this kind of data, one needs either to somehow normalize the size of the sequence of input space feature vectors or to find a suitable kernel function that can deal with sequential data.

Several methods have been explored to adapt SVMs to sequence processing [Die02]. The most common approach is to extract some statistical parameters from the sequence of vectors and thus transform the problem into that of fixed-length vector spaces. For example, the mean and the standard deviation of the features extracted from every frame of an audio clip were taken as feature vector for audio analysis in [GL03]. Despite the good results we obtained using this approach for acoustic event classification in Section 4.3, when frame-level features are transformed into statistical event-level features there exist an unavoidable loss of information.

In the work reported in this section, we aim at using SVMs for AEC but preserving the information contained in the sequentiality of data, i.e. the temporal structure of the acoustic events. For that purpose, after choosing a set of meaningful reported techniques, we have compared their performance in the framework of our meeting-room AEC task. The fact that the used set of acoustic event types includes time structured sounds (e.g. music) but also sounds whose time evolution is not relevant (e.g. liquid pouring), allows us to investigate the appropriateness of the various techniques to classify the different types of sounds.

While in our previous work we tested several feature sets and several multi-class schemes for SVM, here we use only the best feature set from Section 4.3 and a Directed Acyclic Graph (DAG) [PCS00] classification scheme. Moreover, the influence of the generative model parameters' estimation error on the Fisher score derivative is investigated.

The section is organized as follows: Subsection 4.4.2 quickly reviews the SVM-based methods used in the work, Subsection 4.4.3 presents experimental results and discussions, and Subsection 4.4.4 concludes the work.

4.4.2 SVM-based sequence discriminant techniques

We have chosen three different SVM kernels techniques that make use of dynamic time warping (DTW), namely: dynamic time-alignment kernel (DTAK) [SNN01], Gaussian dynamic time warping (GDTW) kernel [BHB02], and the recent polynomial dynamic time warping kernel (PolyDTW) [WC05]. Additionally, we included in the comparison the Fisher score kernel [JH99] and the Fisher-ratio kernel [WR05] [SG02], which aim at using generative model classifiers like GMM in the discriminative framework, and have been applied for speech/speaker recognition using SVM [WR05] [SG02]. On the other hand, among the algorithms reported in the literature that normalize the size of the vector sequences [ASS04], we have chosen the simple outerproduct of trajectory matrix method, which was the winner in [ASS04]. As references for comparison, we also use a standard GMM classifier, and an SVM classifier with statistical event-level features. Besides, several promising sequential kernels like GMM SuperVector kernel [CSR+06] or Incomplete Cholesky Decomposition Sequence Kernel [LDB06] were not used in the work as they appeared a little after the work was done.

4.4.2.1 Fisher kernel

Fisher kernel is one of the most successful approaches that enable SVM to classify whole sequences. Inspired by using statistical modelling method, Fisher kernel recently has become very popular in the areas that involve time-series recognition. The generalized idea of Fisher kernel the score-space kernel was applied to speech recognition in [SG02]. Modification of likelihood score space kernel (i.e. Fisher kernel) known as likelihood ratio score-space kernel has shown comparative results in the sphere of speaker verification [WR05].

The idea of Fisher kernel includes in mapping the variable length sequence to a single point in fixed-dimension space, the so-called *score-space*. To perform such a mapping, Fisher kernel applies the first derivative operator to the likelihood score of the generative model. Given an input sequence X, and a model M, parameterized by θ, the Fisher score is defined as

$$\psi_{fisher}(X) = \nabla_{\theta} \log P(X|M,\theta) \tag{4.4.1}$$

The Fisher score can be interpreted in the following way. When a generative model is trained by ML (maximum likelihood) criterion, it uses the same set of derivatives to compute how close it is to the local extreme. Another motivation of using Fisher score is that the gradient of the log-likelihood can capture the generative process of the whole sequence better than just a posterior probability. Furthermore, in [JH99] it was shown that, under the condition that the class variable is a latent variable in the probability model, the learning machines, that use Fisher kernel, are asymptotically at least as good as making decision based on the generative model itself (maximum a posteriori). In [JH99] applied to bio-sequences recognition Fisher kernel performed significantly better than HMM.

4.4.2.2 Outerproduct of trajectory matrix

The time analysis of the data gives a sequence of l-dimensional parametric vectors. The sequence is considered as a trajectory in the l-dimensional space. If we define the *l-by-m* trajectory matrix as $X = [x_1, x_2, \ldots x_m]$, the outerproduct matrix Z [ASS04] is defined as

$$Z=X^T X \tag{4.4.2}$$

Thus the outerproduct matrix Z is l-by-l and no longer depends on the length of the sequence. The vectorized outerproduct thus can feed the SVM classifier directly. It is obvious that this method explicitly considers sequence duration information. Despite the simplicity of the given approach, it showed considerably better results than *Compaction and Elongation* method in the task of spoken letters recognition [ASS04].

4.4.2.3 Gaussian dynamic time warping (GDTW)

This approach as well as a previous one does not assume a model for the generative class conditional densities. The GDTW [BHB02] method addresses the problem of variable length sequences classification by introducing the DTW technique to SVM kernel. Recalling the standard RBF kernel for SVM

$$K(T,R)=\exp\left(-\gamma\left\|T-R\right\|^2\right) \tag{4.4.3}$$

where T, R denote two patterns to compare. As mentioned in Subsection 4.4.1, if the two patterns are sequences of different length, they cannot be compared in the kernel evaluation directly. An obvious modification of (4.4.3) is to substitute the squared Euclidian distance computation with the equivalent that can cope with temporally distorted variable length sequences. Thus, in [BHB02] GDTW kernel was defined as

$$K(T,R)=\exp\left(-\gamma D(T,R)\right) \tag{4.4.4}$$

where $D(T,R)$ is a DTW distance between sequences T and R.

The proposed method was successfully applied to handwriting recognition and showed comparative and at times superior results to HMM and MLP in [BHB02].

4.4.2.4 Dynamic time alignment kernel (DTAK)

The approach proposed in [SNN01] also deals with DTW. Instead of substituting the Euclidian distance in Gaussian kernel (4.2.3) by DTW distance, it substitutes the Euclidian distance in definition of DTW local distance by a kernel.

$$K(T,R) = D_\phi(T,R) = \frac{1}{N}\sum_{n=1}^{N} k\left(t_{\phi_T(n)}, r_{\phi_R(n)}\right) \qquad (4.4.5)$$

where *k(.)* is a kernel function that can be either a simple dot product or any conventional SVM kernel and *Φ* is the optimal DTW path. Actually, DTAK performs DTW in the feature space. Unlike the original DTW, which finds the optimal path that minimizes the accumulated distance/distortion, the DTAK algorithm maximizes the similarity. In the task of phoneme recognition, the proposed DTAK method outperformed HMM with a small or medium amount of training data and it got comparable results with a larger dataset [SNN01].

4.4.2.5 Polynomial dynamic time warping (PolyDTW)

The method shares the same idea of performing DTW in transformed feature space. After spherical normalization [WR05] each vector *t* of a sequence is projected onto the sphere surface as

$$\hat{t} = \frac{1}{\sqrt{t^2 + \alpha^2}} \begin{bmatrix} t \\ \alpha \end{bmatrix} \qquad (4.4.6)$$

Then the arcos of the dot product between normalized vectors can be taken as a local distance for DTW. Thus, the kernel is given as

$$K(T,R) = \cos^m\left(\frac{1}{N}\sum_{n=1}^{N} \arccos\left(\hat{t}_{\phi_T(n)} \cdot \hat{r}_{\phi_R(n)}\right)\right) \qquad (4.4.7)$$

This method has been successfully applied to the task with high intra-class variation such as dysarthric speech recognition and showed superior results to HMM [WC05].

4.4.3 Experiments and discussion

4.4.3.1 Experimental setup

Our previous efforts in Section 4.3 were focused on developing a variable-feature-set clustering scheme and using SVM with statistical event-level features. In this work, for simplicity, we use DAG [PCS00] multi-class scheme, and only one feature set, the one that showed best results in Section 4.3, namely, a concatenation of perceptual features (ZCR, Spectral Flux, etc) and frequency filtering features [NHG95] (plus their first and second derivatives). The number of features per frame is 50 and there is a frame each 10ms.

In all the experiments we use the databases of acoustic events described in Subsection 4.3.2. The database contains the 16 classes of meeting-room acoustic events that are summarized in Table 4.3.1.

For the outerproduct, DTAK, and GDTW methods we use a Gaussian kernel, and a 5-fold cross-validation on the training database was applied to find the optimal kernel parameter. The techniques that exploit DTW required some optimization steps to be feasible in practice (beam search strategy, kernel caching). For PolyDTW, a polynomial of third degree was chosen with α=1, as suggested in [WC05]. Also, we chose the linear SVM kernel for the Fisher score and the likelihood ratio methods, since it performed better than RBF.

The mean of individual class accuracies was chosen as a metric as in Section 4.3.

4.4.3.2 Comparison results

Figure 4.4.1 shows the results of the 8 considered techniques when applied to the database of acoustic events. The best average result is obtained with the Fisher kernel, 88.13%, and it is followed by the results from PolyDTW, likelihood ratio kernel and GMM. All mentioned results are better than 83.1%, the score of the non-sequential SVM technique that uses statistical event-level features (SVM stat). A similar result was observed in Section 4.3 using a binary tree instead of a DAG scheme: 82.9%.

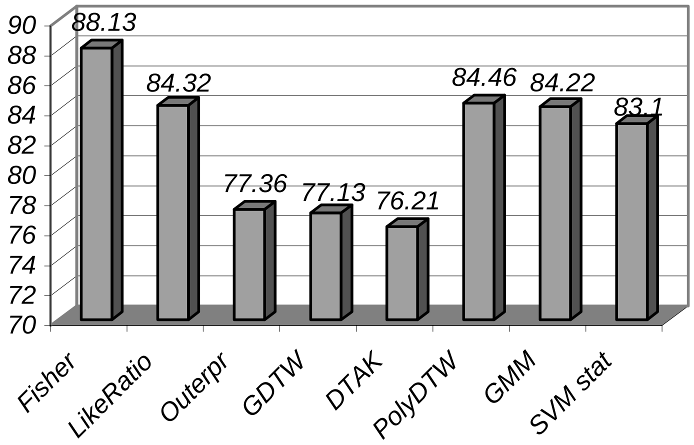


Figure 4.4.1. Classification accuracy for the 8 techniques

It is also worth noticing that the result with the Fisher kernel (88.13%) is comparable to the best result in Section 4.3 using non-sequential SVM techniques: 88.29%. However, the latter result was obtained by using a variable-feature-set clustering, a classification scheme that is more developed than DAG, and by using the most discriminative feature set on each step of classification.

4.4.3.3 Influence of the number of Gaussians on the derivatives of the generative model

Interesting enough that the best results for GMM were obtained with 8 Gaussians, while for Fisher kernel the appropriate generative model that leaded to the best performance was 1-Gaussian GMM.

Figure 4.4.2 shows the dependence of performance of Fisher kernel, Likelihood ratio kernel and GMM on the number of Gaussians. As can be seen from Figure 4.4.2 there is an apparent inconsistency in the results, in the sense that the recognition rate improves in the case of the GMM classifier as the number of Gaussians increases, but at the same time, the results degrade in the case of the Fisher kernel. There is a two-fold explanation of this phenomenon. The first is related to the fact that the likelihood of the observation given the model is computed by means of a linear combination of Gaussians. The weight of each Gaussian is proportional to the number of samples that are assigned to it. Therefore, the parameters estimated with a small number of samples (i.e. that have a higher estimation error), have a lower influence in the likelihood. In the case of the Fisher score, the derivative of the likelihood with respect to each parameter inherits the estimation error, and it is not concealed, as it is the case of the GMM. Furthermore this effect is augmented by the fact that the dimensionality of the Fisher kernel increases proportionally to the number of Gaussians, and the

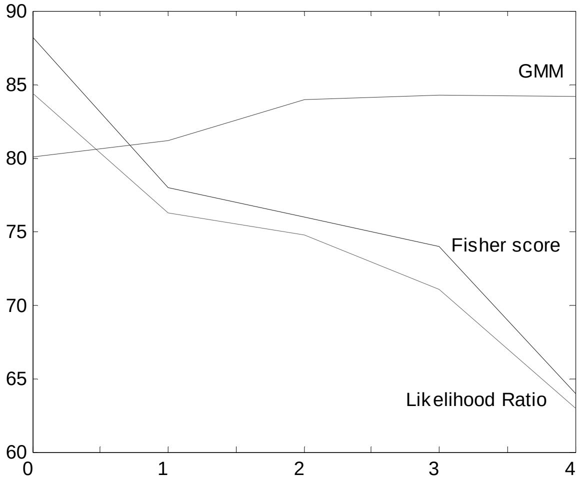


Figure 4.4.2. Dependence of the performance of the Fisher score kernel, likelihood ratio kernel and GMM on the number of Gaussians (log_2N_g)

number of noisy coordinates can be majority [TKM03]. The second explanation uses the concept of sensitivity, which is the percentage change of a function for a given percentage change of one of the parameters:

$$S = \frac{\Delta f(x) \,/\, f(x)}{\Delta x / x} \approx \frac{x}{f(x)} \frac{df(x)}{dx} \qquad (4.4.8)$$

We computed the sensitivity of the likelihood of a GMM, and the Fisher kernel associated to the GMM. The resulting expressions are highly complicated. Nevertheless, simulations for one Gaussian confirmed that the sensitivities to the mean and the weight of each Gaussian are similar for both GMM and Fisher kernel, but the sensitivity to the variance is at least three times higher in the case of the Fisher kernel.

4.4.3.4 Dependence of the classifier performance on the temporal structure of the acoustic event signals

The signals to be classified are quite heterogeneous, and have different temporal structures. Therefore, as was expected the performance of each classifier was biased to a given subset of the classes. For instance the DTW based classifiers behaved better with signals such as “music”, or “sneeze”, while classifiers that did not take into account the temporal structure of the signal did better with other signals that did not have that structure, such as “pen writing” or “liquid pouring”. Ranking eight classifiers for a given class (giving the score 1 to the best one and 8 to the worst one) these properties can be summarized in Figure 4.4.3 and Figure 4.4.4, where we compare the 8 classifiers for above-mentioned pairs of classes.

In Figure 4.4.3 it can be seen that in the case of “music” and “sneeze” the best classifiers, i.e. highest ranking and recognition rate, are DTW-based such as GDTW, PolyDTW and DTAK. While the classifiers that do not take into account the temporal structure, give inferior results. In Figure 4.4.4 the ranking of classifiers is opposite, and the classifiers that specifically dismiss the temporal order fare better; the highest ranking corresponds to the GMM, and the Fisher Ratio. Another general feature that was detected, and that is reflected in these figures, is that there are signals that are easier to classify. It can be seen that systematically the results for a given class are better than for the others consistently for all the 8 classifiers, i.e. the distribution of the results for all classification systems are separated, although the order of the systems can be different for each signal.

As a general summary, we can assert that there was a correlation between the classes and the classifiers, which is masked in the mean values presented in Figure 4.4.1. For both types of signals, with time structure or without it, the overall best accuracy with Fisher kernel is usually in the middle offering a good balance between the two groups of classes.

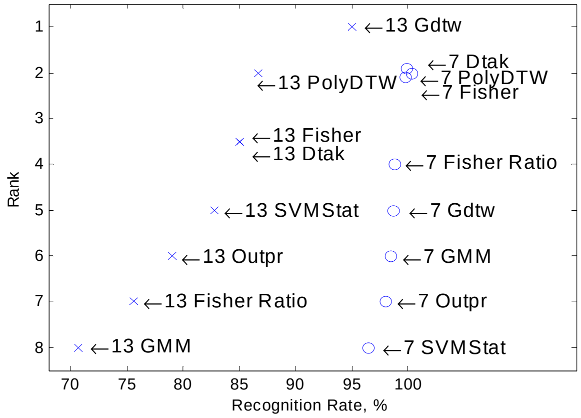


Figure 4.4.3. Comparison results for the classes "music" (7) and "sneeze" (13)

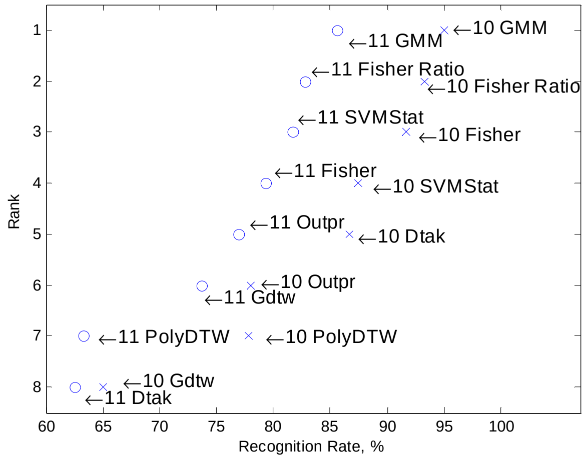


Figure 4.4.4. Comparison results for the classes "pen writing" (10) and "liquid pouring" (11)

4.4.4 Conclusions

Several methods that adapt SVMs to sequence processing have been reviewed and applied to the classification of sounds from the meeting room environment. We have seen that the dynamic time warping kernels work well for sounds that show a temporal structure, but due to the presence of less-time-structured sounds in the database the best average score is obtained with the Fisher kernel. Moreover, only one Gaussian is used in that method due to its high sensitivity to the variance parameters as a consequence of the scarcity of data. On the other hand, the observed bias of the classifiers to specific types of classes is a good condition for a successful application of fusion techniques.

4.5 Fuzzy Integral Based Information Fusion for Classification of Highly Confusable Non-Speech Sounds

4.5.1 Introduction

A rich variety of information sources is obtained in this work by extracting a set of ten different kinds of features and using them as inputs of ten different SVM classifiers, whose outputs are combined to give a final classification score. Besides the above-mentioned fusion of information sources at the decision level, and for clarity purposes, we also consider information fusion at the feature level, i.e. an early integration of information sources, and will be carried out by the SVM. These two kinds of fusion are depicted in Figure 4.5.1.

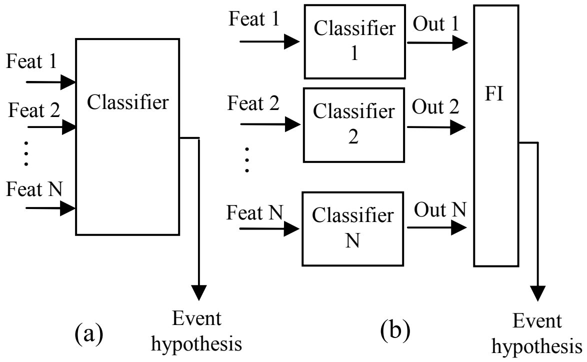


Figure 4.5.1. Fusion at the feature level (a) and at the decision level (b).

Usual combinations of classifier outputs like sum, product, max, min, weighted arithmetical mean (WAM), etc [Kun03], assume that each output represents an independent source of information that can be treated separately. Often, this is not the case, and an approach that considers the interactions among the classifier outputs is needed. Over the past several years there have been a number of successful applications of the FI [Kun03] [Sug74] in decision-making and pattern recognition using multiple information sources (e.g. [Gra95a] [CG03] [Gra95b]). FI is a meaningful formalism for combining classifier outputs which can capture interactions among the various sources of information. Moreover, the FM, which is associated with the FI, furnishes a measure of importance for each subset of information sources, allowing feature selection and giving a valuable insight into the classification problem itself.

Both feature-level fusion and decision-level fusion are compared in our AEC experiments. As a default classifier we use the SVM classifier, which helps to overcome the problem of the high-dimensionality [WCC+04] of the input feature space.

In this section, we focus on the classification of a particular type of acoustic events, a set of five human vocal-tract non-speech sounds (cough, laughter, sneeze, sniff and yawn), which were found responsible for a large part of errors in the classification of meeting-room acoustic events in Section 4.3. In fact, those sounds contributed with 70% of the total classification error, in spite of accounting only for 30% of the acoustic events included in the testing database. Additionally, it was observed in Section 4.3 that those human non-speech sounds were mainly confused among themselves. Using the same small database and keeping SVM as the basic classifier, the work presented in this section is intended to reduce the classification error rate of the above mentioned set of highly confusable human non-speech sounds by turning to the fusion of different information sources that in our case consists of the combination of classifier outputs.

Finally, as the FI aggregation may be appropriate when the feature-level fusion is difficult (e.g. due to the different nature of the involved features), or when it is beneficial to preserve the application or technique dependency (e.g. when fusing well established feature-classifier configurations), we have also conducted experiments to combine HMM that use frame-level features with the SVM using signal-level features, and have witnessed an additional improvement. As smart-rooms are usually equipped with a network of microphones and video cameras that provide multimodal information, fusion of information with the FI may find a useful application in such a framework.

The rest of the section is organized as follows: Subsection 4.5.2 gives the details of the FM learning algorithm. Audio features investigated in this work are presented in Subsection 4.5.3. Subsection 4.5.4 presents the experiments and discussion. Finally, conclusions are given in Subsection 4.5.5.

4.5.2 Fuzzy measure learning

From Section 3.4 it is obvious that FI completely relies on the FM. The better the FM describes the real competence and interaction among all classification systems, the more accurate results can be expected. There are two methods of calculating the FM known to the authors (if it is not provided by an expert knowledge): one based on fuzzy densities [Kun03], and the other based on learning the FM from training data [CG03] [Gra95b]. In our work, we have used the latter method: a supervised, gradient-based algorithm of learning the FM, with additional steps for smoothing the unmodified nodes:

Step 1. Initialize the FM to the equilibrium state $\mu(i) = 1/Z$, where Z is the number of information sources and FM is additive, i.e. $\mu(i,j) = \mu(i) + \mu(j)$

Step 2. For a data point x with label c_n

Step 2.1. Obtain the DP(x) and calculate the FIs M_n for each of N classes (i.e. for each column of the DP).

Step 2.2. Calculate the error for each of N classes: $\varepsilon_n = c_n - M_n$, where c_n is one for the correct class and zeros for the others.

Step 2.3. For each of N classes, update the FM μ values that were used in the calculation of M_n (e.g. in Figure 3.4.1, those that are on the red line, i.e. μ_{234}, μ_{23} and μ_3) using the formula derived from a mean-squared-error criterion [CG03]. Note that for each class the order of classifiers may differ, what implies that different μ values are used for the calculation of M_n.

Step 2.4. Verify the monotonicity condition for the μ values that were used in the calculation of M_n.

Step 3. Due to the scarcity of data, verify the monotonicity condition of the unmodified μ values and smooth their values. The smoothing is based on the average values of the upper and lower neighbours of the current node.

For the detailed description of the algorithm and exact parameter update equations refer to [CG03] [Gra95b].

4.5.3 Feature extraction

Although the best feature sets for AEC in Section 4.3 consisted of combinations of features used in automatic speech recognition and other perceptual features, in the current work we only focus on the latter, since their contribution to vocal-tract sounds is not so well-established. 10 types of features were chosen with a substantial degree of redundancy in order to use FM to find out their relative importance and their degree of interaction. The following types of frame-level acoustic features with the number of features in parenthesis are investigated in this thesis:

1. Zero crossing rate (1)
2. Short-time energy (1)
3. Fundamental frequency (1)
4. Sub-band log energies (4)
5. Sub-band log energy distribution (4)
6. Sub-band log energy correlations (4)
7. Sub-band log energy time differences (4)
8. Spectral centroid (1)
9. Spectral roll-off (1)

10. Spectral bandwidth (1)

Therefore, 22 acoustical measures are extracted from each frame, using 16ms/8ms frame length/shift. Then, from the whole time sequence of each acoustical measure in an event, four statistical parameters are computed: mean, standard deviation, autocorrelation coefficient at the second lag, and entropy. Those four statistical values per acoustical measure are used to represent the whole acoustic event.

4.5.4 Experiments and discussion

4.5.4.1 Experimental setup

Database

Due to the lack of an acceptable corpus, the acoustic event database used in this work has been assembled using different sources. Part of the database was taken from the seminar recordings employed within the CHIL project [EVA]. The other part has been found in a large number of Internet websites.

All sounds were down-sampled to 8 kHz. The fact that the acoustic events were taken from different sources makes the classification task more complicated due to the presence of several (sometimes unknown) environments and recording conditions. Table 4.5.1 shows the five acoustic classes considered in this work and Figure 4.5.2 shows their sample spectrograms. Notice that each realization of "cough" and "sniff" (there are two in the depicted time interval) shows a rather stationary behaviour, and "laughter" is almost periodic. Conversely, both "sneeze" and "yawn" have more spectral change. Actually, the "sneeze" sound results from the concatenation of two very different waveforms, and the "yawn" sound shows a decreasing pitch in its first segment.

There is a high variation in the number of samples per class, which represents an additional difficulty. In order to achieve a reasonable testing scenario, the data has been approximately equally split into the training and testing parts in such a way that there was the same number of representa-

Table 4.5.1. Sound classes and number of samples per class

	Event	**Number**
A	Cough & Throat	119
B	Laughter	37
C	Sneeze	40
D	Sniff	37
E	Yawn	12

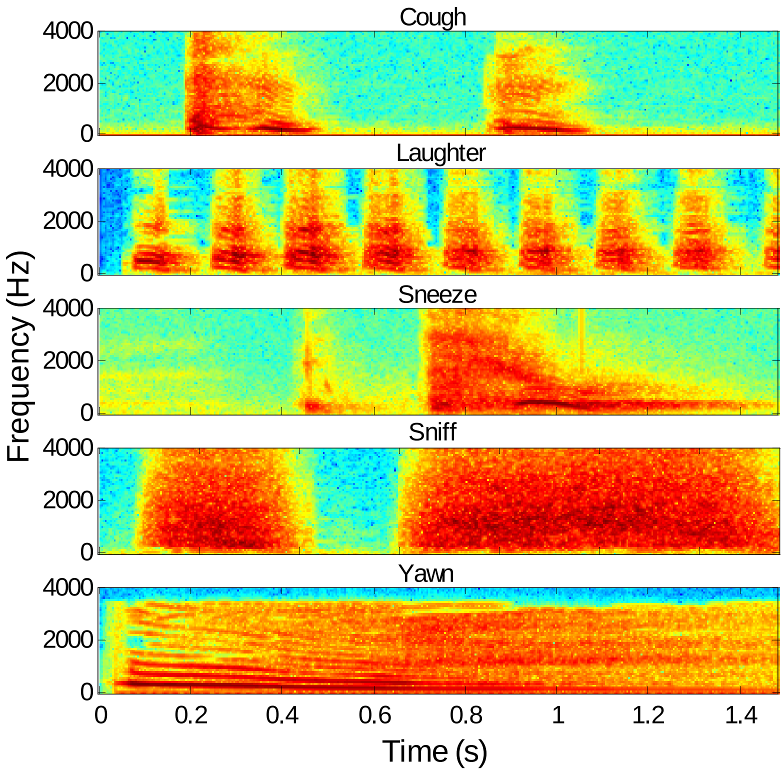


Figure 4.5.2. Sample spectrograms of acoustic events from

tives from the two data sources in the training and testing part. 10 runs were done in all the experiments.

SVM setup

The training data for each binary SVM classifier were firstly normalized anisotropicly to be in the range from –1 to 1, and the obtained normalizing template was then applied also to the testing data that are fed to that classifier. In the experiments with the SVM we used the Gaussian kernel. Leave-one-out cross validation [SS02] was applied to search for the optimal kernel parameter σ. To cope with the data imbalance we introduce different generalization parameters (C_+ and C_-) for positively- and negatively-labelled training samples: $C_+ = K\frac{A_-}{A_+}$, $C_- = K\frac{A_+}{A_-}$ where A_+ and A_- are the number of positive and negative training samples, respectively. In this way, the training errors of the two classes contribute equally to the cost of misclassification (see Section 4.3). K was set to value 10 for all experiments as it was done in Section 4.3. MAX WINS (pairwise majority voting) [HL02] scheme was used to extend the SVM to the task of classifying several classes. The softmax function was applied to the class densities, which were calculated with pairwise majority voting, in order to obtain probability-like values.

Metrics

For comparison of the results, three metrics are used. One is the overall system accuracy, which is computed as the quotient between the number of correct hypothesis (outputs) given by the classifier for all the classes and the total number of instances in the testing set. The other two metrics are the mean per class recall and the mean per class precision, which are defined as:

$$\text{Prec} = \frac{1}{|C|}\sum_{c\in C}\frac{|h_{corr}(c)|}{|h(c)|} \quad \text{Rec} = \frac{1}{|C|}\sum_{c\in C}\frac{|h_{corr}(c)|}{|r(c)|} \tag{4.5.1}$$

where $|.|$ denotes cardinality of a set, *C* is the set of classes, *c* is a specific class, *r(c)* is the number of reference (manually-labelled testing) instances and *h(c)* is the number of hypothesis instances for class *c*. The subscript $_{corr}$ refers to a correct hypothesis. Due to the imbalance in amount of data per class, we think that the recall measure is more meaningful than the overall accuracy, but we use both of them for our comparisons, together with the precision measure.

4.5.4.2 Shared, semi-shared, and individual fuzzy measure

The FM can be defined for all classes (shared FM), as we did in all experiments reported below in this section, or it can be defined for each class separately (individual FM), or for a group of classes (we call it semi-shared FM). When shared FM is used, it is learned using the error of all classes. Thus, one FM covers all class-classifier dependences. When using individual FM, the error of a given class contributes to change only its own FM. In that way, the various FMs allow different order of importance of classifiers for each class. In that individual FM case, enough data should be available to train each class FM. As an intermediate solution, semi-shared FM may be used, assigning each FM to a group of similar classes. Table 4.5.2 shows the results obtained for each case.

Table 4.5.2. FI result for individual, semi-shared and shared fuzzy measure

	FI (ind)	**FI (semi-sh) 15vs234**	**FI (semi-sh) 35vs124**	**FI (sh)**
Prec	81.24±3.1	80.16±2.0	81.75±2.4	81.22±1.8
Rec	80.80±2.4	79.88±1.5	81.11±1.4	81.47±1.2
Acc	83.02±1.9	82.76±1.6	83.79±1.1	83.88±0.6

As it can be seen from Table 4.5.2 shared, semi-shared and individual FMs show similar results, although shared FM is preferable than individual FM in our case when a small database is available, due to slightly better average recall and lower standard deviation of the results. Columns 2 and 3 show that, when using semi-shared FM, one should define FM for a meaningful group of classes, as done in column 3 when classes are grouped into two sets (3-5 and 1-2-4) according to the degree of non-stationarity of the corresponding types of sounds. On the contrary, in column 2, classes are divided simply to have an equal amount of data for each group, and the fusion performance is lower.

4.5.4.3 Feature and decision level information fusion

In this section, the two ways of information fusion mentioned in the Introduction are compared. For the feature-level fusion (see Figure 4.5.1 (a)), all ten types of features were used to feed the input of one SVM classifier. For the decision-level fusion (see Figure 4.5.1 (b)), ten independent SVM-based classifiers were trained, one for each feature type. The ten input criteria, represented by these ten classifiers, were then combined by WAM operator and FI with learned shared FM. For the weights in WAM operator we use uniform class noise model with the weights computed as $\mu_i = E_i^{E_i}(1-E_i)^{1-E_i}$ where E_i is the training error of class c_i [Kun04].

As we can see from Figure 4.5.3, all fusion approaches show a strong improvement in comparison to the SVM with the best single feature type (number 4). As expected, feeding all the features to the SVM classifier increased significantly the performance (SVM, 10 feature types). Interestingly enough, the fusion at the decision-level by FI showed comparable results to the powerful SVM classifier, which uses all the features. To gain an insight into the way FI works, we compare in Table 4.5.3 the individual recall score of the best feature type (column 2) for a given class, and the FI score (column 3) for the same class. Notice that, for the most represented class (A), the FI performance is lower, whereas for two less represented classes (C and D) it is higher. As the FM was trained using the errors of the particular classes as cost functions, we observe that, at the expense of accepting more errors for the most represented classes, the FI can recover a few errors for infrequent classes and thus obtain higher recall.

However, the accuracy and precision measures for both FI and WAM were slightly worse than that of the SVM: Accuracy=83.9 and Precision=81.2 for FI, versus Accuracy=84.8 and Precision=84.5 for SVM. Notice also that FI fusion has approximately a 10 times higher computation cost than SVM feature-level fusion (10 independent SVM classifiers vs. one), and therefore the latter would seem preferable in this case.

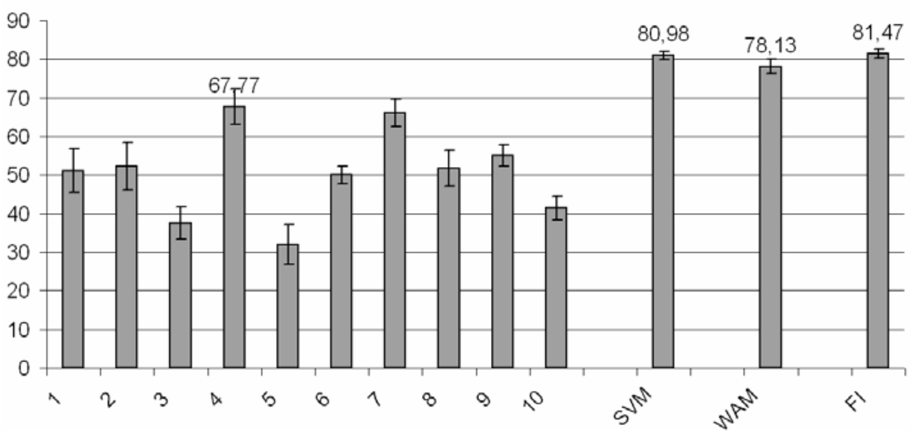


Figure 4.5.3. Recall measure for the 10 SVM systems running on each feature type, the combination of the 10 features at the feature-level with SVM, and the fusion on the decision-level with WAM and FI operators.

Table 4.5.3. Comparison of individual recall scores for each class

Class	Best score	FI
A(119)	0.85	0.81
B(37)	0.61	0.61
C(40)	0.95	1.00
D(37)	0.77	1.00
E(12)	0.67	0.67

4.5.4.4 Feature ranking and selection

An information source consists of two parts: a classifier and a set of features. When using the same classifier for each information source, we can interpret the FM as the importance of features for the given classification task and we can use it for feature ranking and selection.

The information about both the importance of each feature type and the interaction among different feature types can be extracted applying the Shapley score to the FM. Using this approach, Figure 4.5.4 shows that in our case the new feature type 6 (SBE correlations) is the most important followed by feature type 7 (SBE time difference). As both feature types measure the changes of the spectral envelope along the time, we can conclude that that information is of high importance. The only other feature type with importance score above the average is number 4 (SBE). Interestingly that although the new feature type described in Section 4.2 has the highest overall importance, individual accuracy is only around 50% as it can be seen from Figure 4.5.4. We also observed that without calculating the maximum absolute value in (4.2.4) the new feature individual accuracy increases to around 63% while the fusion result decreases to 79.4 %.

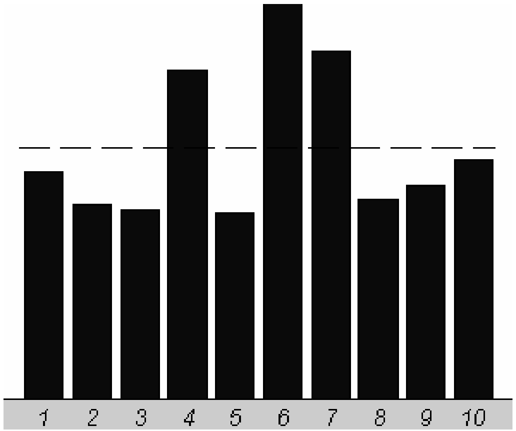


Figure 4.5.4. Importance of features extracted from FM.
Dashed line shows the average importance level.

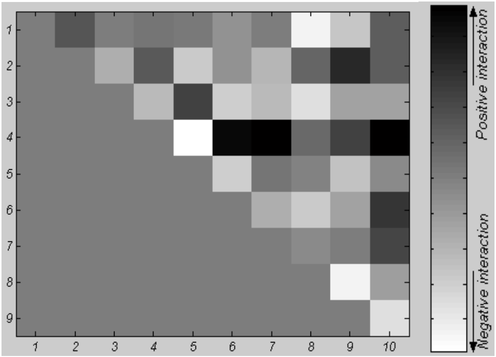


Figure 4.5.5. Interaction of features extracted from FM.

On the other hand, Figure 4.5.5 shows the interaction among the feature types in our task; it can be seen that feature types 6 (SBE time correlation) and 7 (SBE time difference) express a negative interaction, which coincide with their similar character. As an extreme case, the light cell (4,5) has a large negative value and thus indicates a high competitiveness (redundancy) of the mentioned feature types. Therefore it would be better to consider only one of the two feature types. Actually, feature type 4 (SBE) and the feature type 5 (SBE Distribution) become roughly the same feature after using the SVM normalization. In a similar way, as feature types 1 (ZCR) and 8 (Sp. Centroid) are both targeting the "main" frequency, their cell is also rather light. Also, from the two lighter cells in the bottom of the Figure 4.5.5, one can conclude that feature type 9 is redundant if feature types 8 and 10 are considered. On the contrary, feature types 4 and 6, or 4 and 7, or 4 and 10 seem to be highly complementary, and thus are preferable to be considered together.

In the following AEC tests, we use the information from Figure 4.5.4 and Figure 4.5.5 to perform the feature selection. In the first test, we select the 5 best feature types according to the individual feature type importance (Method 1), while to select the 5 best features in the second test, both the individual feature type importance and the interaction indices are used (Method 2, see [MZ99] for a detailed description). The selected features are then fed to the SVM classifier.

The performance of the SVM with all features is considered as a baseline in this part. It can be seen from the results in Table 4.5.4 that Method 1 did not lead to a better performance, while Method 2 obtained a slight improvement over the baseline.

The last column in Table 4.5.4 shows that the FI scores resulting from using the feature types chosen by Method 2 are clearly worse than the SVM ones. Notice that, although apparently FI should benefit from a feature selection based on FM, the 5 features have been selected according to a FM computed from 10 information sources, while FI scores in Table 4.5.4 result from a different FM, since it has been trained using only data corresponding to the 5 selected features.

Note that the recall score in the last column of Table 4.5.4 is much lower than the one shown in Figure 4.5.3 (and last column in Table 4.5.2) for the FI technique when using the whole set of features, in spite of the fact that FI technique apparently should benefit from a feature selection based on FM. There are two reasons for this behaviour. First, the 5 features have been selected according to a FM computed from 10 information sources, while FI scores in Table 4.5.4 result from a different FM, since it has been trained using only data corresponding to the 5 selected features. The second reason is based on the measure of uncertainty defined by (3.4.7). As it was mentioned in Section 3.4, if that entropy measure is close to 1 almost all information sources are equally used. In fact, for the 10 features case, it is 0.86, meaning that to achieve the results shown in Figure 4.5.3, the FI operator uses in average 8-9 out of 10 information sources, so preserving only 50% of all features is not sufficient.

Table 4.5.4. Classification results using feature selection based on FM

	Support Vector Machines			**FI**
	Baseline	**Method 1**	**Method 2**	
Features	10 (all)	5(1,4,6,7,10)	5(4,6,7,8,10)	Method 2
Prec	84.50±2.1	82.76±1.3	86.14±1.7	81.74±2.4
Rec	80.98±1.1	75.31±2.1	80.14±1.6	74.79±2.5
Acc	84.83±2.3	83.97±2.2	85.86±1.4	83.79±1.6

4.5.4.5 Fusion of different classifiers using FI

In previous subsections we showed that the FI decision-level fusion obtains comparative results to the feature-level fusion using the SVM classifier. Indeed, from the computational cost point of view the feature-level fusion is preferred. However, when the resulting feature space has a too high dimensionality or when features are conveyed by different data types (strings, matrices, etc) the feature-level fusion is not an option.

On the other hand, it may be beneficial to combine the outputs of different well-established classification configurations for a given task; for example, the output of a SVM classifier which is discriminative but uses features from the whole signal with the output of a HMM generative classifier which considers time localized features. Based on that, we have tested with the FI formalism the combination of a SVM classifier that uses statistical (event-level) features with a HMM classifier that uses acoustic (frame-level) features. In these experiments, the best 5 feature types selected in the previous subsection by Method 2 are used with the SVM classifier. For HMM, we use a standard configuration coming from speech recognition: a 3 state left-to-right continuous density HMM model per class, with 8 Gaussians per state, and 13 frequency-filtered filter-bank energies (FFBE) [NHG95] as features.

The first four columns in Table 4.5.5 show the performance of the SVM classifier and several HMM classifiers, where ΔFFBE means the time derivatives of FFBE features [NMH01]. HMM-ΔFFBE gives low performance because the time derivatives only carry information about dynamics of sound but lack the basic static representation of the audio signal. The low score resulting from the HMM classifier when it uses as features both FFBE and their time derivatives (fourth column in Table 4.5.5), indicates that the amount of data we use is not enough to train the 26-dimensional vector data properly. Then, we decided to fuse the outputs of the previous classifiers: SVM, HMM-FFBE and HMM-ΔFFBE. From the second last column of Table 4.5.5 an improvement can be observed by FI fusion of the SVM and HMM-FFBE outputs. A further improvement is obtained by

Table 4.5.5. Individual performance of SVM, HMM on FFBE with and without time derivatives, and FI fusion

	SVM (1)	**HMM-FFBE (2)**	**HMM-ΔFFBE (3)**	**HMM-FFBE+ΔFFBE**	**FI(1,2)**	**FI (1,2,3)**
Prec	86.14±1.7	69.28±3.5	51.06±4.7	66.70±3.2	88.23±1.8	**89.47±1.9**
Rec	80.14±1.6	67.36±2.7	60.73±3.8	59.31±2.5	81.43±1.5	**82.43±1.0**
Acc	85.86±1.4	84.48±2.1	52.59±4.6	79.17±2.6	87.07±2.2	**87.93±1.8**

fusion of the SVM output with two information sources that separately give much lower individual performances, but use different features, as it is shown in the last column of Table 4.5.5.

Note from Figure 4.5.3 that a much higher improvement was observed by fusing a larger number of information sources (10). Actually, the higher is the number of information sources the larger is the degree of interaction between them, and thus the better is the performance expected from the FI with an appropriately-learned FM. However, the difficulty of learning FM increases with the number of information sources. From our experience in this work, we would suggest to apply the FI formalism to fuse a number of information sources between 3 and 10.

4.5.5 Conclusion

In this work, we have carried out a preliminary investigation about the fusion of a relatively large number of information sources with the FI approach. We have shown an improvement over the baseline SVM approach in the task of classifying a small set of human vocal-tract non-speech sounds. By interpreting an information source as a specific combination of a classifier and a set of features, we have been able to carry out different types of tests.

In the experiments, fusion of several information sources with the FI formalism has shown a significant improvement with respect to the best single information source. Moreover, the FI decision-level fusion approach has shown comparable results to the high-performing SVM feature-level fusion. The experimental work has also indicated that the FI may be a good choice when feature-level fusion is not an option.

We have also observed that the importance and the degree of interaction among the various feature types given by the FM can be used for feature selection, and it gives a valuable insight into the problem.

4.6 Chapter Summary

The problem of classifying a set meeting-room acoustic events has been tackled in this chapter. A database has been defined and a set of experiments has been carried out.

Firstly, a confusion matrix based variable-feature-set clustering algorithm based on SVM classifier has been developed and applied to the problem. A 31.5% relative average error reduction with respect to the conventional binary tree scheme has been achieved.

Various sequential kernels have been tried to adapt the SVM classifier to sequence processing. The results of comparison has shown that using dynamic kernels a better performance can be obtained for sounds with a temporal structure; however the worse results on less-time-structured sounds and high computational cost of sequential kernels make their usefulness low at present.

Finally, fusion of several information sources with the FI formalism has been performed and has shown a significant improvement with respect to the best single information source. It has also been observed that the importance and the degree of interaction among the various feature types given by the FM can be used for feature selection, and it gives a valuable insight into the problem.

Chapter 5. Acoustic Event Detection

5.1 Chapter Overview

In the previous chapter the work done on classification of acoustic events was reported. More complex is the problem of Acoustic Event Detection, which purpose is to determine the presence of a given acoustic event of interest.

In this chapter we describe the AED systems developed at the UPC and submitted to the CLEAR evaluations that were carried out in March 2006 and March 2007, respectively. The system of year 2006, which is explained in Subsection 5.2.1, is based on two steps: performing silence/non-silence segmentation and then classification of non-silence portions by SVM classifiers. A set of features described in Section 4.3 is used. The system of year 2007, which is explained in Section 5.2.2, merges the two steps (segmentation and classification) and is also based on SVM classifiers. Besides, according to the importance and degree of interaction shown in Section 4.5, several features are selected and added to the set of features used in the AED system 2006 and one feature is eliminated. Additionally, multi-microphone decision fusion is added to the AED system 2007.

The acoustic event classification system used for evaluations 2006 is also explained in this chapter in Section 5.2.1.

As the systems have only been evaluated through participation in the international evaluation campaigns, the results are not presented in this chapter but in the next one.

5.2 Acoustic Event Detection systems

5.2.1 Acoustic event detection and acoustic event classification systems 2006

5.2.1.1 General description

The systems are based on SVM. A DAG [PCS00] multi-classification scheme was chosen to extend the SVM binary classifier to the multi-classification problem. 5-fold cross-validation [SS02] on the training data was applied to find the optimal SVM hyper parameters that were σ for the chosen Gaussian kernel, and C, a parameter that controls the amount of data allowed to be misclassified during the training procedure. In all the experiments the third channel of the Mark III microphone array was used.

Firstly, the sound is downsampled from the initial 44 kHz sampling rate to 22 kHz, and framed (frame length = 25 ms, overlapping 50%, Hamming window). For each frame, the set of spectral parameters that showed the best results in Section 4.3 was extracted. It consists of the concatenation of two types of parameters: 1) 16 Frequency-Filtered (FF) log filter-bank energies [NHG95] taken from ASR, and 2) a set of other perceptual parameters: zero-crossing rate, short time energy, 4 sub-band energies, spectral flux calculated for each of the defined subbands, and pitch. The first and second time derivatives were also calculated for the FF parameters. In total, a vector of 59 components is build to represent each frame.

5.2.1.2 AEC system

The mean, standard deviation, entropy and autocorrelation coefficient of the parameter vectors were computed along the whole event signal thus forming one vector per audio event with 4x59 elements. Then, that vector of statistical features was used to feed the SVM classifier, which was trained on the training set of the two databases of isolated acoustic events. The resulting system was used to test both UPC and ITC databases of isolated acoustic events, which are described in Chapter 6, so neither features nor system adaptation related to a specific database were applied.

5.2.1.3 AED system

The scheme of the AED system is shown in Figure 5.2.1. Using a sliding window of one second with a 100 ms shift, a vector of 4x59 statistical features was extracted like in the AEC system described in the last subsection for each position of the window (every 100 ms).

The statistical feature vector is then fed to an SVM-based silence/non-silence classifier trained on silence and non-silence segments of the two isolated acoustic events databases. At the output, a

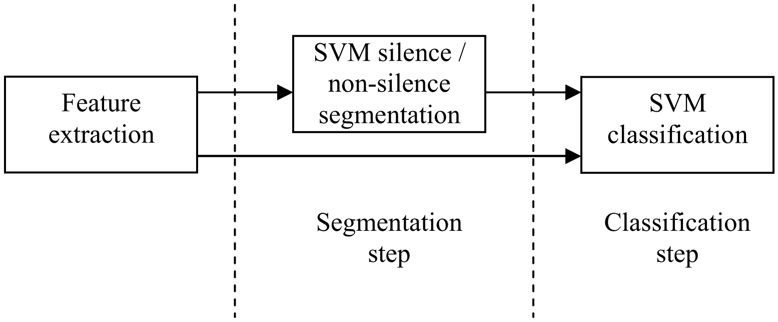


Figure 5.2.1. UPC acoustic event detection system 2006

binary sequence of decisions is obtained. A median-filter of size 17 is applied to eliminate too short silences or non-silences.

Then, the SVM-based event classifier is applied to each detected non-silence segment. The event classifier was trained on a parameters extracted from a sliding window with 100 ms shift applied to each event in the way that the first and the last windows still include more than 50% of the event content. The event classifier is trained on both isolated acoustic events and seminar databases to classify a set of 12 defined acoustical classes, plus classes “speech” and “unknown”. A sequence of decisions made on a 1-second window every 100 ms is obtained within the non-silence segment. That sequence is smoothed by assigning to the current decision point the label that is most frequent in a string of five decision points around the current one. Also, a confidence measure is calculated for each point as the quotient between the number of times that the chosen label appears in the string and the number of labels in the string (5).

The sequence of decisions from the non-silence segment is then processed again to get the detected events. In that step, only the events that have their length equal or larger than the average event length are kept, and the number of events kept in the non-silence segment is forced to be lower than a number which is proportional to the length of the segment. The average length of the events is estimated from the training and development databases. Finally, if the average of the above-mentioned computed confidences in a detected event is less than a threshold, the hypothesized event is marked as “unknown”; otherwise, it maintains the assigned label.

5.2.2 Acoustic event detection system 2007

The general scheme of the proposed system for AED is shown in Figure 5.2.2. Firstly, in the data pre-processing step, the signals are normalized based on the histograms of the signal energy. Then, a set of frame-level features is extracted from each frame of 30 ms and a set of statistical parameters is computed over the frames in a 1-second window. The resulting vectors of statistical parameters are fed to the SVM classifier associated to the specific microphone. A single-microphone post-processing is applied to eliminate uncertain decisions. At the end, the results of 4 microphones are fused to obtain a final decision.

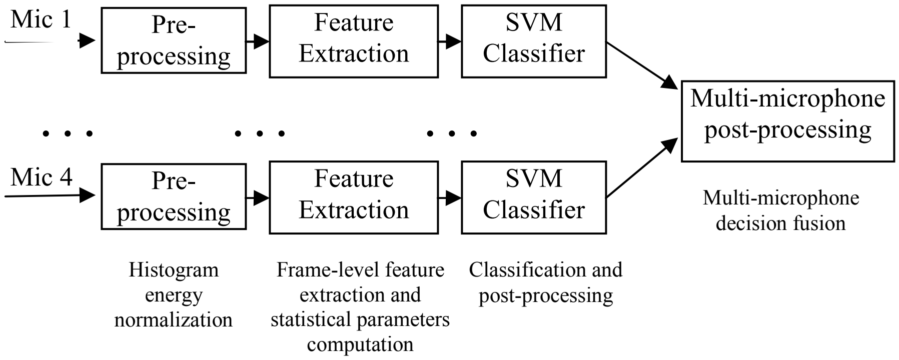

Mic 1
Pre-processing
Feature Extraction
SVM Classifier
. . .
. . .
. . .
Mic 4
Pre-processing
Feature Extraction
SVM Classifier
Multi-microphone post-processing
Multi-microphone decision fusion
Histogram energy normalization
Frame-level feature extraction and statistical parameters computation
Classification and post-processing

Figure 5.2.2. The block-scheme of the developed AED system 2007

5.2.2.1 Histogram-based energy normalization

The development database that is explained in Chapter 6 has been recorded in 5 different rooms. Due to this fact, the energy level of audio signals varies from one audio file to another. In this work as a pre-processing step we decided to perform energy normalization of all audio files to a predefined level. Because the energy level of a given AE depends both on its type, the manner it is produced, and the position of the person who produces it, the energy normalization is based on the energy level of silence. For this the histogram of the audio signal log-energy calculated each 30 ms with 10 ms shift has been plotted. The results for one development seminar are shown in Figure 5.2.3. The lower-energy hump corresponds to the silence energy level. A 2-Gaussians GMM has been trained on the energy values and the lowest mean has been taken as the estimation of the silence energy. In Figure 5.2.3, the estimated silence level corresponds to the point 10.41 whereas the true value of silence energy level, calculated on the annotated silence segments, is 10.43. The normalizing coefficient is then calculated as $coef = \sqrt{\exp(9)/\exp(a)}$, where a is the estimated silence level and 9 is the predefined final silence energy level. The exponential is used to come from the log scale back to the initial signal amplitude scale. Then, the development seminar signal is multiplied by *coef.*

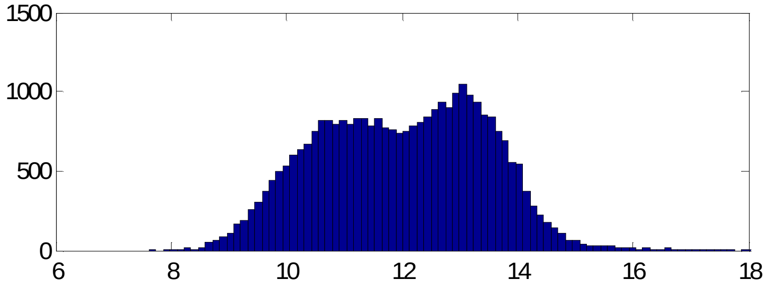


Figure 5.2.3. Frame log-energy histograms calculated over the whole seminar signal

5.2.2.2 Feature extraction

The sound signal is down-sampled to 16 kHz, and framed (frame length/shift is 30/10 ms, a Hamming window is used). For each frame, a set of spectral parameters has been extracted. It consists of the concatenation of two types of parameters (see Section 4.2): 1) 16 FFBE along with the first and the second time derivatives, and 2) a set of the following parameters: zero-crossing rate, short time energy, 4 sub-band energies, spectral flux, calculated for each of the defined sub-bands. Additionally, according the importance and degree of interaction shown in see Section 4.5, two features are added, namely, spectral centroid, and spectral bandwidth, and pitch is eliminated. In total, a vector of 60 components is built to represent each frame. The mean and the standard deviation parameters have been computed over all frames in a 1-second window with a 200ms shift, thus forming one vector of 120 elements.

5.2.2.3 One-microphone SVM system

For AED, SVM classifiers [SS02] have been implemented. They have been trained using the isolated AEs from the two DBs of IAE explained in Chapter 6, along with segments from the development data seminars that include both isolated AEs and AEs overlapped with speech. The segments that contain the overlapping of two or more AEs with or without speech are not used. In both training and testing processes, a vector of 120 statistical parameters has been computed from each 1-second window. The 1 vs. 1 multiclass strategy has been chosen to classify among 14 classes that include “Speech”, “Unknown”, and the 12 evaluated classes of AEs. Besides, “Silence” vs. “Non-silence” SVM classifier has been trained where “Non-silence” class includes all 14 classes. In that case, in order to decrease the number of training vectors and make training feasible, the dataset reduction technique described in following section of this chapter has been applied.

The testing stage scheme is shown in Figure 5.2.4. An input vector of statistical components computed over the frames from a 1-second window is firstly fed to the “Silence” vs. “Non-silence”

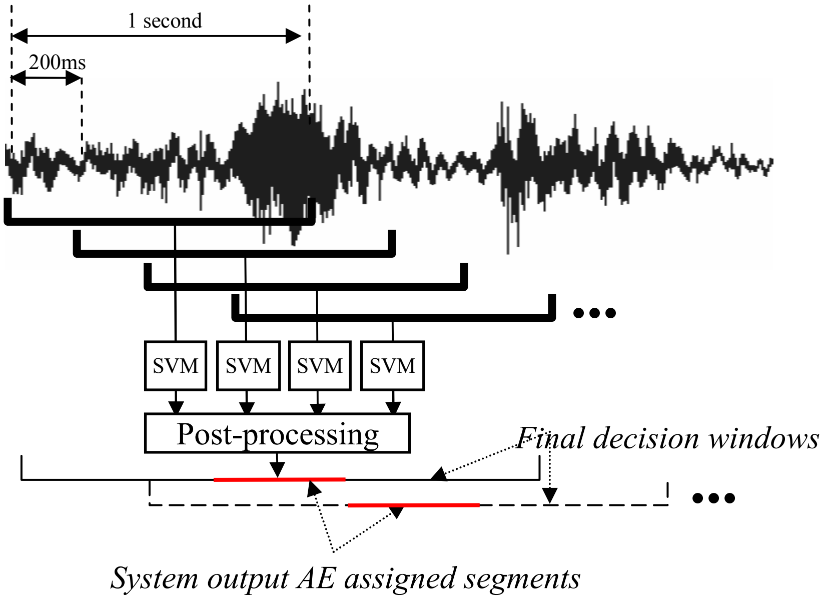


Figure 5.2.4. One microphone AED system

classifier and if the decision is "Non-silence", the vector is further fed to a SVM multiclass (14 classes) classifier based on the DAG testing scheme [PCS00]. The most frequent event (the "winner") is taken from the final decision window of 4 decisions that corresponds to the time interval of 1.6 seconds. If the number of votes of the "winner" does not exceed the threshold the event is marked as "Unknown". The threshold has been set in order that the winner has to get at least 3 votes. The final decision window is shifted by 2 decisions, i.e. 400 ms. Consequently, the temporal resolution of the produced system output AEs is 400 ms, and the corresponding AE label is assigned to the central 400 ms of the 1.6-second window.

For instance, for the first window of 4 decisions that corresponds to the time interval from 0 to 1.6s, the starting and ending timestamps of the system output AE will be 0.6 and 1s.

5.2.2.4 Multi-microphone processing

The database used in the evaluation has been recorded with a set of microphones. Depending on the site where the part of the database was recorded, which were Universitat Politèchnica de Catalunya (UPC), Instituto Trentino di Cultura (ITC), Athens Information Technology (AIT), and University of Karlsruhe (UKA), the following audio equipment has been used: one or two Mark III (array of 64 microphones), 3-7 T-shape clusters (4 mics per cluster), and several tabletop and omni directional microphones. To construct a multi-microphone AED system it has been decided to choose one microphone from each wall of the room and train a SVM classifier for each wall microphone. Due to the different configuration of the rooms where the development and testing data have been recorded and due to different numbering of the microphones, a mapping of the microphones across the sites has been performed. The Mark III microphone array has been chosen as the fixed point. For the remaining walls the T-shape cluster microphones have been chosen. An example of choice of the cluster microphones for the UPC's smart-room is shown in Figure 5.2.5. The following microphone numbers have been chosen 1-5-9, 6-1-25, 1-5-9, 1-5-9 for the AIT/ITC/UKA/UPC smart-rooms, respectively. For instance, one SVM has been trained on audio signals from microphones 1, 6, 1, 1 taken from AIT/ITC/UKA/UPC, respectively. For the Mark III array the 3rd microphone has been chosen across all sites.

For multi-microphone decision fusion, the voting scheme has been used. The AE label with the largest number of votes is sent to the system output. In case of draw the event is chosen randomly.

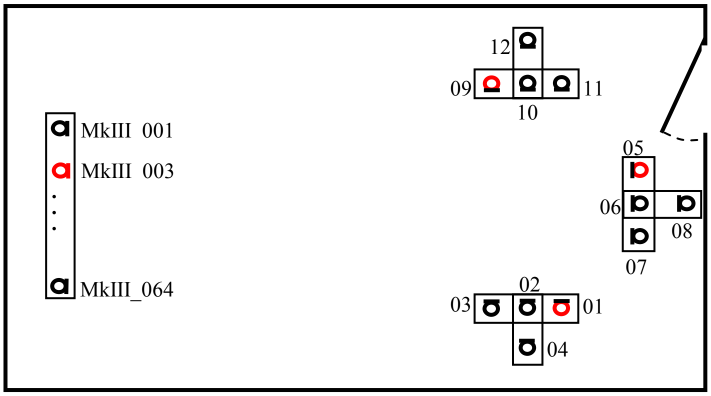


Figure 5.2.5. The choice of the microphones for the UPC's smart-room

5.3 Chapter Summary

In the current chapter the AED/C systems developed at UPC for the international evaluations of years 2006 and 2007 have been presented. The features and classifiers have been described. As the systems have only been evaluated through participation in the international evaluation campaigns, the results have not been presented in this chapter but will be reported in the next one.

Chapter 6. Participation in International Evaluations

6.1 Chapter Overview

The chapter reviews the results obtained with the developed systems for Acoustic Event Classification (AEC) and Acoustic Event Detection (AED).

Section 6.2 presents the results of the very first dry-run evaluation on AEC. The definition of the task, metrics and a set of meeting-room acoustic events are given. Then the results of the AEC system are presented and discussed.

The modifications of the first AEC task definitions and the evaluation setup of the second international evaluation on AEC are presented in Section 6.3. New metrics are defined and the results of the new systems tested on both the previous and the new databases are reported.

In Section 6.4, we present the results of the AED and AEC evaluations carried out in February 2006 by the three participant partners from the CHIL project. The primary evaluation task was AED of the testing portions of the isolated sound databases and seminar recordings produced in CHIL. Additionally, a secondary AEC evaluation task was designed using only the isolated sound databases. The set of meeting-room acoustic event classes and the metrics were agreed by the three partners and ELDA was in charge of the scoring task.

Next, the AED system developed at the UPC and its results in the CLEAR evaluations carried out in March 2007 are reported in Section 6.5. The system is based on SVM classifiers and multi-microphone decision fusion. Also, the current evaluation setup and, in particular, the two new metrics used in this evaluation are presented.

6.2 CHIL Dry-Run Evaluations 2004

6.2.1 Introduction

The CHIL-sponsored dry-run evaluations were carried on in spring 2004. The presented technologies were: ASR – Automatic Speech Recognition, SAD – Speech Activity Detection, Speaker ID – Speaker Identification, ASL – Acoustic Speaker Localization, and AEC – Acoustic Event Classification.

Crucial to the goal of the CHIL project is the ability to determine human context from auditory or visual cues in the environment. Toward this end, systems to identify common acoustic events in the first CHIL scenario seminars were developed and evaluated. In this section we describe the first evaluations that were carried out for the task of AEC.

The section is organized as follows. In Subsection 6.2.2 we present the database of gathered sounds and the evaluation setup with metrics. The classification techniques are overviewed in Subsection 6.2.3. The experiments and discussion of the results are presented in Subsection 6.2.4. Finally, conclusions are given in Subsection 6.2.5.

6.2.2 Database & evaluation setup

The evaluation used CHIL seminar data collected at Universität Karlsruhe in 2003. The seminar database consists of seven technical seminars. The natural meeting-room settings were designed without planning acoustic events.

Audio was collected with a combination of microphones. The 3rd channel of a wall-mounted 64-microphone array (MarkIII array) was used for the AEC evaluation. The data were transcribed with 36 noise classes. Over 2800 individual noise instances were collected. These instances were transcribed with tight temporal bounds, allowing to perform an isolated-sound test.

The sound classes that were transcribed are presented in Table 6.2.1. Additionally, Table 6.2.1 shows number of sound instances that appeared in training and testing data. From all the acoustic classes the ones that had more than 8 instances for both training and testing were chosen. The dropped acoustic classes are shown in grey in Table 6.2.1.

Table 6.2.1. Evaluated acoustic event classes

Name	Train	Test	Comments
Breath	24	33	
Bang	2	6	
Bump	59	79	
Chair moving	5	1	A chair being moved
Click	34	48	
Conv	8	4	Conversation (simultaneous speech)
Cough	4	10	
Crump	3	6	Paper crumple
Door	11	8	Door slams
E	11	8	Expiration
Fan	0	3	
Foot	3	10	Steps
I	288	267	Inspiration
Keyb	83	76	Keyboard typing
Knock	1	0	Door/table knock
Laugh	1	1	
Metal	3	7	Metallic noise
Mic	15	14	Microphone noise
Mn	4	2	An unidentified mouth noise
Mov	8	27	Movement, someone moving
N	1	3	Generic noise
Pen	2	10	Pen, pencil, whiteboard-pen writing
Pop	5	6	
Punch	0	1	Puncher & stapler
Rattle	1	1	
Shh	24	17	Steady environmental noise
Silence	715	630	
Smack	19	15	Smack, pressing the lips together
Snap	8	12	
Sniff	4	2	
Speech	1309	1209	
Squeak	10	14	
Tap	10	5	
Throat	10	4	Throat noise
Wh	2	0	Whistle
Whir	2	5	Whirring

The dry-run evaluation had two participants: Interactive System Laboratories from Carnegie Mellon University (ISL-CMU) [Mal06] and our TALP research group from UPC. In this corpus, we found 25 classes suitable for use in the evaluation: breathing, bang, bump, click, conversation (i.e. background speech between two parties which is not part of the seminar interaction), cough, paper crumple, door, exhale, footsteps, inhale, metal, microphone, chair moving, pen, pop, electrical noise, silence, lip smack, snap, speech, squeak, tap, throat clear, and typing. This set was *ad hoc* in the sense that we did not know *a priori* what kinds of sounds would be present in the database; hence we relied on transcriber's judgment to select the noise set. This decision resulted in a large amount of class overlap (e.g. "bang" and "bump"), but it was important to determine which classes were actually present in quantity.

The dry run data consisted of isolated sound segments only. There were 2805 total segments, which we divided into training (1425 segments) and evaluation sets (1380) at random.

Accuracy and recall were used as metrics in the evaluations. The former is defined as the number of correctly classified acoustic events divided by the total number of acoustic events. Recall is defined as a mean of the individual class recalls calculated as the number of correctly-classified events of a particular class divided by the number of events of that class.

6.2.3 Developed systems

In the evaluations we used the front-end described in Subsection 4.3.3. Namely, the signals from all the sounds in the database presented above were downsampled to 8kHz, normalized to be in the range [-1 1], and partitioned in frames using: frame length=128, overlapping of 50%, and a Hamming window. The silence portions of the signals were removed using an energy threshold. We tested all 9 acoustic feature sets presented in the Subsection 4.3.3, specifically, a set of perceptual features (Perc), a set of cepstral coefficients (MFCC), a set of frequency-filtered features (FF), and combinations of the formers. The mean, standard deviation of those features, estimated by averaging over the whole acoustic event signal, were taken for classification, thus forming one final statistical feature vector per audio event with a number of elements which doubles the length of the acoustic feature set. Besides, along with the mean and standard deviation we decided to calculate the autocorrelation coefficient at the second lag and the entropy, to compare the results with and without the last two statistical parameters.

GMM and SVM classifier were used as alternative back-ends of the developed systems. Both classifiers were compared across all available feature sets. For the SVM case, we used the binary tree scheme that is explained in Subsection 4.3.5.1.

6.2.4 Results and discussion

The best results were obtained using the 3rd feature set (E + MFCC) for GMM and the 8th for SVM (Perc + FF + ΔFF + ΔΔFF). Interestingly enough, that the best results with GMM were obtained with mean and standard deviation of the 3rd feature set while, in the case of SVM, the set of mean, standard deviation, autocorrelation coefficient at the second lag, and entropy calculated over the 8th feature set showed the best performance. The best GMM and SVM results are summarized in Table 6.2.2.

As it can be seen from Table 6.2.2, the worst (at times 0%) performance is obtained for the classes with small number of acoustic event instances for training, like “bang”, “crump”, “foot”. Also we can see from Table 6.2.2, that for most classes, SVM shows better performance than GMM, finally achieving better accuracy and recall. Additionally, Table 6.2.2 shows the baseline recall and accuracy calculated as if the system always guesses the most frequent class i.e. “speech” in our case. As it can be seen, the accuracy of GMM is even worse than that of the baseline; however the GMM recall is much higher. SVM system clearly outperforms the baseline for both metrics.

The accuracy metric is affected by the imbalance of the number of instances per acoustic event

Table 6.2.2. Results of the dry-run evaluations on AEC

	Recall for Each Class (%)	
Event	**GMM**	**SVM**
b	10.61	3.03
bang	0	0
bump	22.78	41.77
click	19.57	30.43
conv	25.00	0
cough	15.00	40.00
crump	0	0
door	50.00	62.50
e	25.00	0
foot	0	0
i	52.81	74.00
keyb	37.50	60.53
metal	0	0
mic	3.57	7.14
mov	1.85	0
pen	0	0
pop	0	0
shh	8.82	17.65
silence	56.20	58.00
smack	13.33	26.67
snap	12.50	0
speech	96.00	100.00
squeak	21.43	7.14
tap	0	0
throat	62.50	75.00
Baseline (Recall)	**4.0**	
Baseline (Accuracy)	**47.8**	
Recall	**21.38**	**24.15**
Accuracy	**47.4**	**55.1**

classes, so that the good performance shown for “speech” class contributed significantly to the accuracy metric.

It is worth to note that the low system performance is attributable to the noisy conditions of the recorded seminars (far-field microphone, reverberation, etc). Besides, the annotation of acoustic events describes them from a semantic point of view while acoustically most of classes are similar (“bump” and “bang”, “shh” and “silence”, etc.). Additionally, the high number of acoustic classes made it rather difficult to correctly transcribe the seminars, resulting in a number of outliers.

6.2.5 Conclusions

The first official evaluation of acoustic event classification was carried out in 2004 and has been described in this section. In that pioneering work, the set of meeting room acoustic events has been defined based on the number of acoustic event instances and the metric has been agreed by the participants. Previously developed systems have been applied to the AEC task and comparative results have been obtained.

6.3 CHIL Evaluations 2005

6.3.1 Introduction

The first year of the CHIL project concluded with the CHIL evaluation campaign in January 2005, followed by the first CHIL evaluation workshop, which took place in Athens on 20th and 21st of January 2005.

During this campaign, 12 technological components were evaluated: 5 vision technologies (face detection, visual person tracking, visual speaker identification, head pose estimation, and hand tracking); 6 sound and speech technologies (close-talking automatic speech recognition, far-field automatic speech recognition, acoustic person tracking, acoustic speaker identification, speech activity detection, acoustic scene analysis; and 1 contents processing technology (automatic summarization). AEC, along with acoustic environment classification, were considered subtasks of the acoustic scene analysis task.

As it was mentioned the goal of the AEC efforts in the CHIL project is to provide situation awareness to smart CHIL spaces by monitoring ambient audio. Many events which carry semantic relevance to scene understanding cannot be detected by visual analysis, but are relatively easy to detect with auditory analysis. Some of these events are speech-related and can thus be handled by SAD or ASR systems. Many others, however, are not speech-related and must be dealt with separately. Examples of these types of events include applause, doors opening and closing, knocking on doors, telephones ringing, music, and electrical noise characteristic of some piece of office equipment like a printer or fax machine. The CHIL AEC task was conceived to reliably classify sounds like these, along with speech and other human noises.

The section is organized as follows. In Subsection 6.3.2 we present the database of gathered sounds and the evaluation setup with metrics. The classification techniques are overviewed in Subsection 6.3.3. The experiments and discussion of the results are presented in Subsection 6.3.4. Finally, conclusions are given in Subsection 6.3.5.

6.3.2 Database & evaluation setup

ISL-CMU and UPC were also the only participants in the AEC evaluation 2005. For this evaluation, we worked to limit the number of classes to those which were both easy for transcribers to identify and semantically relevant to the CHIL task. However, as we wished to retain a label for every sound in the corpus, whether it was easily identifiable or not, we split the label set into two types, semantic labels and acoustic labels. Semantic labels correspond to specific named sounds with CHIL relevance; e.g. doors slamming, speech, etc. The semantic classes that were annotated are presented in Table 6.3.1. In total there are 8 human noises and 13 environmental noises. Based on the availability of samples per class, the following 15 semantic classes were finally chosen for evaluation: breathing, chair moving, click, door, footsteps, laughter, mouth noise, papers, silence, speech, throat, typing, and electrical noise.

Table 6.3.1. Annotated semantic classes

Class	Description
	Human Noises
[b]	Breathe (in general, when it is not possible to be more precise)
[lgh]	Speaker laughing
[thr]	Throat noise /Cough
[tsk]	Willful noise made to express one's disagreement: "tsk tsk tsk…"
[conv]	Whisper or conversation in the background
[mn]	Generic mouth noise (including smacks)
[snif]	Sniffing
[sp]	Speech segment
	Non-speech, environment noises
[app]	Hand clapping, audience applauding
[beep]	Some device beeping
[click]	Click
[chr]	A chair being moved
[door]	A door opening, closing, slamming or grating
[fst]	Footsteps
[key]	Keys jiggling or being knocked on a surface.
[mus]	Some music, e.g. radio or mobile phone
[pap]	The noise of some action done with paper sheets
[sil]	Silence (more or less, event if there is a background noise global to the recording)
[typ]	Someone typing on a keyboard
[unk]	Unknown
[whir]	Some kind of electrical whirring

Acoustic labels correspond to unnamed sounds which are either unidentifiable or have no CHIL relevance. The acoustic labels use names describing both tonal and rhythmic features of a sound. The set of acoustic-labelled sounds consists of continuous non-tonal sounds, continuous tonal sounds, single non-continuous sounds, non-continuous sounds repeated in a regular pattern, non-continuous sounds repeated in an irregular pattern, and other noises. Table 6.3.2 shows the acoustic classes used in the evaluations.

Table 6.3.2. Evaluated acoustic classes

Class	Description
[c-t]	Continuous tone
[c-nt]	Continuous sound without tone
[nc-s]	Single non-continuous sound
[nc-xreg]	Regular repetitive non-continuous sound
[nc-xirr]	Irregular repetitive non-continuous sound
[n]	Generic noise, all other kinds of sounds

Table 6.3.3. Semantic acoustic mapping

Semantic label	Acoustic label
[lgh], [sp]	c-t
[b], [snif], [pap], [whir], [thr]	c-nt
[click], [chr], [door], [mn]	nc-s
[fst]	nc-xreg
[typ]	nc-xirr

It was decided to perform two independent evaluations: acoustic and semantic. For acoustic evaluation, all semantically-labelled classes were mapped to the corresponding acoustic classes. The mapping is shown in the Table 6.3.3.

Like in the dry-run, the AEC evaluation set consisted of isolated sounds only, collected in seminars at Universität Karlsruhe. The data were split into a training set, a development test set, and an evaluation set. There were 7092 total segments; 3039 were used for training (1946 speech, 333 breath, 333 silence, 232 unk, 44 footsteps, 24 throat, 16 click, 15 paper…), 2949 for development testing (749 speech, 183 unk, 139 silence, 9 throat, 9 breath, 7 typing…), and 1104 for evaluation (2084 speech, 348 silence, 274 unk, 123 breath, 30 throat, 25 footsteps, 18 chair…).

The far-field microphone, that was the 4th channel of MarkIII microphone array, was used in the entire evaluation. Participants were permitted to use for system training only the data distributed for this evaluation and identified as training data. No other data were allowed for training purposes, though development data may be used for strobe testing and cross-validation.

For measuring the performance, the error rate metric was exploited. It is defined as 1 – accuracy. The accuracy is calculated as the number of correctly classified acoustic events divided by the total number of acoustic events.

6.3.3 Developed systems

In the AEC evaluation 2005, we used an SVM-based variable-feature-set clustering approach, i.e. an enhanced version of the dry-run SVM binary tree scheme system. The idea is to choose the most appropriate feature sets on each step of classification. The hierarchical structure of the final system is constructed based on the confusion matrices obtained from initial experiments. The system is described in details in Subsection 4.3.

As feature sets, various perceptual and conventional spectral representations of the signal were used. The experiments in the dry-run evaluations explained above showed that SVM obtained better results with two additional statistical parameters – autocorrelation and entropy. Thus, instead of only mean and standard deviation, both the mean, standard deviation, autocorrelation coefficient at the second lag, and entropy were calculated from the whole event.

6.3.4 Results and discussion

The results of the evaluations were presented at the HSCMA'05 workshop in March 2005 [MMT+05] and are shown in Table 6.3.4. As it can be seen from Table 6.3.4 the proposed confusion-matrix-based SVM clustering approach improves the results obtained with the SVM binary tree on the dry-run evaluation database. Additionally, Table 6.3.4 shows the baseline error rate calculated as if the system always guesses the most frequent class i.e. "speech" in case of semantic set and "continuous tone" in case of acoustic set. The obtained results are clearly better than the baseline.

Table 6.3.4. Results of the AEC evaluations 2005

	Dry-run database			**2005 year database**	
	Dry-run systems		2005 year SVM system	2005 year SVM system	
	GMM	SVM		Acoustic set	Semantic set
Error rate	52.6%	44.9%	37.1%	**22.11%**	**18.51%**
Baseline Error rate	52.2%			29.3%	29.4%

The AEC evaluation 2005 was unfortunately suffering from problems of corpus. Transcription mistakes were still quite frequent; hence, the labels were not as reliable as they could have been. Further, the corpus was extremely unbalanced; a large majority of the segments were made up of speech. Many interesting classes had only a few examples in the training or test sets, and hence were not well-modelled by our systems.

6.3.5 Conclusions

The 2005 CHIL evaluation of acoustic event classification has been carried out and described in this section. The set of meeting room acoustic events has been defined. Along with a semantic AEC, an acoustic AEC task has been proposed and performed. An appropriate mapping between the semantic set and the acoustic set of acoustic events has been established. The developed SVM-based variable-feature-set clustering scheme presented in Subsection 4.3.5.2 has been applied to the AEC task. The results of the 2004 AEC evaluations have been improved and comparative results for the new database of 2005 have been obtained. For the future, it was decided to limit to a group of events relevant to actual CHIL services. For the purpose of measuring the performance of AEC, the largely prevailing "speech" class was proposed to be eliminated from scoring. Besides, we planned to move from classification to detection of a limited number of transcribable acoustic events like doors, applause, laughing, etc. In order to have a sufficient number of non-speech acoustic events, introducing the scenario of the recordings is crucial.

6.4 Classification of Events, Activities and Relationships – CLEAR'06 Evaluation and Workshop

6.4.1 Introduction

The spring 2006 CLEAR evaluation and workshop was an international effort to evaluate systems that are designed to analyze people, their identities, activities, interactions and relationships in human-human interaction scenarios, as well as related scenarios. CLEAR was meant to bring together projects and researchers working on related technologies in order to establish a common international evaluation campaign in this field. The CLEAR 2006 evaluation was supported by the European Integrated project CHIL, the US ARDA VACE program, and the NIST.

The tasks to be addressed in CLEAR 2006 were the following: Person Tracking (2D and 3D, audio-only, video-only, and multimodal), Face Tracking, Head Pose Estimation (2D, 3D), Person Identification (audio-only, video-only, and multimodal), Acoustic Event Detection and Classification (AED/C). These tasks were conducted on various multimodal data sets collected in lecture and meetings domains, as well as on broadcast news data.

The results of the evaluations were presented during the CLEAR 2006 evaluation workshop held on April 6-7, in Southampton, UK. The CLEAR 2006 post-workshop proceedings are available under the Springer LNCS book series: LNCS 4122: Multimodal Technologies for Perception of Humans.

In this section, we present the results of the AED/C CLEAR evaluations carried out by three participants UPC, CMU and Instituto Trentino di Cultura (ITC). The primary evaluation task was AED of the testing portions of the two isolated sound databases (from ITC and UPC) and 4 UPC’s seminar recordings produced in CHIL. Additionally, a secondary AEC evaluation task was designed using only the isolated sound databases and it is also included in this report. All the participants agreed the set of acoustic classes a priori before recording the databases. A common metrics was also developed at the UPC and agreed with the other partners. ELDA was in charge of the scoring task.

The section is organized as follows: Subsection 6.4.2 gives the experimental setup. Specifically, the databases used in the evaluations are described in Subsection 6.4.2.1, while the evaluation scenario and metrics are given in Subsection 6.4.2.2 and 6.4.2.3, respectively. Subsection 6.4.3 reviews the systems used by each of the AED/C evaluation participants. The results obtained by the detection and classification systems in the CLEAR evaluations are shown and discussed in Subsection 6.4.4. Conclusions are presented in Subsection 6.4.5.

6.4.2 Evaluation setup

6.4.2.1 Databases

The conducted experiments were carried out on 2 different kinds of databases, namely: 2 databases of isolated acoustic events recorded at the UPC and ITC, and 5 interactive seminars recorded at the UPC.

The two former databases contain a set of isolated acoustic events that occur in a meeting room environment and were recorded specially for the CHIL AED/C task. The recorded sounds do not have temporal overlapping and no interfering noises were present in the room.

The UPC database of isolated acoustic events (see Appendix A for the detailed description) was recorded using 84 microphones, namely, Mark III (array of 64 microphones), three T-shape clusters (4 mics per cluster), 4 tabletop directional, and 4 omni-directional microphones. The database consists of 13 semantic classes plus “unknown”. Approximately 60 sounds per each of the sound classes were recorded as shown in Table 6.4.1. Ten people participated in recordings: 5 men and 5 women. There are 3 sessions per each participant. At each session, the participant took a different place in the room out of 7 fixed different positions.

The ITC database of isolated acoustic events [ZO05] was recorded with 32 microphones. They were mounted in 7 T-shaped arrays (composed by 4 microphones each one) plus there were 4 table microphones. The database contains 16 semantic classes of events. Approximately 50 sounds per almost each of the sound classes were recorded as shown in Table 6.4.1. 9 people participated at the recordings. For each experiment 4 positions in the room were located. People swapped their positions after every session. During each session every person reproduced a complete set of acoustic events.

Additionally, the AED techniques were applied to the database of the interactive seminars [CS04] recorded at the UPC. 5 interactive seminars have been collected. The difference with two previous databases of isolated acoustic events is that seminars consist of real environment events that may have temporal overlapping with speech and/or other acoustic events. Each seminar consists of a presentation of 10-20 minutes to a group of 3-5 attendees in a meeting room. During and after the presentation there are questions from the attendees with answers from the presenter. There is also activity in terms of people entering/leaving the room, opening and closing the door, standing up and going to the screen, some discussion among the attendees, coffee breaks, etc. The databases was recorded using 88 different sensors that include 3 4-microphoned T-shaped arrays, 1 64-microphone

Mark III array, 4 omni-directional table-top microphones, 4 directional table-top microphones, and 4 close-talk microphones. The number of events of one of the seminars is summarized in Table 6.4.1.

Table 6.4.1. Number of events for the UPC and ITC databases of isolated acoustic events, and the UPC interactive seminar

Event type	Number of events		
	UPC-isolated	ITC-isolated	UPC-seminar
Door knock	50	47	4
Door open	60	49	7
Door slam	61	51	7
Steps	73	50	43
Chair moving	76	47	26
Spoon/cup jingle	64	48	15
Paper work	84	48	21
Key jingle	65	48	2
Keyboard typing	66	48	14
Phone ring	116	89	6
Applause	60	12	2
Cough	65	48	5
Laugh	64	48	8
Unknown	126		12
Mimo pen buzz		48	
Falling object		48	
Phone vibration		13	
Speech			169

6.4.2.2 Evaluation scenario

The AED/C evaluation is done on 12 semantic classes that are defined as:

• Knock (door, table)	[kn]
• Door slam	[ds]
• Steps	[st]
• Chair moving	[cm]
• Spoon (cup jingle)	[cl]
• Paper wrapping	[pw]
• Key jingle	[kj]
• Keyboard typing	[kt]
• Phone ringing/Music	[pr]
• Applause	[ap]

- Cough [co]
- Laugh [la]

Also there are two other possible events that are present but are not evaluated

- Speech [sp]
- Unknown [un]

Actually, the databases of isolated acoustic events contain more semantic classes than the above-proposed list as shown in Table 6.4.1. For that reason, the classes that are out of the scope of the current AED/C evaluation were marked as "unknown".

Two main series of experiments are performed: AED and AEC. AED was done in both isolated and real environment conditions. For the task of AEC and isolated AED the databases of isolated acoustic events were split into training and testing parts, namely, for the UPC database sessions 1 and 2 were used for training and session 3 for testing; for the ITC database sessions 1-3 were used for training and session 4 for testing. For the task of AED in real environment all databases of isolated acoustic events and one of five seminars were allowed to use for training and developing, while for testing a 5-minute extract from each of the remaining 4 seminars was proposed forming in total 4 five-minute segments. The selection of extracted parts was done by ELDA.

The primary evaluation task was defined as AED evaluated on both the isolated databases and the seminars.

6.4.2.3 Metric

As it was mentioned above, the acoustic events that happen in real environment may have temporal overlapping. The appropriate metric was developed to score the system outputs. It consists of two steps: projecting all levels of overlapping events into a single-level reference transcription and comparing a hypothesized transcription with the single level reference transcription.

For instance, let's suppose we have a reference that contain overlapping of level 2 and can be represented as shown in Figure 6.4.1 and

REF_1: _la_kt_

REF_2: _co_ds_cl_la_

where REF_1 and REF_2 model two overlapping acoustic event sequences. Then we can form the single-level reference transcription and a list of events to detect as shown in Table 6.4.2.

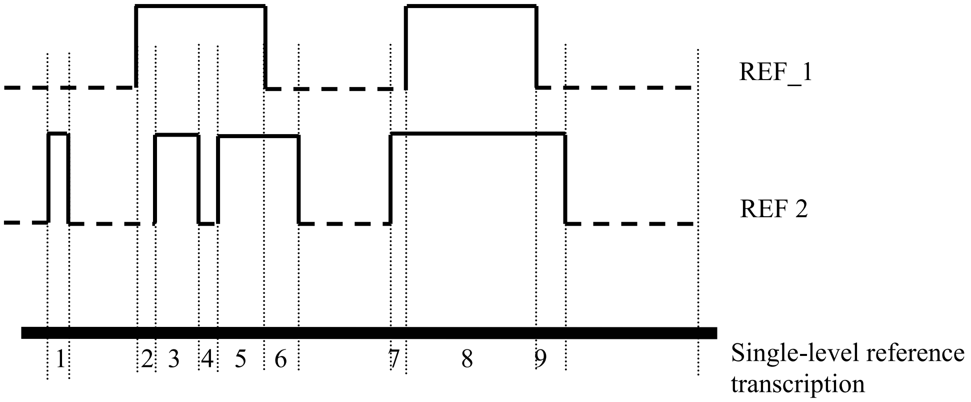


Figure 6.4.1. From reference transcription with overlapping of level 2 to reference single-level transcription

Table 6.4.2. Obtained single-level reference transcription and a list of events to detect

Single-level reference transcription	List of events to detect:
1 – co1	1 – cough1
2 – la1	2 – laugh1
3 – la1_ds1	3 – ds1
4 – la1	4 – spoon1
5 – la1_cl1	5 – laugh2
6 – cl1	6 – keyboard1
7 – la2	
8 – kt1_la2	
9 – la2	

Following definitions are needed to compute the metric:

An event is ***correctly detected*** when the hypothesized temporal centre is situated in the appropriate single-level reference interval and the hypothesized label is a constituent or a full name of this interval single-level reference label. After an event is claimed to be correctly detected, it is marked as detected in the list of events to detect.

Empty intervals are the reference intervals that contain speech, silence or events belonging to the “unknown” class.

A substitution error occurs when the temporal centre of the hypothesized event is situated in the appropriate single-level reference interval and the label of the hypothesized event is not constituent or the full name of the label of that single-level reference interval.

An insertion error occurs when the temporal centre of the hypothesised event is not situated in any of the single-level reference intervals (i.e. are situated in empty intervals)

A deletion error occurs when there is an event in the list of events to detect that is not marked as detected.

Finally, Acoustic Event Error Rate (AEER) is computed as

AEER= (D+I+S)/N * 100

where N is the number of events to detect, D – deletions, I – insertions, and S – substitutions.

6.4.3 Acoustic event detection and classification systems

The system of AED and AEC are explained in Subsection 5.2.1. Briefly, for classification, a vector of statistical parameters that include mean, standard deviation, autocorrelation and entropy is calculated from the frame-level acoustic features of the whole event, and fed to the SVM-based event classifier (system UPC-C). For detection, a vector of statistical parameters is calculated from a sliding window and then fed to an SVM-based silence/non-silence classifier to perform the segmentation step. The silence/non-silence classifier is trained on silence and non-silence segments of the two isolated acoustic events databases. At the output, a binary sequence of decisions is obtained. After a post-processing of the sequence the SVM-based event classifier, which is trained on the events taken from both two isolated acoustic event databases and development seminars, is applied to each detected non-silence segment. After smoothing a final decision is made (system UPC-D).

6.4.4 Results and discussion

Table 6.4.3 shows classification error rates obtained using the classification system described above. The UPC system used one set of models for the both testing databases. In fact, the SVM-based system obtained best error rate among all the participants despite the fact that database-specific systems were not used for SVM.

In the detection task we took and approach of first performing segmentation and then classification. Table 6.4.3 shows detection error rates for the two isolated event databases and the interactive seminar database. Although our system achieved the best results among all submitted systems in classification, in detection the results are much worse. If we add up the results obtained for the detection task for both isolated and seminar conditions the error rate of 69.6% is calculated. Although there might be a number of reasons to explain the bad performance of the AED-D system we conjecture that the initial segmentation step is the main cause of the lower overall detection performance. Further investigation is needed in the direction of the approach to see whether it can outperform the well-established scheme that is used in ASR. Besides, it can be seen from the Table 6.4.3, the error rates increase significantly for the UPC seminar database, although being the lowest among all submitted systems. One of possible reasons of such a bad performance is that it is difficult to detect low-energy acoustic classes that overlap with speech, such as e.g. “chair moving”, “steps”, “keyboard typing”, and “paper work”. Actually, these classes cover the majority of the events in the UPC seminars and probably they are the cause of the bad results we obtained in the seminar task. A usage of multiple microphones might be helpful in this case.

Table 6.4.3. Error rate (in %) for acoustic event classification and detection tasks

Systems Databases	UPC-C	UPC-D
ITC isolated DB	4.1	64.6
UPC isolated DB	5.8	58.9
UPC seminars DB		97.1

6.4.5 Conclusions

The presented work has focused on the CLEAR evaluation tasks concerning the detection and classification of acoustic events that may happen in a lecture/meeting room environment. In this context, we have evaluated two different tasks, acoustic event classification and acoustic event detection, AED being the primary objective of the evaluation. Two kinds of databases have been used: two databases of isolated acoustic events and a database of interactive seminars containing a significant number of acoustic events of interest.

Preliminary detection and classification systems have been presented. Our system is based on the SVM discriminative approach and uses FF features and four kinds of perceptual features. In the classification task, the UPC SVM-based system showed the best performance over all participants. In the detection task, first performing segmentation and then classification showed worse performance than merging the segmentation and classification in one step as performed by the Viterbi search in the state-of-the-art ASR systems.

6.5 Classification of Events, Activities and Relationships – CLEAR'07 Evaluation and Workshop

6.5.1 Introduction

After the AED evaluation within the CLEAR evaluation campaign 2006, explained in the previous section, organized by the CHIL project, several modifications have been introduced into the task for the CLEAR evaluation campaign 2007. The old metric has been substituted by two new metrics: Accuracy and Error Rate, which are based, respectively, on precision/recall and on a temporal measure of detection error. Additionally, AED is performed only in seminar conditions, where the AEs are often overlapped with speech and/or other AEs. The definition of the classes of AEs is kept.

Six participants submitted their systems for CLEAR 2007, namely: Athens Information Technology (AIT), Institute for Infocomm Research (IIR), Foundation Bruno Kessler (IRST), Tampere University of Technology (TUT), University of Illinois (UIUC), Technical University of Catalonia (UPC).

The results of the evaluations were presented during the CLEAR 2007 evaluation workshop held on May 9-10, in Baltimore, USA. The CLEAR 2007 post-workshop proceedings will soon be available under the Springer LNCS book series: Multimodal Technologies for Perception of Humans.

In this section, after presenting the current evaluation setup and, in particular, the two new metrics used in this evaluation, we describe the AED system developed at the UPC and submitted to the CLEAR evaluations carried out in March 2007 along with its results.

The section is organized as follows. In Subsection 6.5.2 the evaluation setup is presented. Specifically, the definition of the task is given in Subsection 6.5.2.1. Subsection 6.5.2.2 describes the databases assigned to development and testing. Metrics are given in Subsection 6.5.2.3, and Subsection 6.5.2.4 states the main evaluation conditions. The short overview of the proposed system is given in Subsection 6.5.3. The results obtained by the detection system in the CLEAR evaluations are shown and discussed in Subsection 6.5.4. Conclusions are presented in Subsection 0.

6.5.2 Evaluation setup

6.5.2.1 Acoustic event classes

The AED evaluation use the same 12 semantic classes, i.e. types of AEs, used in the past evaluations CLEAR 2006. The semantic classes with the corresponding annotation label are shown in black in the first column of Table 6.5.1. Apart from the 12 evaluated classes, there are 3 other possible events shown in grey in Table 6.5.1 which are not evaluated.

6.5.2.2 Databases

The database used in the CLEAR evaluation campaign 2007 consists of 25 interactive seminars of approximately 30 min long each that have been recorded by AIT, ITC, IBM, UKA, and UPC in their smart-rooms.

Five interactive seminars (one from each site) were assigned for system development. Along with the seminar recordings, the databases of isolated AEs recorded at UPC (Appendix A) and ITC [ZO05] have been used for development.

The development database details in terms of the number of occurrences per AE class are shown in Table 6.5.1. In total, development data consists of 7495 seconds, where 16% of total time is AEs, 13% is silence, and 81% is "Speech" and "Unknown" classes.

Table 6.5.1. Number of occurrences per acoustic event class for the development and test data

Event Type		**Number of Occurrences**			
		Development			**Test**
		UPC iso	**ITC iso**	**Seminars**	**Seminars**
Door knock	[kn]	50	47	82	153
Door open/slam	[ds]	120	100	73	76
Steps	[st]	73	50	72	498
Chair moving	[cm]	76	47	238	226
Spoon/cup jingle	[cl]	64	48	28	28
Paper work	[pw]	84	48	130	88
Key jingle	[kj]	65	48	22	32
Keyboard typing	[kt]	66	48	72	105
Phone ring	[pr]	116	89	21	25
Applause	[ap]	60	12	8	13
Cough	[co]	65	48	54	36
Laugh	[la]	64	48	37	154
Unknown	[un]	126	-	301	559
Speech	[sp]		-	1224	1239
Silence		Not annotated explicitly			

The remaining interactive seminars have been conditionally decomposed into 5 types of acoustic scenes: "beginning", "meeting", "coffee break", "question/answers", and "end". After observing the "richness" of each acoustic scene type in terms of AEs, 20 5-minute segments have been extracted by ELDA maximizing the AE time and number of occurrences per AE class. The details of the testing database are given in Table 6.5.1. In total, the test data consist of 6001 seconds, where 36% are AE time, 11% are silence, and 78% are "Speech" and "Unknown" classes. Noticeably, during about 64% of time, the AEs are overlapped with "Speech" and during 3% they are overlapped with other AEs. In terms of AE occurrences, more than 65% of the existing 1434 AEs are partially or completely overlapped with "Speech" and/or other AEs

6.5.2.3 Metrics

Two metrics have been developed at the UPC, with the agreement of the other participating partners which are involved in CHIL: an F-score measure of detection accuracy (which combines recall and precision), and an error rate measure that focuses more on the accuracy of the endpoints of each detected AE. They have been used separately in the evaluations, and will be called, respectively, AED-ACC and AED-ER.

AED-ACC

The aim of this metric is to score detection of all instances of what is considered as a relevant AE. With this metric it is not important to reach a good temporal coincidence of the reference and system output timestamps of the AEs but to detect their instances. It is oriented to applications like real-time services for smart-rooms, audio-based surveillance, etc. AED-ACC is defined as the F-score (the harmonic mean between precision and recall):

$$AED - ACC = \frac{(1+\beta^2) * Precision * Recall}{\beta^2 * Precision + Recall},$$

where

$$Precision = \frac{number\ of\ correct\ system\ output\ AEs}{number\ of\ all\ system\ output\ AEs}$$

$$Recall = \frac{number\ of\ correctly\ detected\ reference\ AEs}{number\ of\ all\ reference\ AEs}$$

and β is a weighting factor that balances precision and recall. In this evaluation the factor β has been set to 1. A *system output AE* is considered *correct* or *correctly produced* either if there exist at least one reference AE whose temporal centre is situated between the timestamps of the system output AE and the labels of the system output AE and the reference AE are the same, or if the temporal centre of the system output AE lies between the timestamps of at least one reference AE and the labels of the system output AE and the reference AE are the same. A *reference AE* is considered *correctly detected* either if there exist at least one system output AE whose temporal centre is situated between the timestamps of the reference AE and the labels of the system output AE and the reference AE are the same, or if the temporal centre of the reference AE lies between the timestamps of at least one system output AE and the labels of the system output AE and the reference AE are the same.

AED-ER

For some applications it is necessary to have a good temporal resolution of the detected AEs. The aim of this metric is to score AED as a task of general audio segmentation. Possible applications can be content-based audio indexing/retrieval, meeting stage detection, etc.

In order to define AED-ER, the NIST metric for speaker diarization [Spr06] has been adapted to the task of AED. The audio data is divided into adjacent segments, whose borders coincide with the points whether either a reference AE or a system output AE starts or stops, so that, along a given segment, the number of reference AEs and the number of system output AEs do not change.

The AED-ER score is computed as the fraction of time, including regions of overlapping, in which a system output AE is not attributed correctly to a reference AE, in the following way:

$$AED - ER = \frac{\sum\limits_{\substack{all \\ seg}} \left\{ dur(seg) * \left(\max\left(N_{REF,} N_{SYS} \right) - N_{correct}(seg) \right) \right\}}{\sum\limits_{\substack{all \\ seg}} \left\{ dur(seg) * N_{REF}(seg) \right\}}$$

where, for each segment *seg*:

dur(seg): duration of *seg*

N_{REF} *(seg)*: number of reference AEs in *seg*

N_{SYS} *(seg)*: number of system output AEs in *seg*

$N_{correct}$ *(seg):* number of reference AEs in *seg* which correspond to system output AEs in *seg*

Notice that an overlapping region may contribute with several errors. Also, “Silence” is not explicitly transcribed, but is counted in the context of this metric as an AE.

The numerator of the AED-ER expression includes the substitution time, that corresponds to the wrong AE detection, the deletion time (missed AEs), and the insertion time (AE false alarms).

Only the 12 above-mentioned evaluated classes can cause errors. For example, if the reference label is “Speech” and the system output is “Unknown”, there is no error; however if the system output is one of the 12 classes, it will be counted as an error (insertion). Similarly, if the reference is one of the 12 classes and the system output is “Speech”, it will be also counted as an error (deletion).

6.5.2.4 Evaluation scenario

In order to have systems comparable across sites, a set of evaluation conditions were defined:
- The evaluated system must be applied to the **whole** CLEAR 2007 test DB.
- Only **primary** systems are submitted to **compete**.
- The evaluated systems must use **only audio** signals, though they can use **any** number of **microphones**.

6.5.3 Acoustic event detection system

The system of AED is described in Subsection 5.2.2. In a nutshell, on the data pre-processing step, the signals are normalized based on the histograms of the signal energy. Then, a set of frame-level features is extracted from each frame of 30ms and a set of statistical parameters is computed over the frames in a 1-second window. The resulting vectors of statistical parameters are fed to the SVM classifier associated to the specific microphone. A single-microphone post-processing is applied to eliminate uncertain decisions. At the end, the results of 4 microphones are fused to obtain a final decision.

6.5.4 Results and discussion

The results obtained with the primary system submitted to the evaluation are shown in Table 6.5.2. Along with the main metrics, accuracy and error rate, the intermediate values are also given. They are precision and recall for accuracy, and DEL (deletions), INS (insertions), and SUB (substitutions) for error rate. A contrast system has been also submitted, showing little worse results than the primary system: ACC=23, ER=141.57. The difference between the primary and contrast system is that for multi-microphone fusion the former uses voting among the “winners” of the one-microphone systems while the contrast system performs voting adding up the confidences of the “winners” calculated as the number of times the “winner” is found in the 4-decision window.

Table 6.5.3 shows the results of each one-microphone SVM system before applying the voting decision. Actually, the final results of the multi-microphone system shown in Table 6.5.2 are worse that the results of the one-microphone SVM system obtained on the 3rd microphones of MarkIII array (Mic4). This fact may indicate that simple fusion methods, i.e. voting, do not work properly when the scores of the various systems differ significantly.

The individual class accuracies are shown in Table 6.5.4. Interestingly enough, we have observed that the low accuracy and high error rate are mostly attributable to the bad recognition of the class “steps”, which occurs more than 40% of all AE time.

Besides, more than 76% of all error time occurs in the segments where AEs are overlapped with speech and/or other AEs. If the overlapped segments were not scored, the error rate of the primary submitted system would be 32.33%.

Table 6.5.2. Official results obtained by the submitted AED primary system

Accuracy (%) **(Precision / Recall)**	**Error Rate (%)** **(DEL/INS/SUB)**
23.0 (19 / 29)	136.69 (50.3 / 57.1 / 29.3)

Table 6.5.3. The results obtained with each one-microphone SVM system before applying voting

	Mic1	**Mic2**	**Mic3**	**Mic4**
Accuracy (%) (Precision / Recall)	20.5 (17/27)	22.6 (19/28)	19.9 (15/29)	**26.8** **(34/22)**
Error Rate (%) (DEL/INS/SUB)	145 (51/64/30)	136 (54/55/27)	155 (46/74/34)	**98** **(69/13/16**)

Table 6.5.4. Accuracy scores for each class obtained with the primary system

ap = 0.81	cl = 0.29	cm = 0.22	co = 0.19
ds = 0.42	kj = 0.18	kn = 0.05	kt = 0.08
la = 0.38	pr = 0.28	pw = 0.12	st = 0.16

6.5.5 Conclusions

The presented work focuses on the CLEAR evaluation task concerning the detection of acoustic events that may happen in a lecture/meeting room environment. The evaluation has been performed on the database of interactive seminars that have been recorded in different smart-rooms and contain a significant number of acoustic events of interest. Two different metrics have been proposed and implemented. One is based on the precision and recall of the detection of the AEs as semantic instances, and the other is based on a more time-based error. Although the proposed system, which was the only submission not using HMM, ranked the second among 6 participants, there is still a big room for improvement.

6.6 Chapter Summary

The results of the systems developed for acoustic event classification and acoustic event detection international evaluation campaigns have been presented in this chapter. The evaluation setups that include the evaluation databases, metrics and evaluation rules have been also reviewed.

The first CHIL evaluations on the recent discipline of AEC have been carried out in 2004. The semantic set of meeting room acoustic events was defined based on the number of acoustic event instances and the metric was agreed. Initial systems for the task were developed and compared among the participants.

In the next evaluation in 2005 both a semantic AEC and an acoustic AEC tasks were proposed and performed. An appropriate mapping between the semantic set and the acoustic set of acoustic events was established. The previously developed SVM-based variable-feature-set clustering scheme was applied to the AEC task. The results of the 2004 AEC evaluations were improved and comparative results for the new database of 2005 were obtained.

The CLEAR evaluation tasks in 2006 concerned the detection and classification of acoustic events that may happen in a lecture/meeting room environment. In this context, two different tasks were evaluated, AEC and AED, AED being the primary objective of the evaluation. Two kinds of databases were used: two databases of isolated acoustic events and a database of interactive seminars containing a significant number of acoustic events of interest. A preliminary detection system and its results were presented.

The CLEAR evaluations 2007 were performed on the database of interactive seminars. Two different metrics were proposed and implemented. The proposed SVM-based system ranked among the best being the only submission not using HMMs. However the results indicate there is still a big room for improvement.

Chapter 7. Speech Activity Detection

7.1 Chapter Overview

Speech Activity Detection (SAD) is a key objective in speech-related technologies. Although speech usually is the most informative acoustic event, other kind of sounds may also carry useful information. Detection of speech may be seen as a subtask of the general sound detection task. And, conversely, a set of acoustic events may be considered as a refinement of the non-speech class in SAD. In this chapter, work done on SAD is described.

An enhanced version of the training stage of a SAD system based on the SVM classifier is presented in Section 7.2, and its performance is tested with the Rich Transcription 2005 (RT05) and RT06 evaluation tasks. A fast algorithm of data reduction based on proximal SVM is developed and, furthermore, the specific characteristics of the metric used in the US National Institute of Standards and Technology (NIST) SAD evaluations are taken into account during training.

In Section 7.3, we summarize the systems developed in our lab in last years and the results obtained with them in the previous NIST RT SAD evaluations, and also present the SAD results that have been obtained for the last RT-07 evaluation with the developed SVM-based system within the Speaker Diarization task performed on conference meetings.

7.2 Enhanced SVM Training For Robust Speech Activity Detection

7.2.1 Introduction

In smart-room environments, the availability of a robust SAD system is a basic requirement. Detecting the presence of speech is a key objective in speech-related technologies. In fact, the use of SAD usually allows an increase of recognition rate in automatic speech or speaker recognition, and it is also required in both speech/speaker recognition and speech coding to save computational resources (and batteries) in the devices where the processing of non-speech events is not needed.

In the previous work done at our lab [PMN05], a SAD algorithm was developed and compared with other reported techniques using a subset of the SPEECON database. The SAD system was based on a decision tree classifier and FFBE. That system was posteriorly improved by adding two additional features (measures of energy dynamics at low and high frequencies) [MNT06], and by developing two alternative classifiers based, respectively, on GMM [MNT06] and SVM [SS02]. Here only the SVM-based SAD system will be described.

A set of several hundred of thousand of examples is a usual amount of data for classical audio and speech processing techniques that involve GMM. However, it is an enormous number of feature vectors to be used for a usual SVM training process and hardly makes such training feasible in practice. A number of methods of dataset reduction for SVM have been recently proposed. In [LZL03], a speech / non-speech classification with SVM has been done by changing from frame-based to segment-based decisions and computing mean and deviation of all feature vectors inside the chosen segment. The proposed method, however, results in a temporal resolution decrease of the SAD system and thus is better suited to audio indexing (for what it was actually designed) than to SAD. In [RYG+06], SVMs have been also applied to the SAD problem using a training set that consists of an arbitrarily chosen small portion of the whole database (12 utterances out of 4914). In [ZJZ+06], a method based on regression trees has been proposed to reduce the available dataset for audio classification, and a cross-training method has been exploited in [BBW04]. Unfortunately, none the above mentioned methods is suitable for our SAD task, either because they show a small ratio of data reduction or they have been applied to relatively small datasets on which it was possible to train a classical SVM. Active learning literature [TK01] propose several alternatives to deal with moderately large databases, however they involve continuous retraining that with accurate sub-sampling strategy and large initial dataset becomes computationally very expensive.

In this work, the usual training algorithm of the SVM classifier has been enhanced in order to cope with that problem of dataset reduction, proposing a fast algorithm based on Proximal SVM (PSVM) [FM01]. Besides that, the SVM learning process has been adjusted in order to take into account the specific characteristics of the metric used in the NIST RT evaluations. The resulting SVM SAD system has been tested with the RT06 data, and it has shown better scores than the GMM-based system which, submitted by the authors, ranked among the best systems in the RT06 evaluation.

The whole chapter is organized as follows. The databases are described in Subsection 7.2.2. The features used by the SAD system are explained in Subsection 0. Subsection 7.2.4 gives the metrics, and Subsection 7.2.5 provides with the detailed description of the developed system. The experimental results and discussion are proposed in Subsection 7.2.6. Finally, Subsection 7.2.7 concludes the work.

7.2.2 Databases

Several databases have been used in this work. A subset of the Spanish SPEECON database, already used in [PMN05] [MNT06], was used for classifier training. The single distant microphone evaluation database from the RT05 "conference room" meeting task was used for development in the first stage and for training in the second one. It contains 10 extracts from 10 English language meetings recorded at 5 different sites. Each extract is about 12 minutes long. The proportion of speech / non-speech is highly unbalanced: approximately 90% of the whole signal is speech.

For testing, we have used the RT06 dataset that consists of two kinds of data, conference meetings ("confmtg") and lecture meetings ("lectmtg"). The "confmtg" dataset is similar to the previously described RT05 data. The "lectmtg" data were collected from lectures and interactive seminars across the smart-rooms of different CHIL (Computers in the Human Interaction Loop) project partners.

SPEECON and the RT data are similar in the sense that they are recorded in closed environments using far-field microphones, thus the recordings have a relatively low SNR due to reverberation and environmental noise. However, there are some differences that should be mentioned: different speech and non-speech proportion and also the fact that the main attention of a speaker in SPEECON was the recording itself, while in the RT databases the recording was secondary. As a consequence, the RT databases are more spontaneous, speakers speak not necessarily heading the microphone, and the data contain overlapped speech. Other features of the databases used in the work are presented in Table 7.2.1.

Table 7.2.1. SPEECON, RT05 and RT06 databases summary

Database	SPEECON	RT05	RT06
Language	Spanish	English	English
Type	Single utterances	Conference	Conference & Lecture
Microphone	2-3 m in front of a speaker	On the table	On the table
Signal	16kHz, 16b	16kHz, 16b	16kHz, 16b

7.2.3 Features

The same feature set from [MNT06] was used. The first part of it extracts information about the spectral shape of the acoustic signal in a frame. It is based on Linear Discriminant Analysis (LDA) of FF parameters [PMN05]. The size of the FF representation (16FF+16ΔFF+16ΔΔFF+ΔE=49) is reduced to a single scalar measure by applying LDA. The second part of the feature set focuses more on the dynamics of the signal along the time observing low- and high-frequency spectral components [MNT06].

The contextual information is involved in several ways. First, before applying the LDA transform, the current delta and delta-delta features involve an interval of 50 and 70 ms, respectively, in their calculation. Next, for the representation of the current frame, eight LDA measures are selected from a time window spanning the interval of 310 ms around the current frame. Finally, low and high frequency dynamics involve a smoothed derivative calculation that uses 130 ms interval.

The first and the second part of the feature set form a vector of 10 components. Additionally, for RT06 evaluation task, a cross-frequency energy dynamic feature, which is obtained as a combination of low and high frequency dynamics and was also introduced in [MNT06], is added to the final feature vector.

7.2.4 Metrics

As a primary metric we use the one defined for the SAD task in the NIST RT evaluation. It is defined as *the ratio of the duration of* incorrect *decisions to the duration of all speech segments in reference*. We denote this metric as NIST metric in our results.

Notice that the NIST metric depends strongly on the prior distribution of speech and non-speech in the test database. For example, a system that achieves a 5% error rate at speech portions and a 5% error rate at non-speech portions, would result in very different NIST error rates for test databases with different proportion of speech and non-speech segments; in the case of 90-to-10% ratio of speech-to-non-speech the NIST error rate is 5.6%, while in the case of 50-to-50% ratio it is 10%. Due to this fact we also report three metrics that are used for the CHIL project SAD evaluations: Mismatch Rate (MR), Speech Detection Error Rate (SDER), and Non-Speech Detection Error Rate (NDER) defined as:

MR = duration of incorrect decisions / duration of all utterances

SDER = duration of incorrect decisions at speech segments / duration of speech segments

NDER = duration of incorrect decisions at non-speech segments / duration of non-speech segments

7.2.5 SVM-based speech activity detector

A set of several hundreds of thousand of feature vectors hardly makes SVM training process feasible in practice. Alternative methods should be effectively applied to reduce the amount of data. In [MNT06] a hard data reduction was imposed by randomly selecting 20 thousand examples where the two classes of interest are equally represented. In this section we propose two modifications of the SVM training process that aim to improve SAD performance of the SVM classifier from [MNT06]. We use the same pre-processing steps. The training data are firstly normalized anisotropicly to be in the range from –1 to 1, and the obtained normalizing template was then applied also to the testing dataset. In all experiments the Gaussian kernel is used. To train the system the SVMlight software [SVM] was used.

7.2.5.1 Dataset reduction by PSVM

Proximal Support Vector Machine (PSVM) has been recently introduced in [FM01] as a result of the substitution of the inequality constraint of a classical SVM $y_i(wx_i+b)\geq 1$ by the equality constraint $y_i(wx_i+b)=1$, where y_i stands for a label of a vector x_i, w is the norm of the separating hyperplane H_0, and b is the scalar bias of the hyperplane H_0.

This simple modification significantly changes the nature of the optimization problem. Unlike conventional SVM, PSVM solves a single square system of linear equations and thus it is very fast to train. As a consequence, it turns out that it is possible to obtain an explicit exact solution to the optimization problem [FM01].

Figure 7.2.1 shows a geometrical interpretation of the change. H_{-1} and H_1 planes do not bound the negatively- and the positively-labelled data anymore, but can be viewed as “proximal” planes around which the points of each class are clustered and between which the separating hyperplane H_0 lies.

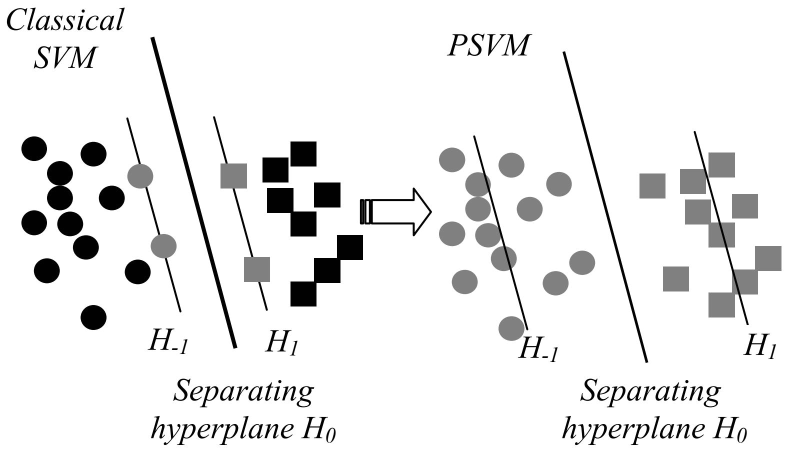


Figure 7.2.1. Geometrical interpretation of PSVM

In the nonlinear case of PSVM (we use a Gaussian kernel) the concept of Support Vectors (SVs) (Figure 7.2.1, in grey) disappears as the separating hyperplane depends on all data. In that way, all training data must be preserved for the testing stage.

Our proposed algorithm of dataset reduction consists of the following steps:

Step 1. Divide all the data into chunks of 1000 samples per chunk.

Step 2. Train a PSVM on each chunk performing 5-fold cross-validation (CV) to obtain the optimal kernel parameter and the C parameter that controls the training error.

Step 3. Apply an appropriate threshold to select a pre-defined number of chunks with the highest CV accuracy

Step4. Train a classical SVM on the amount of data selected in *Step 3*.

The proposed approach is in fact similar to Vector Quantization (VQ) used for dataset reduction for SVM in [LCC04]. With *Step 2* some kind of clustering is performed, and *Step 3* chooses the data that corresponds to the most separable clusters. However, unlike VQ, SVs, which are obtained with the proposed algorithm in *Step 4*, are taken from the initial data. Besides, additional homogeneity is achieved because the PSVM data clustering is performed in the transformed feature spaces with the transformation functions that correspond to the Gaussian kernel and the same kernel type is applied to the chosen data in *Step 4*. Additionally, as it will be shown in the experimental part, the proposed algorithm gives flexibility to select an efficient dataset for different levels of difficulty of the tested databases.

7.2.5.2 Adjustment to NIST metric

The second modification makes use of the knowledge of the specific NIST metric during the training phase. As it has been mentioned in Subsection 7.2.4, NIST metrics depends on the prior distribution of speech and non-speech in the test database. For this reason, if we want to improve the NIST scores we should penalize the errors from the speech class more than those from the non-speech class. That is possible for a discriminative classifier as SVM in the training stage by introducing different costs for the two classes. In that way, the separating hyperplane H_0 will no longer lie exactly in the middle of the H_{-1} and H_1 hyperplanes (Figure 7.2.1). In our case the SVMlight coefficient *j* was fixed to 10.

For a GMM classifier, however, it is possible to favour one of the classes only in the testing stage as it was done in [MNT06]. In that work the final decision was made from the condition $\alpha p_1(x)$-$(1$-$\alpha)p_2(x) > 0$, where α is a balancing factor, $p_1(x)$ and $p_2(x)$ are the likelihoods calculated with non-speech and speech GMMs, respectively. When positive, a non-speech label is assigned. α was fixed to 0.4. Although it was not done in this work, it is worth to mention that favouring a class in the testing stage could be done for SVM in a similar way through the bias *b* of the separating hyperplane.

7.2.6 Experiments

7.2.6.1 RT05 results

For the RT05 evaluation, the SPEECON database was used for training and development as it was done in [MNT06].

For SVM training we select the same number of data: 20 chunks = 20 thousand samples. Table 7.2.2 shows results of the RT05 evaluation with the SVM system, modified according to Subsections 7.2.5.1 and 7.2.5.2, along with the ones obtained with the best SVM and GMM systems in [MNT06].

From Table 7.2.2 we observe that, as it can be expected after the second modification, the NDER score has increased but the SDER score, which has the major influence on the NIST measure, has strongly decreased. In consequence, after both modifications, the NIST error for the modified SVM system decreases from 11.45% to 8.03%, showing comparable results to the best GMM system.

Table 7.2.2. Error rates obtained for RT05 with the modified SVM system

	NIST **MR / SDER / NDER**
GMM [MNT06].	8.47 7.69 / 4.61 / 38.42
SVM [MNT06]	11.45 10.41 / 7.99 / 34.56
SVM **modified**	8.03 7.30 / 2.51 / 55.07

7.2.6.2 RT06 results

In [MNT06] for the "confmtg" task and for the GMM classifier both SPEECON and RT05 databases were used for training. For the "lectmtg" task also a small amount of data collected in CHIL was added into training of the "lectmtg" system. For the SVM classifier, the dataset reduction algorithm was applied to the whole database available for training for RT06 task, namely, SPEECON, RT05, and the small amount of CHIL data. Only 10 thousand samples were selected for the final SVM training. Table 7.2.3 shows the results obtained with SVM for the RT06 task.

Table 7.2.3. SVM SAD results for two RT06 evaluation tasks

	"confmtg"	**"lectmtg"**
SVM	**4.88** (4.6 / 0.8 / 72)	13.86 (12.2 / 0.2 / 98)

As it can be seen from Table 7.2.3, the SVM SAD system while performing well for the "confmtg" task becomes almost a dummy system (the one that says everything is speech) for the "lectmtg" task with a non-speech error rate of 98%. The "lectmtg" part actually is quite different from "confmtg" part and due to the spontaneous character of the former it is more difficult for SAD. As well as a small amount of CHIL data, which can be considered noisier than the RT05 data, was added to the training dataset of the GMM system, we decided to change *Step 3* of the algorithm of dataset reduction and choose for the "lectmtg" training the lowest CV accuracy instead of choosing the highest CV accuracy as it was done for the "confmtg" task.

Table 7.2.4 shows the error rate of the GMM and SVM systems for the "confmtg" and "lectmtg" parts of the database. The values in bold in the GMM part were submitted for the NIST evaluations where our GMM SAD system outperformed all other submitted systems in the single distant microphone (sdm) condition.

Table 7.2.4. Error rates obtained for the RT06 evaluation for the "confmtg" and the "lectmtg" parts of the database. The results for matched conditions are given in bold.

	NIST MR / SDER / NDER			
	SVM		**GMM**	
Test **Train**	confmtg	lectmtg	confmtg	lectmtg
confmtg	**4.88** (**4.6 / 0.8** / 72)	13.86 (12.2 / 0.2 / 98)	**5.45** **(5.1 / 3.1 / 41.4)**	11.71 (10.3 / 0.1 / 83)
lectmtg	11.84 (11.2 / 11 / 14)	**6.16** **(5.4 / 1.4 / 33)**	9.54 (9 / 8.2 / 22.4)	**7.1** **(6.2 / 0.4 / 48)**

The diagonal elements of the SVM part show lower error rates than the diagonal elements of the GMM part. That indicates that the proposed algorithm managed to select the appropriate 10000 samples out of the whole training database available that consists of more than 1.5 million examples.

From Table 7.2.4 we observe that for the "lectmtg" case the change of *Step 3* of the proposed algorithm has an intermediate influence. Chunks with the lowest CV accuracy, which contain less separable data, are more important for the final classical SVM training in *Step 4* for the given subtask.

Notice that the NIST evaluation scenario allows having an independent system for each subtask so the comparison conditions for the GMM and for the SVM are the same.

On the other hand, the off-diagonal elements of the GMM part from the Table 7.2.4 show lower error rates than the off-diagonal elements of the SVM part. That can be either an indication that the GMM is not so sensitive to the mismatch between the training and testing databases or can be the result of the fact that GMM used much larger amount of data for training.

Actually, the off-diagonal elements are not considered in NIST but here we include them to show the behaviour of the GMM and SVM classifiers for the case when the characteristics of the training and testing databases do not match.

Note that, for comparison with GMM, the feature extraction process was left unchanged. Actually, taking one LDA measure and reducing the dimension of the final feature vectors can be beneficial for a generative model classifier as GMM since it means decreasing the difficulty of the estimation problem [DHS00] but in this way one of the main advantages of SVM classifiers – to make use of a much larger feature set – is not exploited. To check it we made a straightforward experiment. Instead of taking 1 LDA measure we decided to preserve 4 LDA measures for each frame, thus multiplying the total number of feature in a vector approximately by 4 (the 3 features based on energy dynamics remain the same). We tested it on the “lectmtg” task and observed an improvement of the error rate from 6.16% to 4.51% (the best GMM results were 7.1%). In consequence, further work should be done to design the front-end that can better fit the capacity of the SVM classifier.

7.2.7 Conclusions

The presented work is oriented towards robust SVM-based speech activity detection systems for smart-room environments.

Two modifications of the usual training algorithm of the SVM-based classifier presented in [MNT06] have been developed in order to cope with two problems of that classifier in our application: the very large amount of training data and the particular characteristics of the NIST metric. With those two modifications, the SVM system has reduced the error rate on the RT05 database from 11.45% to 8.03%, score comparable to the best GMM score of 8.47%. With the RT06 SAD evaluation task, the modified SVM system has achieved an error reduction with respect to the GMM system from 5.45% to 4.88% for the “confmtg” task, and from 7.1% to 6.16% for the “lectmtg” task. Additionally, the error rate for “lectmtg” task has been further decreased to 4.51% by preserving 4 LDA measures.

7.3 SAD Evaluation in NIST Rich Transcription Evaluations 2006 -2007

7.3.1 Introduction

The Rich Transcription 2006-2007 spring meeting recognition evaluation were the fourth and fifth NIST sponsored evaluation of speech technologies within the meeting domain. The evaluations are related to the CLEAR evaluations since both are concerned with multimodal signals and sensor fusion experiments in the meeting domain.

The RT-06 evaluation included three meeting domain tasks in the evaluation: Speech-To-Text (STT), diarization “who spoke when” (SPKR also known as “Speaker Diarization”), and SAD. The RT-07 evaluation dropped the task of the SAD however the task of speaker diarization needs SAD as a component of the system.

In Section 7.2 we already presented the results obtained by the proposed SVM-based SAD system for the RT-05 and RT-06 SAD evaluations. In this section we summarize the results of the previous RT SAD evaluations and also present the SAD results that were obtained for the last RT-07 evaluation within the speaker diarization task performed on conference meetings [LAT+07].

7.3.2 SAD systems overview and results on referenced datasets

In this subsection we present the results of the last SAD systems developed in our lab and tested in various RT evaluations conducted in the conference room environment. Table 7.3.1 shows the NIST metric error rates obtained by three UPC’s systems on the RT datasets. The system based on the Decision Tree (DT) classifier with the basic feature set that consists of the Frequency-Filtering-and-Linear-Discriminant-Analysis-extracted features (FF-LDA) was developed by J. Padrell et. al. in [PMN05] where on Speecon and SpeechDat databases it showed better results in comparison to the commercial GSM cell-phone standard SAD system and two SAD systems taken from the ETSI Advanced Front-End standard for noisy speech recognition [ETS02]. D. Macho et. al. in [MNT06] proposed three new energy dynamics features in addition to the basic FF-LDA feature set and substituted the DT classifier by the GMM classifier. The proposed GMM-based system showed better performance than DT-based system on RT-05 dataset in the tested sdm condition as it can be seen from Table 7.3.1. Besides, the GMM-based SAD system has been submitted to the RT-06 evaluation and outperformed all other submitted systems in sdm subtask in both the “lectmtg” and “confmtg” conditions. The proposed SVM-based SAD system substitutes the GMM classifier by SVM and proposes the solutions to the problems that appear when applying SVM to the SAD task. As it can be seen from Table 7.3.1, the SVM-based SAD system showed better results than the

GMM system on the RT-05 and RT-06 datasets. Additionally, Table 7.3.1 shows the results obtained with the proposed SVM-based system on the RT-07 sdm. The result obtained on a signal enhanced by beamforming signals from the multiple distant microphones (mdm) is also presented in Table 7.3.1.

Table 7.3.1. NIST error rates obtained for the "confmtg" task with the RT 05-07 evaluation databases by the UPC SAD systems.

	RT-05 sdm	**RT-06 sdm**	**RT-07 sdm**	**RT-07 mdm**
SVM	8.03	4.88	7.03	4.72
GMM	8.47	5.45	-	-
DT	11.54	-	-	-

7.3.3 Conclusions

In this section, the results obtained with the NIST RT evaluation datasets by the SAD systems developed in our lab have been shortly overviewed. The comparison has shown that the recently developed SVM-based SAD system performed better than both the GMM and the DT-based systems on the tested RT datasets. Additionally, the error rates produced with the proposed SVM-based SAD system on the last RT-07 evaluation dataset have been presented.

7.4 Chapter Summary

An enhanced version of the training stage of the SVM-based SAD system has been presented. It consists of a fast algorithm of data reduction and an adjustment to the specific characteristics of the metric used in the NIST SAD evaluations has been presented. Tested with the RT06 data, the resulting SVM SAD system has shown better scores than the best GMM-based system developed by the authors and submitted to the past RT06 evaluation.

The results obtained on the NIST RT evaluation datasets by the SAD systems developed in last years in our lab have been shortly overviewed showing better performance obtained by the developed SVM-based SAD system.

Chapter 8. UPC’s Smart-Room Activities

8.1 Chapter Overview

In this chapter the activities concerning Acoustic Event Detection (AED) in the UPC’s smart-room are described.

The remaining sections are organized as follows. In Section 8.2, a brief description of the Computer in the Human Interaction Loop (CHIL) project is proposed. The smart-room built at UPC in the framework of CHIL project is described in Section 8.3. Section 8.4 presents the information concerning the recording of the database of isolated acoustic events and the recording of seminars that were used in the CLEAR evaluation campaign on AED. Section 8.5 gives basic information on the implementation of the AED component in the smart-room. Finally, three different demos developed in the UPC’s smart-room, in which the implemented AED component has participated, are presented in Section 8.6.

8.2 CHIL Project

The project CHIL [CHI] is an Integrated Project (IP 506909) funded by the European Union under its 6th framework program. The project started on January 1st, 2004 and has a planned duration of three years.

The CHIL team is a consortium of internationally renowned research labs in Europe and the US, who collaborate to bring friendlier and more helpful computing services to society. Rather than requiring user attention to operate machines, CHIL services attempt to understand human activities and interactions to provide helpful services implicitly and unobtrusively.

Considerable human attention is expended in operating and attending to computers, and humans are forced to spend precious time on fighting technological artefacts, rather than on human interaction and communication. CHIL aims to radically change the way we use computers. Rather than expecting a human to attend to technology, CHIL attempts to develop computer assistants that attend to human activities, interactions, and intentions. Instead of reacting only to explicit user requests, such assistants proactively provide services by observing the implicit human request or need, much like a personal butler would. To achieve this goal, machines must understand the human context and activities better; they must adapt to and learn from the humans' interests, activities, goals and aspirations. This requires machines to better perceive and understand all the human communication signals including speech, facial expressions, attention, emotion, gestures, and many more.

Based on the perception and understanding of human activities and social context, a new type of context aware and proactive services can be developed. Within the years of the CHIL project, four instantiations of such CHIL services have been implemented:

- The connector: This service attempts to connect people at the best time by the best media, whenever it is most opportune to connect them. In lieu of leaving streams of voice messages and playing phone tag, the Connector tracks and knows its masters' activities, preoccupations and their relative social relationships and mediates a proper connection at the right time between them.
- The memory jog: This is a personal assistant that helps its human user remember and retrieve needed facts about the world and people around him/her. By recognizing people, spaces and activities around its master, the memory jog can retrieve names and affiliations of other members in a group. It provides past records of previous encounters and interactions, and retrieves information relevant to the meeting.

- Socially supportive workspaces: This service supports human gathering. It offers meeting assistants that track and summarize human interactions in lectures, meetings and office interactions, and provide automatic minutes and create browseable records of past events.
- The attention cockpit: This agent tracks the attention of an audience and provides feedback to a lecturer or speaker.

CHIL represents a vision of the future - a new approach to more supportive and less burdensome computing and communication services. The research consortium includes 15 leading research laboratories from 9 countries representing today's state of the art in multimodal and perceptual user interface technologies in European Union and the US. The team sets out to study the technical, social and ethical questions that will enable this next generation of computing in a responsible manner.

The CHIL results are disseminated and made available to a wide community of interested parties.

8.3 UPC's Smart-Room

The UPC has built the smart-room – a room equipped with multiple cameras and microphones – in order to investigate the video and audio perception of the computer systems. The main objective is to make the computer systems be aware of the activity that is going on in the room and to stop them being only the tools from which the humans can only obtain help as a reaction to the very special request. If computers know the environment they can interact with us in the same manner we interact with each other. The technologies of the perceptual interface have to enable computers help us with their information services better do our everyday work.

The smart-room is an intelligent space designed as a meeting-room with a table in the centre and chairs around it. The configuration of the UPC's smart-room can be found in Appendix A. Among others, there are several audio-visual sensors (cameras and microphones), synchronization and acquisition equipments, working computers, and a video projector. The smart-room is the indispensable installation for the UPC research groups that work on multimodal interfaces. The acquired audio-visual signals allow both developing the technologies of audio and video analysis and making demos that can offer specific services in the configuration of meeting rooms or teaching rooms.

The UPC's smart-room forms the part of the CHIL project, described in the previous subsection, along with other 15 participants, universities, and research groups from Europe and the United States.

The speech-related technologies like speech recognition are the fundamentals of the analysis of the human activity in the smart-rooms. At present, robust speech recognition systems are investigated that use a signal from a far-field microphone in order to avoid bothering people wear cables or close-talk microphones. On the other hand, the video technologies analyze the presence, localization and movements of the peoples, face recognition, gesture detection, postures and attention tracking, in order to classify the events, activities, and relationships. The detection technologies, classification and recognition based on multiple sensors, like audio and visual localization, person identification based on speech and face, activity detection based on acoustics or images, can increase the robustness of existing systems.

As a practical examples consider a meeting room. Imagine that you come late to the meeting. The system of perceptual analysis recognized who spoke and what was when you were absent. Then, when you joined the meeting, the system proposed you the summary of what was said during the time when you was absent. In order to achieve the objective the system had to: 1) localize the speakers, 2) focus the acoustics of the room to obtain the signal cleaned from noises and interferences of the far-field microphone, 3) identify the interval when something was said, 4) process the signal with a speech recognizer to generate the transcription of what was said, 5) finally, process the transcription to generate the summary.

With respect to the video analysis, the extraction of the data about the position, activity or gestures in the scene allow to obtain high level semantic information like knowing whether the person is sitting or standing, if the person makes a voting gesture (a hand picked up), etc. Besides, the UPC's smart-room allows reconstructing the virtual 3D scene from the images of multiple cameras that will be described in Subsection 8.6.3.

8.4 Recordings of the Databases in the Smart-Room

To work in real environments acoustic event detection problem has to be faced. For the purposes of AED a database of isolated acoustic events has been designed and collected at the UPC, which will be publicly disseminated by the European Language Resources Association. This database has been used as a training material and as a testing material to evaluate the algorithm performance for AED/C as it has been reported in Chapter 6. Along with other databases, it has been used in the international CLEAR evaluation campaigns that have taken place in spring 2006 and spring 2007, where the AED/C evaluation task has been coordinated by our UPC's group, which has defined the AED metrics and developed the corresponding evaluation tools. The details on the database of isolated acoustic events are given in Appendix A. Apart from the database of isolated acoustic events, UPC contributed to the seminar recordings that were also used as a part of the development and testing datasets in the international evaluation campaigns. In order to increase the number of acoustic events in the recorded seminars, a list of suggestions was produced and disseminated among the partners that contributed to the recorded database. The suggestions include instructions on how to introduce acoustic events into the seminars in a natural and unobtrusive way. The details of the instructions as well as a trade-off between the naturalness of the seminar recordings and AE recordings are discussed in Appendix B.

8.5 Acoustic Event Detection Component Implementation

Our system, which is described in Section 6.5, is written in C++ programming language and is a part of the smartAudio++ software package developed at UPC which includes other audio technology components (such as speech activity detection, acoustic source localization, and speaker identification) for the purpose of real-time activity detection and observation in the smart-room environment.

The software architecture chosen in the UPC's smart-room is based on NIST smartflow system [NIS] and KSC socket messaging system. The lower level of the software architecture consists of the video and audio sensors. The signal capture software is implemented as smartflow clients in the computers with the corresponding acquisition hardware. The resulting data streams are transferred as smartflow flows into other computers that can either pre-process the data streams or directly analyze the raw data streams (as in the case of the speech activity detection audio technology). Smartflow also provides a mechanism to dynamically decide on which computer in the local area network a specific technology should run. The KSC message server and the KSC client library allow sending results of data analysis asynchronously.

Figure 8.5.1 shows the smartAudio map that corresponds to the AED system described in Subsection 6.5.3. The map shows the needed smartflow clients and the interconnections among them. Firstly, a audio signal from cluster microphones and the MarkIII microphone array are captured with data acquisition clients RMEAlsaCapBlock and UPCMarkIIICapturev0.1, respectively. Three cluster microphones (one from each cluster) and the 3rd channel of the MarkIII are extracted with the RMEChannelExtractors and the MarkIIIChannelExtractor, respectively. Then, with the Resample-Clients the signals are downsampled to 16 kHz. Feature extraction and SVM-based sliding window classification are performed for each channel with the AEDOnLine client, and the fusion of decisions is applied with the AEDFusion client. Depending on the demo, in which the AED perceptual component is involved, there can be clients shared among several perceptual components, for instance data acquisition or resample clients, and clients responsible for results visualization.

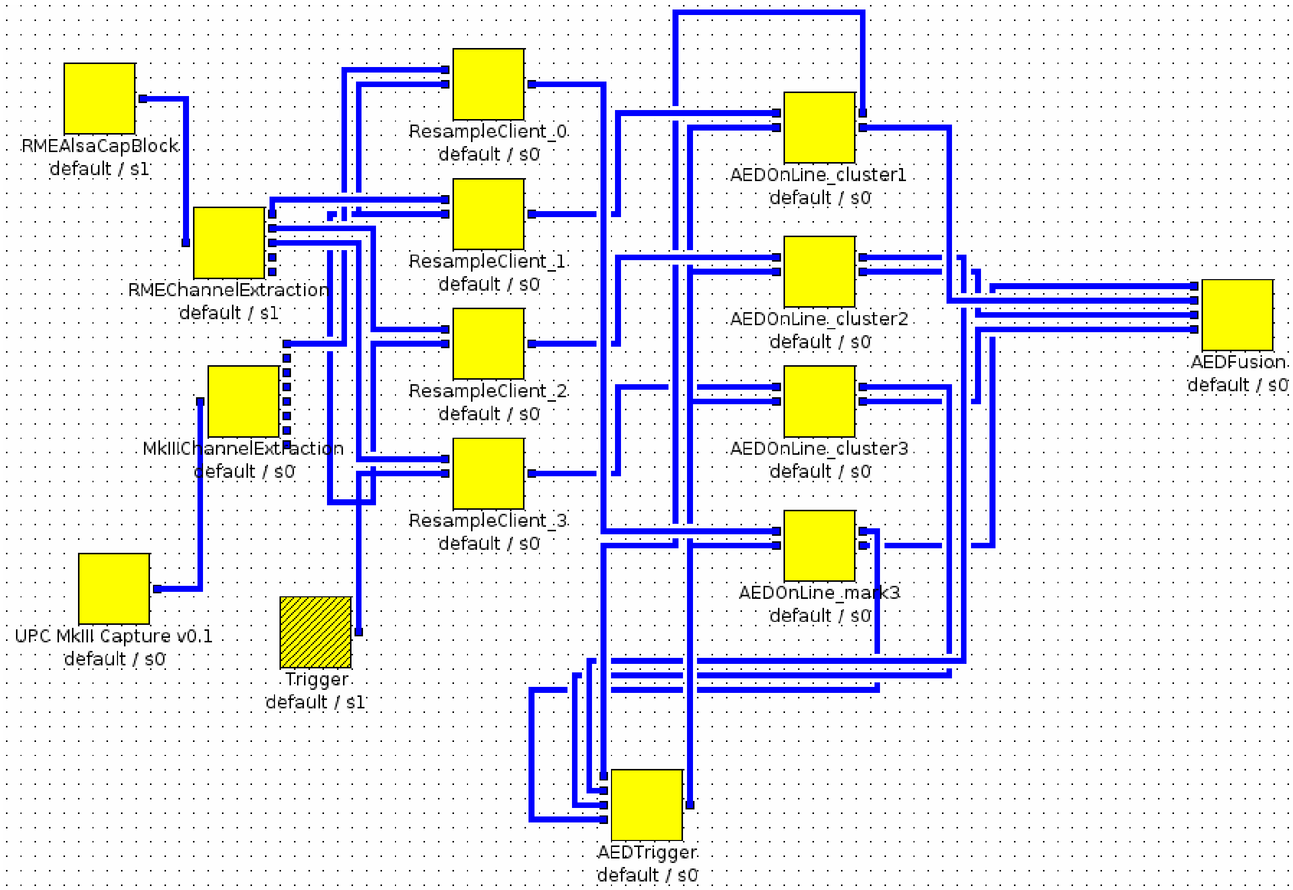


Figure 8.5.1. SmartAudio map that corresponds to the AED system

8.6 Acoustic Event Detection Demonstrations

8.6.1 Acoustic event detection and acoustic source localization demo

Acoustic event detection and acoustic source localization (ASL) are two of the functionalities implemented in the UPC’s smart-room.

A Graphic User Interface (GUI) that shows both functionalities working together has been developed and it is currently running in real time in the smart-room. It is used to test the technologies and to demonstrate them. A video has been recorded with the output of the GUI during a session lasting about 2', where four people in the room speak, are silent, or make one of the 12 meeting-room sounds defined in CHIL and a few others[1]. The 12 defined sounds, ordered according to time of occurrence in the session, are: knock (door), door slam (door open, door close), steps, chair moving, spoon clings (cup jingle), paper wrapping, key jingle, keyboard typing, phone ringing, applause, cough and laugh. The screenshot of the GUI is given in Figure 8.6.1 when a laugh sound is produced.

There are two screens in the GUI output as it is shown in Figure 8.6.2. One corresponds to the real video captured from one of the cameras installed in the UPC’s smart-room, and the other is a graphical representation of the output of the two technologies. The video has not been edited at all, and it shows what can be seen in the room in real time.

The two functionalities are simply juxtaposed in the GUI, so e.g. it may happen that the AED output is correct but the output of acoustic source localization is not, so showing the right event in a wrong place. There is some clutter noise in the localization output due to the fact that the algorithm allows sudden changes of position and no other information has been used for smoothing the output position during an event.

The AED technology includes an “unknown” output, symbolized with “?”. There are two different situations when the “unknown” label may appear. Firstly and most frequently, it appears when the AED algorithm does not have enough confidence to assign a detected non-silent event to one of the above-mentioned 12 classes. Secondly, the “unknown” label is produced when an out-of-list acoustic event is detected.

[1] The video is downloadable from http://gps-tsc.upc.es/veu/personal/temko/presents/AEDLdemo_UPC.avi

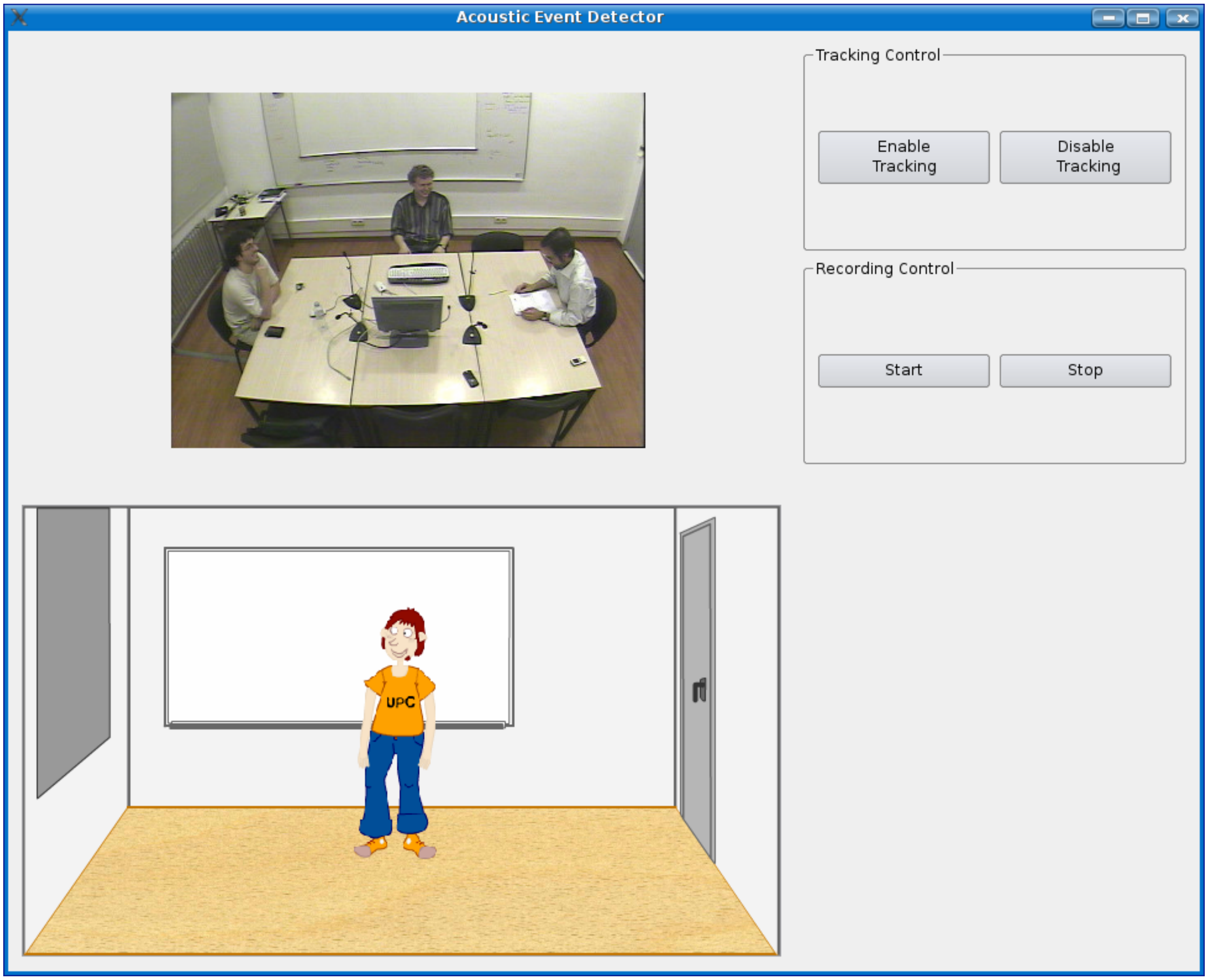
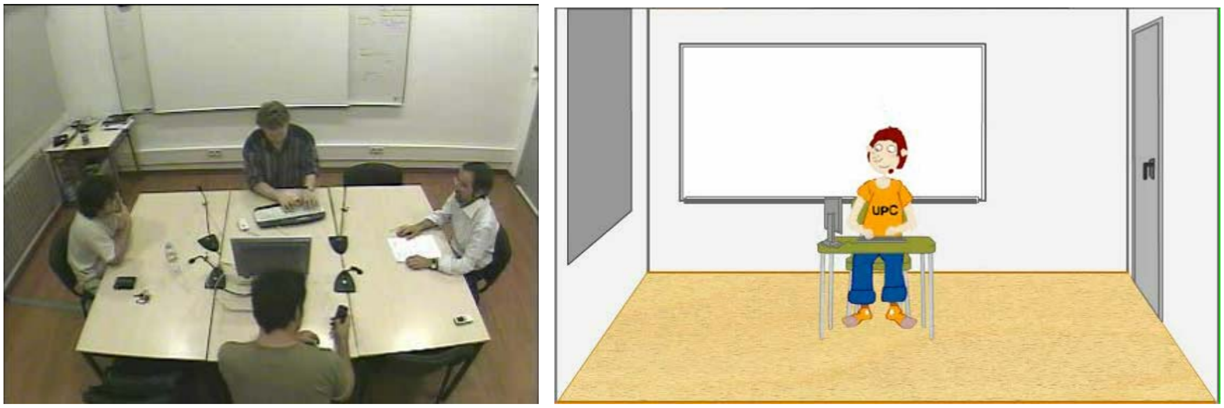


Figure 8.6.1. The developed GUI for demonstration of AED and ASL functionalities ("laugh" is being produced)



(a) (b)

Figure 8.6.2. The two screens of the GUI: real-time video (a) and the graphical representation of the AED and ASL functionality ("keyboard typing" is being produced)

8.6.2 Acoustic event detection in CHIL mockup demo

The aim of the mockup demonstration [CN07] designed at UPC is to gain context awareness in the context of the CHIL memory jog assistant. It is achieved by means of detection of people, objects, events, and situations in the interaction scene. The information needed to build the relevant context awareness stems from the analysis of the signals acquired in real-time from a collection of sensors. Specifically, the memory jog service developed at UPC focuses at providing information to a group of newspaper journalists gathered together in the CHIL smart-room. Figure 8.6.4 shows the screen-shot of the journalist's laptop. In the lower right part of the Figure 8.6.4, the Skype-based bi-directional audio communication allows talking to the journalists in the room. The upper right shows the real-time video stream from one of the cameras of the meeting room. An automatic cameraman is choosing the optimal camera from five possible angles. This decision is based on the location of the last acoustic event and smoothed by a hysteresis to avoid rapid camera-changes. The real-time video streaming also displays annotations in the form of subtitles that explain the situation, e.g., "people enter", "interaction with ASR", "sound of keys", "front page published", "The meeting has started". On the left side of the screen, a graphical user interface allows the field journalist of add a piece of news (a test and an image) to the decision GUI of the journalists in the room. Within ten minutes the front page of tomorrow's edition of their newspaper has to be decoded. One of the most outstanding means of the memory jog to interact with the journalists is a talking head shown in Figure 8.6.3 that not only informs the journalists about available resources, and points out events such as the arrival of a latecomer or news being contributed by remote colleagues, but also facilitates information requests from the journalists in a human-like interface based on automatic speech recognition technologies.

In the service implemented at the UPC's smart-room, context awareness consists of knowledge about the number of persons in the room, their identification, position in the room and their orientation. Objects in the room and acoustic events also add to the context awareness. It is worth to mention that when humans experience the computer-driven service like the Memory Jog, another subjective bias naturally arises: unexpected actions of the service triggered by a false-positive detection of one of the technologies turn out to be far more annoying than a service not provided due to false-negative detection. Due to that fact, only acoustic events that can be reliably detected are chosen: door knock, door opening/closing, speech, applause, and key jingles.

Perceptual components are computing modules that analyze the signals provided by the network of sensors in order to detect and classify objects of interest, persons and events adding information to context awareness. In total 8 perceptual components which are based on around 42 smart-flow clients, are integrated into the single application called central logic. The combination of video-based and audio-based systems allows the system to gain a basic understanding of what happens in the smart-room. Among others it is possible to do the following:

a) A person of interest (e.g. the latecomer) can be tracked in the room. This location is used to direct the talking head and an automatic cameraman to his current position.

b) The position of all participants can be used to guesstimate changes of the state of the session, e.g. between the states “people enter”, “meeting starts” or “coffee break”.

c) The position and identity of sudden acoustic event can be determined. The automatic cameraman has been configured to capture these events by choosing the camera that is positioned furthest from the location of the acoustic event.

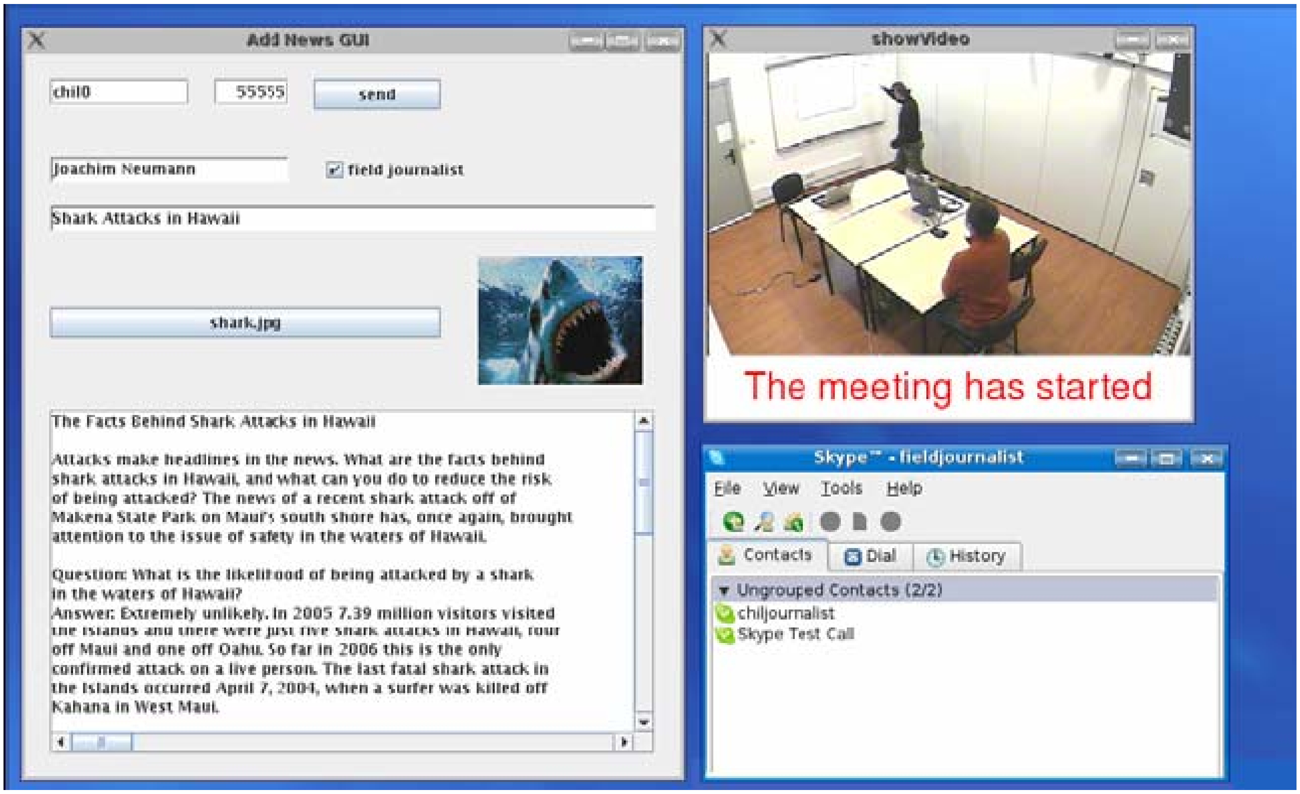
d) In the current implementation of the context awareness, the detection of a latecomer is based on a multitude of criteria amongst which the first two depend on the person and object tracking: increase of the number of person, appearing of a new object close to the door, detection of the acoustic signal of a door-knock, a door-slam or steps close to the door.

e) Person identification is performed based on face ID and speaker ID technologies.

f) The dialogue system allows a human-like verbal interaction with the memory jog system. It is based on two components: a commercially available 2D animation of a talking head and an ASR based dialogue system that utilizes the HTK recognizer [You93].

g) Interactive behaviour of the talking head depending on an acoustic event detected, like an utterance “Don’t forget your keys!” when “key jingle” is detected or exclamation “Great! Well done!” when “applause” is detected.

Figure 8.6.3. The talking head is a mean of demonstrating the context awareness given by perceptual components



chil0 55555 send

Joachim Neumann ☑ field journalist

Shark Attacks in Hawaii

shark.jpg

The Facts Behind Shark Attacks in Hawaii

Attacks make headlines in the news. What are the facts behind shark attacks in Hawaii, and what can you do to reduce the risk of being attacked? The news of a recent shark attack off of Makena State Park on Maui's south shore has, once again, brought attention to the issue of safety in the waters of Hawaii.

Question: What is the likelihood of being attacked by a shark in the waters of Hawaii?
Answer: Extremely unlikely. In 2005 7.39 million visitors visited the islands and there were just five shark attacks in Hawaii, four off Maui and one off Oahu. So far in 2006 this is the only confirmed attack on a live person. The last fatal shark attack in the Islands occurred April 7, 2004, when a surfer was killed off Kahana in West Maui.

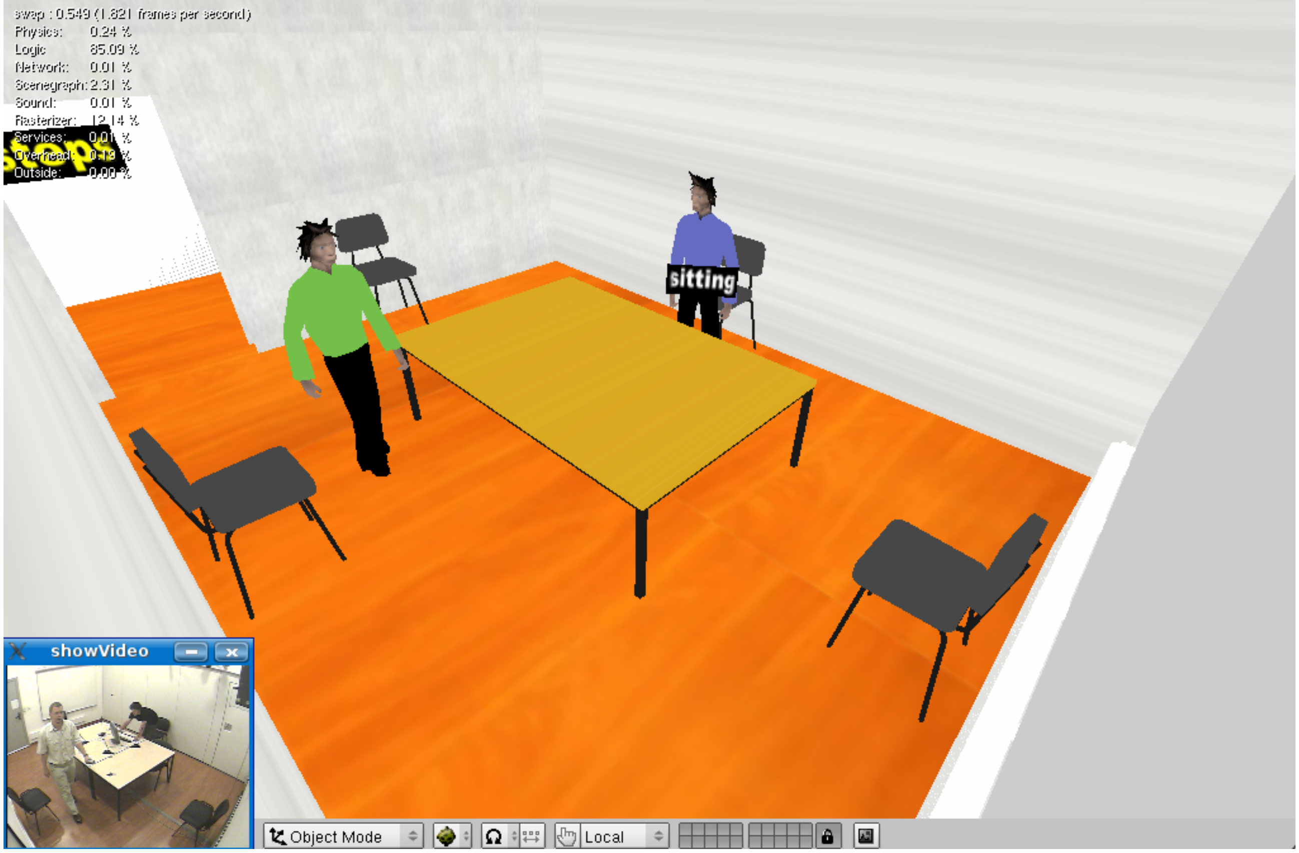
The meeting has started

Figure 8.6.4. Screenshot of the field journalist's laptop

8.6.3 Acoustic event detection and 3D virtual smart-room demo

The last demo is developed to demonstrate the UPC's smart-room remotely. The functionalities that are currently involved in the demonstration are the 3D person tracking, ASL, and AED.

The virtual 3D scene is reconstructed from the images of multiple cameras in the smart-room. Figure 8.6.5 shows the developed 3D visualizer. Specifically, it shows one detected person sitting, and the other passing in the room. "Steps" are detected with the AED and localized in space with the ASL. The text label "steps" is assigned to the place where the event happens. Additionally, the small screen at the lower left corner shows the corresponding real video.



```
swap : 0.549 (1.821 frames per second)
Physics:       0.24 %
Logic          85.09 %
Network:       0.01 %
Scenegraph: 2.31 %
Sound:         0.01 %
Rasterizer:    12.14 %
Services:      0.01 %
Overhead:      0.19 %
Outside:       0.00 %
```

Figure 8.6.5. A snapshot that shows the built virtual UPC's smart-room

8.7 Chapter Summary

In this chapter the activities concerning Acoustic Event Detection (AED) in the UPC’s smart-room have been described.

A brief description of the CHIL project has been proposed and the main objectives have been highlighted. The smart-room built at UPC in the framework of CHIL project has been described. The basic information concerning the recording of the database of isolated acoustic events and the recording of seminars that were used in the CLEAR evaluation campaign on AED has been reported. The implementation of AED component has been reviewed. Finally, three different demos developed in the UPC’s smart-room and in which the implemented AED component participated have been presented. Specifically, the demo of AED and acoustic source localization with a cartoon animation, the role of AED in the versatile mockup demo, and the 3D demonstration of the UPC’s virtual smart-room using the 3D person tracking, acoustic source localization, and AED, have been described.

Chapter 9. Conclusions and Future Work

9.1 Summary of Conclusions

This thesis is a pioneering work in the area of audio classification that, by focusing on the acoustic events which are naturally produced in a meeting-room environment, ranges from classification of previously segmented acoustic events to detection of acoustic events in seminar sessions, and its real-time implementation in the smart-room of the UPC. SVM classifier is chosen as a basic classification technique in this thesis.

The first main contribution of this thesis is an attempt to deal with the problem of **classifying acoustic events**. When trying to deal with the problem of acoustic event classification in the framework of the CHIL project [CHI], we soon noticed that reported works are scarce. Actually, classification of sounds has usually been carried out so far to segment digital audio streams using a limited number of categories, like music/speech/silence/environmental sound. We have focused on acoustic events that may take place in meeting-rooms or classrooms and on the preliminary task of classifying isolated sounds. The number of sounds encountered in such environments may be large, but in the initial work we have chosen 16 different acoustic events, including speech and music, and a database has been defined for training and testing. Several feature sets and classification techniques have been tested with it. In our tests, the SVM-based techniques show a higher classification capability than the GMM-based techniques, and the best results were consistently obtained with a *confusion matrix based variable-feature-set clustering scheme*. With it, a large relative average error reduction with respect to the best result from the SVM conventional binary tree scheme has been obtained. That good performance is mostly attributable to the proposed clustering technique, and to the fact that SVM provides the user with the ability to introduce knowledge about data unbalance and class confusions.

A drawback of SVMs when dealing with audio data is their restriction to work with fixed-length vectors. Both in the kernel evaluation and in the simple input space dot product, the units under processing are vectors of constant size. However, when working with audio signals, although each signal frame is converted into a feature vector of a given size, the whole acoustic event is represented by a sequence of feature vectors, which shows variable length. In order to apply an SVM to this kind of data, one needs either to normalize somehow the size of the sequence of input space feature vectors or to find a suitable kernel function that can deal with sequential data.

Several methods that adapt *SVMs to sequence processing* have been reviewed and applied to the classification of sounds from the meeting room environment. We have seen that the dynamic time warping kernels work well for sounds that show a temporal structure, but due to the presence of less-time-structured sounds in the database the best average score is obtained with the Fisher kernel. Moreover, only one Gaussian is used in that method due to its high sensitivity to the variance parameters as a consequence of the scarcity of data.

Usual combinations of classifier outputs like sum, product, max, min, weighted arithmetical mean, assume that each output represents an independent source of information that can be treated separately. Often, this is not the case, and an approach that considers the interactions among the classifier outputs is needed. *Fuzzy integral* fusion can capture interactions among the various sources of information. Moreover, the *fuzzy measure*, which is associated with the fuzzy integral, furnishes a measure of importance for each subset of information sources, allowing *feature selection* and giving a valuable insight into the classification problem itself. Experiments with fuzzy integral have been carried out with a set of five human vocal-tract non-speech sounds (cough, laughter, sneeze, sniff and yawn) which was found responsible for a large part of errors in the classification of meeting-room acoustic events. Ten types of features were chosen with a substantial degree of redundancy in order to use the fuzzy measure to find out their relative importance and their degree of interaction.

In the experiments, a system which fuses several information sources with the fuzzy integral formalism has shown a significant improvement with respect to the best single information source. Moreover, the fuzzy integral decision-level fusion approach has shown comparable results to the high-performing SVM feature-level fusion. Finally, the experimental work also indicates that the fuzzy integral may be a good choice when feature-level fusion is not an option e.g. when the feature-level fusion is difficult (e.g. due to the different nature of the involved features), or when it is beneficial to preserve the application or technique dependency (e.g. when fusing well-established feature-classifier configurations). For that purpose we have also conducted experiments to combine hidden Markov models that use frame-level features with the SVM using signal-level features, and have witnessed an additional improvement.

Systems of acoustic event classification developed in this thesis have participated in the dry-run evaluation on acoustic event classification in 2004, in the first official evaluation on acoustic event classification in 2005, and in the international CLEAR evaluation campaign in 2006. In all those evaluations, the system ranked among the best, and, in the last one, outperformed the other two submitted systems.

The second main contribution of this thesis is the development of systems for **detection of acoustic events**. AED is more complex than AEC since it includes both classification and determination of the time intervals where the sound takes place. Two acoustic event detection systems were developed at the UPC for CLEAR evaluations.

The first system has participated in the CLEAR 2006 evaluation tasks concerning the detection of acoustic events that may happen in a lecture/meeting room environment. Two kinds of databases have been used: two databases of isolated acoustic events, and a database of interactive seminars containing a significant number of acoustic events of interest.

The system of year 2006 was based on two steps: performing silence/non-silence segmentation and then classification of non-silence portions. Our system was based on an SVM discriminative approach and used frequency filtering features and four types of perceptual features. The detection results indicated that first doing segmentation and then classification performs worse than merging both segmentation and classification in one step, as it is performed by Viterbi search in the state-of-the-art ASR systems that have been developed for many years and therefore can be considered as a challenging reference for other presented approaches/systems in the acoustic event detection task like our SVM-based system.

The next AED system has participated in the CLEAR 2007 evaluation. The evaluation has been performed with the database of interactive seminars that has been recorded at different smart-rooms and contains a significant number of acoustic events of interest. Two different metrics have been proposed and implemented. One is based on precision and recall of the detection of the AEs as semantic instances, and the other is more time. The system of 2007 merges the two steps (segmentation and classification) and is also based on SVM classifiers. Each sliding window is classified with SVM classifiers and a post-processing is applied to the sequence of decisions. According to the importance and degree of interaction of features from the work with the fuzzy integral, several features were added to the set of features used in the AED system 2006 and one feature was eliminated. Additionally, multi-microphone decision fusion was introduced into the AED system 2007. The proposed system, which was the only submission not using HMM, ranked the second out of six participants.

A work oriented towards robust *SVM-based SAD* for smart-room environments has also been carried out. A set of several hundred of thousand of samples is a usual amount of data for classical audio and speech processing techniques that involve GMM. However, it is an enormous number of feature vectors to be used for a usual SVM training process and hardly makes such training feasible in practice. In this thesis, the usual training algorithm of the SVM classifier has been enhanced in order to cope with that problem of dataset reduction, proposing a fast algorithm based on Proximal SVM. Besides that, the SVM learning process has been adjusted in order to take into account the specific characteristics of the metric used in the NIST RT evaluations. The resulting SVM SAD system has been tested with the RT06 data, and it has shown better scores than our GMM-based system which was submitted to the RT06 evaluations and ranked the first among all submitted systems in single distant microphone condition.

This thesis has proactively contributed to provide the tools and resources that make the research possible, including: recordings and labelling of the databases, providing support to worldwide open competitions organized in CHIL, the organization of AED/C evaluations, definition of classes, evaluation scenarios and conditions, databases, etc. The metrics were changing starting from the first evaluations in 2004. Finally, after almost four years of task evolution, two grounded metrics have been proposed, agreed, and used in the last CLEAR evaluation campaign. The evaluation plans as well as other coordinating activities have been reflected in several CHIL deliverables, revised implementation plans, and UPC internal reports.

Another contribution of this thesis is the real-time implementation of the developed AED and SAD systems. The system based on four extracted LDA measures and SVM classifier has been used in UPC's smart-room for real-time SAD. A GUI that shows AED and acoustic source localization functionalities working together has been developed and it is currently running in real time in the smart-room. It is used to test the technologies and to demonstrate them. A video has been recorded with the output of the GUI during a session lasting about 2', where four people in the room speak, are silent, or make one of the 12 meeting-room sounds defined in CHIL and a few others. Besides, the developed real-time AED component contributed to two more demonstrations of technologies and services developed within CHIL project.

9.2 Future Work

From the work done in this thesis a set of problems and limitations have been detected and should be faced in future. In this subsection we will critically summarize the drawbacks of the techniques that were developed and used throughout the work, and also propose a few envisaged research lines that seem promising.

9.2.1 Feature extraction and selection

In this thesis work several feature sets have been used for the AEC task. In Section 4.5, a set of what we called perceptual features was investigated and one new feature was proposed. For the feature selection, the importance and interaction indices were calculated with FI. However, we concentrated on the interrelations inside the perceptual set of features and so did not calculate the interaction between the conventional ASR feature set and the perceptual features. We think it can be useful to group all perceptual and conventional ASR features into several acoustic groups according to the way each feature describes an audio signal. In this way, we plan to investigate the importance of and interactions among the mentioned groups of features in order to see which combinations of groups may be beneficial for audio processing.

The normalization of the acoustic features to make different instances of a given event appear as similar as possible is also an important problem in classification and detection of acoustic events. More time should be also spent on the low-level features to try to ensure good generalization across different channel characteristics.

When applying SVM in our work we used statistical parameters like mean and variance, or mean, variance, autocorrelation, and entropy in order to transform the frame-level features into segment-level features. Indeed, the performed averaging over frames results in a huge loss of information. Alternative approaches can be envisaged like the recently proposed GMM SuperVector kernel [CSR+06] where the final vector is constructed from the parameters of GMMs trained on every segment of an audio signal.

9.2.2 Sequence-discriminative SVM

The ability to model dynamics of the observed data is one of the major characteristics of the state-of-the-art HMM techniques in speech and audio processing, and it is a big advantage over static classification techniques like SVM classifiers. However, the good performance of SVM for several classification tasks and its excellent theoretical background stimulate the research community to keep looking for ways to enable SVM to work with variable-length sequences. In our work in Section 4.4, we compared several sequential kernels for the task of AEC. The experiments were performed on a small database and it would be interesting to see if the same conclusions can be drawn from much larger databases. Besides, the observed bias of classifiers in our results with sequential kernels to specific types of AE classes is a good basis for a successful application of fusion techniques. On the other hand, the efficient way to introduce the dynamics of the sequences into the kernel is still an open research area.

9.2.3 Acoustic event detection in real environments

Detection of acoustic events appeared to be a very interesting and difficult task. The initial works carried out in this direction in this thesis and the results obtained within the international evaluation campaigns showed that, although the proposed system, which was the only submission not using HMM, ranked among the best, there is still a big room for improvement.

The biggest problem in real environment AED is overlappings – i.e. temporal intervals where the AE of interest is overlapped with speech and/or other AEs. It was found that the overlapping segments account for more than 70% of errors produced by every submitted system. The problem of overlapping of different speakers has been addressed since the NIST RT-07 [Spr06] evaluation campaign where the tasks (e.g. Speaker Diarization) have been evaluated on overlapped segments as well. Actually, the problem of acoustic overlappings is closely related to the “cocktail-party” problem [Bre90] [WB06]. In the latter, however, one usually tries to separate one speech source from others. Conversely, in our application we would like to separate acoustic events from speech. Conceptually, the problem of overlapping can be addressed at different system levels. At the signal level, it can be dealt with source separation techniques like ICA. The overlapping problem can be addressed at the level of models by modelling also the possible combination of sounds by classifiers. Finally, at the level of decision, different weights can be assigned within the multi-microphone system architecture to particular microphones. In the latter case the main assumption is that the audio sources (in our case, speech and acoustic events) are well separated in space, and an acoustic event of interest can be the most powerful signal in some microphone. Future work will be devoted to search a better way to deal with overlapping sounds.

Additional improvement is expected by integrating the developed variable-feature-set clustering scheme (see Section 4.3) into the AED system.

Multimodal AED is another approach from which a performance improvement can be expected. Some sounds can be detected by video technologies, e.g. “steps” can be assumed when detecting an object moving around the smart-room, etc.

The choice of the system structure is also very important. In fact, none of the AED systems presented to the evaluations was built as a set of isolated detectors. That is, there were no systems which intended to detect one particular sound. This approach can be addressed in future.

When an SVM-based AED/C system is trained, it would be interesting to be able to adapt it to a new environment keeping the same acoustic event classes. For this it is necessary either to design a mechanism of online learning or perform an adaptation of the learnt SVM classifier to new environmental acoustics similar to MAP or MLLR adaptation for GMM. Some works on the former approach can be found in the literature [DC03] while the latter is still an open question.

Detection of higher-level semantics like the stage of a meetings based on the statistics of occurrences of AEs is an interesting topic and deserves attention. For example, detection of frequent cup/spoon jingles may indicate that the meeting is in its “coffee break” stage, etc.

9.2.4 Fuzzy integral fusion for multi-microphone AED

A few information sources were fused in our work with the FI formalism. The use of semi-shared and individual FMs is a promising approach. Unfortunately, we were not able to explore it more due to the scarcity of the data in the evaluation corpus. Future work will also be devoted to the application of the FI to multi-microphone classification and detection of acoustic events with a much larger dataset recorded in meeting rooms (see Section 6.5). Also, a further improvement can come from the fact that signals captured from microphones placed at different positions in the room may carry different information about the acoustic events taking place in it.

9.2.5 Acoustic source localization for AED

Combination with other audio technologies can be very beneficial for AED. For instance, based on the position of the localized audio source and its orientation, different weights can be efficiently assigned to the microphones in the smart-room to increase the performance of AED.

9.2.6 Speech activity detection

The work concerning SAD presented in this thesis mostly intended to show how SVM can be efficiently applied to the SAD task. In Chapter 7, it was shown that the proposed SVM-based SAD system showed results which were competitive and at times significantly superior to GMM and decision tree classifiers. As it was reported in Chapter 7, making use of a much longer feature set by preserving 4 LDA measures for each frame improved the error rate for SVM. Further work should be done to design the front-end that can better fit the capacity of the SVM classifier.

The system based on four extracted LDA measures and an SVM classifier has been used in the UPC's smart-room for real-time SAD. However, although the algorithm has shown a very good performance in the offline tests, as reported in Chapter 7, in the online tests it produces lots of confusion of speech with high-energy acoustic events (cough, door slam, etc). In fact, we also tried the GMM method but it performed badly either. Actually, although most existing SAD methods are energy based as usual testing datasets designed for the SAD task do not have a rich variety of acoustic events, but just speech and silence, the Speech vs. Non-Speech task becomes a Silence vs. Non-Silence task. Again, this fact shows that AED and SAD are two interlaced problems which require a common solution when working in real seminar environments. Further investigation will be devoted to a closer integration of both technologies.

Appendix A. UPC-TALP Database of Isolated Meeting-Room Acoustic Events

Introduction

This database contains a set of isolated acoustic events that occur in a meeting room environment and were recorded for the CHIL Acoustic Event Detection (AED) task. The recorded sounds do not have temporal overlapping. The database can be used as a training material for AED technologies as well as for testing AED algorithms in quite environments without temporal sound overlapping.

Description of the acoustic events

For recording, we used the same list of sounds that was defined in CHIL with conventional labels, except for “door slam” that was further divided into “door open” and “door close”:

Acoustic event	Label
Knock (door, table)	kn
Door open	do
Door close	dc
Steps	st
Chair moving	cm
Spoon (cup jingle)	cl
Paper work (listing, wrapping)	pw
Key jingle	kj
Keyboard typing	kt
Phone ringing/Music	pr
Applause	ap
Cough	co
Laugh	la
Unknown	un

Description of the recording setup

The whole database was recorded using the following audio equipment: Mark III (array of 64 microphones), three T-shape clusters (4 mics per cluster), 4 tabletop and 4 omni directional microphones. In total 64+12+8=84 microphones. The positions of the microphones in the UPC CHIL - room are described in Figure A.1. Figure A.2 describes the configuration of the T-shaped clusters. Data was recorded at 44.1 kHz, 24-bit precision, and then converted to 16-bit Raw Little-Endian format. All the channels were synchronized. During all the recordings two-three additional people were inside the room for a more realistic scenario.[2]

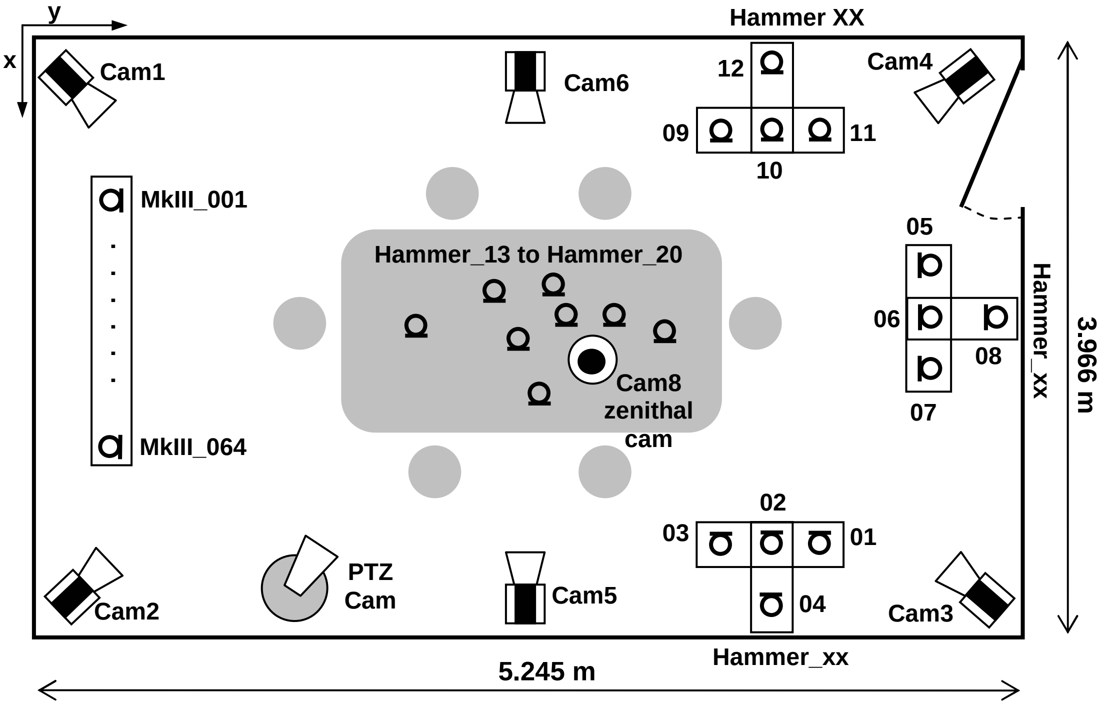


Figure A.1. Microphone and camera positioning in the UPC's smart-room

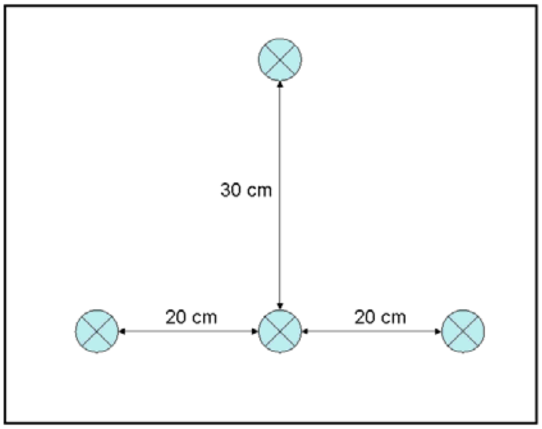


Figure A. 2. Configuration & orientation of the T-shaped microphone clusters

[2] Video data was also acquired simultaneously to audio data.

Description of the recorded database

Approximately 60 sounds per each of the sound classes were recorded. Ten people participated in recordings: 5 men and 5 women. There are 3 sessions per each participant. At each session, the participant took a different place in the room out of 7 fixed different positions that are marked in Figure A.3. The exact coordinates of the positions are given in Table A.1**.** Participant positions for each session are shown in Table A.2.

Table A.1. X, Y coordinates of the positions

Position	X (meters)	Y(meters)
P1	1.28	1.58
P2	1.28	2.40
P3	1.28	3.05
P4	2.28	3.53
P5	3.03	3.05
P6	3.03	2.40
P7	2.19	1.26

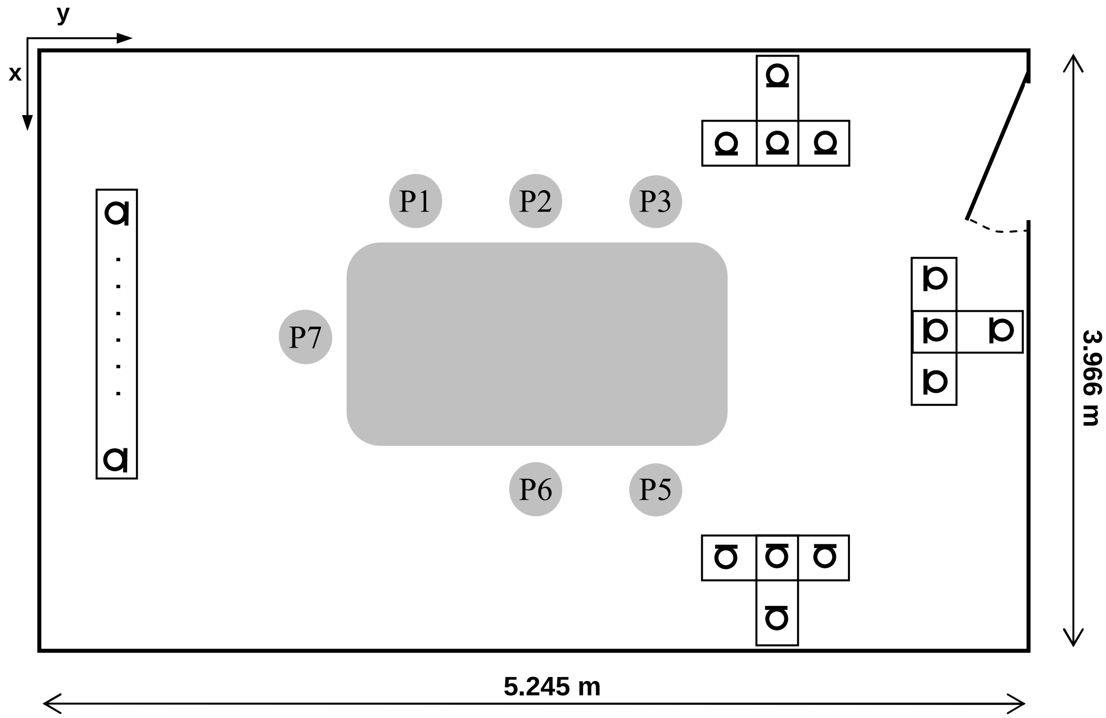


Figure A.3. Graphical illustration of participants' positions

During each session a person had to produce a complete set of sounds two times. A script indicating the order of events to be produced was given to each participant. Almost each event was followed and preceded by a pause of several seconds. All sounds were produced individually, except “applause” and several “laugh” that were produced by the people that were inside the room altogether

Table A. 2. Position of each participant for each session

	Session 1	Session 2	Session 3
UPC_AE01(m)	P2	P7	P3
UPC_AE02(m)	P4	P6	P1
UPC_AE03(m)	P4	P5	P6
UPC_AE04(m)	P2	P7	P3
UPC_AE05(f)	P4	P5	P1
UPC_AE06(f)	P4	P2	P3
UPC_AE07(f)	P7	P6	P5
UPC_AE08(m)	P1	P4	P5
UPC_AE09(f)	P2	P3	P7
UPC_AE10(f)	P1	P6	P3

Annotation of the database

The annotation was done manually by listening at signals from a single channel (the 3rd channel from Mark III microphone array). The following criterion was used during the annotation. If an event of class X includes a pause of minimum 300ms and both parts of the event, the one before the pause and the one after the pause, can be (subjectively) assigned a label X, then the event is annotated as two separated events of class X. If either the pause length is less than 300ms or the first/second part of the event is not recognizable without hearing the other part, the whole event is marked as only one event of class X. That kind of events only occurs for classes “cough”, “laugh”, and “phone ring”.

Contents of the distributed database

The database that is distributed in 3 DVDs contains signals corresponding to 23 audio channels and the corresponding labels. The 23 audio channels correspond to: 12 microphones of the 3 T-shaped clusters, 4 tabletop omni directional microphones, and 7 channels of the Mark III array: 3rd, 13th 23rd, 33rd and 43rd, 53rd, and 63rd. The 7 mics from the array can be viewed as three clusters, as shown in Figure A.4.

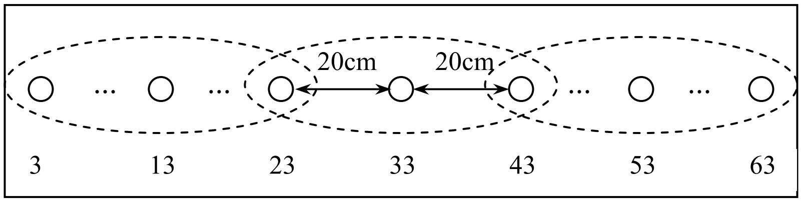


Figure A. 4. Selected channels of Mark III array, distance between them and symbolic grouping into clusters

The splitting of the data for purposes of training and testing can be based on either participants or sessions. To produce the DVDs, we chose the latter option, so the database is distributed on three DVDs each one containing one session. Table A.3 shows the distribution of the audio material among the three sessions.

Table A. 3 Number of annotated acoustic events in each session

Event type	**Session 1**	**Session 2**	**Session 3**
kn	15	18	17
do	20	20	20
dc	20	21	20
st	28	24	21
cm	23	28	25
cl	23	21	20
pw	31	29	24
kj	21	21	23
kt	21	25	20
pr	37	36	43
ap	20	20	20
co	22	22	21
la	22	21	21
un	38	46	42

The name of a signal file is raw_K_44100_16b_upc_aeM_N.raw, where K is the number of the microphone, 44100 is the sampling frequency, 16 is the number of bits per sample, M is the person number (from 01 to 10), and N is the session number (from 1 to 3). There is a different number ordering for the Mark III microphones and the other microphones (T-shaped clusters and tabletop omni directional microphones). The former ones are ordered from 001 to 064 (although only 7 of them are included), and the latter from 001 to 016, according to the ordering indicated in Figure A.1.

The name of an annotation file is upc_aeM_N.csv (e.g. upc_ae01_1.csv – person 1, session 1). The format of its content is analogical to that of the AGTK ".csv" format, i.e. “start_ts, end_ts, event_id”, where the labels start_ts, end_ts, event_id denote the starting time stamp (from he beginning of the file), the ending time stamp, and the event label, respectively. The time stamps are given in seconds from the beginning of the file.

DVD structure

The structure of a DVD_N (the division is session-wise) is:

```
/hammer         //T-shape and omni-directional microphones – see Figure A.1
        raw_001_44100_16b_upc_ae01_N.raw
        ...
        raw_001_44100_16b_upc_ae10_N.raw
        ...
        raw_016_44100_16b_upc_ae10_N.raw
/markiii                //Mark III chosen channels – see Figure A.4
        raw_003_44100_16b_upc_ae01_N.raw
        ...
        raw_003_44100_16b_upc_ae10_N.raw
        raw_013_44100_16b_upc_ae10_N.raw
        raw_023_44100_16b_upc_ae10_N.raw
        ...
        raw_063_44100_16b_upc_ae10_N.raw
/transcr                //annotation files
        upc_ae01_N.csv
        upc_ae02_N.csv
        ...
        upc_ae10_N.csv
/IAE_UPC_database.pdf           // this document
/license_agreement.pdf          // license agreement
/readme.txt                     // short explanation of database content
```

Appendix B. Guidelines for Having Acoustic Events within the 2006 CHIL Interactive Meeting Recordings

In order to evaluate properly the AE detection systems, a sufficient number of acoustic events (AE) must appear in the recordings. Ideally, they should appear in a natural way inside the meetings, but as the duration of meetings is limited, the number of occurrences of some events would not be large enough. However, forcing the recording of a given number of AE per meeting may cause some lack of naturalness, which should be avoided. On the other hand, if AE are produced outside the meeting, they may suffer of lack of naturalness. Consequently, there is a tradeoff between “natural meeting recordings” and “natural AE recordings”.

We consider that an hybrid approach may be adequate: as many AE as possible are recorded during the main part of the interactive meeting, and the remaining ones are recorded in a short time interval at the end of the meeting. Each site may find its own concrete way of dealing with it; anyway, we give some guidelines in the following.

Types of acoustic events

The whole set of acoustic events of interest include 12 events that can be tentatively divided into two sets:

AE1) Those which can be produced more or less naturally within a recorded meeting:

- Door knock
- Door slam
- Steps
- Chair moving
- Applause
- Keyboard typing

AE2) Those which are more difficult to be produced naturally, at least in a sufficient number:

- Paper work (listing, wrapping)
- Phone ringing/Music
- Spoon/cup jingle
- Key jingle
- Cough
- Laugh

Inclusion of AE within the interactive meeting scenario

1. Try to produce sounds included in set AE1 within the meeting in a natural way. For that:
    a. each participant knocks the door before entering the CHIL room, closes it once is inside walk to the chair and seat (enter one by one);
    b. at the end, each participant leaves the room separately and produces a door slam;
    c. have somebody taking notes of the meeting on a laptop not far from a microphone;
    d. clap after each (short) presentation;
    e. etc.
2. If appropriate, try to include also sounds from AE2. For example:
    a. call a participant on the phone from outside the smart-room;
    b. distribute handouts of the presentations among the participants so that they may look and take notes on them;
    c. etc.
3. Remind the participants about all these sounds just before the recording starts.
4. It helps to have a person (or two) which are responsible for either doing the noises or reminding it to the other participants: starts to clap, typewrites, etc.

Production of the remaining AE after the interactive meeting scenario

AE from the set AE2 (and those from AE1 which have not been produced within the interactive meeting) can be produced purposefully at the end of the interactive meeting. For that:

1. At least two people should be performing in order to have some overlapped events and, specially, AE overlapped with speech.
2. They can either stay in the room after the other participants have left or re-enter.
3. It is recommended that they are doing a natural activity like:
    a. Coffee break (drinking coffee/tea, moving around the room, commenting the meeting, laughing, etc)
    b. Clear up the room (moving chairs, picking papers up, putting keys away, etc)
    c. Any other activity that does not break the semantic integrity of the meeting scenario. For example: one person, who is drinking, makes a question to another (who may be one of the presenters), they walk to the whiteboard and the latter answers the question writing on it.

Number of AE per interactive meeting of approximately half an hour

The recommended minimum number of sounds from AE2 per interactive meeting is 5, but indeed a larger number is preferable.

Own publications

- A. Temko, D. Macho, C. Nadeu, "**Fuzzy Integral Based Information Fusion for Classification of Highly Confusable Non-Speech Sounds**", *Pattern Recognition*, in print, Elsevier

- A. Temko, C. Nadeu, J-I. Biel, "**Acoustic Event Detection: SVM-based System and Evaluation Setup in CLEAR'07**", CLEAR 2007 Evaluation Campaign and Workshop, Baltimore MD, USA, May 2007, to appear in LNCS, Springer.

- J. Luque, X. Anguera, A. Temko, J. Hernando, "**Speaker Diarization for Conference Room: The UPC RT07s Evaluation System**", *NIST 2007 Rich Transcription Meeting Recognition Evaluations*, Baltimore MD, USA, May 2007, to appear in LNCS, Springer.

- M. Farrús, P. Ejarque, A. Temko, J. Hernando, "**Histogram Equalization in SVM Multimodal Person Verification**", *IAPR/IEEE International Conference on Biometrics*, ICB'07, Seoul, Korea, August 2007.

- A. Temko, D. Macho, C. Nadeu, "**Enhanced SVM Training for Robust Speech Activity Detection**", *IEEE International Conference on Acoustics, Speech, and Signal Processing*, ICASSP'07, Honolulu, Hawaii, USA, April 2007.

- A. Temko, R. Malkin, C. Zieger, D. Macho, C. Nadeu, M. Omologo, "**Acoustic Event Detection and Classification in Smart-Room Environment: Evaluation of CHIL Project Systems**", *The IV Biennial Workshop on Speech Technology*, Zaragoza, Spain, November 2006.

- D. Macho, A. Temko, C. Nadeu, "**Systems for Robust Speech Activity Detection and Their Results with the RT05 and RT06 Evaluation Tests**"*, The IV Biennial Workshop on Speech Technology*, Zaragoza, Spain, November 2006.

- A. Temko, R. Malkin, C. Zieger, D. Macho, C. Nadeu, M. Omologo, "**CLEAR Evaluation of Acoustic Event Detection and Classification systems**", CLEAR 2006 Evaluation Campaign and Workshop, Southampton, UK, April 2006, *LNCS,* Vol. 4122, pp. 311-322, Springer, January 2007.

- D. Macho, C. Nadeu, A. Temko, "**Robust Speech Activity Detection in Interactive Smart-Room Environment**", 3rd Joint Workshop on Multimodal Interaction and Related Machine Learning Algorithms, Washington DC, USA, May 2006, *LNCS*, Vol. 4299, pp. 236-247, Springer, 2007.

- A. Temko, E. Monte, C. Nadeu, "**Comparison of Sequence Discriminant Support Vector Machines For Acoustic Event Classification**", *IEEE International Conference on Acoustics, Speech, and Signal Processing*, ICASSP'06, Toulouse, France, May 2006.

- A. Temko, C. Nadeu, "**Classification of Acoustic Events using SVM-based Clustering Schemes**", Pattern Recognition, Vol. 39, Issue 4, pp. 682-694, Elsevier, April 2006.

- R. Malkin, D. Macho, A. Temko, C. Nadeu, “**First Evaluation of Acoustic Event Classification Systems in CHIL Project**”, *Joint Workshop on Hands-Free Speech Communication and Microphone Array*, HSCMA'05, New Jersey, USA, March 2005.

- A. Temko, C. Nadeu, “**Classification of Meeting-Room Acoustic Events with Support Vector Machines and Variable-Feature-Set Clustering**”, *IEEE International Conference on Acoustics, Speech, and Signal Processing*, ICASSP 2005, pp. 505-508, Philadelphia, USA, March 2005.

- A. Temko, D. Macho, C. Nadeu, “**Improving the Performance of Acoustic Event Classification by Selecting and Combining Information Sources using the Fuzzy Integral**”, 2nd Joint Workshop on Multimodal Interaction and Related Machine Learning Algorithms, Edinburgh, UK, July 2005, *LNCS*, Vol. 3869, pp. 357-368, Springer, February 2006.

- A. Temko, D. Macho, C. Nadeu, “**Selection of Features and Combination of Classifiers using a Fuzzy Approach for Acoustic Event Classification**”, *European Conference on Speech Communication and Technology*, Interspeech 2005, pp. 2989-2992, Lisbon, Portugal, September 2005.

Bibliography

[Alp04] E. Alpaydin, *Introduction to Machine Learning*, MIT Press, 2004.

[AMK06] P. Atrey, N. Maddage, M. Kankanhalli, “Audio Based Event Detection for Multimedia Surveillance”, in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2006.

[AN00] M. Abe, M. Nishiguchi, “Content-Based Classification of Audio Signals Using Source and Structure Modelling”, in *Proc. IEEE Pacific Conference on Multimedia*, pp. 280-283, 2000.

[And04] T. Anderson, *Audio Classification and Content Description*, MSc Thesis, Luleå University of Technology, Luleå , Sweden, 2004.

[APA05] J. Arias, J. Pinquier, R. André-Obrecht, “Evaluation of classification techniques for audio indexing”, in *Proc. European Signal Processing Conference*, 2005.

[Aro50] N. Aronszajn, “Theory of Reproducing Kernels”, *Transactions of the American Mathematical Society*, Vol. 68, no. 3, pp. 337-404, 1950.

[ASS04] R. Anita, D. Satish, C. Sekhar, “Outerproduct of trajectory matrix for acoustic modelling using support vector machines”, in *Proc. IEEE International Workshop on Machine Learning for Signal Processing,* 2004.

[BBW+03] F. Beaufays, D. Boies, M. Weintraub, Z. Zhu, “Using speech/non-speech detection to bias recognition search on noisy date”, in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2003.

[BBW04] G. Bakr, L. Bottou, J. Weston, “Breaking SVM Complexity with Cross-Training”, in *Proc. Advances in Neural Information Processing Systems*, Vol. 17, pp. 81-88, 2004.

[Ber95] D. Bersekas, *Nonlinear programming*, Athena Scientific, 1995.

[Ber90] M. Berger, “Convexity”, *The American Mathematical Monthly*, Vol. 97, no. 8 pp. 650-678, 1990.

[BHB02] C. Bahlmann, B. Haasdonk, H. Burkhardt, “On-line Handwriting Recognition using Support Vector Machines - A kernel approach”, In *Proc. International Workshop on Frontiers in Handwriting Recognition*, 2002.

[BHM+04] I. Boesnach, M. Hahn, J. Moldenhauer, T. Beth, U. Spetzger, “Analysis of Drill Sound in Spine Surgery”, in *Proc. International Workshop on Medical Robotics, Navigation and Visualization*, pp. 11-12, 2004.

[Bre90] A. Bregman, *Auditory Scene Analysis*. MIT Press, Cambridge, 1990.

[Buc02] M. Büchler, *Algorithms for Sound Classification in Hearing Instruments*, PhD Thesis, Swiss Federal Institute of technology, Zurich, Switzerland, 2002.

[Bur98] C. Burges, “A tutorial on support vector machines for pattern recognition”, *Data Mining Knowledge Discovery*, Vol. 2, no. 2, Kluwer, pp. 955–975, 1998.

[Cas02] M. Casey, “Sound Classification and Similarity Tools”, *Introduction to MPEG-7: Multimedia Content Description Language,* J. Wiley, 2002.

[CER05] C. Clavel, T. Ehrette, G. Richard, “Events Detection for an Audio-Based Surveillance System”, in *Proc. IEEE International Conference on Multimedia and Expo*, 2005.

[CG03] S. Chang and S. Greenberg, “Syllable-proximity evaluation in automatic speech recognition using fuzzy measures and a fuzzy integral”, in *Proc. IEEE Fuzzy Systems conference*, pp. 828- 833, 2003.

[CHI] CHIL - Computers in the Human Interaction Loop, http://chil.server.de/

[CLH05] R. Cai, L. Lu A. Hanjalic, “Unsupervised content discovery in composite audio”, in *Proc. ACM International Conference on Multimedia*, pp. 628-637, 2005.

[CN07] J. Casas, J. Neumann, “Context Awareness triggered by Multiple Perceptual Analyzers”, to appear in *Emerging Artificial Intelligence Applications in Computer Engineering*, IOS Press, 2007.

[Cow04] M. Cowling, *Non-Speech Environmental Sound Classification System for Autonomous Surveillance*, PhD Thesis, Griffith University, Australia, 2004.

[CS02] M. Cowling, R. Sitte, “Analysis of speech Recognition Techniques for use in a Non-Speech Sound Recognition System”, in *Proc. International Symposium on Digital Signal Processing for Communication Systems*, 2002.

[CS03] M. Cowling, R. Sitte, “Comparison of techniques for environmental sound recognition”, *Pattern Recognition Letters*, Vol. 24, no. 15, pp. 2895-2907, 2003.

[CS04] J. Casas, R. Stiefelhagen, “Multi-camera/multi-microphone system design for continuous room monitoring,” CHIL-WP4-D4.1-V2.1-2004-07-08-CO, CHIL Consortium Deliverable D4.1, July 2004.

[CSR+06] W. Campbell, D. Sturim, D Reynolds, A. Solomonoff, “SVM Based Speaker Verification using a GMM Supervector Kernel and NAP Variability Compensation”, in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing,* 2006.

[CSW+06] R. Collobert, F. Sinz, J. Weston, L. Bottou, “Trading convexity for scalability”, in *Proc. International Conference on Machine Learning*, 2006.

[CTK+03] Y. Cao, W. Tavanapong, K. Kim, J. Oh, “Audio-Assisted Scene Segmentation for Story Browsing”, in *Proc. International Conference on Imaging and Video Retrieval,* pp. 446-455, 2003.

[CW03] S. Cheng, H. Wang, “A Sequential Metric-based Audio Segmentation Method via The Bayesian Information Criterion”, in *Proc. European Speech Processing Conference*, 2003.

[CW04] S. Cheng, H. Wang, “METRIC-SEQDAC: A Hybrid Approach for Audio Segmentation” in *Proc. International Conference on Spoken Language Processing*, 2004.

[DBA+00] A. Dufaux, L. Besacier, M. Ansorge, F. Pellandini, “Automatic sound detection and recognition for noisy environment ", in *Proc. European Signal Processing Conference*, 2000.

[Die02] T. Dietterich, “Machine Learning for Sequential Data: A Review”, *LNCS*, Vol. 2396, pp 15-30, Springer, 2002.

[DC03] C. Diehl, G. Cauwenberghs, “SVM incremental learning, adaptation and optimization”, in *Proc. International Joint Conference on Neural Networks*, 2003.

[DHS00] R. Duda, P. Hart, D. Stork, *Pattern Classification*, (2nd Edition), Wiley-Interscience, 2000.

[DL04] P. Doets, R. Lagendijk, “Stochastic Model of a Robust Audio Fingerprinting System”, in *Proc. International Symposium on Music Information Retrieval*, 2004.

[RD06] R. Radhakrishnan, A. Divakaran, “Generative Process Tracking for Audio Analysis”, in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2006.

[EL04] D. Ellis, K. Lee, “Minimal-Impact Audio-Based Personal Archives”, in *Proc. ACM workshop on Continuous Archiving and Recording of Personal Experiences*, 2004.

[Ell01] D. Ellis, “Detecting Alarm Sounds”, in *Proc. Workshop on Consistent and Reliable Acoustic Cues,* 2001.

[EPT+06] A. Eronen, V. Peltonen, J. Tuomi, A. Klapuri, S. Fagerlund, T. Sorsa, G. Lorho, and J. Huopaniemi, “Audio-Based Context Recognition”, *IEEE Transactions on Audio, Speech, and Language Processing*, Vol. 14, no. 1, 2006.

[ETS02] ETSI ES 202 050 Ver. 1.1.1, “Speech Processing, Transmission and Quality Aspects (STQ); Distributed speech recognition; Advanced feature extraction algorithm”, 2002.

[EVA] "Evaluation Packages for the First CHIL Evaluation Campaign", CHIL project Deliverable D7.4, downloadable from http://chil.server.de/servlet/is/2712/, 2005.

[FM01] G. Fung, O. Mangasarian, "Proximal Support Vector Machine Classifiers", in *Proc. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 77-86, 2001.

[Ger03a] D. Gerhard, "Silence as a Cue to Rhythm in the Analysis of Speech and Song", *Journal of the Canadian Acoustical Association*, Vol. 31, no. 3, pp. 22-23, 2003.

[Ger03b] D. Gerhard, "Audio Signal Classification: History and Current Techniques", Technical Report TR-CS 2003-07, 2003.

[GL03] G. Guo, Z. Li, "Content-based Audio Classification and Retrieval using Support Vector Machines", *IEEE Transactions on Neural Networks*, Vol. 14, pp. 209-215, January, 2003.

[GL94] J. Gauvain, C. Lee, "Maximum a Posteriori Estimation for Multivariate Gaussian Mixture Observations of Markov Chains", *IEEE Transactions on Speech and Audio Processing,* Vol. 2, no. 2, pp. 291-298, 1994.

[GMR+04] K. Goh, K. Miyahara, R. Radhakrishan, Z. Xiong, A. Divakaran, "Audio-Visual Event Detection Based on Mining of Semantic Audio-Visual Labels", in *Proc. SPIE Conference on Storage and Retrieval for Multimedia Databases*, pp. 292-299, 2004.

[GR79] I. Gradshteyn, I. Ryzhik, *Tables of Integrals, Series, and Products*, 5th ed., Academic Press, 1979.

[Gra04] M. Grabisch, "The Choquet integral as a linear interpolator", in *Proc. International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pp. 373-378, 2004.

[Gra95a] M. Grabisch, "Fuzzy integral in multi-criteria decision-making", *Fuzzy Sets & Systems*, Vol. 69, pp. 279-298, 1995.

[Gra95b] M. Grabisch, "A new algorithm for identifying fuzzy measures and its application to pattern recognition", in *Proc. IEEE International Conference on Fuzzy Systems,* pp.145-50, 1995.

[Har03] A.Härmä, "Automatic recognition of bird species based on sinusoidal modeling of syllables", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2003.

[HKS05] D. Hoiem, Y. Ke, and R. Sukthankar, "SOLAR: Sound Object Localization and Retrieval in Complex Audio Environments", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2005.

[HL02] C. Hsu, C. Lin, "A Comparison of Methods for Multi-class Support Vector Machines", *IEEE Transactions on Neural Networks*, Vol. 13, pp. 415-425, 2002.

[HMS05] A. Härmä, M. McKinney, J. Skowronek, "Automatic surveillance of the acoustic activity in our living environment", in *Proc. International Conference on Multimedia and Expo*, 2005

[JH99] T. Jaakkola, D. Haussler, "Exploiting generative models in discriminative classifiers", in *Proc. Advances in Neural Information Processing Systems,* Vol. 2, pp.487-493, 1999.

[JJK+05] C. Jianfeng, Z. Jianmin, A. Kam, L. Shue, "An automatic acoustic bathroom monitoring system", in *Proc. IEEE International Symposium on Circuits and Systems*, 2005.

[KBS04] H. Kim, J. Burred, T. Sikora, "How efficient is MPEG-7 for General Sound Recognition", in *Proc. International AES Conference Metadata for Audio*, pp. 17-19, 2004.

[KE03] L. Kennedy, D. Ellis, "Pitch-based emphasis detection for characterization of meeting recordings", In *Proc. IEEE workshop on Automatic Speech Recognition and Understanding,* 2003.

[KE04] L. Kennedy, D. Ellis, “Laughter Detection in Meetings”, NIST Meeting Recognition Workshop, in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2004.

[KMR02] I. Kojadinovic, J. Marichal, M. Roubens, “An axiomatic approach to the definition of the entropy of a discrete Choquet capacity”, in *Proc. International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pp. 763–768, 2002.

[KMS04] H. Kim, N. Moreau, T. Sikora, “Audio Classification Based on MPEG-7 Spectral Basis Representations”, *IEEE Transactions on Circuits and Systems for Video Technology*, Special Issue on Audio and Video Analysis for Multimedia Interactive services, Vol. 14, no. 5, pp. 716-725, 2004.

[Kun03] L. Kuncheva, “’Fuzzy’ vs ‘Non-fuzzy’ in combining classifiers designed by boosting”, *IEEE Transactions on Fuzzy Systems*, Vol. 11, no. 6, pp. 729-741, 2003.

[Kun04] L. Kuncheva, *Combining Pattern Classifiers*, John Wiley & Sons, Inc, 2004.

[KZD02] B. Kostek, P. Zwan, M. Dziubinski, “Statistical Analysis of Musical Sound Features Derived from Wavelet Representation”, *Audio Engineering Society*, 2002.

[LAT+07] J. Luque, X. Anguera, A. Temko, J. Hernando, “Speaker Diarization for Conference Room: The UPC RT07s Evaluation System”, NIST 2007 Rich Transcription Meeting Recognition Evaluations, Baltimore MD, USA, May 2007, to appear in *LNCS.*

[LCC04] G. Lebrun, C. Charrier, H. Cardot, “SVM Training Time Reduction using Vector Quantization”, in *Proc. International Conference on Pattern Recognition*, Vol. 1, pp. 160-163, 2004.

[LDB06] J. Louradour, K. Daoudi, F. Bach “SVM Speaker Verification using an Incomplete Cholesky Decomposition Sequence Kernel”, in *Proc. Odyssey: The Speaker and Language Recognition Workshop*, 2006.

[LLZ03] L. Lu, S. Li, and H. Zhang, “Content-based Audio Classification and Segmentation by Using Support Vector Machines”, *ACM Multimedia Systems Journal*, Vol. 8, no. 6, pp. 482-492, 2003.

[Luk04] B. Lukic, *Activity Detection in Public Spaces*, M.Sc. Thesis, Royal Institute of Technology, Stockholm, Sweden, 2004.

[LYC02] Y. Liu Y. Yang, J. Carbonell, “Boosting to correct inductive bias in text classification”, in *Proc. International Conference on Information and Knowledge Management*, pp. 348 – 355, 2002.

[LZJ02] L. Lu, H. Zhang, H. Jiang, “Content Analysis for Audio Classification and Segmentation”, *IEEE Transactions on Speech and Audio Processing*, Vol. 10, no. 7, pp. 504-516, 2002.

[LZL03] L. Lu, H. Zhang, S. Li, “Content-based Audio Classification and Segmentation by Using Support Vector Machines”, *ACM Multimedia Systems*, Vol. 8, no. 6, pp. 482-492, 2003.

[Mal06] R. Malkin, *Machine Listening for Context-Aware Computing*, PhD Thesis, Carnegie Mellon University, 2006.

[Mar00] J. Marichal, “Behavioral analysis of aggregation in multicriteria decision aid, Preferences and Decisions under Incomplete Knowledge”, *Studies in Fuzziness and Soft Computing*, Vol. 51, pp. 153-178, Physica-Verlag, Heidelberg, 2000.

[Mar02] J. Marichal, “Entropy of discrete Choquet capacities”, *European Journal of Operational Research,* Vol. 137, no. 3, pp. 612-624, 2002.

[MMR+01] K. Müller, S. Mika, G. Rätsch, K. Tsuda, and B. Schölkopf, “An Introduction to Kernel-Based Learning Algorithms”, *IEEE Transactions on Neural Networks*, Vol. 12, pp. 181-202, 2001.

[MMT+05] R. Malkin, D. Macho, A. Temko, C. Nadeu, "First Evaluation of Acoustic Event Classification Systems in CHIL Project", in *Proc. Joint Workshop on Hands-Free Speech Communication and Microphone Array*, 2005.

[MNT06] D. Macho, C. Nadeu, A. Temko, "Robust Speech Activity Detection in Interactive Smart-Room Environment", *LNCS*, Vol. 4299, pp. 236-247, Springer, 2007.

[MP04] J. Mauclair, J. Pinquier "Fusion of descriptors for speech / music classification", in *Proc. European Signal Processing Conference*, 2004.

[MSM03] L. Ma, D. Smith, B. Milner, "Context awareness using environmental noise classification", in *Proc. European Speech Processing Conference*, pp. 2237-2240, 2003.

[MZ99] L. Mikenina, H. Zimmermann, "Improved feature selection and classification by the 2-additive fuzzy measure", *Fuzzy Sets and Systems*, Vol. 107, no. 2, pp. 197-218, 1999.

[NIS] NIST Smart Flow System: http://www.nist.gov/smartspace/nsfs.html

[NHA+00] S. Nakamura, K. Hiyane, F. Asano, T. Nishiura, and T. Yamada, "Acoustical Sound Database in Real Environments for Sound Scene Understanding and Hands-Free Speech Recognition", in *Proc. International Conference on Language Resources & Evaluation*, 2000.

[NHG95] C. Nadeu, J. Hernando, and M. Gorricho "On the decorrelation of filter-bank energies in speech recognition", in *Proc. European Speech Processing Conference*, pp. 1381-1384, 1995.

[NMH01] C. Nadeu, D. Macho, J. Hernando, "Frequency and time filtering of filter-bank energies for robust HMM speech recognition", *Speech Communication*, Vol. 34, pp. 93-114, 2001.

[NNM+03] T. Nishiura, S. Nakamura, K. Miki, K. Shikano, "Environmental Sound Source Identification Based on Hidden Markov Model for Robust Speech Recognition", in *Proc. European Speech Processing Conference*, pp. 2157-2160, 2003.

[Nol67] A. Noll, "Cepstrum Pitch Determination", *Journal of the Acoustical Society of America*, Vol. 41, no. 2, pp. 293-309, 1967.

[Nor04] P. Nordqvist, *Sound Classification in Hearing Instruments*, PhD Thesis, Royal Institute of Technology, Stockholm, Sweden, 2004.

[PAA04] J. Pinquier, J. Arias, and R. André-Obrecht, "Audio Classification by Search of Primary Components", in *Proc. International Workshop on Image, Video and Audio Retrieval and Mining*, 2004.

[PCC01] O. Pietquin, L. Couvreur, P. Couvreur, "Applied Clustering for Automatic Speaker-Based Segmentation of Audio Material", *Belgian Journal of Operations Research, Statistics and Computer Science*, Vol. 41, 2001.

[PCS00] J. Platt, N. Cristianini, J. Shawe-Taylor, "Large Margin DAGs for Multiclass Classification", in *Proc. Advances in Neural Information Processing Systems* 12, pp. 547-553, 2000.

[Pfe01] S. Pfeiffer, **"**Pause concepts for audio segmentation at different semantic levels", in *Proc. ACM International Conference on Multimedia*, pp.187-193, 2001.

[PMN05] J. Padrell, D. Macho, C. Nadeu, "Robust Speech Activity Detection Using LDA Applied to FF Parameters", *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2005.

[PO04] J. Pinquier, R. André-Obrecht, "Jingle detection and identification in audio documents", *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing,* 2004.

[PRO02] J. Pinquier, J. Rouas, R. André-Obrecht, "Robust Speech / Music Classification in Audio Documents“, in *Proc. International Conference Spoken Language Processing,* pp. 2005-2008, 2002.

[RAS04] S. Ravindran, D. Anderson, M. Slaney, "Low Power Audio Classification for Ubiquitous Sensor Networks", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2004.

[RJ93] L. Rabiner, B.H. Juang, *Fundamentals of Speech Recognition,* Prentice Hall, 1993.

[RK04] R. Rifkin, A. Klautau, "In Defense of One-Vs-All Classification", *Journal of Machine Learning Research*, Vol. 5, pp.101-141, 2004.

[Rob83] H. Robbins, "Some Thoughts on empirical Bayes Estimation", *The Annals of Statistics*, Vol. 11, no. 3, pp. 713-723, 1983.

[RYG+06] J. Ramirez, P. Yelamos, J. Gorriz, C. Puntonet, J. Segura, "SVM-Enabled Voice Activity Detection", *LNCS,* Vol. 3972, pp. 676-681, Springer, 2006.

[SA02] S. Sukittanon, L. Atlas, "Modulation Frequency Features for Audio Fingerprinting", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing,* pp.1173-1176, 2002.

[SAH+07] C. Segura, A. Abad, J. Hernando, C. Nadeu, "Multispeaker Localization and Tracking in Intelligent Environments", CLEAR'07 Evaluation Campaign and Workshop, Baltimore MD, USA, May 2007, to appear in *LNCS.*

[SG02] N. Smith, M. Gales, "Using SVMs and Discriminative Models for Speech Recognition", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp. 77-80, 2002.

[SG84] L. Shapley, B. Grofman, "Optimizing group judgmental accuracy in the presence of interdependencies", *Public Choice*, 1984.

[ShA] ShATR Multiple Simultaneous Speaker Corpus, http://www.dcs.shef.ac.uk/research/groups/spandh/projects/shatrweb/index.html

[SKI07] T. Sainath, D. Kanevsky, G. Iyengar, "Unsupervised Audio Segmentation using Extended Baum-Welch Transformations", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2007.

[Sla02a] M. Slaney, "Semantic–Audio Retrieval", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 2002.

[Sla02b] M. Slaney, "Mixtures of Probability Experts for Audio Retrieval and Indexing", in *Proc. IEEE International Conference on Multimedia and Expo,* 2002.

[SLP+03] M. Stäger, P. Lukowicz, N. Perera, T. von Büren, G. Tröster, T. Starner, "Sound Button: Design of a Low Power Wearable Audio Classification System", in *Proc. IEEE International Symposium on Wearable Computers*, pp. 12-17, 2003.

[SMR05] D. Smith, L. Ma, Nick Ryan, "Acoustic environment as an indicator of social and physical context", *Personal and Ubiquitous Computing*, 2005.

[SN07] S. Sundaram, S. Narayanan, "Discriminating Two Types of Noise Sources using Cortical Representation and Dimension Reduction Technique", in *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing,* 2007.

[SNN01] H. Shimodaira, K. Noma, M. Nakai, "Dynamic Time-Alignment Kernel in Support Vector Machine", in *Proc. Advances in Neural Information Processing Systems,* 14, Vol. 2, pp. 921-928, 2001.

[SPP99] S. Srinivasan, D. Petkovic, and D. Ponceleon, "Towards Robust Features for Classifying Audio in the CueVideo System", in *Proc. ACM International Conference on Multimedia*, pp. 393-400, 1999.

[Spr06] "Spring 2007 (RT-07) Rich Transcription Meeting Recognition Evaluation Plan", NIST, December, 2006.

[SS02] B. Schölkopf, A. Smola, *Learning with Kernels*, MIT Press, Cambridge, MA, 2002.

[SLT04] M. Stäger, P. Lukowicz, G. Tröster, "Implementation and Evaluation of a Low-Power Sound-Based User Activity Recognition System", in *Proc. IEEE International Symposium on Wearable Computers*, pp. 138-141, 2004.

[Sug74] M. Sugeno, *Theory of fuzzy integrals and its applications*, PhD thesis, Tokyo Institute of Technology, 1974.

[SVM] SVMlight: http://svmlight.joachims.org/.

[TC99] G. Tzanetakis, P. Cook, "Multi-Feature Audio Segmentation for Browsing and Annotation," in *Proc. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, 1999.

[TK01] S. Tong, D. Koller, "Support Vector Machine Active Learning with Applications to Text Classification", *Journal of Machine Learning Research*, Vol. 2, pp. 45-66, 2001.

[TKM03] K. Tsuda, M. Kawanabe, K. Müller, "Clustering with the fisher score", in *Proc. Advances in Neural Information Processing Systems*, 15, pp. 729-736, 2003.

[Vap79] V. Vapnik, "Estimation of dependences based on empirical data", *Nauka* [in Russian], Moscow, 1979.

[Vap95] V. Vapnik, *The Nature of Statistical Learning Theory*, Springer, New York, 1995.

[Vap99] V. Vapnik, "An overview of statistical learning theory", *IEEE Transactions on Neural Networks*, Vol. 10, no. 5, 1999.

[VC71] V. Vapnik, A. Chervonenkis, "On the uniform convergence of relative frequencies of events to their probabilities", *Theory of Probability and its Applications,* Vol. 16, no. 2, pp. 264-280, 1971.

[VCC99] K. Veropoulos, C. Campbell, N. Cristianini, "Controlling the Sensitivity of Support Vector Machines", in *Proc. International Joint Conference on Artificial Intelligence,* pp. 55-60, 1999.

[VIB+03a] M. Vacher, D. Istrate, L. Besacier, E. Castelli, J. Serignat, "Smart audio sensor for telemedicine", in *Proc. Smart Object Conference*, 2003.

[VIB+03b] M. Vacher, D. Istrate, L. Besacier, J. Serignat, E. Castelli, "Life Sounds Extraction and Classification in Noisy Environment", in *Proc. IASTED International Conference on Signal & Image Processing*, 2003.

[VIS04] M. Vacher, D. Istrate and J. Serignat , "Sound Detection and Classification through Transient Models using Wavelet Coefficient Trees", in *Proc. European Signal Processing Conference,* pp. 1171-1174, 2004.

[VIS+05] M. Vacher, D. Istrate, J.F. Serignat and N. Gac, "Detection and Speech/Sound Segmentation in a Smart Room Environment", in *Proc. International Conference on Speech Technology and Human - Computer Dialogue*, 2005.

[Voo86] E. Voorhees, "Implementing Agglomerative Hierarchical Clustering Algorithms for use in Document Retrieval", *Information Processing and Management*, Vol. 22, pp. 465-476, 1986.

[WB06] D. Wang, G. Brown, *Computational Auditory Scene Analysis: Principles, Algorithms and Applications*, Wiley-IEEE Press, 2006.

[WBK+96] E. Wold, T. Blum, D. Keislar, J. Wheaton, "Content-Based Classification, Search, and Retrieval of Audio", in *Proc. IEEE Multimedia*, Vol. 3, no. 3, pp. 27-36, 1996.

[WC05] V. Wan, J. Carmichael, "Polynomial Dynamic Time Warping Kernel Support Vector Machines for Dysarthric Speech Recognition with Sparse Training Data", in *Proc. Interspeech*, pp. 3321-3324, 2005.

[WCC+04] Y. Wu, E. Chang, K. Chang, J Smith., "Optimal Multimodal Fusion for Multimedia Data Analysis", in *Proc. ACM International Conference on Multimedia*, pp. 572-579, 2004.

[WMC+00] J. Weston, S. Mukherjee, O. Chapelle, M. Pontil, T. Poggio, and V. Vapnik, “Feature Selection for SVMs”, in *Proc. Advances in Neural Information Processing Systems*, 2000.

[WR05] V. Wan, S. Renals, “Speaker Verification using Sequence Discriminant Support Vector Machines”, *IEEE Transactions on Speech and Audio Processing*, Vol. 13, no. 2, pp. 203-210, 2005.

[XRD+03] Z. Xiong, R. Radhakrishnan, A. Divakaran, T. Huang, “Audio Events Detection Based Highlights Extraction from Baseball, Golf and Soccer Games in a Unified Framework”, in *Proc. IEEE International Conference on Multimedia and Expo*, pp. 401-404, 2003.

[You93] S.J. Young, “The HTK Hidden Markov Model Toolkit: Design and Philosophy”, Technical Report 152, Cambridge University Engineering Dept, Speech Group, 1993.

[Zha01] B. Zhang, “Is the Maximal Margin Hyperplane Special in a Feature Space”, Hewlett Packard report, 2001.

[ZJZ+06] S. Zhang, H. Jiang, S. Zhang, B. Xu, “Fast SVM Training based on the Choice of Effective Samples for Audio Classification”, in *Proc. Interspeech*, 2006.

[ZK01] T. Zhang, C. Kuo, “Audio content analysis for on-line audiovisual data segmentation”, *IEEE Transactions on Speech and Audio Processing*, Vol. 9, no. 4, pp. 441-457, 2001.

[ZO05] C. Zieger, M. Omologo, “Acoustic Event Detection - ITC-irst AED database”, Internal ITC report, 2005.