POLITECNICO DI MILANO
Scuola di Ingegneria dell'Informazione

POLO TERRITORIALE DI COMO
Master of Science in Computer Engineering

FEATURE-BASED CLASSIFICATION FOR AUDIO BOOTLEG DETECTION

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Academic Year 2011-2012

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Corso di Laurea Magistrale in Ingegneria Informatica

CLASSIFICAZIONE BASATA SU FEATURE PER IL RICONOSCIMENTO DI BOOTLEG AUDIO

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Anno Accademico 2011-2012

"An idea is like a virus.
Resilient.
Highly contagious.
And even the smallest seed
of an idea can grow.
It can grow to define
or destroy you."
Cobb - Inception

Abstract

In the last few years, with the rapid proliferation of inexpensive hardware devices that enable the acquisition of audio-visual data, many types of multimedia digital objects (audio, images and videos) can be readily created, stored, transmitted, modified and tampered with. In case of legal trials, proving the authenticity of multimedia evidences, such as pictures or audio recordings, may be vital.

In order to solve some of these problems, many multimedia forensic detectors have been studied. Typically they rely on the detection of footprints left by tampering operations. However, a simple yet effective method to remove these footprints and fool many detectors consists in re-capturing the multimedia object (e.g., taking a picture of a still image projected on a screen). For this reason, being able to detect re-capturing is an important task for a forensic analyst. As it regards re-capture detection, some algorithms have been proposed for still images and videos. However not much has been done for audio.

The goal of this work is then to propose a method to identify audio recaptured tracks, often known as *bootlegs*. This detector is based on tools developed and studied in the *Multimedia Information Retrieval* field, based on the analysis of audio features.

More specifically, we use classic features together with others derived from the analysis of bootleg tracks, and we perform a comparison between different feature selection methods to choose the one that best fits our needs. In this way we are able to train a classifier using the most significant features.

We validate our system by means of a set of experiments performed on a dataset that we built to accommodate different bootleg definitions. The results achieved are promising, showing a high bootleg detection accuracy.

Sommario

Negli ultimi anni, con la rapida proliferazione di dispositivi hardware a basso costo che consentono l'acquisizione di dati audiovisivi, molti tipi di contenuti digitali multimediali (audio, immagini e video) possono essere facilmente creati, memorizzati, trasmessi, modificati e alterati. In caso di studi legali, dimostrare l'autenticità di prove multimediali, come immagini o registrazioni audio, può essere di vitale importanza.

Per risolvere alcuni di questi problemi, sono stati studiati alcuni detector multimediali forensi. Si basano tipicamente sul rilevamento di impronte lasciate dalle operazioni di manomissione. Tuttavia, un metodo semplice ma efficace per rimuovere queste impronte e quindi ingannare molti detector, consiste nel ricatturare nuovamente l'oggetto multimediale (ad esempio, scattare una foto di un fermo immagine proiettata su uno schermo). Per questo motivo, essere in grado di rilevare questa ricattura è un compito importante per un analista forense. A tale scopo, sono stati proposti alcuni algoritmi per immagini e per video. Tuttavia, sono stati effettuati pochi studi per l'audio.

L'obiettivo di questo lavoro è quindi quello di proporre un metodo in grado di identificare tracce audio registrate nuovamente, spesso conosciute come *bootleg*. Questo detector utilizza strumenti già sviluppati e studiati nel campo della *Multimedia Information Retrieval*, basandosi sull'analisi dei descrittori audio.

Più in particolare, introduciamo a quelli classici alcuni descrittori basati sull'analisi dei singoli bootleg, effettuando poi un confronto tra diversi metodi che selezionano i descrittori ritenuti significativi, in modo da scegliere quello che meglio si adatta alle nostre esigenze. Siamo così in grado di allenare un classificatore, utilizzando le caratteristiche più significative.

Abbiamo validato poi il nostro sistema attraverso una serie di esperimenti, eseguiti su un set di dati che abbiamo costruito appositamente per includere definizioni diverse di bootleg. I risultati ottenuti sono promettenti, con un'alta precisione di rilevamento dei bootleg.

Contents

List of Figures

List of Tables

Acknowledgements

We want to thank Professor Augusto Sarti for the confidence shown in us and for giving us the opportunity to work on a topic that we particularly appreciated.

Our sincere thanks go to Paolo, for his willingness, for the continuous support offered during the preparation of our thesis, for the invitations to the brewery and to football games.

We thank our many student colleagues who constituted a stimulating and fun environment in which to learn and grow, especially our friends of the V2.13.

Luca wants to thank his family who always believed in him in all these years and his girlfriend Elisa for her encouragement and her love. A special thanks goes to his grandmother Felicita for the immense love that she gives him. He also thanks his friends (too many to list here but you know who you are!) for providing support and friendship that he needed.

Andrea would like to thank his family, especially his parents, for all the support, financial and moral, received in all these years.
Special thanks also go to all the other relatives.
In the end a big thank to all his friends: Aldo, Villa, Noe, Juliet, Vale, Prosi, Robi, Ale, Luca, Boss, Ali, Anna, Sara, Gloria, Posca, Fra, Canta, Vero and so many more...
Least but not last, his colleague Albo: good job, buddy!

Introduction

Investigating the past history of objects, either natural or man-made, given just a few clues collected at the present time is a challenging research topic in many fields of science. A typical example is that of geology, where it is customary to analyse rock fragments and their metamorphoses to determine their origins. Another example is computer science, where software products may be reverse-engineered by dissecting their components with the goal of obtaining the original source code from the compiled executables. In the last few years, with the rapid proliferation of inexpensive hardware devices that enable the acquisition of audio-visual data, many types of multimedia digital objects (audio, images and videos) can be readily created, stored, transmitted, modified and tampered with. The need of methods and tools that enable reverse engineering of this kind of content is therefore more of an urgent necessity. For example, in case of legal trials, proving the authenticity of multimedia evidences, such as pictures or audio recordings, may be vital. Of equal importance is the ability of automatically recognize illegally distributed material over the web.

In order to solve some of these problems, many multimedia forensic detectors have been proposed for both audio and visual data [1, 2]. These tools usually rely on the fact that every non-invertible processing operation on a multimedia object leaves some distinctive imprints on the data, as a sort of digital footprint. Therefore, the analysis of such footprints permits determining the origin of image, video, or audio data, and to establish digital content authenticity.

In this thesis, we deal with the forensic problem of automatically recognize audio re-captured data. More specifically, our goal is that of building a detector capable of discriminating between audio tracks that have been professionally processed and released by artists, from tracks that have been illegally recorded and distributed, known as *bootlegs*. In doing so, we first propose an audio classification tool that is general enough to be applied even to other classification problems. Then we propose how to modify it in order to target the specific problem of audio bootleg detection. In particular, this classification tool makes use of concepts from both *Multimedia Information Retrieval* (*MIR*) (i.e., acoustic features extraction), and machine learning (i.e., *Support Vector Machine* and *Gaussian Mixture Model* classifiers). In order to specialize the tool to target the bootleg detection problems, some concepts from *audio forensics* are then used.

In the forensic literature, the most part of the works concerning recapture detection is specialized to images and videos. As it regards still-images, in [3] the authors show how to detect if an image has been re-acquired from a screen by looking at characteristic artefacts on sharp edges. Furthermore, works on camera artefacts introduced by *CCD/CMOS* sensors that are left during the acquisition pipeline have been proposed. These artefacts are named *Photo-Response Non-Uniformity* (*PRNU*) noise. PRNU has been exploited both for digital camera identification [4] and for image integrity verification [5], and it proves to be a reliable trace also when an image is compressed using the JPEG codec. As it regards video, in [6] projected videos recaptured with a camera placed off-axis with respect to the screen are identified by detecting inconsistencies in the camera intrinsic parameters. In [7], the authors show how to detect whether a sequence has been recaptured by analysing the high-frequency jitter introduced by, e.g., a hand-held camcorder.

Forensic analyses related to audio recorded signals usually target instead slightly different problems. As an example, in [8] the authors try to determine the microphone model used to record a given audio sample. The persistence of sound, due to multiple reflections from various surfaces in a room, causes temporal and spectral smearing of the recorded sound. This distortion is referred to as audio reverberation time and some works related to the room detection have been proposed [9]. In [10] the authors have presented a system for identifying the room in an audio or video recording based on Mel Frequency Cepstral Coefficient related acoustical features.

We focused on audio bootleg detection because this problem has never been addressed before. It can be considered related to classification problems already developed and studied in the MIR field, based on the analysis of audio features. This kind of analysis is usually done to discriminate between musical instruments, musical genres, and between variations of speech, non-speech and music. As an example, Tzanetakis and Cook in [11] explore the problem of automatic classification of audio signal between musical genres using feature sets representing timbral texture, rhythmic content and pitch content. Other works, as [12], use features of higher level to analyse the user's mood and preferences to automatic create a play-list.

We have introduced the task of classification, i.e., the task of assigning an object to a class on the basis of currently available information, but what is a class? It is important to know the nature of the classes and their definition. A *class* is a collection of objects that can be unambiguously defined by a property that all its members share. Classes depend on foundational context: they could be labels for different populations (e.g., dogs and cats form separate classes) and the membership of a class is determined by an independent authority (*Supervisor*). The properties, that all members of a class share, are in general called *features.* The features may variously be categorical (e.g. "A", "B", "AB" or "O", for blood type), ordinal (e.g. "large", "medium" or "small"), integer-valued (e.g. the number of occurrences of a part word in an email) or real-valued (e.g. a measurement of blood pressure).

Since in our problem we want to discriminate between bootlegs and other audio tracks, we can consider it as a classification problem. More specifically, we can define a bootleg class, that contains audio considered as bootlegs, and a second class including official live and studio recorded songs. In order to implement this type of audio classification, we analyse a set of acoustical features. We have created a large dataset of files for this purpose. In order to solve our problem, we extract a lot of features from each audio in the dataset. Then, we find, through different methods, a subset of these features with discriminative characteristics. Finally, we can train now a classifier to distinguish songs belongs to different classes based on these feature values.

We have first built a general classification tool. This tool is modular, so it is possible to make in any moment any changes. It is composed by three phases *i)* Training Phase, *ii)* Validation Phase and *iii)* Test Phase. Through different methods, we find several feature subsets considered significant. In order to find the optimal one, we train the tool by each of these. In this case, *Support Vector Machine* (SVM) and *Gaussian Mixture Model* (GMM) classifiers have been utilised to train the tool with vectors of features. In the Validation phase the best subset of feature and the best classifier between GMM and SVM are found. Then, considering only this subset and the best classifier, the tool can perform the classification, predicting a class label for unclassified observations.

The general classification tool has been then modified, with the addition of new features and a new feature selection method regarding the special purpose of Bootleg Detection problem. We have then performed tests with all the possible combinations of feature selection methods and classifiers, in order to show the accuracy achieved for the Bootleg detection purpose.

The results achieved are satisfactory, since we have reached a good level of bootleg detection accuracy. As expected, the tool has better performance in distinguish bootlegs from audio recorded in studio than bootlegs from official live releases. Anyway, the accuracy in this last case is high, in average only few percentage points lower than the bootleg from studio case.

The rest of the thesis is structured as follows. Chapter 1 focuses on the background of our work, analysing the State of the Art of the works related to ours, and describing the principal tools that we used (i.e., features, feature selection/reduction methods and classifiers). In Chapter 2, we present the general version of the audio classification tool. In particular we describe how to perform the training and test phases, and how to select the features that most suit a specific classification problem. In Chapter 3, we analyse in detail the problem of Audio Bootleg Detection. To this purpose, we first clarify what we mean by audio bootleg and then we explain how to modify the classification tool. We propose a set of new features derived from the analysis of bootleg tracks, both in time and frequency domain. In Chapter 4 we validate our system by means of a set of experiments. We explain how we built the used audio database and perform some statistical analyses on the results obtained. Finally, in the last Chapter we draw some conclusions about the proposed work, and present some possible future extensions to improve our tool performances.

Chapter 1

State of the art

This Chapter aims to provide the background knowledge needed to introduce and understand the rest of the work. To this purpose, we first focus on the forensics techniques related to audio and to multimedia re-capture, then we describe more in depth the tools typically used for music genre classification, here adapted to our work. More specifically, in the latter part, we focus on feature extraction, feature selection, and classification tools.

1.1 Multimedia Forensics

The broad availability of tools for the acquisition and processing of multimedia signals has recently led to the concern that audio signals, images and videos cannot be considered a trustworthy evidence, since they can be altered rather easily. This possibility raises the need to verify whether a multimedia content, which can be downloaded from the internet or acquired by any recording device, is original or not. The versatility of the digital support allows copying, editing and distributing the multimedia data with little effort. As a consequence, the authentication and validation of a given content have become more and more difficult, due to the possible diverse origins and the potential alterations that could have been operated.
From these premises, a significant research effort has been recently devoted to the forensic analysis of multimedia data [1].

Image Forensics
A large part of the research activities in forensics are devoted to the analysis of still images, since digital photographs are largely used to provide objective evidence in legal, medical, and surveillance application. In particular,

several approaches target the possibility of validating, detecting alterations, and recovering the chain of processing steps operated on digital images [13].

There are several studies dealing with performing image authentication. An image recapture detector is described in [3], where the authors are able to automatically identify the devices used for first and second capture when sharp edges are present in the image.

Many source identification techniques in image forensics exploit the PRNU noise introduced by the sensor. Although not being the only kind of sensor noise [4] [5], PRNU has proven to be the most robust feature. Indeed, being a multiplicative noise, it is difficult for device manufacturers to remove it.

If the image has been compressed, in [14] the authors propose a method capable of identifying the used encoder. Finally, a method to infer the quantization step used for a JPEG compressed image is shown in [15].

Video Forensics

All the potential modifications concerning digital images can be operated both on the single frames of a video sequence and along the temporal dimension. With the increasing availability of small, inexpensive video recording devices, casual movie making is now within everyone's reach. It is then easy for everyone to put these video sequences on-line. As it regards video forensics, bootleg detection (or re-capture detection) is an important forensic task for two main application scenarios: the detection of illegally distributed movie copies, and the detection of the use or re-capturing as anti-forensic technique. The former scenario is related to the problem of identification of videos re-captured at the cinema and made available on-line. The latter scenario is related to the use of anti-forensics. Indeed, when a video is maliciously modified, a common technique to hide the traces left by the tampering operation is to re-capture the sequence using a camera. The re-captured video is visually similar to the original one, but traces left by the editing step are mostly removed. Detecting re-capturing is then a precious hint for a forensic analyst.

The possibility of distinguishing between original and recaptured sequences is then of great help for a forensic analyst: a positive recapture test for a video sequence is a strong indicator of tampering activity having taken place. To this end, several methods have been proposed in the literature. In [6], projected videos recaptured with a camera placed off-axis with respect to the screen are identified by detecting inconsistencies in the camera intrinsic parameters. In [7], the authors show how to detect whether a sequence has been recaptured by analysing the high-frequency jitter introduced by, e.g., a hand-held camcorder.

Audio Forensics

The other works that have received some interest in the last few years are about *audio forensics*. In this section we present a small overview of the most relevant audio forensic techniques. Audio forensics [2] refers to the acquisition, analysis, and evaluation of audio recordings that may ultimately be presented as admissible evidence in a court of law or some other official venues. Audio forensic evidence is typically obtained as part of a civil or criminal law enforcement investigation or as part of the official inquiry into an accident or other civil incident. The principal concerns of audio forensics are establishing the authenticity of audio evidence performing enhancement of audio recordings to improve speech intelligibility and the audibility of low-level sounds and interpreting and documenting sonic evidence, such as identifying talkers, transcribing dialogues, and reconstructing crime or accident scenes and time lines.

In addition to the above-mentioned techniques, it is worth noticing that some interesting forensic-related algorithms are often used in different fields. An example is that of robotic navigation, in which environmental sounds are recognized in order to understand a scene or context surrounding an audio sensor [16]. Another one is that of event detection [17], in which the authors have created an audio event detection system which automatically classifies an audio event as ambient noise, scream or gunshot.

A possible way to determine the authenticity of an audio track is to extract information about the room in which the audio track has been recorded. To this purpose there are systems that identify the room in an audio or video recording through the analysis of acoustic properties. In order to extract information from a reverberant audio stream, the human auditory system is well adapted. Based on accumulated perceptual experiences in different rooms, we can often recognize a specific environment just by listening to the audio content of a recording. In [10], the authors propose a system for identifying the room in an audio or video recording through the analysis of acoustical properties, e.g., distinguishing a recording made in a reverberant church from a recording captured in a conference room. While in [9], the authors estimate the reverberation time from the recorded track and use it as a clue for estimating the room dimension.

Another way to verify the authenticity of a recorded audio is to determine the originating device of a signal. There are works, like [8], that provide a paradigm to determine the microphone model used to record a given audio sample. In criminology and forensics, recognizing the microphone type and model of a given alleged accidental or surveillance recording of a committed crime can help determining the authenticity of that record. Furthermore microphone forensics can be useful also to determine if the audio of a video recording is original and taken with the integrated microphone of the device used, or if the audio has been tempered with or even completely replaced.

There are some works in audio forensics that meet Music Information Retrieval, in particular they are related to *Music-plagiarism*. Music-plagiarism is the use or close imitation of another author's music without proper acknowledgement. Given the large number of new musical tracks released each year, automated approaches to plagiarism detection are essential to help us track potential violations of copyright. Most current approaches to plagiarism detection are based on musical similarity measures, which typically ignore the issue of polyphony in music. In [18], the authors present an approach that tackles the problem of polyphony, presenting a novel feature set derived from signal separation based on compositional models.

1.2 Audio Classification

Researches in audio classification are mostly related to *Musical Genre* classification [11]. This is the study of automatic classification of audio signals into a hierarchy of musical genres. Musical genres are categorical labels created by humans to characterize pieces of music. A musical genre is characterized by the common characteristics shared by its members. These characteristics typically are related to the instrumentation, rhythmic structure, and harmonic content of the music. Genre hierarchies are commonly used to structure large collections of music available on the Web. In [12], the authors implement a system for dynamic play-list generation analysing low-level and high-level features representing the user's mood and preferences. Typically, in order to solve a general audio classification problem, the solution can be obtained in two steps: *feature extraction* and *classification*.

1.2.1 Features

The goal of feature extraction is to give a formal description of an audio signal, i.e., providing numerical values of its characteristics. These descriptors, that are able to characterize the audio signals, are called *features*. Many common audio analysis methods make use of acoustic features to describe and classify audio excerpts. A typical example is that of audio genre classification. There are sets of features that can be formalized and described in a hierarchy going from lower level, related to sound signals, to the higher level, which is related to the perception of sound. There are three main levels of features:

- **Low-Level Features**: they are low-complexity content-based descriptors extracted directly from the signal using signal processing techniques. They are used to characterize any type of sound.
- **Mid-Level Features**: they introduce a first level of semantics and they intend to fill the gap between audio signal and music annotation description. They combine the Low-Level features with musical knowledge and they refer to structural components of music such as *Harmony* and *Rhythm*.
- **High-Level Features**: they carry a high degree of abstraction in the semantics, which makes them easily understandable by humans. They are related to cognitive aspects.

In our thesis we have used only features belonging to the first two levels (low and mid).
We have introduced a further division of the features used, on the basis of the operation needed to extract their values [19]. In Figure 1.1 a schema of this subdivision is shown.

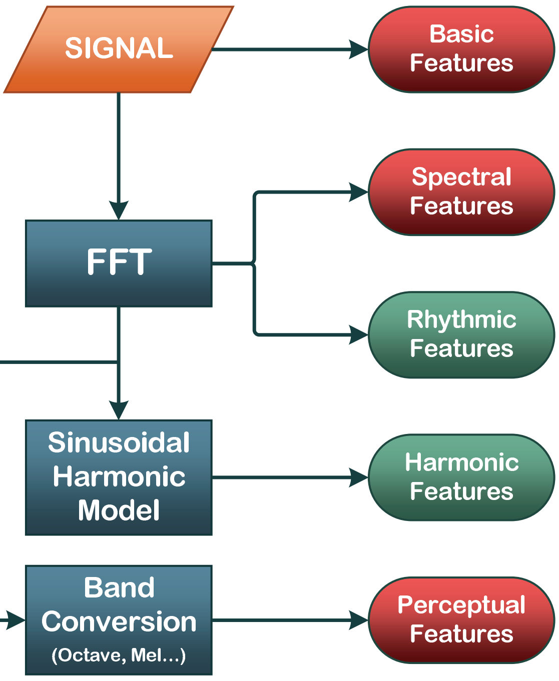


Figure 1.1: Division of the features in 5 groups: we have highlighted in red the Low-Level Features, in green the Mid-Level Features

In order to present the definition of the features used in this work, let us define a common notation:

- x is a mono-dimensional discrete signal of size N (number of samples). x_n corresponds to the value of n-th sample of the signal, with $n = 0, 1, ..., N-1$.
- considering x divided into T frames, let x^t denote the t-th frame of length N^t.

  $$x_i^t = x_{i-tH}\, w_i \ , \tag{1.1}$$

  indicates the value of i-th sample of frame x^t, with $i = (0, 1, ..., N^t - 1)$. H is the hop size, i.e., the number of samples between adjacent frames. w is the *window* function that is zero-valued outside of some chosen interval with size N^t. There are many types of windows, e.g., the rectangular window that is constant inside the interval and zero elsewhere.
- let X denote the spectrum of size K of the signal, computed as

  $$X = FFT(x) \ , \tag{1.2}$$

  where for FFT we mean the *Fast Fourier Transform.* X_k is the spectrum of the signal x related to k-th bin and f_k is the frequency of k-th bin, with $k = (0, 1, ..., K-1)$.

1.2.1.1 Basic Features

The *Basic Features* are Low-Level features that are extracted directly from the signal in the time domain.

Root Mean Square Energy - RMS

The *Root Mean Square* is a measure of the energy contained in the signal. It is defined as the root average of the squared signal samples,

$$rms = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} x_n^2} \ . \tag{1.3}$$

Considering the t-th frame of signal, we can compute also the RMS of the single signal, defined as

$$rms^t = \sqrt{\frac{1}{N^t}\sum_{n=0}^{N^t-1} (x_n^t)^2} \ . \tag{1.4}$$

Zero Crossing Rate - ZCR

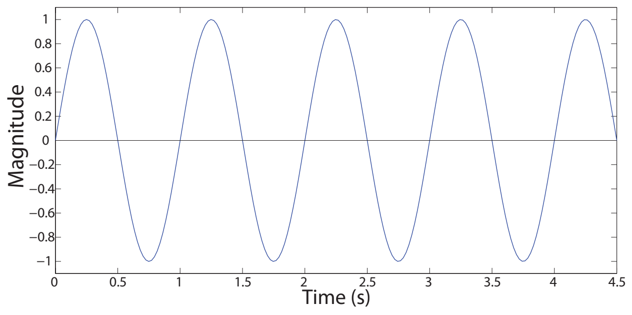
The *Zero Crossing Rate* indicates the number of times that the audio samples changes of sign, and it can be computed as

$$zcr = \frac{1}{2} \sum_{n=1}^{N-1} |y_n - y_{n-1}| \frac{F_s}{N} , \tag{1.5}$$

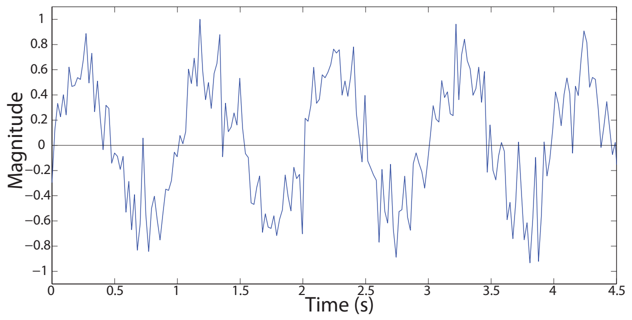
where y_n is defined as

$$y_n = \begin{cases} 1 & \text{if } x_n \geq 0 \\ 0 & \text{otherwise} \end{cases} .$$

The time-domain zcr provide a rough measure of the noisiness of a signal, because high noise involves a high zcr value [19]. A clear example is the simple case of a pure sinusoidal signal with and without noise. Indeed, a sinusoidal signal of length S seconds and frequency F crosses the y-axis K times. If we add a Gaussian IID noise to the pure sinusoidal signal, the ripples generated by the noise itself will increase the number of zero-crossings considering the same time window of length S seconds (see Figure 1.2).



(a) Pure sinusoidal signal with frequency 1 Hz.



(b) Same sinusoidal signal with Gaussian IID noise

Figure 1.2: Zero Crossing Rate: a sinusoidal pure signal cross the y-axis K times, but with the addition of a Gaussian IID noise, the ripples increase the number of crossings, and so the zcr value.

This feature can be also considered as a measure of the dominant frequency of a signal, as it is explained in [20].

Low Energy

The *Low Energy* feature estimates the percentage of frames with energy lower than a given threshold. This estimation provides information to see if the temporal distribution of energy remains constant throughout the signal, or if some frames are more different than others. Low Energy is defined as the percentage of frames showing the *rms* value smaller than the average *rms* along the whole piece, and it can be computed as

$$LE = \frac{1}{T}\sum_{t=1}^{T} l^t \ , \tag{1.6}$$

where l^t is the variable used to control if the *rms* of the t-th frame is lower than *rms* of the signal

$$l^t = \begin{cases} 1 & \text{if } rms^t \leq rms \\ 0 & \text{otherwise} \end{cases} \ , \tag{1.7}$$

Figure 1.3 shows a visual example of how this feature is computed.

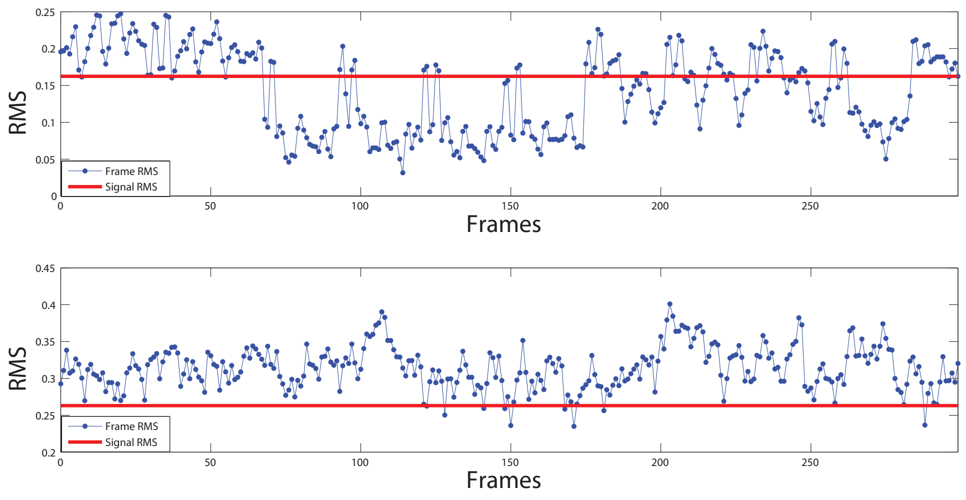


Figure 1.3: Low Energy computation example. The first signal (top) has a Low Energy value of 0.54, in-fact an high number of frames has RMS lower than the signal RMS. The second signal (bottom), on the contrary, has a Low Energy of 0.018, in-fact very few frames have RMS lower than signal RMS.

Waveform - WF

The *Waveform* describes simply the shape and form of a signal. We consider as feature the maximum and the minimum values of the *WF* in a frame of the signal x. Let us consider x_t as the t-th frame of the signal, so the *Waveform* feature values are

$$WF^t_{max} = \max\left(x^t\right) \ , \tag{1.8}$$

$$WF^t_{min} = \min\left(x^t\right) \ . \tag{1.9}$$

1.2.1.2 Spectral Features

Spectral Features are Low-Level features highly related to the *Timbre*. This makes them good descriptors in MIR applications. *Spectral Features* are computed through the analysis of the *Spectrum* of the signal x, so the FFT is needed.

Spectral Roll-Off

The *Spectral Roll-Off* is defined as the frequency below which 85% of the magnitude distribution is concentrated [11]. It can be computed as

$$sroll = \min\left\{ f_{K_{roll}} | \sum_{k=0}^{K_{roll}-1} X_k \geq 0.85 \cdot \sum_{k=0}^{K-1} X_k \right\} \ , \tag{1.10}$$

where K_{roll} is the spectral roll-off frequency bin and $f_{K_{roll}}$ is the frequency associated to that bin. The roll-off is another measure of spectral shape.

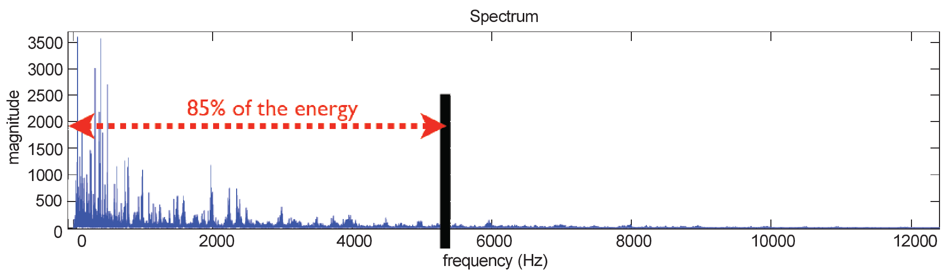


Figure 1.4: Spectral roll-off, graphic illustration

Spectral Brightness

The *Brightness* is the result of the ratio between the amount of the spectral energy for frequencies higher than 1500Hz and the total amount of spectrum energy. It can be computed as

$$sbright = \frac{\sum_{k=K_c}^{K-1} |X_k|}{\sum_{k=0}^{K-1} |X_k|} \,, \tag{1.11}$$

where K_c is the bin corresponding to a frequency of 1500Hz.

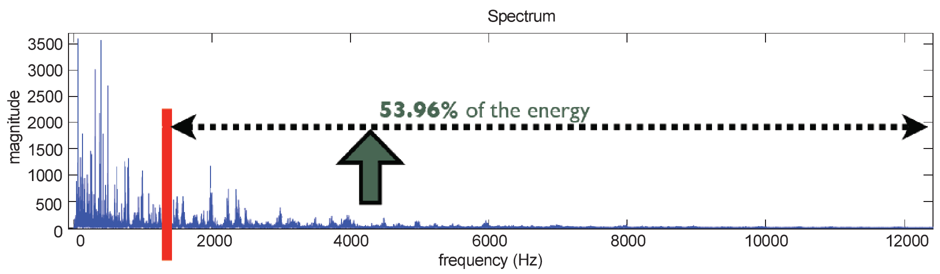


Figure 1.5: Spectral Brightness, graphic illustration

Spectral Flux

Spectral flux is a measure of how quickly the power spectrum of a signal is changing [11]. It is computed as the Euclidean distance between the spectral distributions of two adjacent frames,

$$sflux^t = \sqrt{\sum_{k=0}^{K-1} \left(X_k^t - X_{k,}^{t-1}\right)^2} \,, \tag{1.12}$$

where $X_{k,t}$ is the magnitude of k-th bin of the spectrum of the t-th frame of x and $X_{k,t-1}$ is the magnitude of k-th bin of the spectrum of the previous frame $t-1$.

Spectral Entropy

The *Spectral Entropy* is the Shannon's entropy of the signal spectrum,

$$sentr = -\frac{\sum_{k=0}^{K-1} X_k \cdot \log(X_k)}{\log(K)} \,. \tag{1.13}$$

The presence of $\log(K)$ at the denominator makes the feature independent from the window's length.

Spectral Flatness

The *Spectral Flatness* is a measure of how tone-like a sound is. A sound is noise-like if the spectrum is flat (i.e., it is white noise, with similar amount of power in all spectral bands), whereas it is considered tone-like in presence of peaks or resonant elements. If it approaches to 0, it indicates that the spectral power is concentrated in small number of bands. The spectral flatness is calculated by dividing the geometric mean of the power spectrum by the arithmetic mean of the power spectrum,

$$sflat = \frac{\sqrt[K]{\prod_{k=0}^{K-1} X_k}}{\frac{\sum_{k=0}^{K-1} X_k}{K}} \ . \tag{1.14}$$

Spectral Irregularity

The *Irregularity* of the spectrum is a measure of the variation of successive peaks of the spectrum. A peak is defined as a local maximum of the magnitude spectrum. The *Spectral Irregularity* is computed as the sum of the squared differences of adjacent peaks,

$$sirr = \frac{\sum_{m=0}^{M-2} (p_m - p_{m+1})^2}{\sum_{m=0}^{M-1} p_m^2} \ , \tag{1.15}$$

where p_m is the m-th peak amplitude and M the number of the peaks. The approach used for the irregularity computation is the one described in [21].

Roughness

The *Roughness* is an estimation of sensory dissonance [22] related to the beating phenomenon perceived when two sinusoids are close in frequency. According to the MIRToolBox [23] which provides an implementation of this feature, the peaks of the spectrum are first computed and then the average dissonance between all the possible pairs of peaks is taken, as proposed in [24]. For all the pairs of frequency peaks (i, j), we define p_i,p_j as i-th and j-th peak amplitudes, and f_i, f_j as frequencies corresponding to i-th and j-th frequency peaks. The roughness $r_{i,j}$ is defined as

$$r_{i,j} = \frac{1}{2} \times (p_i p_j)^{0.1} \times \left(\frac{2p_{min}}{p_i + p_j} \right)^{3.11} \times \left(e^{-3.5Z|f_i - f_j|} - e^{-5.75Z|f_i - f_j|} \right) \ , \tag{1.16}$$

where

$$\begin{aligned} p_{min} &= \min(p_i p_j) \ , \\ f_{min} &= \min(f_i f_j) \ , \end{aligned} \tag{1.17}$$

$$Z = \frac{0.24}{0.0207 \times f_{min} + 2\pi \times 18.96} \ . \tag{1.18}$$

It is possible to obtain an estimation of the total roughness of the signal by taking the average of dissonances between all the possible pairs of peaks.

Spectral Centroid

According to the view of the *Magnitude Spectrum* as a distribution function, the first four statistical *moments* of the distribution are *Spectral Centroid*, *Spectral Spread*, *Spectral Skewness* and *Spectral Kurtosis.* The *Spectral Centroid* is the barycentre of the spectrum. It is calculated as the weighted average between each frequency component, using as weight the spectral magnitude at that frequency

$$sc = \frac{\sum_{k=0}^{K-1} f_k X_k}{\sum_{k=0}^{K-1} X_k} \ . \tag{1.19}$$

The spectral centroid is commonly associated with the measure of the brightness of a sound [25]. Many kinds of music involve percussive sounds, which introduce high-frequency components that increase the centroid value. [26]. This is real also for a rough ”detection” of other type of noise in our sound samples. The centroid is also called *first moment* (mean). In-fact some use *Spectral Centroid* to refer to the median of the spectrum, although there is a difference with the classical statistical first moment, the difference being essentially the same as the difference between the un-weighted median and mean statistics. Since both are measures of central tendency, in some situations they will exhibit some similarity of behaviour.

Spectral Spread

The *Spectral Spread* is a measure of the standard deviation of the spectrum with respect to the spectral centroid. It can be computed as

$$sspread = \sqrt{\frac{\sum_{k=0}^{K-1} X_k \left(f_k - sc\right)^2}{\sum_{k=0}^{K-1} X_k}} \ , \tag{1.20}$$

where sc is the spectral centroid. It is the *second central moment.*

Spectral Skewness

The *Spectral Skewness* is the *third central moment* and is a measure of the symmetry/asymmetry of the spectrum related to its mean value. It is defined as

$$sskew = \frac{\sum_{k=0}^{K-1} X_k \left(f_k - sc\right)^3}{K\sigma^3} \ , \tag{1.21}$$

where σ is the spectral spread. If the skewness value is zero, the spectrum is symmetrically distributed.

Spectral Kurtosis

The *Spectral Kurtosis* is the *fourth central moment.* It indicates the flatness of the spectrum around its mean value. It is defined as

$$skurt = \frac{\sum_{k=0}^{K-1} X_k \left(f_k - sc\right)^4}{K\sigma^4} \; . \tag{1.22}$$

If the value of the kurtosis is 3, the spectrum behaves as a Gaussian distribution. If the value of kurtosis is higher, the spectral distribution takes a slower decay and the tails are heavier.

1.2.1.3 Harmonic Features

The *Harmonic Features* are Mid-Level features computed from the *Sinusoidal Harmonic Modelling* of the signal. SHM represents the signal as the linear combination of concurrent slow-varying sinusoids, grouped together under harmonic frequency constraints.

Chroma Features and Chromagram

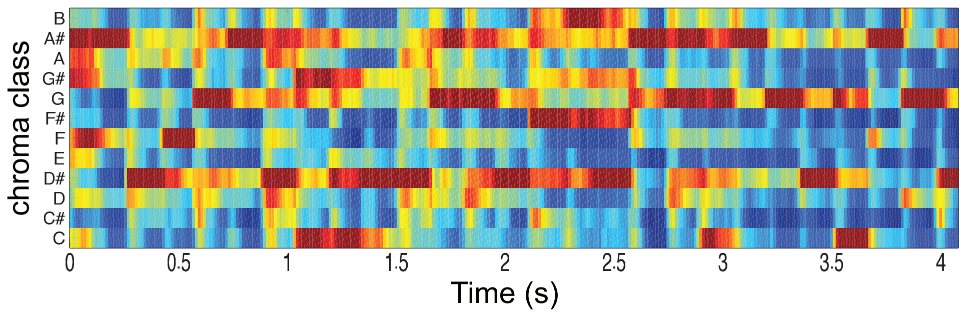
The *Chroma Features* provide a representation of audio data according to note frequency values of the *musical octave*. Musical octave is an interval whose highest note has a sound-wave frequency of vibration twice that of its lowest note. In the chromatic scale an octave is divided by 12 equally spaced pitches, corresponding to 12 semitones. Chroma features consist in a redistribution of the spectrum energy along the different 12 pitches classes. If we consider a signal x divided in several frames, the chroma features of each frame can be computed using MIRToolBox [23]. An example of chroma features is shown in Figure 1.6(b). *Chromagram* is defined as a time-ordered set of vectors containing chroma features of all frames composing the signal. An example of chromagram is shown in Figure 1.6(a).

Chromatic Flux

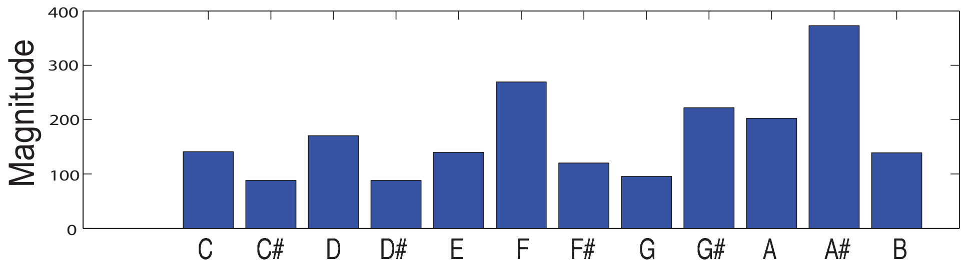
Chromatic flux is computed as the Euclidean distance between the chroma features vectors belonging to two successive frames of the audio signal,

$$CF^t = \sqrt{\sum_{i=1}^{12} \left(C_i^t - C_i^{t-1}\right)^2} \; , \tag{1.23}$$

where C_i^t is the i-th value of Chroma features vector of the frame t and C_i^{t-1} is the i-th value of Chroma features vector of the previous frame $t-1$.
This descriptor can be helpful to detect the harmonic alteration by measuring the changes from frame to frame.



(a)



(b)

Figure 1.6: (a) Chromagram of the entire signal that shows the time distribution of the 12 *pitch classes (b) Chroma-Features of a single frame that show how the spectrum magnitude is distributed into* 12 *bins, representing the* 12 *distinct semitones of the musical octave*

Inharmonicity

In music, *inharmonicity* provides a measure of the amount of partials that are non-multiples of the fundamental frequency. More precisely, in our situation the inharmonicity takes into account the ideal and expected positions of harmonics compared to the actual spectrum harmonics. According to the MIRToolBox [23], a simple function estimating the inharmonicity of n-th partial given the fundamental frequency f_0 is given by

$$h_n = \frac{|f_n - nf_0|}{nf_0} , \tag{1.24}$$

where f_n is n-th succeeding partial, i.e., the n-th frequency of the signal that is an integer multiple of the fundamental frequency f_0.

1.2.1.4 Rhythmic Features

Rhythmic Features are Mid-Level Features that are highly related to the *rhythmic patterns* played sequentially on drums. Rhythmic features are generally based on the onset note curve, where for onset note we intend a peak in the time-energy diagram corresponding to the attack time of a note.

Event Density

The *Event Density* is the temporal average number of acoustic events, i.e., the average frequency of notes per second. According to the MIRToolBox [23], it can be evaluated by counting the number of note onsets per second. For this purpose it is needed to compute the onset detection curve, than it is only necessary to count the onset contained by the function [23].

Pulse Clarity

Pulse Clarity estimates the rhythmic clarity, indicating the strength of the beats. It is related to the listener's perception of the underlying rhythmic or metrical pulsation [27]. According to the MIRToolBox [23], it is computed by taking the autocorrelation function of the onset detection curve and normalizing it to its maximum value.

1.2.1.5 Perceptual Features

Perceptual Features are Low-Level features computed using a human perceptual model. In this case, the spectrum, where the frequency bands are positioned logarithmically, can better approximate the human auditory system's response.

Mel-Frequency Cepstral Coefficients - MFCC

The *Mel Frequency Cepstral Coefficients* are a set of features derived from the speech recognition systems [11]. MFCCs are perceptually motivated feature and although they were developed at first for speech classification, they have also been applied to music genre classification [11]. The MFCCs are widely used due to their ability to represent the spectrum in a very compact form. The computation of the *Mel-Frequency Cepstral Coefficients* follows the schema illustrated in Figure 1.7 [28].

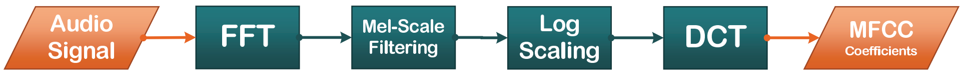


Figure 1.7: Mel-Frequency Cepstral Coefficients computational flow

The signal is divided in windowed frames and for each frame:

- The FFT $X(\omega)$ of the frame x^t is computed.

- As shown in Figure 1.8, the amplitude spectrum X is filtered using a set of, typically, 40 overlapping triangular band-pass filters, based on *Mel-Frequency scale.* The Mel-Frequency scale is a scale of pitches judged by listeners to be perceptually equal in distances one from another. The following equation is used to compute the Mel for given frequency f in Hz.

$$Mel = 1127.0148 \log\left(1 + \frac{f}{700}\right) \ . \tag{1.25}$$

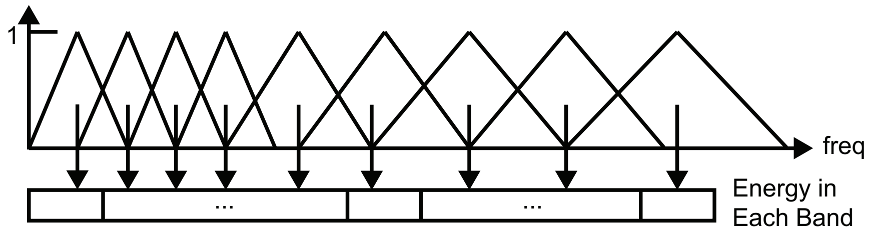


Figure 1.8: Mel-Frequency Filter Bank

- MFCCs are obtained as the coefficients of the *Discrete Cosine Transform* (DCT) applied to the reduced *Power Spectrum.* The reduced Power Spectrum derived as the log-energy of the spectrum is measured within the pass-band of each filter of a Mel-filter bank. The m-th MFFC coefficient is finally formalized as

$$MFFC_m = \sum_{j=0}^{J-1} \left\{ \log(E_j) \cos\left[m\frac{\pi}{J}\left(j - \frac{1}{2}\right)\right]\right\} \ , \tag{1.26}$$
$$0 \leq m \leq L-1 \ ,$$

  where L is the number of Mel filters and J is the number of MFCCs derived for each frame. E_j is the spectral energy measured in the critical band of the m-th Mel filter.

- The averaged MFCCs of all frames in a music piece are used as feature of the whole file.

The Mel scale is used because it approximates the human auditory system's response more closely than the linearly-spaced frequency bands. The DCT is used in place of the (inverse) Fourier transform because it has a strong compactness, since the signal information are normally concentrated in a few low-frequency components of the DCT. This is also why typically only 13 coefficients are used.

Octave-Based Spectral Contrast - OSC

The *Octave-based Spectral Contrast* coefficients consider the peak and the valley of the spectrum and the difference in each sub-band. Typically in music strong spectral peaks roughly correspond with harmonic components, while non-harmonic components (noise) often appear at spectral valleys [29]. The MFCCs average the spectral distribution in each sub-band and thus lose relative spectral information. The OSC computational flow is very similar to the MFCCs one, as shown in Figure 1.9.

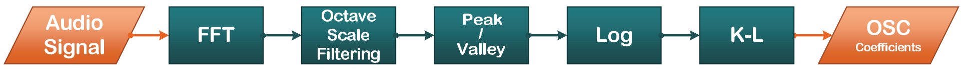


Figure 1.9: Octave-Based Spectral Contrast computational flow

- The FFT is performed on the digital samples of the signal.

- The frequency domain is divided in sub-bands by several Octave-scale filters, which are more suitable than Mel-scale for music processing. An example of these sub-bands is given in [29], where the authors divide the frequency domain into six Octave-scale sub-bands: $0Hz \sim 200Hz$ (we can see with refer to Table 1.1 that this first sub-band includes two octaves), $200Hz \sim 400Hz$, $400Hz \sim 800Hz$, $800Hz \sim 1.6kHz$, $1.6kHz \sim 3.2kHz$, $3.2kHz \sim 8kHz$ (another octave out of the bound indicated in Table 1.1).

- The strength of spectral peaks and valleys can be estimated in each sub-band. In order to ensure the steadiness of the feature, the strength of spectral peaks and spectral valleys are estimated by the average value in the small neighbourhood around maximum and minimum value respectively, instead of the exact maximum and minimum value themselves. Thus, neighbourhood factor α is introduced to describe the small neighbourhood. α is set to 0.02 (typically is set between 0.02 and 0.2, but it does not affect the performance significantly). The FFT of each of the j-th sub-band of the signal is returned as a vector, than is sorted in descending order of magnitude, such that $X_{j,1} > X_{j,2} > ... > X_{j,K}$, where K is the total number of FFT bins. The strength of spectral peaks and spectral valleys are estimated as

$$Peak_j = \frac{1}{\alpha K} \sum_{i=1}^{\alpha K} X_{j,i} \ , \tag{1.27}$$

$$Valley_j = \frac{1}{\alpha K} \sum_{i=1}^{\alpha K} X_{j,K-i+1} \ . \tag{1.28}$$

- Applying the log-scaling, the *Spectral Contrast* of j-th sub-band is given by
$$SC_j = \log\left(\frac{Peak_j}{Valley_j}\right) \ . \tag{1.29}$$

- Finally, the *Karhunen-Loeve transform* can be performed in order to map the Spectral Contrast coefficients into an orthogonal space, obtaining the final uncorrelated OSC coefficients.

Table 1.1: Frequencies relative to the notes of the first six octaves. Each octave is divided into 12 *notes. Each note, in a certain octave, has a frequency value twice that of the same note of the previous octave (Oct).*

Note	Oct=1	Oct=2	Oct=3	Oct=4	Oct=5	Oct=6
A	55.00	110.00	220.00	440.00	880.00	1,760.00
A♯/B♭	58.27	116.54	233.08	466.16	932.33	1,864.66
B	61.74	123.47	246.94	493.88	987.77	1,975.53
C	65.41	130.81	261.63	523.25	1,046.50	2,093.01
C♯/D♭	69.30	138.59	277.18	554.37	1,108.73	2,217.46
D	73.42	146.83	293.67	587.33	1,174.66	2,349.32
D♯/E♭	77.78	155.56	311.13	622.25	1,244.51	2,489.02
E	82.41	164.81	329.63	659.26	1,318.51	2,637.02
F	87.31	174.61	349.23	698.46	1,396.91	2,793.83
F♯/G♭	92.50	185.00	370.00	739.99	1,479.98	2,959.96
G	98.00	196.00	392.00	783.99	1,567.98	3,135.96
G♯/A♭	103.83	207.65	415.31	830.61	1,661.22	3,322.42

1.2.2 Classifiers

In *machine learning*, *classification* is the problem of identifying to which classes an observation belongs. Classes correspond to labels for different populations (e.g., dogs and cats form separate classes). Classification has two distinct meanings:

- on the basis of data containing observations whose class is known, the classifier defines a rule whereby a new observation can be classified into one of the existing classes.

- given a set of unlabelled observations, the classifier establishes the existence of classes or clusters in the data.

The first method is known as *Supervised Learning*, while the second is called *Unsupervised Learning* (or *Clustering*) [30].
The classifier is an algorithm with features as input, and the output is usually a label, but it can contain confidence values [31]. In supervised learning, the set of data containing objects whose class is known, is called *training set*, in which the classifier uses feature vectors to estimate a model describing a class, provided that there are enough good samples available. Through this model, a new object can be categorized into one of the classes analysed. In unsupervised learning, the data are not labelled and the classifier, according to some rules, tries to find clusters and form classes.
Since in our problem we assume that a training set is available, we have used only supervised classifiers, and, more specifically, *Gaussian Mixture Model* and *Support Vector Machine* [32].

1.2.2.1 Gaussian Mixture Model - GMM

Bayesian classification is based on probability theory and on the principle of choosing the most probable option. let us assume that we need to classify some observed data into C different classes. Each observation $\mathbf{s}$ is characterised by a feature vector of size D. The probability that $\mathbf{s}$ belongs to class w_c is $p(w_c|\mathbf{s})$, and it is often referred to as a posteriori (or posterior) probability. The classification of the observations is done according to posterior probabilities or decision risks calculated from the probabilities.
The posterior probabilities can be computed with the Bayes formula

$$p(w_c|\mathbf{s}) = \frac{p(\mathbf{s}|w_c)p(w_c)}{p(\mathbf{s})} \ , \tag{1.30}$$

where $p(\mathbf{s}|w_k)$ is the probability density function of class w_c in the feature space and $p(w_c)$ is the a priori probability, which is the probability of the class w_c without any knowledge on the feature values. If prior probabilities are not actually known, they can be estimated by the class proportions in the training set. The divisor

$$p(\mathbf{s}) = \sum_{c=1}^{C} p(\mathbf{s}|w_c)p(w_c) \tag{1.31}$$

is merely a scaling factor to assure that posterior probabilities are really probabilities, i.e., their sum is one.

Choosing the class of with highest posterior probability produces the minimum error probability. The major problem in the Bayesian classifier is estimating the class-conditional probability density function $p(\mathbf{s}|w_c)$, that describes the distribution of feature vectors in the feature space inside a particular class.
GMM approach assumes that the class-conditional probability density of the observed process can be modelled as a weighted sum of G multivariate Gaussian probability density functions

$$p(\mathbf{s}|\theta) = \sum_{g=1}^{G} \alpha_g b_g(\mathbf{s}) \ , \tag{1.32}$$

where $\mathbf{s}$ is a vector of size D, α_g is the weight corresponding to the g-th component. $b_g(x)$ is a g-th Gaussian density function, that is defined as

$$b_g(\mathbf{s}) = \frac{1}{2\pi^{D/2}|\sum|^{1/2}} e^{-\frac{1}{2}(x-\mu_g)^\top \left(\sum_g\right)^{-1}(x-\mu_g)} \ , \tag{1.33}$$

where μ_g is the mean vector and $\sum_g$ is the covariance matrix of $\mathbf{s}$. The parameter list θ defines a particular Gaussian mixture probability density function

$$\theta = \left\{\alpha_1, \mu_1, \sum\nolimits_1, \alpha_2, \mu_2, \sum\nolimits_2, ..., \alpha_G, \mu_G, \sum\nolimits_G\right\} \ . \tag{1.34}$$

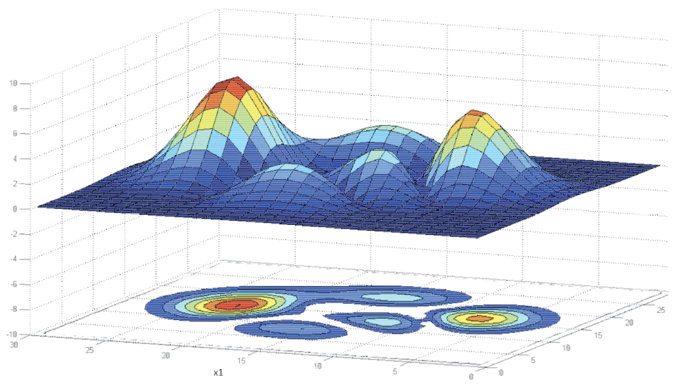


Figure 1.10: An example surface of a two-dimensional Gaussian mixture PDF

In Figure 1.10 is shown an example of 2-dimensional Gaussian probability density function. In construction of a Bayesian classifier, the class-conditional probability density functions need to be determined. The initial model selection can be done for example by visualizing the training data, but the adjustment of the model parameters requires some measure of goodness, i.e., how well the distribution fits the observed data. Data likelihood is a such goodness value. Let us assume that there are M independent observations $\mathbf{s} = [s_1, s_2, ..., s_M]^\top$ drawn from a single distribution described by a probability density function $p(\mathbf{s}|\theta)$, a likelihood function is defined as

$$\mathcal{L}(\mathbf{s}|\theta) = \prod_{m=1}^{M} p(s_m|\theta) \ . \tag{1.35}$$

This function supplies the likelihood of the samples with respect to the distribution. The goal is to find $\hat{\theta}$ that maximize the likelihood as

$$\hat{\theta} = \arg\max_{\theta} \mathcal{L}(\mathbf{s}|\theta) \ . \tag{1.36}$$

Usually this function is not maximized directly, but the logarithm

$$L(\mathbf{s}|\theta) = \ln \mathcal{L}(\mathbf{s}|\theta) = \sum_{m=1}^{M} \ln p(s_m|\theta) \ , \tag{1.37}$$

called the log-likelihood function, is analytically easier to handle. Because of the monotonicity of the logarithm function the solution to Eq. 1.36 is the same using $L(\mathbf{s}|\theta)$ or $\mathcal{L}(\mathbf{s}|\theta)$.
Depending on $p(\mathbf{s}|\theta)$, it might be possible to find the maximum analytically by setting the derivatives of the log-likelihood function to zero and solving θ. It can be done for a Gaussian probability density function, which leads to the intuitive estimates for a mean and variance, but usually the analytical approach is intractable. In practice an iterative method such as the *Expectation Maximization(EM)* algorithm is used. EM algorithm is employed to estimate the GMM parameters that maximize the likelihood of a set of M data vectors. Assuming the use of diagonal covariance matrices, the process iteratively updates the searched parameters as expressed by the following equations

$$\mu_g^{new} = \frac{\sum_{m=1}^{M} p(g|s_m,\theta) s_m}{\sum_{m=1}^{M} p(g|s_m,\theta)} \ , \tag{1.38}$$

$$\sum\nolimits_g^{new} = \frac{\sum_{m=1}^{M} p(g|s_m,\theta)(s_m - \mu_g)^\top (s_m - \mu_g)}{\sum_{m=1}^{M} p(g|x_m,\theta)} \ , \tag{1.39}$$

$$\alpha_g^{new} = \frac{1}{M} \sum_{m=1}^{M} p(g|s_m,\theta). \tag{1.40}$$

The element $p(g|s_m,\theta)$ is computed as

$$p(g|s_m,\theta) = \frac{\alpha_g b_g(s_m)}{\sum_{g=1}^{G} c_g b_g(s_m)}. \tag{1.41}$$

The weight α_g of a component is the portion of samples belonging to that component. It is computed by approximating the component-conditional probability density function with the previous parameter estimates and taking the posterior probability of each sample point belonging to the component g. The component mean μ_g and the covariance matrix $\sum_g$ are estimated in the same way. The samples are weighted with their probabilities of belonging to the component, and then sample mean and sample covariance matrix are computed.
It is worth to note that so far the number of Gaussian components G is assumed to be known, and the output is calculated depending on an initial guess of the parameters to be maximized.

1.2.2.2 Support Vector Machine - SVM

SVM is a machine learning instrument defined as a binary classifier, meaning that is able to infer the boundary that separates elements belonging to two different classes. It essentially searches for an appropriate hyperplane able to separate the classes within the feature space, i.e., able to maximize its distance from the closest training points. Given M training vectors in the D-dimension space, the m-th observation $\mathbf{s}_n$ is associated to a binary class $y_m \in \{1, -1\}$. Assuming that data are linearly separable, it is then possible to delineate the separation hyperplane between the two dataset groups, in the form

$$\beta^\top \mathbf{s} + \beta_0 = 0 \ , \tag{1.42}$$

where β is the vector normal to the plane, β_0 is the offset, $\frac{\beta_0}{||\beta||}$ is the distance from the hyperplane to the origin.
For each $\mathbf{s}_m$,

- if $\beta^\top \mathbf{s}_m + \beta_0 \geq 0$, $\mathbf{s}_m$ belongs to the positive class, so $y_m = +1$.
- if $\beta^\top \mathbf{s}_m + \beta_0 < 0$, $\mathbf{s}_m$ belongs to the negative class, so $y_m = -1$.

More precisely, the operation of the SVM algorithm is based on finding the optimal separating hyperplane, which separates data belonging to two classes and maximizes the distance to the closest observations from either class. Not only does this provide a unique solution to the separating hyperplane problem, but, maximizing the *margin* between the two classes on the training data, this leads to better classification performance on test data. As shown in Figure 1.11, the margin is equal to $\frac{2}{||\beta||}$, so SVM wants to minimize $||\beta||$. Since it's difficult to solve this optimisation problem because $||\beta||$ involves a square root, SVM training process substitutes the equation

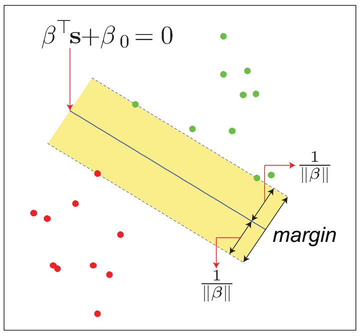


Figure 1.11: Support vector classifier. The decision boundary, represented by the solid blue line, separates the observations belonging to different classes. Broken lines bound the shaded maximal margin of width $\frac{2}{||\beta||}$

without changing the solution, and solves the following quadratic programming optimization through Lagrange multipliers

$$\begin{aligned} &\underset{\beta,\beta_0}{\text{minimize}} && \frac{1}{2}||\beta||^2 \ , \\ &\text{subject to} && y_m(\beta^{\top}\mathbf{s}_m + \beta_0) \geq 1, \forall m \in M \ . \end{aligned} \tag{1.43}$$

An example of SVM applied to audio classification can be observed in [33]. Most of the practical problems addressed through SVM present observations that are not separable by a hyperplane, since the edges between the classes are not linear. In this case it is possible to turn a non-linear problem to a linear one by using *Kernel* functions $x \to \phi$. The input vectors, which the kernel function is applied on, are projected into a transformed feature space where the data are linearly separable (Figure 1.12).

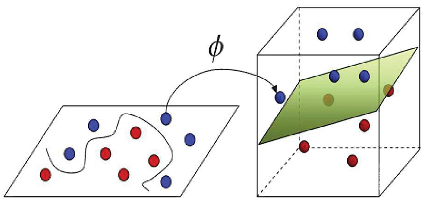


Figure 1.12: A Kernel function projects the input data into a new space where a hyperplane can be used to separate the classes

Given a finite set of observations, it is always possible to find a dimension where all the data points are separated by a hyperplane. Hence, after mapping the input elements to a sufficiently high-dimensional space, it is possible to employ the linear SVM training approach in order to find the optimal separating plane. The SVM is a binary classifier, but there are several approaches to classify problems with three or more classes. The dominant approach is to reduce the single multi-class problem into multiple binary classification problems. Building binary classifiers which distinguish between one of the labels and the rest (*one-versus-all*) or between every pair of classes (*one-versus-one*). Classification of new instances for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class. For the one-versus-one approach, classification is done by a voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with the most votes determines the instance classification. We have used the one-versus-one approach.

1.2.3 Feature Selection and Feature Reduction

Since not all features or attributes are relevant to a problem, we need a way to recognize important features and assign a larger weight to information provided by them [34]. Indeed some features prove to be highly discriminative when used to solve a specific problem, but they may interfere and reduce accuracy for another problem. In addition, dealing with a large number of features is costly, so using approaches to reduce features number are useful also to improve performances. In this section we introduce the feature selection and feature reduction methods used in our work.

1.2.3.1 Feature Selection Methods

A first approach used to reduce feature number is called *Feature Selection*, which aims to select a subset of the existing features without applying any transformation on the set. More specifically, given a set $\mathbf{s} = [s_1, s_2, ..., s_D]^\top$ of size D, feature selection aims to find a subset $\hat{\mathbf{s}}$ of size $\hat{D}$, with $\hat{D} < D$, that maximizes an objective function $J(\hat{\mathbf{s}})$ and so has the greatest ability to discriminate between classes.
The quality of a particular feature subset is evaluated using an objective function. There are two type of objective functions: filters and wrappers.
Filters rate feature based on general characteristics, such as interclass distance or statistic independence, without employing any mining algorithm. Wrappers, on the other hand, evaluate subsets based on their predictive accuracy when employing a particular classifier. Filters are advantageous for their speed and for more general solutions, but they tend to create larger

subsets. Wrappers are slower but typically do not suffer from the problem of over-fitting, and also tend to result in subsets with higher classification accuracy because they are trained to work with a specific classifier.
Filters select features independently of the used learning machine, using a relevance criterion, while wrappers select feature subsets on the basis of how well a learning machine performs. We focused on wrappers methods, and the object function chosen is based on *K Nearest Neighbour (K-NN)*. K-NN is a method for classifying objects based on closest training examples in the feature space: an object is classified by a majority vote of its neighbours, assigning it to the most common class among its K nearest neighbours. In our case $k = 1$, then the object is simply assigned to the class of its nearest neighbour. Given a subset of features, KNN is firstly performed, then the number of correct classified object can be computed. The subset with the highest number of correct classifications is considered the best.

Forward Feature Selection - FWD
Forward Feature Selection is a greedy search algorithm that determines an optimal set of features by starting from an empty set and sequentially adding a single feature to the set if it increases the value of the chosen objective function. The problem with this sequential approach is that it gravitates toward local minima due to the inability to re-evaluate the usefulness of features that were previously added. The goodness of a particular feature subset is evaluated using an objective function, $J\left(\hat{\mathbf{s}}_{\hat{D}}\right)$.
Starting from the empty set, forward sequentially adds a feature s^+ that maximizes $J\left(\hat{\mathbf{s}}_i + s^+\right)$ when combined with the features $\hat{\mathbf{s}}_i$ that have already been selected [35]. The steps performed by FWD are given in Algorithm 1.

Algorithm 1 FWD algorithm

```
1: Start with the empty set $\hat{\mathbf{s}}_0 = \{\emptyset\}$
2: Select the best feature $s^+ : \arg\max_{s \notin \hat{\mathbf{s}}_i} J\left(\hat{\mathbf{s}}_i + s\right)$
3: **if** $J\left(\hat{\mathbf{s}}_i + s^+\right) > J\left(\hat{\mathbf{s}}_i\right)$ **then**
4:     Update $\hat{\mathbf{s}}_{i+1} = \hat{\mathbf{s}}_i + s^+$;
5:     Got to 2
6: **end if**
```

Backward Feature Selection - BWD
Backward feature selection is similar to FWD but works in the opposite direction. At the beginning, all the features are included into set of con-

sidered features. At each step, the feature s^- that improves the objective function $J(\hat{\mathbf{s}} - s^-)$ is removed from the set. As FWD, BWD is a greedy algorithm that gravitates toward local minima due to the inability to re-evaluate the usefulness of features that were previously discarded[35]. The steps performed by BWD are given in Algorithm 2.

Algorithm 2 BWD algorithm

```
1: Start with the full set $\hat{\mathbf{s}}_0 = \mathbf{s}$
2: Select the worst feature $s^- : \arg\max_{s \in \hat{\mathbf{s}}_i} J(\hat{\mathbf{s}}_i - s)$
3: if $J(\hat{\mathbf{s}}_i - s^-) > J(\hat{\mathbf{s}}_i)$ then
4:     Update $\hat{\mathbf{s}}_{i+1} = \hat{\mathbf{s}}_i - s^-$;
5:     Go to 2
6: end if
```

Stepwise Feature Selection - SW

Stepwise selection is a mixed method between forward and backward selection. The problem with this sequential approaches is that they gravitate toward local minima due to the inability to re-evaluate the usefulness of features that were previously added or discarded. Stepwise selection starts from an empty set and sequentially adds a single feature to the subset if it increases the value of the chosen objective function. The added features can be removed if its elimination from the subset improves the objective function [35]. The steps performed by SW are given in Algorithm 3.

Algorithm 3 SW algorithm

```
1: Start with the empty set $\hat{\mathbf{s}} = \{\emptyset\}$
2: Select the best feature $s^+ : \arg\max_{s \notin \hat{\mathbf{s}}_i} J(\hat{\mathbf{s}}_i + s)$
3: if $J(\hat{\mathbf{s}}_i + s^+) > J(\hat{\mathbf{s}}_i)$ then
4:     Update $\hat{\mathbf{s}}_{i+1} = \hat{\mathbf{s}}_i + s^+$;
5: end if
6: Select the worst feature* $s^- : \arg\max_{s \in \hat{\mathbf{s}}_i} J(\hat{\mathbf{s}}_i - s)$
7: if $J(\hat{\mathbf{s}}_i - s^-) > J(\hat{\mathbf{s}}_i)$ then
8:     Update $\hat{\mathbf{s}}_{i+1} = \hat{\mathbf{s}}_i - s^-$;
9:     Go to 3
10: else
11:     Go to 2
12: end if
```

* Notice that you'll need a condition to avoid infinite loops.

Genetic Algorithm - GA

Genetic Algorithms are a general adaptive optimization search methodology based on a direct analogy to Darwinian natural selection and genetics in biological systems. It has been proved to be a promising alternative to conventional heuristic methods. Based on the Darwinian principle of *survival of the fittest*, GA works with a set of candidate solutions called a *population* and obtains the optimal solution after a series of iterative computations [36]. A population is composed by group individuals with different *chromosomes*. As shown in Figure 1.13, a chromosome is long as the feature number, which contains zeros and ones. One stand for the presence of the feature, zero for the absence of the feature.

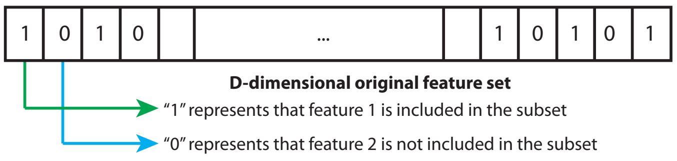

1 0 1 0 ... 1 0 1 0 1
D-dimensional original feature set
"1" represents that feature 1 is included in the subset
"0" represents that feature 2 is not included in the subset

Figure 1.13: GA Chromosome for GA-based Feature Selection

GA evaluates each individual's *fitness*, i.e., the quality of the solution, through a fitness function. Individual's fitness indicates the goodness of the present features. Several methods have been proposed as fitness function, and we choose the ratio of *within-class* scatter and *between-class* scatter [37]. The within-class scatter $\mathbf{S_W}$ and between-class scatter $\mathbf{S_B}$ are described as follow

$$\mathbf{S_B} = \sum_{c=1}^{C} (\mu_c - \overline{\mu}) (\mu_c - \overline{\mu})^\top \ , \tag{1.44}$$

$$\mathbf{S_W} = \sum_{c=1}^{C} \frac{1}{M_c} \sum_{m=1}^{M_c} (s_m^c - \mu_c) (s_m^c - \mu_c)^\top \ , \tag{1.45}$$

where $\overline{\mu}$ is the overall mean of the data-cases, $\mu_\mathbf{c}$ is the mean of the class c. C is the overall number of classes, M_c indicates the number of points belonging to class c and s_m^c represents the m-th value of feature vector of class c.

GA finds the optimal solution, and then the optimal features, after several evolutions of the population. The crossover and mutation functions are the main operators that randomly transform the chromosomes and finally impact their fitness value. The evolution will not stop until acceptable results are obtained. Crossover, the critical genetic operator that allows new solution regions in the search space to be explored, is a random mechanism for exchanging genes between two chromosomes using the one point crossover, two point crossover, or homologue crossover. In mutation the genes may occasionally be altered, for example, changing the gene value from 0 to 1 or vice versa in a binary code chromosome. The fitter chromosomes have higher probability to be kept in the next generation or be selected into the recombination pool using the tournament selection methods. If the fittest individual or chromosome in a population cannot meet the requirement, successive populations will be reproduced to provide more alternate solutions. The principal steps of GA algorithm are the following:

1. Create an initial population of certain size.
2. Calculate the fitness value of each individual in the initial population and rank them according to their fitness.
3. Select a certain number of individuals with high fitness value as *elitism* of the population and retain them in the next generation.
4. Check whether the termination conditions are satisfied. If so, the evolution stops and the optimal result represented by the best individual is returned. Otherwise, the evolution continues and the next generation is produced. The termination conditions can be either a predefined fitness threshold or number of generation evolved.
5. If the population continues to evolve, the next generation is produced following the procedure below. First, a certain number of individuals are selected randomly to compete the mating right. Two individuals of the highest fitness values are selected as a pair of parents. Crossover is operated on their chromosomes to produce two children individuals. Location of the crossover point on the chromosomes is also randomly determined; second, a floating-point number in the range of 0.0 to 1.0 is generated randomly. If it is less than the predefined mutation possibility, mutation is operated for the two children individuals; Repeat these steps to produce all the children individuals (except the elitism individuals) in the new generation.
6. Go to step 2.

Feature Selection with RELIEF algorithm - RE

This method addresses the feature selection problem by proposing a two-step algorithm [38]: the first step uses a variation of the well-known Relief algorithm to remove irrelevance; the second step clusters features using K-means to remove redundancy. Relief is a feature weight based algorithm inspired by instance-based learning. Given training data, and a threshold of relevancy r, Relief detects those features which are statistically relevant to the target concept. Taken at random an instance $\mathbf{s}$, the nearest element, according to the Euclidean distance, of the same class and the nearest one of the another class are picked. If the features values of instances that belong to different classes are far, their weights are increased, otherwise if the values of instances of the same class are different, their weights are decreased. Differences of feature values between two instances $\mathbf{s}_1$ and $\mathbf{s}_2$ are defined by the following function

$$\mathrm{diff}\left(s_{1,d}, s_{2,d}\right) = \frac{s_{1,d} - s_{2,d}}{s_{1,d} + s_{2,d}} \ , \tag{1.46}$$

where $s_{1,d}$ and $s_{2,d}$ are the values of d-th feature of s_1 e s_2.
We show in Algorithm 4, the pseudo-code of the RELIEF algorithm [39], where D is the total amount of features and only two classes are considered.

Algorithm 4 RE algorithm

```
1: Separate $\mathbf{S}$ into
        $\mathbf{S}_1 = \{$instances of first class$\}$
        $\mathbf{S}_2 = \{$instances of second class$\}$
2: $\mathbf{W} = \mathbf{0}_D$
3: for $m = 1$ to $M$ do
4:     Pick at random an instance $\mathbf{s} \in (S_1)$
5:     Pick the instance closest to $\mathbf{s}, \mathbf{z}_1 \in \mathbf{S}_1$
6:     Pick the instance closest to $\mathbf{s}, \mathbf{z}_2 \in \mathbf{S}_2$
7:     if $\mathbf{s} \in (S_1)$ then
8:         Near-hit $= \mathbf{z}_1$; Near-miss$= \mathbf{z}_2$
9:     else
10:        Near-hit $= \mathbf{z}_2$; Near-miss$= \mathbf{z}_1$
11:        update-weight ($\mathbf{W}$, $s$, Near-hit, Near-miss)
12:    end if
13: end for
14: for $d = 1$ to $D$ do
15:    if $\mathbf{W}_d \geq r$ then
16:        $f_d$ is a relevant feature
17:    else
18:        $f_d$ is an irrelevant feature
19:    end if
20: end for
```

where *update-weight* is defined in Algorithm 5.

Algorithm 5 Update-Weight

```
1: for $d = 1$ to $D$ do
2:     $\mathbf{W}_d = \mathbf{W}_d - \text{diff}(s_d, \text{Near-hit}_d)^2 + \text{diff}(s_d, \text{Near-miss}_d)^2$
3: end for
```

If $\mathbf{W}_d \leq 0$, then the d-th feature is irrelevant, otherwise it is significant. The second step is a redundancy filter that uses the *k-means* algorithm to cluster features according to how well they correlate to each other. When feature clusters are discovered, only the feature with the highest Relief score is kept; the other features in the cluster are removed from the feature set. This is an unusual application of *K-means* clustering, in which features are clustered (instead of samples). There is a partition of D features into k clusters in which each feature belongs to the cluster with the nearest mean.

1.2.3.2 Feature Reduction Methods

A second approach used to reduce feature number is called *Feature Reduction.* Feature reduction aims to create a subset of new features by combinations of the existing features. Let us consider a vector $\mathbf{s} = (s_1, s_2, ..., x_D)^\top \in R^D$ containing all the D features. Feature Reduction finds a mapping $\tilde{\mathbf{s}} = [\tilde{s}_1, \tilde{s}_2, ..., \tilde{s}_{\tilde{D}}]^\top$ with $\tilde{D} < D$ such that the transformed feature vector $\tilde{s} \in R^{\tilde{D}}$ preserves (most of) the information or structure in R^D. In general, the optimal mapping will be a non-linear function, but since there is no systematic way to generate non-linear transforms, the selection of a particular subset of transforms is problem dependent. For this reason, feature extraction is commonly limited to linear transforms:

$$\begin{bmatrix} \tilde{s}_1 \\ \tilde{s}_2 \\ \vdots \\ \tilde{s}_{\tilde{D}} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1D} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{\tilde{D}1} & \alpha_{\tilde{D}2} & \cdots & \alpha_{\tilde{D}D} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_D \end{bmatrix} \tag{1.47}$$

where $\alpha_{\tilde{d},d}$ is the weight associated to s_d.

Principal Component Analysis - PCA

Principal component analysis is an unsupervised method that involves a mathematical procedure transforming a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*, which present the relevant characteristic of being uncorrelated with respect to each other. In particular, the largest variance of any projection of the data lies on the first variable, the second largest variance on the second variable, and so on (Figure 1.14).

Usually, PCA is used to discover or reduce the dimensionality of the data set, or to identify new meaningful underlying variables. Principal components are found by extracting the eigenvectors and eigenvalues of the covariance matrix of the data. These components are the eigenvectors, which describe an orthonormal basis that is effectively a rotation of the original Cartesian basis [40].

In order to reduce the dimensionality of the space, principal components associated to small eigenvalues can be discarded. Indeed they bring a smaller amount of information than principal components associated to high eigenvalues.

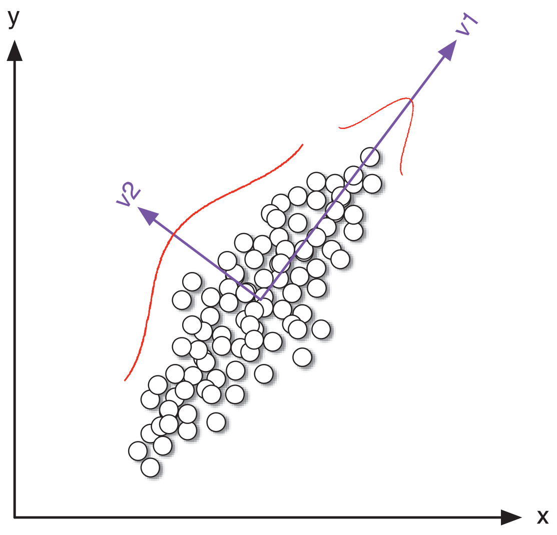


Figure 1.14: PCA transformation in 2 dimensions. The variance of the data in the Cartesian space x, y is best captured by the basis vectors v_1 and v_2 in a rotated space.

The main steps of the PCA algorithm are shown in Algorithm 6.

Algorithm 6 PCA algorithm

```
1: Computing covariance matrix
2: Computing eigenvalues and eigenvectors of the covariance matrix
3: Ordering the eigenvalues $\sigma_1 > \sigma_2 > ... > \sigma_n$
4: If exists $\sigma_k \ll \sigma_1$ then we can eliminate the eigenvalue and relative
   eigenvectors from $k$ to $n$
```

The principal components are the eigenvectors that are not discarded. As said in [41], a slight increase in recognition accuracy can be obtained using PCA of the MFCC.

Linear Discriminant Analysis - LDA

Linear Discriminant Analysis, sometimes known as Fisher's linear discriminant, seeks to reduce dimensionality while preserving as much of the class discriminatory information as possible and maximise class separability. Let us consider the problem separating two classes ($C = 2$) of points described by the feature vectors $\mathbf{s}$. LDA aims to estimate the function:

$$f\left(s\right) = \beta^{\top}\mathbf{s} + \beta_0 \tag{1.48}$$

such that $f\left(\mathbf{s}\right) > 0$ for points belonging to the first class, and $f\left(\mathbf{s}\right) < 0$ for $\mathbf{s}$ belonging to the second class. This function is called *linear discriminant function* in statistical literature. The decision boundary is given by a set of points satisfying $f\left(\mathbf{s}\right) = 0$, which is the separating the classes.
LDA compute vector β maximizing the following objective[42]:

$$J\left(\beta\right) = \frac{\mathbf{s}^{\top}\mathbf{S_B}\beta}{\mathbf{s}^{\top}\mathbf{S_W}\beta} \tag{1.49}$$

where $\mathbf{S_B}$ is the between classes scatter matrix and $\mathbf{S_W}$ is the within classes scatter matrix, defined in Equation 1.44 and in Equation 1.45.

The final solution of β is given:

$$\beta \cong S_w^{-1}\left(\mu_1 - \mu_2\right) \tag{1.50}$$

where μ_1 and μ_2 are the mean vectors of two classes. In a problem of C classes, LDA produces at most $C - 1$ feature projections.

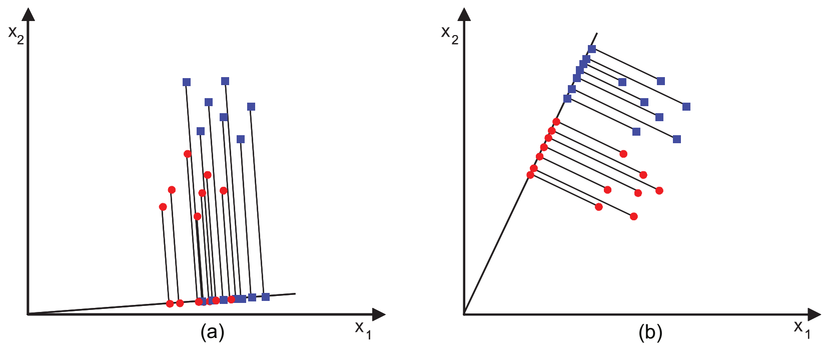


Figure 1.15: (a) Points mixed when projected onto a line. (b) Points separated when projected onto optimal line

Chapter Conclusions

In this Chapter we have presented a brief overview of forensic works related to ours, and the main tools used to solve our classification problem. In the next Chapter we will show how to use these tools for our purpose.

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Chapter 2

Classification Tool

In this Chapter we describe in details how we developed a classification tool that exploits the strengths of the discussed audio classification methods. This tool can be used for any type of audio signals classification, with no limitations due to the number of classes. As we have specified in Section 1.2.2, we have used GMM and SVM classifiers. The aim of the tool is to automatically find the best method of feature selection and classification using a small set of training data. For this purpose 13 different subsets of features have been created, using 13 methods of feature selection/reduction, and they have been used to parallel train the tool. Every subset is then analysed with both GMM and SVM. Considering only the best subset of features and the best classifier, the tool performs the classification. In the first section we show the initialization process that is performed on each audio excerpt. This initialization is necessary in order to correctly extract the features needed to do the classification. The second part of the Chapter is composed by three sections that describe the phases needed to perform the classification once the features are available. In general, a classification problem is divided in two phases, the first is training of the tool with a set of data with known class and the second is testing on new files. We also make use of an additional phase, called Validation. To sum up, the three phases that compose our tool are:

- Training Phase: we use here a small part of the whole dataset (e.g., 10%) as *Train Set*. The two classifiers (GMM and SVM) are both trained for each feature selection/reduction method.
- Validation Phase: in this phase the tool tests, with the trained classifiers, another subset of all dataset, called *Validation Set*, with double length compared to the train set. This phase aims to decide which

feature selection/reduction method gives the most relevant features and which is the best type of classifier (relative to the best feature selection method).

- Test Phase: now the tool is ready to test any file with the methods selected in the validation phase.

We describe out tool starting from the classical composition of a classification tool, then we introduce the details on the Validation Phase.

2.1 Files Initialization

The classification occurs when all the necessary features have been extracted from the audio excerpts. In order to correctly extract all features, an initialization phase is required.

2.1.1 Normalization

The first step is to reduce audio files in stereo (2 channels, so 2 parallel set of samples) to mono signal. This is simply done averaging the two channels sample by sample: in this way also signal with one channel can be processed.

The second, a very important step, is the *normalization*, that is required since it is possible to find signals with very low or very high sample amplitude (i.e., see Figure 2.1 and 2.2), when this happens, features extracted from such an audio excerpt may be distorted and thus not valid.

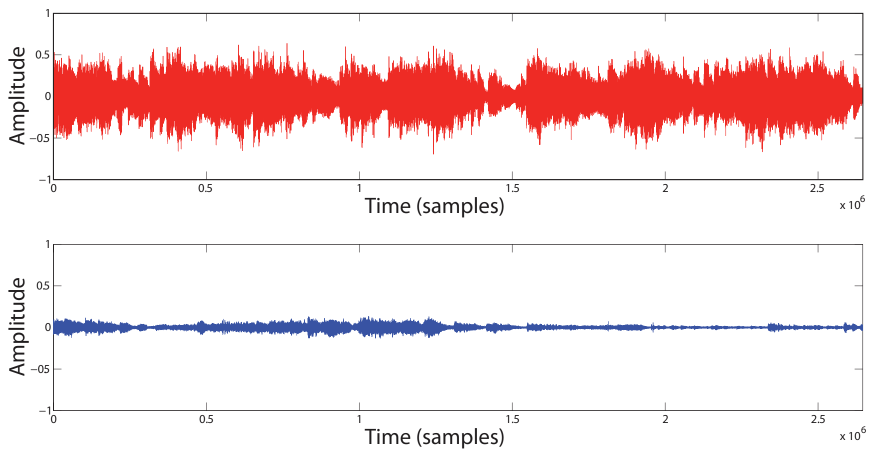


Figure 2.1: Two audio signals with very different amplitude

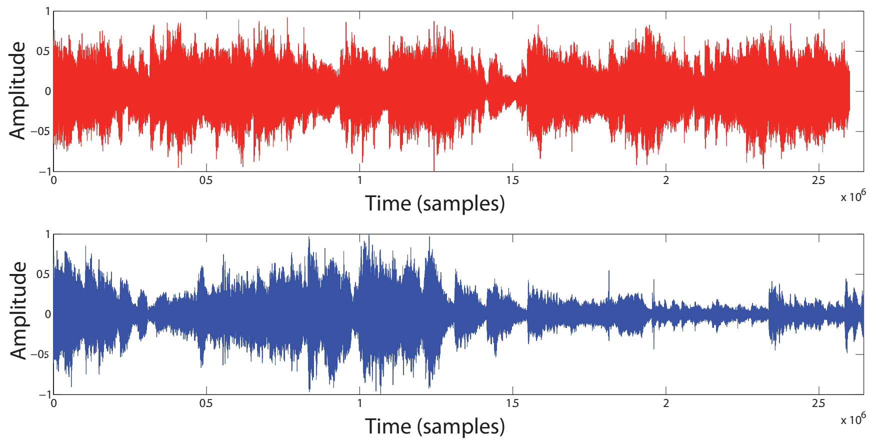


Figure 2.2: The same audio signal as figure 2.1 after the normalization have been performed on each file.

Audio normalization is the application of a constant amount of gain to an audio signal to bring the average or peak amplitude to a target level (the norm). Because the same amount of gain is applied across the given range, the signal-to-noise ratio and relative dynamics are generally unchanged. We have forced the signal to have unitary peak amplitude (maximum peak with amplitude 1 in absolute value). The gain applied to each signal considered is variable and it depends on the signal itself. The equation of the normalization is:

$$x = \frac{x_o}{\max |x_o|} \ , \tag{2.1}$$

where x_o is the original signal before normalization.

2.1.2 Frame Division

Once the normalization has been applied, the signal is subdivided in frames. This division has been performed because some features need to be extracted for frames of signal. Anyway, there are some features extracted for the global signal and others that are extracted in both cases. The frames can have constant or variable length. We have divided each excerpt in a variable number of frames where the length of each frame depends on the energy that it contains. This decision has been made to avoid the presence of frames containing silence, or too much noise. The energy contained in each frame is constant and the amount of audio information carried is somehow equalized. The effect is that part of signal with low amplitude causes the creation of longer frames, while short frames are created in case of part rich in energy.

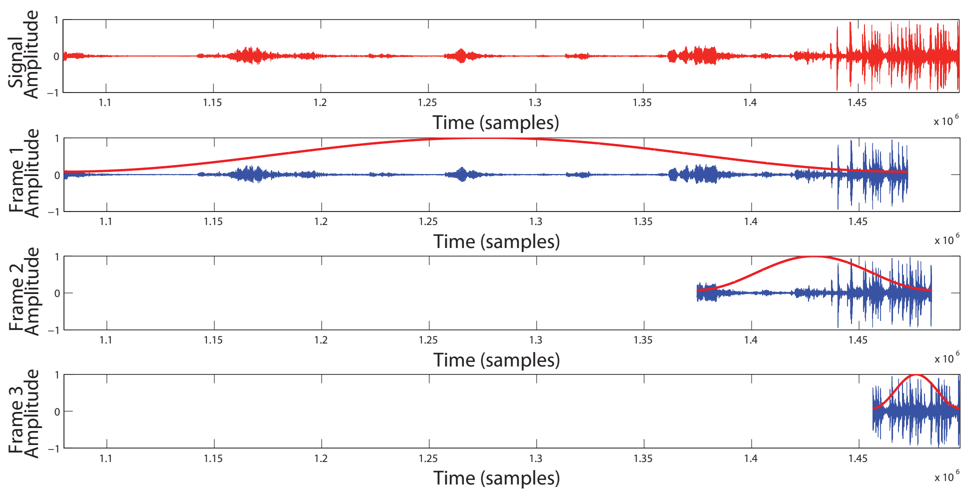


Figure 2.3: An example of frame division on the basis of frame energy. We show only the first three frames. The first part of the signal is near-silence, in-fact the first frame is really long. The other two frames are very shorter.

Each frame is than windowed with an *Hamming Window* (figure 2.4):

$$w_n = \alpha - \beta \cos\left(\frac{2\pi n}{N-1}\right) , \tag{2.2}$$

with $\alpha = 0.54$ and $\beta = 1 - \alpha$, where N is the length of the window, i.e., length of the frame.

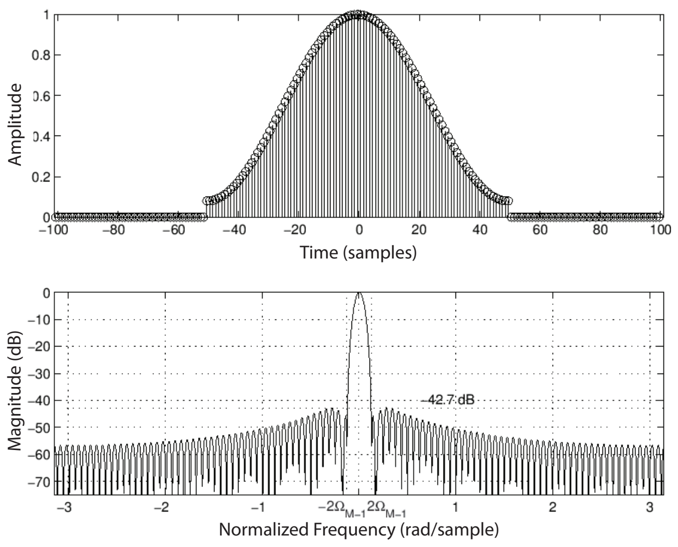


Figure 2.4: Hamming Window and its transform example

2.1.3 Feature Extraction

After the first two phases, the signal is ready and the features can be extracted. Features are extracted both from each frame and from the entire signal. What we obtain is a set of 14 features for each frame (Frame Features) and 20 for the entire signal (Global Features). We have then grouped the features in different sets, as it is shown in Table 2.1. This subdivision is used to train the tool in two different cases, with all the features in a single macro-set and with the features divided in groups. The creation of different groups of features is inspired by [43] and the groups are formed following principally the division explained in Section 1.2.1. This decision has been made mainly to isolate some features as the MFCC, which are statistically very significant and can mask the information derived from other features.

Table 2.1: Subdivision of features in groups. Frame and Global indicate if a feature is extracted frame by frame, from the global file or in both cases. Numbers in parenthesis indicate features composed by multiple values, e.g., the MFCCs have 13 coefficients.

Features Group	Feature Name	Frame	Global
Basic	RMS	✓	✓
	ZCR	✓	✓
	WF (2)	✓	
	Low Energy		✓
Spectral	S. Roll-Off	✓	✓
	S. Brightness	✓	✓
	S. Flux	✓	✓
	S. Entropy	✓	✓
	S. Flatness	✓	✓
	S. Irregularity	✓	✓
	S. Roughness (2)		✓
Centroidal	S. Centroid	✓	✓
	S. Spread	✓	✓
	S. Skewness	✓	✓
	S. Kurtosis	✓	✓
Harmonic	S. Inharmonicity		✓
	Chromatic Flux (2)		✓
Rhythmic	Event Density		✓
	Pulse Clarity		✓
MFCC	MFCC (13)	✓	✓
OSC	OSC (8)	✓	

In the following sections we explain more in detail how the feature subdivision is used in the classification. The tool we have built potentially support multi-class, but for our purpose we have used only two classes. *So, also to simplify the exposition, from now on we consider only the classification between two classes (A and B).*

2.2 Training Phase

When all the features are extracted, the tool can switch to the classification phase, which begins with the *Training Phase*. This phase aims to train the classifiers that the tool will use in the test phase. Starting from all the dataset, the tool randomly choose a small percentage of files with known class membership. It is very important that in the creation of the *Training Set* the number of files belonging to each classes is the same; otherwise the risk is to train the tool with a significant amount of bias. The parameters, needed from the classifiers in the *Test Phase* to recognize the membership classes, are then computed. Motivated by [43], we trained the classifiers with both features taken all together, and features divided into groups (defined in Table 2.1). We show now a flow chart (Figure 2.5) of the steps of *Training Phase* for the case of features taken as macro-set. In case of features grouped in different sets the flow is the same, but each block is further subdivided.

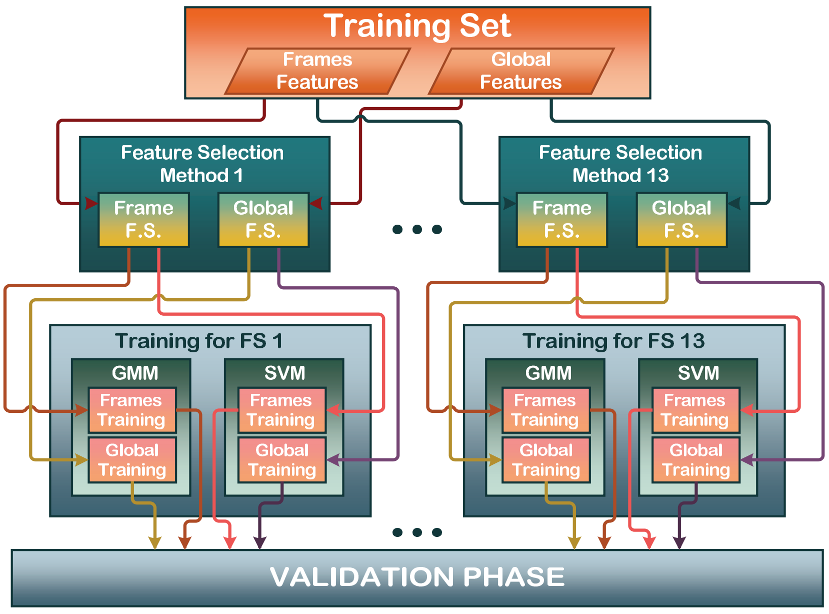


Figure 2.5: Training Phase Flow Chart

To better understand the following description of the *Training Phase*, make reference to Figure 2.5. Once the training set is chosen, the tool can train the classifiers (GMM and SVM). The values of the features extracted for each frame of files in training set are examined by a method of feature selection, which selects only discriminant features. Each method has different way to consider which features are significant and which can be discarded because of their correlation to other features. When the features are considered as a macro-group, feature selection is applied to all the set together, while in case of features divided in groups, the same feature selection is applied inside each group.

2.2.1 Feature Selection and Reduction Methods

Since we extract a lot of features, some of these can be useless for a particular classification. So we want to find an optimal subset of features that contains the most significant ones to be used during the test. For this purpose, we use different types of feature selection and reduction methods.
In particular we made use of the following methods that have been presented in Section 1.2.3:

- Forward Feature Selection (FWD)
- Backward Feature Selection (BWD)
- Stepwise Feature Selection (SW)
- Genetic Algorithm Selection (GA)
- Relieff Algorithm Selection (RE)
- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)

and we combined them in 13 different methods. Each method considers as significant a different subset of feature. Note that most of the computational time is due to the extraction of the features. So testing a high number of feature selection/reduction methods does not contribute to highly increment the tool computational time and complexity.

NO feature selection method applied
In this case, we make use of all the features, without using any feature selection method. It is expected that analysing all the features, the classification accuracy is worse than that obtained after selecting a subset of these features.

FWD selection
A subset of features is obtained by FWD selection algorithm. Starting from an empty set, a single feature is sequentially added in the set if the object function increases, until the optimal subset is found. The object function chosen is based on 1-NN.

BWD selection
A subset of features is obtained by BWD selection algorithm. Starting from the full set, a single feature is removed if its elimination increases or minimally worsens the objective function, in order to obtain the best subset of features. In this case, the object function used is based on 1-NN.

SW selection
A subset of features is obtained by SW selection algorithm. Starting from an empty set, a single feature is sequentially added to the subset if it increases the value of the chosen objective function. The added features can be removed subsequently if its elimination from the subset improves the objective function. The object function used is based on 1-NN.

GA selection
A subset of features is obtained by GA selection algorithm. It is characterized by a heuristic search that mimics the process of natural evolution, obtaining the optimal subset using techniques such as mutation, selection, and crossover.

RE + FWD selection
A subset of features is obtained by a combination between RE and FWD selection algorithms. RE tries to remove irrelevance and redundancy in the set, and FWD selects the features that considers significant. This method is efficient for large data sets with lots of irrelevant and redundant features.

RE + BWD selection
A subset of features is obtained by a combination between RE and BWD selection algorithms. RE tries to remove irrelevance and redundancy in the set, and BWD selects the features that considers significant. This method is efficient for large data sets with lots of irrelevant and redundant features.

RE + SW selection
A subset of features is obtained by a combination between RE and SW selection algorithms. RE tries to remove irrelevance and redundancy in the

set, and SW selects the features that considers significant. This method is efficient for large data sets with lots of irrelevant and redundant features.

PCA
An orthogonal transformation is used to convert a set of possibly correlated features into a set of values of linearly uncorrelated features called principal components. The number of principal components is less than or equal to the number of original features.

PCA + FWD selection
A subset of features is obtained by a combination between PCA and FWD selection algorithms. First of all, PCA transforms the original features in uncorrelated features. Then FWD selects the features that considers significant.

PCA + BWD selection
A subset of features is obtained by a combination between PCA and BWD algorithms. First of all PCA transforms the original features in uncorrelated features. Then BWD selects the features that considers significant.

PCA + SW selection
A subset of features is obtained by a combination between PCA and SW algorithms. First of all PCA transforms the original features in uncorrelated features. Then SW selects the features that considers significant.

LDA
A linear combination of features is used in order to preserve as much of the class discriminatory information as possible, projecting objects from the same class very close to each other and, at the same time, objects from different classes as farther apart as possible.

PCA Group
This method can be used only if the features extracted are divided in groups. The basic idea is to find the feature group that has the best discriminative power. Analysing the classification results obtained using all the features without any selection method, the features group with the best accuracy can be found. The best group is momentarily put aside and the other features groups are combined and transformed by PCA. Then the final optimal subset is composed by the principal components computed in PCA with the addition of the most discriminant feature group previously found [44].

2.2.2 Training Steps

Once the feature selection/reduction is applied, we obtain a subset of all features. The tool trains the classifiers relatively to the features subset. The classifiers are separately trained both for frames and global features, and also the global features are previously selected with the same method used for frames feature selection. The same procedure is then applied to the SVM classifier, also in this case separately for frames and global features. We obtain four classifiers, two for the GMM case and two for the SVM one, trained for each method of feature selection/reduction. We must specify that in case of groups of feature, we have trained a GMM and a SVM for each group and for both Frame Features and Global Features.
In the next section we explain how the classification is done.

2.3 Test Phase

Once the train is performed, the tool is ready to test a new file and to classify it. We specify now how the tool merges the results derived from the decision taken over different frames. As we said, the tool considers each frame as different signal with no correlation between frames derived from same files, then, once a decision has been made for the frames, the tool merge the results. Let us now analyse more in depth how the finale decision is taken. The test is performed using both the global and frame-wise features. In particular, if we consider a single song, we split the classification phase in three steps (as shown in Figure 2.6):

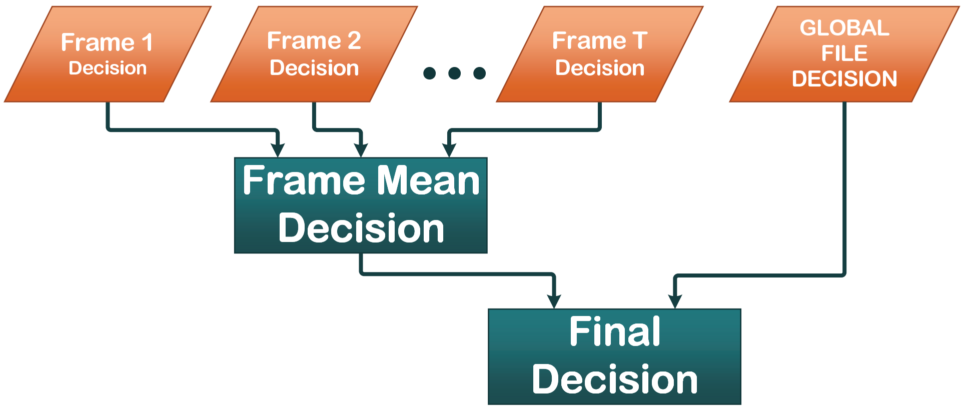
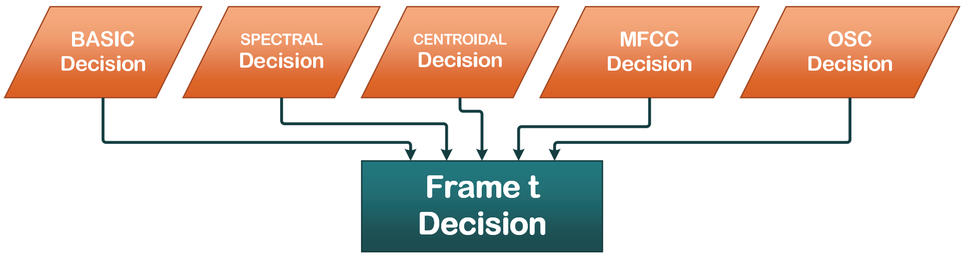


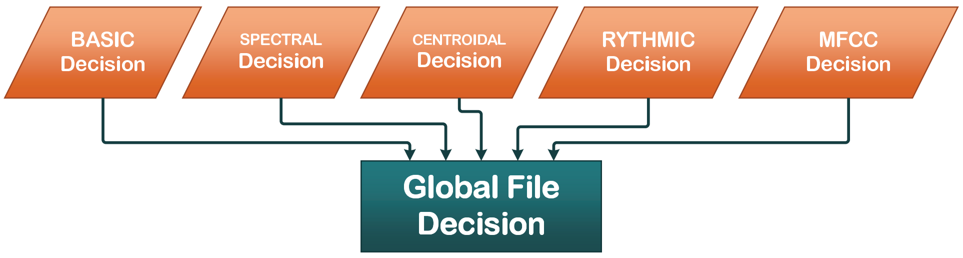
Figure 2.6: Decision merging flow

- first we independently classify every frame (using the features extracted frame-wise);
- then the global features are used to classify the whole song;
- finally results from the previous steps are merged to take the final decision.

In the case of features divided in groups, the followed schema is the same, but an additional step is involved: for each frame we compute the mean of the decisions taken singly for each feature group 2.7(a). The same we can say for the features obtained for the global signal 2.7(b). The two blocks created (Frame t Decision and Global File Decision) are the same blocks that appear in 2.6.



(a) Decision combination for groups of features. Each Frame Decision is the decision taken for a single frame.



(b) Decision combination for groups of features. Global Decision

Figure 2.7: Combination of results in case of training and validation with feature groups.

Let us now consider a single feature selection method. Assuming that a file is subdivided in T frames, we can explain in details how the final classification is computed. Note that in the case of groups of features, the first step is the one shown in Figure 2.7, then the steps are exactly the following. The GMM/SVM trained with the features selected gives to each frame a probability of belonging to a class. Note that GMM provides directly probabilities, but SVM simply returns the class membership of an observation.

From SVM results we can obtain the distance of the observation from separating hyperplane. We have assigned a percentage of membership of an observation to a class according to its distance from the hyperplane. Given, e.g., a set of M_A observations belonging to class A, we give to the observation with maximum distance from the hyperplane a probability of membership of 100%. The probabilities of other observations are directly proportional to their distance from the hyperplane. Computed the percentages of each frame, we take the average of the frame probabilities. Frame probabilities are stored then in a matrix.

$$\mathbf{F} = \begin{bmatrix} f_{1,A} & f_{1,B} \\ f_{2,A} & f_{2,B} \\ \vdots & \vdots \\ f_{T,A} & f_{T,B} \end{bmatrix} , \tag{2.3}$$

where $f_{t,A}$ is the probability of the t-th frame to belong to class A, and $f_{t,B}$ is the probability of the t-th frame to belong to class B.
The *Frame Mean Decision* $\overline{\mathbf{F}}$ is the decision derived by the combination of T frames and it is defined as the average of the probabilities of the frame-wise decision,

$$\overline{\mathbf{F}} = \begin{bmatrix} \overline{f_A} & \overline{f_B} \end{bmatrix} = \frac{1}{T}\mathbf{F}^\top \mathbf{1_T} , \tag{2.4}$$

where $\mathbf{1_T}$ is a column vector of ones of length T. The GMM trained for the global features takes separately his decision

$$\mathbf{g} = \begin{bmatrix} g_A & g_B \end{bmatrix} , \tag{2.5}$$

where g_A is the probability that a file belongs to class A considering only the global feature. Then, averaging the results, the final membership is given. The probability for an audio object to belong to class A or B is given by

$$\mathbf{p} = \begin{bmatrix} p_A & p_B \end{bmatrix} , \tag{2.6}$$

where

$$\begin{aligned} p_A &= \frac{g_A + \overline{f}_A}{2} , \\ p_B &= \frac{g_B + \overline{f}_B}{2} . \end{aligned} \tag{2.7}$$

The object is then assigned to the class with the higher probability.
These steps are repeated for all the feature selection methods and both in case of GMM and SVM classifier. When the tests with all the combination are computed, we can also compare the results of each combination. However, we have introduced an intermediate pre-test phase that compares the method combinations *before* the Test Phase, in order to choose the best classification method beforehand (see Figure 2.8).

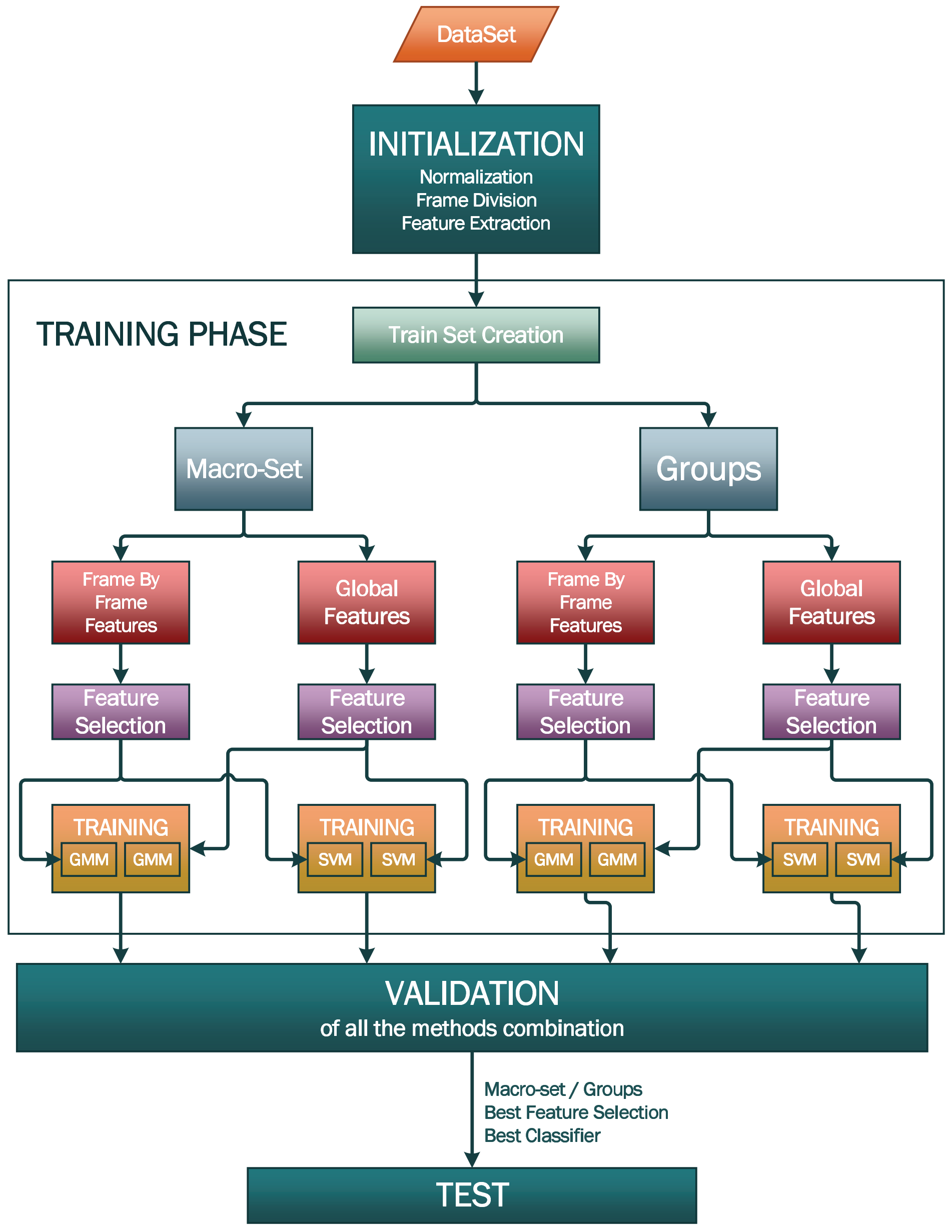


Figure 2.8: Tool Work Flow: the Training Phase is repeated for each Feature Selection/Reduction, each combination is validated and the Test is computed using the information derived from the Validation Phase.

2.4 Pre-Test: Validation Phase

Since we trained many classifiers, we want to be able to choose the one that best fits our needs. In particular, if we want to classify some audio excerpts, we need to know which classifier to use. The *Validation Phase* is then introduced to solve this problem. This phase is inserted between Training and Test phase and can also be considered as a Pre-Test. Indeed, a *Validation Set* of audio excerpts is tested using all the classifiers trained during the training phase. The *Validation Set* is composed by twice the number of tracks than the Training Set, and it contains files whose class is known. This way we evaluate the configuration of feature selection method and classifier that maximize the accuracy in our classification problem. A file is considered both as divided in frame and global, as in the Train Phase. The frames are tested separately and singly, then the average of the results is taken and further averaged with the result obtained with the classification of the global features.

The entire Validation Set is tested, obtaining a final decision for each file both for GMM and SVM. Now, since in the Validation Set we have files with known class, we can evaluate some statistical parameter to determine which configuration is the best one for the classification problem considered.

To do that, we use the combination of three parameters. The first parameter is the *accuracy*, that is defined as

$$\text{accuracy} = \frac{T_A + T_B}{T_A + T_B + F_A + F_B} , \tag{2.8}$$

where T_A and T_B (True member of a class) are the number of files respectively of the first and second classes correctly classified, while F_A (False member of a class) are the number files of the first class classified as files of the second class and F_B is the vice-versa. Since it may happen that the same accuracy level is achieved by different methods, we have introduced also the *class recall* and a sort of *precision* indicator. The recall is the fraction of elements of a class that are correctly classified, that is, for class A and class B

$$\begin{aligned} \text{recall}_\text{A} &= \frac{T_A}{T_A + F_B} , \\ \text{recall}_\text{B} &= \frac{T_B}{T_B + F_A} . \end{aligned} \tag{2.9}$$

When two methods have the same accuracy, we consider as best method the one with lower differences between recalls. This means that the percentage between the recall of the classes is more similar. We have chosen this solution because is preferable to have recall percentages of 78% and 82% respectively for two classes than have percentages of 70% and 90%. Indeed, the second case may indicate that the tool is biased towards one of the classes.

Another parameter considered is what we have called *strictness*, that is the percentage with which the classifier make a good decision. We said that for each file the tool return two percentages. If a result is $p_A = 75\%$ and $p_B = 25\%$ it means that the considered file belongs at 75% to class A. The strictness is the average of all the percentage of the files that have been correctly classified in the validation phase.

Once the tool has detected which combination between macro-set of features or groups of features, feature selection (reduction) and classifiers (GMM-SVM) is the best, the *Test Phase* begins.
The procedure is the same as the one presented in before, but a file is now tested only with the best combination (see Figure 2.9).

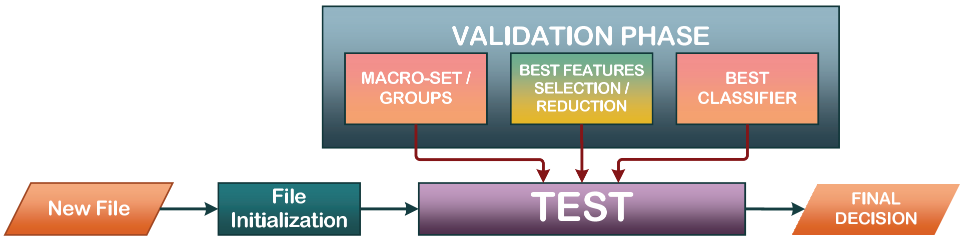


Figure 2.9: Test Phase Flow Chart: the classification is determined by the best combination of feature selection and classifier choose in the Validation Phase

The test phase can be used both to analyse a new file and to validate the pre-test. In this second case we obviously need a set of files with a known class membership, then the same parameters used to evaluate the methods combinations in the *Validation Phase* can be computed.

Chapter Conclusions

We have so designed a tool with the purpose of classifying audio signals, without any restriction on the type of classification that can be carried out. The tool is general because the features extracted are several and standard.

In the next section we present the changes and the addition made to the tool in order to improve the results for the special case of *Bootleg Detection*.

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Chapter 3

Bootleg Detection Application

In the last few years the quality of audio bootleg available on-line is increased, thanks to the development of new technologies. Indeed, nowadays, every smart-phone and camera come equipped with an integrated microphone. A typical example of bootleg availability is given by the huge amount of user-generated music-related videos on websites such as *YouTube*. In this case, even if the video quality may be poor, audio quality is often pretty good. It is worth to note that the definition of bootleg is pretty wide. Indeed both audio files directly recorded at a concert with a hand-held camera, and songs professionally mixed and published without authorization may be considered bootleg. For this reason, in order to cope with this situation, a more in depth analysis of what can be considered bootleg is in order. We define audio bootlegs as all those audio files that are recorded directly, e.g., at a concert, from public with some device, like a smart-phone, video-camera or microphone. In the case that a song is recorded and mixed with professional instruments and then published without the authorization of the owners of the song, we can't be able to recognize the difference.

We can see in Figure 3.1 and Figure 3.2 the flow charts representing the two main possible chains of operations that might lead to bootleg generation. Figure 3.1 shows the case of studio recording. In this situation we can consider as bootleg audio files taken directly in the recording room with a microphone or the audio signal after the first phase of mixing. In the second situation we have an output from the mixer, but it is not already been processed to obtain a perfectly clean audio without noises and with some post-processing add as, e.g., particular reverberation or other effect that can be directly recorded before being processed, e.g., to remove noise or apply audio effects such as reverberation.

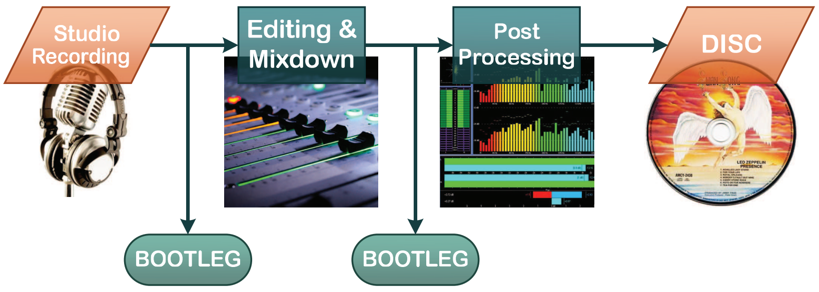


Figure 3.1: Studio Recording Flow Chart

Figure 3.2 shows the live performance case. In this situation we can consider as bootleg a signal recorded directly with some device such as smart-phone, video-camera, voice-recorder, etc. However, we can also consider the files directly taken from the mixer and not post-processed. In this second case is much more difficult to find differences between such a bootleg and an official released live performance. However, this kind of bootleg is pretty rare.

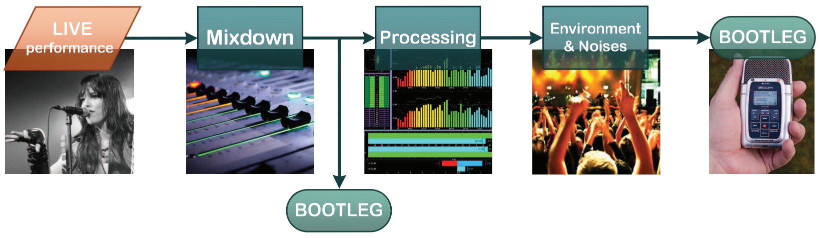


Figure 3.2: Live Performance Flow Chart

In this Chapter we explain in details how to adapt the classification tool described in Chapter 2 to work with the particular case of *Audio Bootleg Detection*. As we said, the classification tool that we implemented is modular and highly configurable. E.g., it is possible to add new features or new methods of feature selection and reduction.
In order to solve the *Audio Bootleg Detection* problem, we propose three specific improvements:

- a pre-processing phase;
- new Bootleg-related features;
- a new feature selection method.

In the following we explain which kind of pre-processing we propose, what are the new features introduced and how the new method of feature selection works.

3.1 Pre-Processing: Filter Bank

This *Pre-Processing* phase is meant to be applied between the normalization of the signal and its subdivision in frames (see Section 2.1). The mono signal is processed by a *Filter-Bank* that creates other 10 versions. We added this filter-bank because the Bootlegs generally have background noises higher that Official files. We expect a better classification accuracy considering features derived from critical bands, where noises are more relevant. So, the goal of the *pre-processing* phase is to extract features not only from the original audio signal, but also for its filtered versions. As filter-bank, we have used 10 different *Finite Impulse Response (FIR) filters* with *Kaiser window* [45], chosen experimentally as good compromise between computational speed and precision in the band filtering.

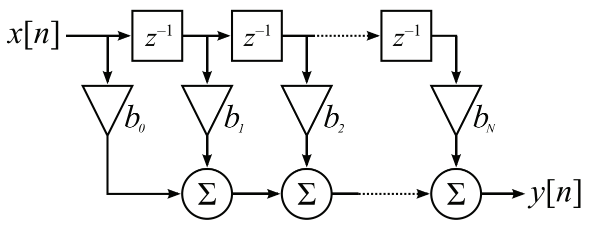
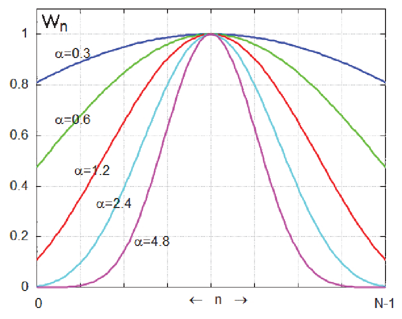


Figure 3.3: A discrete-time FIR filter of order N.

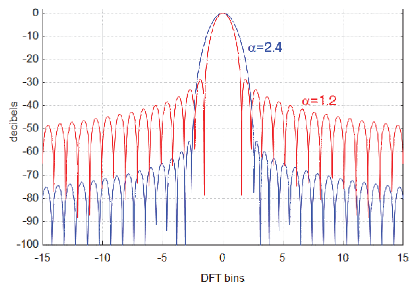
The filter is designed with the Window Method, that is the creation of an ideal *IIR* (Infinite Impulse Response) and then the application of the window function. The result is the convolution between the frequency response of the IIR filter and the frequency response of the window function. The parameters of the Kaiser Window are setted to obtain a side-lobe attenuation of 80 dB.

We have subdivided the signal following the octave scale:

- Band 1: Low-Pass filter with stop frequency at 60 Hz
- Band 2: Band-Pass filter between 60 Hz and 230 Hz
- Band 3: Band-Pass filter between 230 Hz and 500 Hz
- Band 4: Band-Pass filter between 500 Hz and 1 kHz
- Band 5: Band-Pass filter between 1 kHz and 2 kHz



(a) Time Domain



(b) Frequency Domain

Figure 3.4: Kaiser Window for different α

- Band 6: Band-Pass filter between 2 kHz and 4 kHz
- Band 7: Band-Pass filter between 4 kHz and 8 kHz
- Band 8: Band-Pass filter between 8 kHz and 12 kHz
- Band 9: Band-Pass filter between 12 kHz and 16 kHz
- Band 10: High-Pass filter with stop frequency at 16 kHz

These 10 bands are referred to 10 parallel filters, applied to the signal. As output of this filter-bank we have 10 filtered versions of the signal. Even if, in doing the filtering, the number of features to consider may seem increased by ten times, we experimentally prove that the number of significant features kept after feature selection is highly decreased. We must specify that not all features are extracted for the filtered signal, since some do have sense for a particular band. For example the *Electrical Network Frequency* (ENF) search for information around frequencies of 50 Hz, so is useless to extract it for all the filtered versions of the signal. In Figure 3.5 we show the complete initialization applied to the signals in our work on the *Bootleg Detection*.

From now on we refer to the filtered versions of the signal using **Bands** and we call **Mono** the original signal.

Features are extracted for each band and for the mono signal as described in Chapter 2. All the versions of the signal are divided in frames on the basis of their energy, with an overlap of 75%. The features are then extracted frame by frame and considering the global file for each band and for the mono signal.

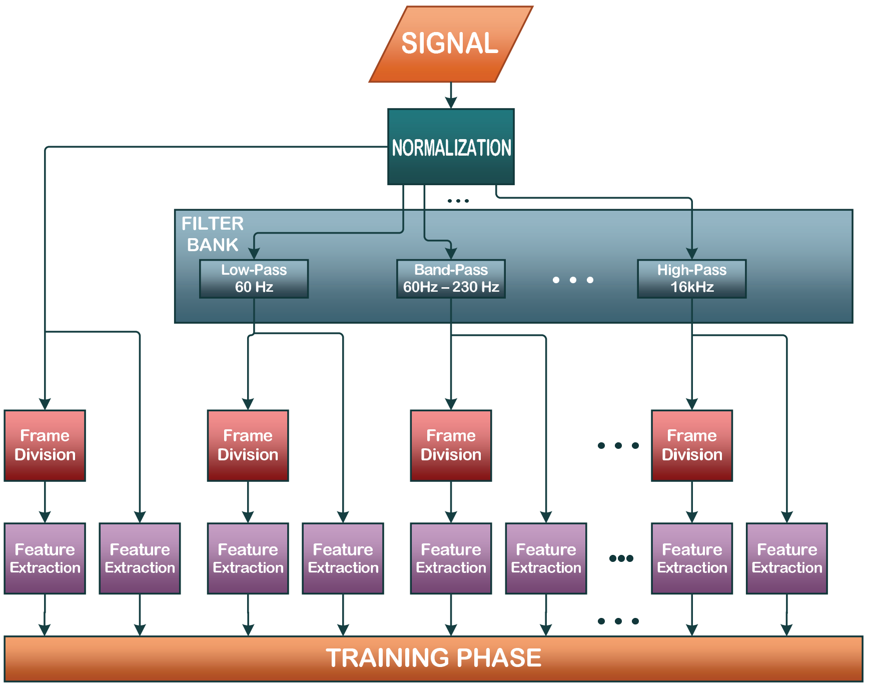


Figure 3.5: File Initialization Flow Chart for Bootleg Detection

3.2 Bootleg Detection Specific Features

In order to improve classification accuracy, we propose some features specifically tailored to the bootleg detection problem. The extracted features are then not only those summarized in Table 2.1, but five new features have been added. More specifically these features are meant to capture specific information in the time and frequency domains that can be helpful to characterize fingerprints found in bootlegs.

3.2.1 Bootleg Features

Very Low Spectral Magnitude - VLSM

We call *Very Low Spectral Magnitude* the sum of the magnitude of the spectrum under 2 Hz. We expect Bootlegs to have noises at very low frequencies due probably to the quality of the recording devices. Noises at these frequencies are not audible to human ear. Experimentally, we have actually seen that in a Bootleg is quite common to have a value of VLSM at least double that the one for other files. The VLSM is defined as:

$$\text{VLSM} = \sum_{k=0}^{K_l} X_k \ , \tag{3.1}$$

where X_k is the spectrum of the signal related to k-th bin. K_l is the frequency bin corresponding to 2 Hz.

High Spectral Magnitude - HSM

The idea beyond the *High Spectral Magnitude* is the inadequacy of not professional microphones to record information at very high frequencies. We call *HSM* the sum of the magnitude of the spectrum above 14 kHz.

$$\text{HSM} = \sum_{k=K_h}^{K} X_k \ , \tag{3.2}$$

where X_k is the spectrum of the signal related to k-th bin. K_h is the frequency bin corresponding to 14 KHz.

Band Magnitude - BM

We computed for each Band a value linked to its power. What we expect is to observe difference between Bootleg files and not Bootleg files, especially in lower and higher bands. These differences may be caused in Bootlegs, e.g., due to noises and artefacts introduced during the recording that would be removed with a post-processing. Anyway we compute this feature for each band, also if we expect interesting results in some critical bands. This feature is computed as the sum of the absolute values of the magnitude of the normalized spectrum.

$$\text{BM}_b = \sum_{k=0}^{K} X_k \ , \tag{3.3}$$

where X_k is the frequency magnitude of the k-th bin of the spectrum of the filtered band b.

Saturation - SAT

We said that Bootlegs are not subject to post-processing. Often these signals have a very high magnitude, i.e., a lot of high peaks and flat waveform. In Figure 3.6 we show an example of difference between a normal signal and a saturated one.

We have set a magnitude threshold of 0.90 in absolute value. The *saturation* of a signal is simply the number of samples that exceed that threshold.

$$y_n = \begin{cases} 1 & \text{if } |x_n| \geq 0.90 \\ 0 & \text{otherwise} \end{cases} ,$$

$$\mathrm{SAT} = \sum_{n=0}^{N-1} y_n \ , \tag{3.4}$$

where x_n is the magnitude of the n-th sample of the signal.

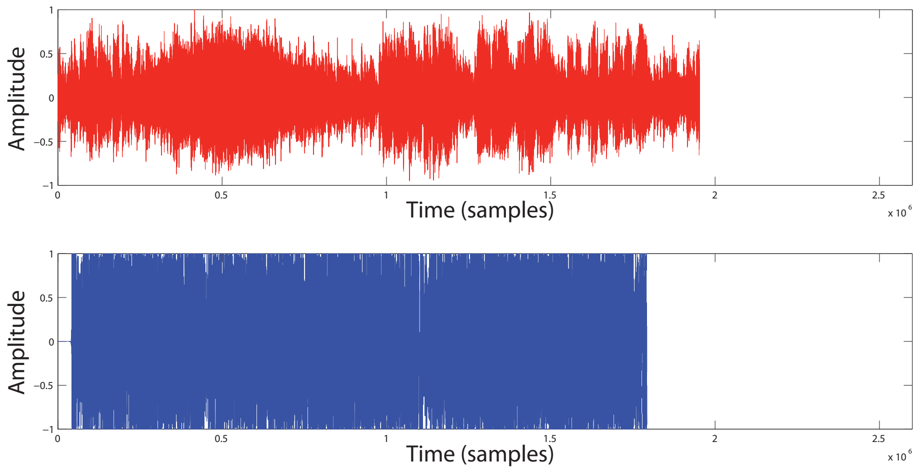


Figure 3.6: Differences between a normal signal (red) and a saturated one (blue).

Electrical Network Frequency - ENF

This is a feature derived from *forensic audio authentication* purpose [46]. When digital equipment is used to record an audio signal, it captures also the 50/60Hz *Electrical Network Frequency* if the recording device is mains-powered and used in absence of an ideal voltage regulator. In forensic authentication, the variance of the signal around the critical frequencies is observed as indicator of manual modification of the signal itself, as cut and paste of different pieces of signal to create, for example, phrases never uttered by someone.

In our case this feature is simply used as a detector of noises caused by power source. The signal is band-pass filtered with a very sharp linear-phase FIR filter. The band pass filter is centered in 55 Hz and has a bandwidth of 6 Hz. The effect of band passing shows the presence of phase discontinuities and amplitude variations. If the signal filtered has a large variation of amplitude, it means that probably the *ENF* has been recorded with the signal. *ENF* is computed as

$$\mathrm{ENF} = \frac{1}{N} \sum_{n=0}^{N-1} (x_n - \mu)^2 \ , \tag{3.5}$$

where x_n is the n-th sample of the signal filtered x, and μ is the mean signal x. N is the length of the signal.

3.2.2 Features Summary

With the introduction of these five new features, we have rearranged also the Feature Groups, creating a new group and adding three features to groups already created. The summary of the final set of features and their groups are shown in Table 3.1.

*Table 3.1: Subdivision of features in groups. Frame and Global indicate if a feature is extracted frame by frame, from the global file or in both cases. Mono and Band indicate if a feature is extracted from the unfiltered signal (Mono) or from its filtered versions (Band) or both. Numbers in parenthesis indicate features composed by multiple values, e.g., the MFCCs have 13 coefficients. On **bold** we have the new features.*

Feat. Group	Feature Name	Frame	Global	Band	Mono
Basic	RMS	✓	✓	✓	✓
	ZCR	✓	✓	✓	✓
	WF (2)	✓		✓	✓
	Low Energy		✓	✓	✓
	ENF		✓		✓
Spectral	S. Roll-Off	✓	✓	✓	✓
	S. Brightness	✓	✓	✓	✓
	S. Flux	✓	✓		✓
	S. Entropy	✓	✓	✓	✓
	S. Flatness	✓	✓	✓	✓
	S. Irregularity	✓	✓	✓	✓
	S. Roughness (2)		✓		✓
	BM		✓	✓	
Centroidal	S. Centroid	✓	✓	✓	✓
	S. Spread	✓	✓	✓	✓
	S. Skewness	✓	✓	✓	✓
	S. Kurtosis	✓	✓	✓	✓
Harmonic	S. Inharmonicity		✓		✓
	Chromatic Flux		✓	✓	✓
Rhythmic	Event Density		✓	✓	✓
	Pulse Clarity		✓	✓	✓
MFCC	MFCC (13)	✓	✓		✓
OSC	OSC (8)	✓			✓
Boot	**VLSM**		✓		✓
	HSM		✓		✓
	SAT		✓		✓

3.3 Bootleg Detection Feature Selection

With the introduction of the analysis by band, we add to the previously considered feature selection methods one that takes this band-division specifically into account. Analysing the Mono signal and the Bands we obtain a lot of features, some of which, obviously, are more important than others. Even if a method of feature selection is applied, some features can still be more significant than others. Furthermore this reflection is valid for the bands, because the analysis of some of the bands can be useless, while only few bands can be significant. The basic idea of this method is showing how much each band is important, removing not significant bands from the computations. Moreover, some groups of features could be less significant than others. With this method we also apply a sort of feature group weighing.

Cross-Validation Selection

We implemented a method, according to our specific problem, that allows to assign importance weights to Bands analysed and to features groups. We called it *Cross-Validation Selection* (CVS). Only the Bands and the features with greater weights are selected, while the others are not considered. This is done during the pre-test phase. A part of data destined to train the machine is used as *Train Set*, the remaining part, called *CVS Set*, is used in Pre-Test. The class membership of each file in these sets is known. After the Pre-Test, classification accuracy is computed. Each Band is considered separately, so the accuracy of each Band can be computed. CVS selects only the three bands with greater weights.
Since, when we consider groups of features, we have different GMM/SVM classifiers for each group, a metric to evaluate the performance of a single classifier can be computed. This evaluation leads to another set of weights.

In Test Phase, a file is classified according to all the weights derived. In the case that only the mono signal is analysed, CVS assigns only the weights to features in the macro-sets or to the groups.
Let us see the steps of the algorithm by means of an example. For the sake of clarity let us focus on one case. In particular let us consider the case in which the classifier to be tested is GMM, and features are divided into groups. For the sake of simplicity let us consider just three groups: *i)* basic, *ii)* spectral *iii)* and MFCC.

1. The Train Set (*TS*) and the CVS Set (*CS*) are chosen.

2. The Train phase can start, training three GMM for each Band and for the Mono signal:

Algorithm 7 Groups Training Steps

```
1: for each Band and the Mono signal do
2:     Extract features from the TS
3:     Train $\text{GMM}_{Basic}$, $\text{GMM}_{Spectral}$, $\text{GMM}_{MFCC}$
4: end for
```

3. The Pre-Test can start, evaluating the files of CS. For each group of features we obtain the classification result (Result_{group}), that indicates the class membership of the file according to testing *group* features:

Algorithm 8 Pre-Test steps

```
1: for each file in CS do
2:     for each band and the mono signal do
3:         Extract features from the CS
4:         Test CS files according to Basic, Spectral and MFCC features
               $\text{Result}_{Basic}$, $\text{Result}_{Spectral}$, $\text{Result}_{MFCC}$ are obtained
5:     end for
6: end for
```

4. Considering results obtained for every file in CS, we count the number of correctly classified files for each group ($Counter_{group}$). The accuracy ($Accuracy_{group}$), that is the percentage of correctly classified files according to *group* features, can be computed:

Algorithm 9 Accuracy computation

```
1: $cnt_{CS}$ = number of files in CS
2: for each file in CS do
3:     for each band and the mono signal do
4:         if $Result_{Basic}$ is correct
5:             $Counter_{Basic}++$
6:         if $Result_{Spectral}$ is correct
7:             $Counter_{Spectral}++$
8:         if $Result_{MFCC}$ is correct
9:             $Counter_{MFCC}++$
10:    end for
11: end for
12: $Accuracy_{Basic} = Counter_{Basic}/cnt_{CS}$
13: $Accuracy_{Spectral} = Counter_{Spectral}/cnt_{CS}$
14: $Accuracy_{MFCC} = Counter_{MFCC}/cnt_{CS}$
```

5. The Weights of each single group of features and of each Band can now be computed.
   $Weight_{group}$ indicates the weight of the feature *group*. $Weight_{band}$ is the weight of the band. The weights are:

Algorithm 10 Weights computation

```
1: for each band and the mono signal do
2:     $Weight_{Basic} = Accuracy_{Basic}$
3:     $Weight_{Spectral} = Accuracy_{Spectral}$
4:     $Weight_{MFCC} = Accuracy_{MFCC}$
5:     $Weight_{Band} = \text{Weight}_{Basic} + \text{Weight}_{Spectral} + \text{Weight}_{MFCC}$
6: end for
```

6. Selection of the three bands with the highest weights. The sum of the weights of these three bands is normalized to 1.

Algorithm 11 Bands Selection

```
1: Select the three bands with highest weights
2: $Weight_{TOTAL}$= sum of weights of the three Bands selected
3: for each of the Band selected do
4:     $Weight_{Band} = Weight_{Band}/Weight_{TOTAL}$
5: end for
```

In the Test phase, each band classifier associated to each group feature is weighted according to the value of $Weight_{group}$. For each band that isn't discarded, $Weight_{Band}$ is considered.

3.4 New Classification Phases

The Bootleg classification tool uses the same principles as the general classification tool explained in Chapter 2, but the pre-processing phase, the new features and the new feature selection method are also considered. The classification is divided in the same three phases as the general machine: Train, Validation and Test. We need a set of file to create the Training-Set and the Validation-Set, that are created randomly, but in which the number of files for each class is the same, to train the machine equally for each class.

The main difference, with respect to the work-flow previously described, is the introduction of the features extracted from the bands. This cause a further branching of the work-flow.

Training Phase
As in the general machine described in the previous chapter, several methods of feature selection are used in order to find the optimal significant subset of features that best describes the classification problem. Using the seven types of selection methods and the new approach described before (CVS), we have created a combination of twenty feature selection methods. With the CVS approach, the selected features and the bands are weighted, so that the tool uses in the test only the significant features and bands. The twenty methods are the followings:

- NO Feature Selection applied
- Cross-Validation Selection
- Forward Feature Selection
- Forward Feature Selection + Cross-Validation Selection
- Backward Feature Selection
- Backward Feature Selection + Cross-Validation Selection
- Stepwise Feature Selection
- Stepwise Feature Selection + Cross-Validation Selection
- Genetic Algorithm
- Genetic Algorithm + Cross-Validation Selection
- RELIEF Algorithm + Forward Feature Selection
- RELIEF Algorithm + Backward Feature Selection
- Principal Component Analysis
- Principal Component Analysis + Cross-Validation Selection
- Principal Component Analysis + Forward Feature Selection
- Principal Component Analysis + Backward Feature Selection
- Principal Component Analysis + Stepwise Feature Selection
- Linear Discriminant Analysis
- Principal Component Analysis Group

- Principal Component Analysis Group + Cross-Validation Selection

Note that the last two methods, *PCA Group* and *PCA Group + CVS*, can be applied only when the features are divided in groups.

Training Phase is performed in 2 ways as shown in Figure 3.7, considering only the Mono signal or the Mono signal together with the Bands. We still utilize one (combination of) method of feature selection/reduction at time. In the first case, as in the general machine, a method selects the significant features only from the Mono signal. In the second case, a method selects a subset of features for each of the 10 Bands and the Mono signal, each of which is used separately to train the machine.
Each preliminary division is then further subdivided in turn in other 4 cases described in the Chapter 2 (Macro-Set or Groups of feature and then GMM or SVM). Considering that we have 18 or 20 methods of features selection depending on whether we analyse the features divided in groups or in Macro-Set, in total we obtain 152 differently training for the machine (76 GMM and 76 SVM).

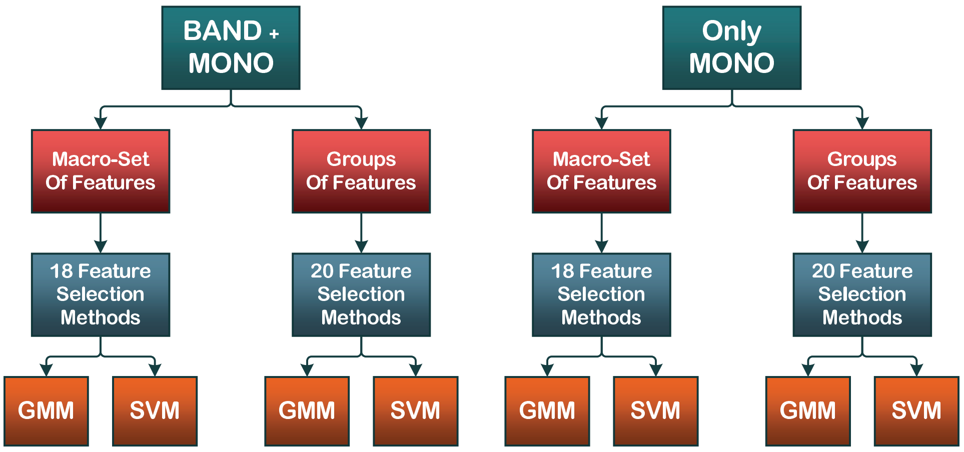


Figure 3.7: Combinations of methods in the Training Phase. We obtain 152 *method combination.*

The method that use the bands, but also the new features, can obviously be used for any type of classification, and so be introduced also as modification of the general machine for purpose different from the Audio Bootleg detection.

Validation Phase

In this phase the machine performs a Pre-test, comparing all the 152 different combinations with a subset of different files from the one used in the

Training-Test (and twice as large), in order to decide which one is the best. So in the end the Validation Phase returns a 4 values decision:

- Only Mono Signal or Mono + Bands
- Macro-Set of features or Groups of features
- Best Feature Selection/Reduction Method
- Best Classifiers (GMM/SVM)

With respect to the general case described in Chapter 2, there is now the decision about using only the Mono signal or also the Bands. When only the Mono signal is selected, the method of combining the results of each step is the same described in Chapter 2 in Figure 2.6. In the case when the Bands are considered, the flow change as shown in Figure 3.8. When all

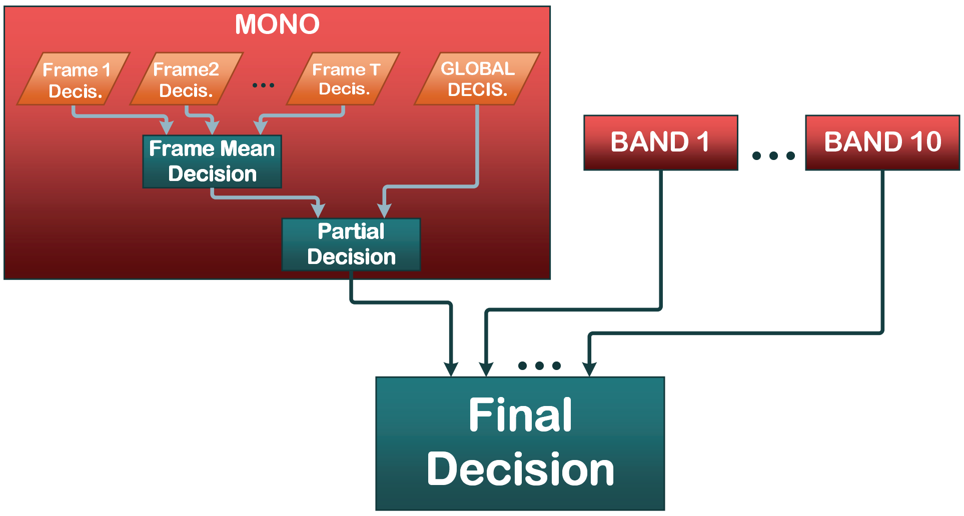


Figure 3.8: Decision merging flow in Bands + Mono case. Each Band block contains the same sub-blocks of the Mono block.

the 10 Bands and the Mono signal are analysed, the tool has to compute another average since each set of features, extracted from all the version of the signal, is considered separately. So the steps are:

- average between the decisions taken for each frame (Frame Mean Decision);
- for each Band and for the Mono we take the average between the Frame Mean Decision and the decision taken for the Global file, that is the Partial Decision;

- average of all the Partial Decision from the Bands and the Mono to obtain the Final Decision.

The machine is now ready to perform the test.

Test Phase
The Test Phase consists in the classification of a new file using the machine trained with the best combination of methods obtained from the Validation Phase. Note that, since we have specified that the CVS method may completely exclude some of the filtered version of the file as feature selection, the number of features that are considered important may be really small.

Chapter Conclusions

In this Chapter we explained in details the proposed modification to the classification tool, in order to best fit the bootleg classification problem. In the next Chapter we will explain how we built the dataset, and will present results from our tests that validate the proposed classification method.

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Chapter 4

Experimental Results

In this Chapter we validate the proposed bootleg detector by means of a wide set of experimental results. More specifically, we start from describing the audio dataset that we built for that purpose, and then we show how we performed the tests. Finally we analyse the obtained results, showing which the most significant features are. This analysis confirms the hypothesis made on the distinctive bootleg traits. Moreover, these results show that the method proposed for combining features from different bands often obtains the highest accuracy. For the sake of compactness, we analyse in details only the most significant part of the results. For the complete set of test results, see the Appendix A.

4.1 Database

The audio dataset used in the proposed work have been built exploiting both our music library and the wide availability of music on the web.
In total we used 594 different files, split in three main categories:

- *Bootleg*: 264 files that fit the bootleg definition given in Chapter 3;

  Home: sub-set of Bootleg, with audio excerpt expressly created at home for our purpose.

- *Official*: 168 audio files recorded from live performance officially released by the artists on CDs.

- *Studio*: 162 audio files recorded in studio, released on CDs and taken directly from original discs.

In general, we selected files from different musical genres, in a balanced way. This choice has been made to avoid that the classification focuses on a specific musical genre and not on Bootleg. While the Official and the Studio files come directly from official supports, the Bootlegs are taken from different sources, e.g., YouTube and sharing fans sites. We have considered as Bootleg also 6 files obtained at a Scorpions concert. Some bands, as the Scorpions, give at the end of the concert the recording of the performance on USB support. These files are directly taken from the hall mixer, without any post-processing (the support is provided instantly at the end of the concert, there is no time to do any sort of post-processing). These files are officially released by the artist, so technically they are not Bootleg. However, in general, audio recorded directly from the mixer during a live performance and without post-processing is considered as Bootleg and there are also sites that provided the download of packages of bootleg created with this method. Furthermore we have introduced in the Bootleg set a list of files that we have specifically created. Bootlegs recorded with any device directly at a concert may have high values of noisiness. The Home subset has been composed on purpose. We have recorded some files from the Studio set, reproduced by a home Hi-Fi and recorded with different type of microphones. We have used 7 different microphones:

- Shure professional microphone
- Nikon Coolpix (Compact Digital Camera) integrated microphone
- Nikon D5000 (Reflex Digital Camera) integrated microphone
- Dell Laptop integrated microphone
- Samsung Galaxy S2 Smart-phone integrated microphone
- Creative Zen (mp3 player) integrated microphone
- Microphone for web chat

To this purpose we have recorded 18 files for each case (they are already included in the Bootleg total number).
In order to obtain uniform comparable files and for computational reasons, each file consists in a minute extracted from the song considered. This decision does not afflict the results. Furthermore, the file excerpts have been selected to have the least possible not-musical parts. If a piece contains long silences (parts with no music played) it is easier to observe ambient noise such as claps or screams. If the tool had been trained with these files, Bootleg with fewer parts of “silence” would not have been identified as such.

4.2 Experimental Test Creation

Using the database that we have created, we tested the bootleg classification tool. We performed 10 different types of tests, considering different combinations of files from our database. In particular we split the database in sub-databases, each of which has been used to test the classification tool in a different situation. The sub-databases are divided in categories as follows:

1. All Dataset (Bootleg class A, Official+Studio class B)
2. Bootleg and Official
3. Bootleg and Studio
4. Bootleg Home Made and Corresponding Studio files
   - 4.1 Shure Microphone and Corresponding Studio
   - 4.2 Nikon Coolpix Microphone and Corresponding Studio
   - 4.3 Nikon D5000 Microphone and Corresponding Studio
   - 4.4 Dell Laptop Microphone and Corresponding Studio
   - 4.5 Samsung Galaxy S2 Microphone and Corresponding Studio
   - 4.6 Creative Zen Microphone and Corresponding Studio
   - 4.7 Web Chat Microphone and Corresponding Studio

For each one of these categories, we have used 10% of the tracks as Training-Set, the 20% of the remaining tracks within the same subset as Validation-Set and the remaining 70% as files to be tested. This means that we have always used a Training-Set of 60 files and a Validation-Set of 120 files. Initially, we performed tests using 10% and 30% of the Database as Training-Set, and without any Validation Phase. Note that, in the fourth category, Bootleg Home Made and Corresponding Studio files, we do not have enough audio excerpts to create a Validation-Set of 60 files. In that case we have used smaller Train and Validation sets.
Since the classification gave nearly the same results, we have decided to use 10% of files as Training-Set and 20% of files as Validation-Set, choice that has improved the results. From this observation, we can also affirm that, when the number of file in the Training-Set is quite high, incrementing the Training-Set does not improve the results. We have tested some different files combinations with the best methods extracted from the Validation Phase. The scope of our work is creating a tool that allows to recognizing Audio Bootleg analysing the optimal subset of features and using the best

classifier, but we have performed tests also to demonstrate the quality of our Validation Phase. In-fact we have performed the tests comparing all feature selection methods and both classifiers. In this way we can show how many Audio Bootleg files are detected, but also that the decisions made in the Validation Phase are consistent. In Table 4.1, we show the summary of the results obtained. For each category, accuracy and the combination of decision after the Validation Phase are reported.

Table 4.1: Best accuracies obtained for tests of each category. ***Bo*** *= Bootleg.* ***S*** *= Studio.* ***O*** *= Official.* ***BH*** *= Bootleg Home Made.* ***Corr*** *= Corresponding Studio.* ***Acc*** *= accuracy.* ***M/Ba*** *= Mono or Mono+Band.* ***Gr/Mcr*** *= Groups of features or Macro-set of features.* ***Class*** *= Classifier.*

Category	**Acc %**	**M/Ba**	**Gr/Mcr**	**Feat-S**	**Class**
1. Bo vs O + S	85	Ba	Mcr	FWD + CVS	GMM
2. Bo vs O	82	Ba	Mcr	FWD + CVS	GMM
3. Bo vs S	89	Ba	Mcr	BWD + CVS	GMM
4. BH vs Corr	97	Ba	Gr	SW + CVS	GMM
5. Shure VS Nikon Coolpix VS Galaxy S2 VS Corr	96	Ba	Mcr	FWD	GMM

In Table 4.1 we have a summary of the results obtain. As we could expect, distinguish Studio excerpts from Bootlegs is easier than any other category of tests. This is due to the fact that Studio are the cleaner excerpts that we have, recorded in recording studios, while Bootlegs are taken during live performance, without any sort of cleaning post-processing. We also expect to have lower accuracies for Bootleg and Official category, since both sets of files are recorded during live performances.
We now analyse the results for each category of files. We also show an analysis for some of the most significant features.

4.3 Result Statistics

We graphically show the accuracy obtained in the performed tests. We have performed each of the 152 type of test 30 times, scrambling each times the set of songs. In order to ensure that the obtained results are not influenced by an ill-conditioned dataset, we average the results obtained from the 30 tests.

4.3.1 Bootleg and Studio

We start the analysis with the easier category of study: Bootleg and Studio files. What we expect in this category is to have the higher accuracies with respect to all the other categories. In-fact in this situation we have Bootleg, that are recorded during live performances, with ambient noises as screams and claps from public, and Studio files, that are recorded in professional recording studios, with no background noises. The best combination of method for this type of test is the Backward plus Cross Validation Selection, with an accuracy of 88.74%. In Table 4.2 we show the 10 best tests chosen in the Validation Phase and their corresponding rank once the Test Phase has been performed. Furthermore we show the accuracy of the worst combination of methods.

*Table 4.2: Combination rank in Bootleg and Studio category. **VP Pos** is the method position in the rank of the Validation Phase and **VP**% **Acc** is the respective accuracy. **Test Pos** and **Test**% **Acc** are the position and the accuracy of the methods combination after the Test Phase. **M/B** indicates if only Mono signal is taken or Mono+Bands. **Gr/Mcr** indicates features divided in Groups or taken as Macro-Set. **Feat-S** indicates the selection method applied and **Class** the classifier used. Only the first* 10 *and the last position are shown. The best combination chosen by the Validation Phase is highlighted in green, while the worst one is highlighted in red.*

VP	Combinations				VP%	Test	Test%
Pos	M/B	Gr/Mcr	Feat-S	Class	Acc	Pos	Acc
1	B	Mcr	BWD+CVS	GMM	87.32	1	88.74
2	B	Mcr	PCAgr+CVS	SVM	87.24	5	87.21
3	B	Gr	BWD+CVS	GMM	87.06	7	86.59
4	B	Gr	SW+CVS	SVM	86.90	12	86.30
5	B	Mcr	SW	SVM	86.82	15	85.87
6	B	Gr	PCAgr	SVM	86.71	3	87.11
7	B	Gr	FWD+CVS	SVM	86.65	4	86.75
8	B	Mcr	SW+CVS	SVM	86.59	2	87.21
9	B	Gr	BWD+CVS	SVM	86.41	6	86.69
10	B	Gr	SW+CVS	GMM	84.25	16	85.86
...							
152	M	Mcr	RE+BWD	SVM	51.90	147	58.80

We can see from the Table that the accuracy difference between the best and the worse combination of methods is 30 percentage points. This supports the idea of adding the Validation Phase to use only the best combination of methods to perform the tests. In this case, the method selected from the Validation has obtained the higher accuracy also in the Test Phase. We can see that, anyway, the differences between the first ten positions are very low. Furthermore, we can see that the best combinations use always the features extracted from the Mono and the Bands. That means that also the addition of the Bands has provided improvements.

In Figures 4.1 and 4.2, two 3D histograms show respectively which are the Global and the Frame features that have been mostly selected by BWD+CVS method and their percentage occurrences. These histograms have been built considering the 30 test repetitions on different training set. The shown features are a subset of all the extracted features, since the less significant ones have already been discarded.

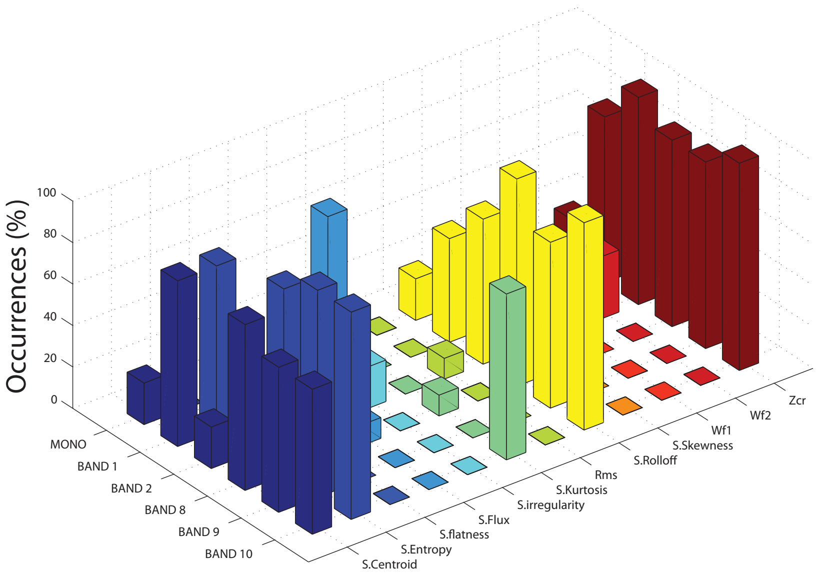


Figure 4.1: Frame feature occurrences referring to Backward + Cross Validation feature selection in Bootleg and Studio category.

Features with higher occurrences have been selected more times on the 30 tests performed, so these features are stable and not related to the composition of the dataset. On the contrary, features that have been selected only few times are more related to the Training Set used. As we can see, not all bands are shown because CVS method selects only the most significant bands. Note that, as said in Section 3.3, the CVS method selects only the three most significant bands. In the graph more than three bands are shown because the best bands considered may be different in each of the 30 test.

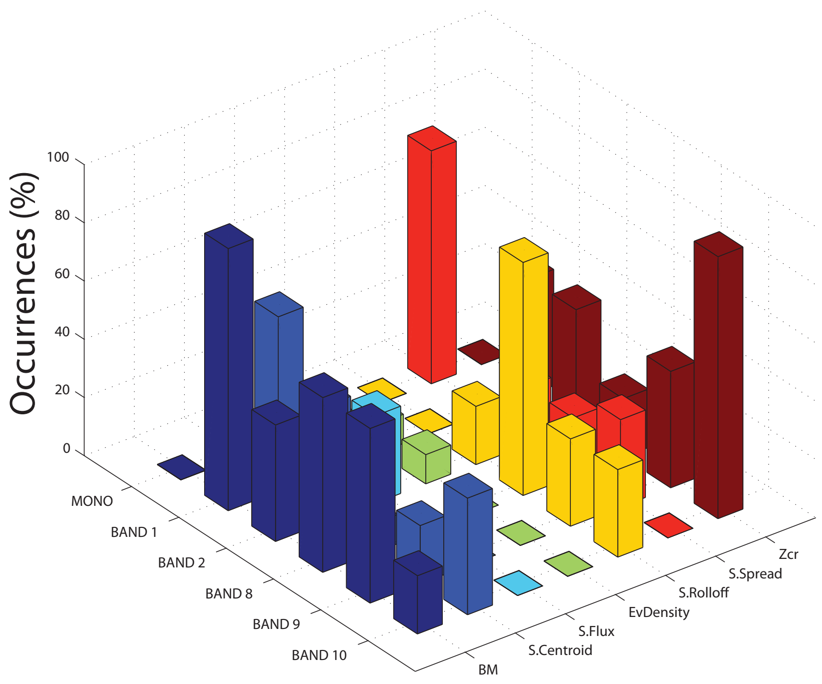


Figure 4.2: Global feature occurrences referring to Backward + Cross Validation feature selection in Bootleg and Studio category.

Figure 4.3 shows the average weights assigned to each Band by the CVS. Bands 9 and 10 are the most significant.

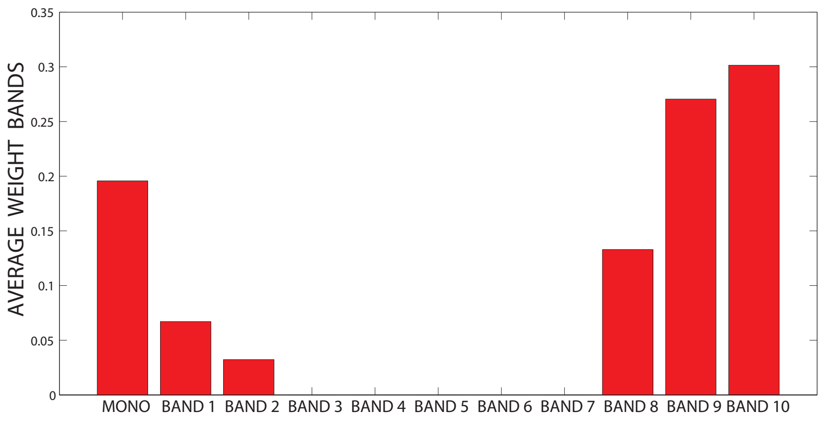
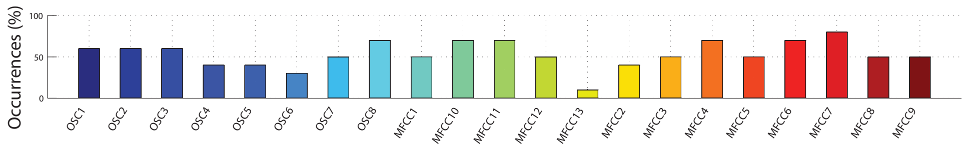
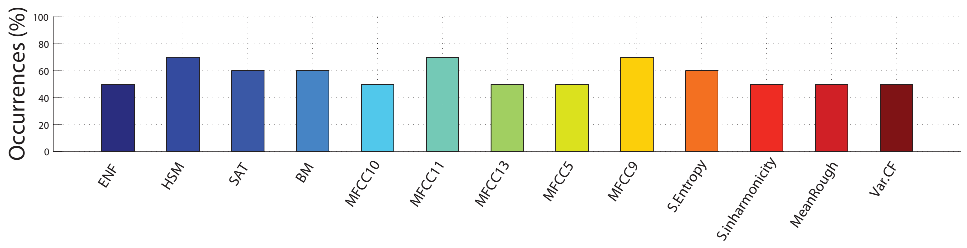


Figure 4.3: Percentage of weight values assigned to each Band and to the Mono signal by the Cross Validation Selection in Bootleg and Studio category.

The same considerations on significance of the features can be done for the features extracted only from the Mono signal (Figure 4.4). Also in this figures only the subset of most significant features is shown.



(a) Frame features



(b) Global features

Figure 4.4: Feature occurrences referring to Backward + Cross Validation selection in Bootleg and Studio category. These graphs refers to features extracted from the Mono.

It is interesting to see that in this category the number of significant features, referring in particular to Figures 4.1 and 4.2, is low. This means that the differences between the two classes are quite evident, and the classification tool needs a lower number of information to distinguish between the classes.

As example, we can refer to what we said on the ZCR. This feature can be an approximative indicator of the noise level of a signal. This feature has been selected as high significant in all the Bands considered. It is quite clear that is due to the ambient noise present in the Bootlegs opposed to the clean recording made with the Studio files. In this case, the ZCR is significant for all the Bands considered.

From the graphs relative to the features extracted from the Mono signal, we can analyse the differences of the High Spectral Magnitude for this category (Figures 4.5 and 4.6). We have selected this feature because it is one of the features proposed for our particular purpose.

It is evident that the Bootlegs have an average HSM lower that the Studio files, because not professional microphones do not capture high frequency very well.

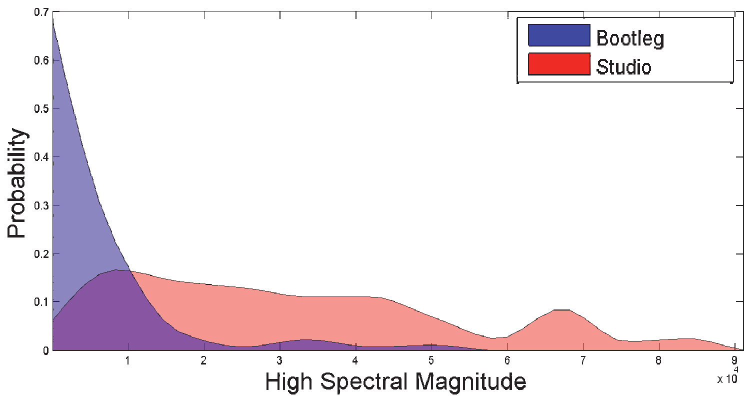


Figure 4.5: Mono, Global, High Spectral Magnitude: distribution of HSM values for Bootleg and Studio files.

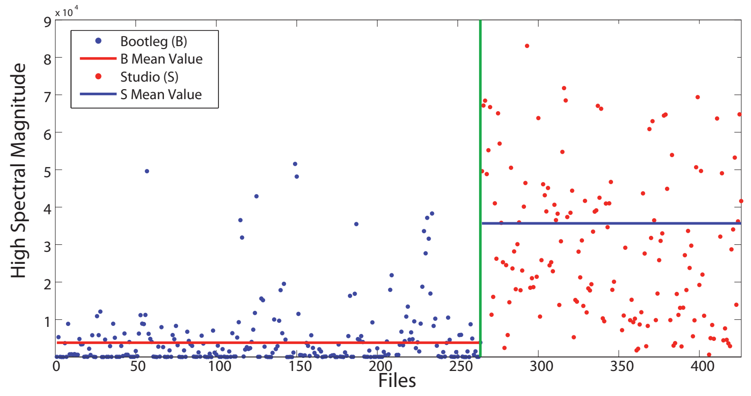


Figure 4.6: Mono, Global, High Spectral Magnitude: HSM values for each file and mean values for Bootleg and Studio files.

4.3.2 All Dataset

This test considers all the files in the Dataset, dividing them in two classes: Bootleg and Official+Studio. The best method selected by the Validation Phase is the Forward plus Cross Validation feature selection (FWD+CVS), when Bands and Mono are considered and the features are analysed in macro-set. The average accuracy is equal to 85%, i.e., 85% of files have been correctly classified.

We said in the analysis of the precedent category, with the Validation Phase we select the best combination of methods and classifier to use in the Test Phase, i.e., we can perform only 1 test and not 152. In Table 4.3 we show the 10 best tests chosen in the Validation Phase and their corresponding rank once the Test Phase has been performed. We also show the worse accuracy obtained.

*Table 4.3: Combination rank in All Dataset category. **VP Pos** is the method position in the rank of the Validation Phase and **VP**% **Acc** is the respective accuracy. **Test Pos** and **Test**% **Acc** are the position and the accuracy of the methods combination after the Test Phase. **M/B** indicates if only Mono signal is taken or Mono+Bands. **Gr/Mcr** indicates features divided in Groups or taken as Macro-Set. **Feat-S** indicates the selection method applied and **Class** the classifier used. Only the first* 10 *and the last position are shown. The best combination chosen by the Validation Phase is highlighted in green, while the worst one is highlighted in red.*

VP	**Combinations**				**VP%**	**Test**	**Test%**
Pos	**M/B**	**Gr/Mcr**	**Feat-S**	**Class**	**Acc**	**Pos**	**Acc**
1	B	Mcr	FWD+CVS	GMM	85.41	2	85.05
2	B	Mcr	LDA	SVM	85.27	5	84.75
3	B	Gr	PCAgr+CVS	SVM	85.04	1	85.24
4	B	Mcr	BWD	GMM	84.91	9	84.37
5	B	Mcr	PCAgr	SVM	84.90	3	84.88
6	B	Mcr	FWD	GMM	84.81	7	84.61
7	B	Mcr	BWD+CVS	SVM	84.65	32	83.07
8	B	Mcr	BWD+CVS	GMM	84.39	20	83.40
9	B	Mcr	SW+CVS	GMM	84.31	24	83.03
10	B	Gr	BWD	GMM	84.25	6	84.72
...							
152	M	Mcr	RE*BWD	SVM	53.60	152	47.80

We can see that the best combination chosen by the Validation is not the best combination in the Test Phase, but it is in second position, with an odds of 0.19% from the first one. The accuracy difference between the first *ten* positions is less than 1%. We can so consider as best the combination given by the Validation Phase.

In Figures 4.7 and 4.8, we show the Global and Frame features that have been mostly selected by FWD+CVS method.

With reference to the precedent category analysed, we can see that the number of features selected is higher. This means that the differences between the classes considered are lower. Furthermore, we can see that the features extracted in each frame are more often selected than global ones. This means that there are not global features that are really characterizing, since each of the 30 tests (more or less) selects different features. The situation is the opposite for features selected frame-wise, where some features prove to be characterizing.

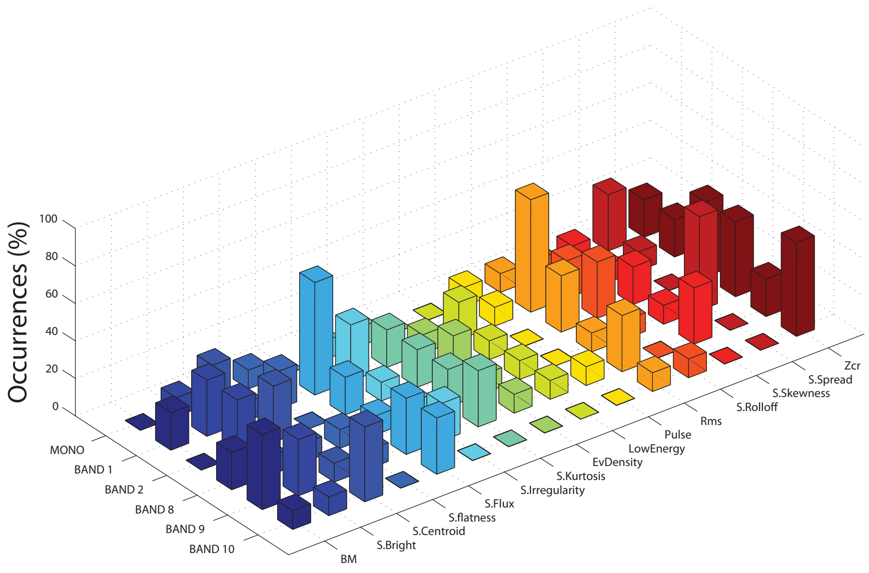


Figure 4.7: Percentage of occurrences of Global feature referring to Forward + Cross Validation feature selection in All Dataset category, averaged on the 30 *test performed.*

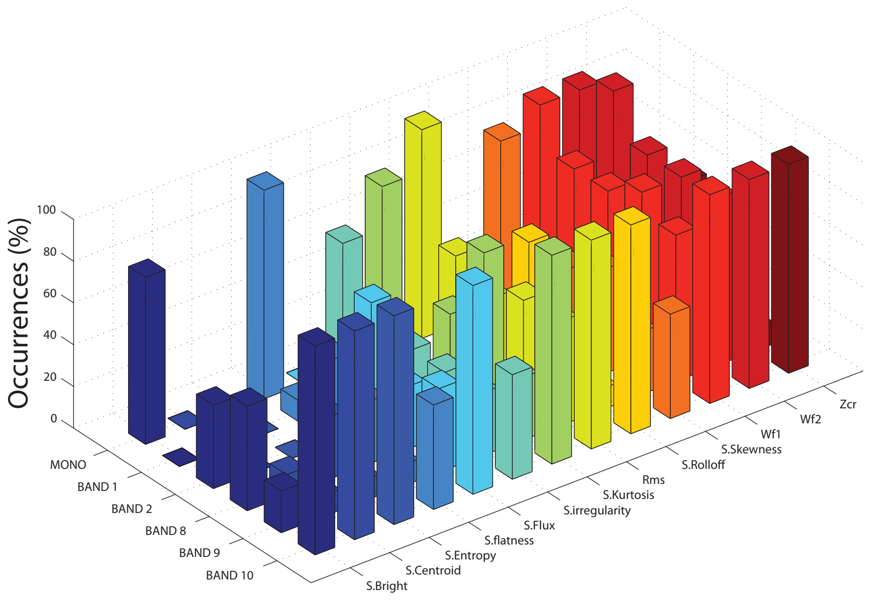
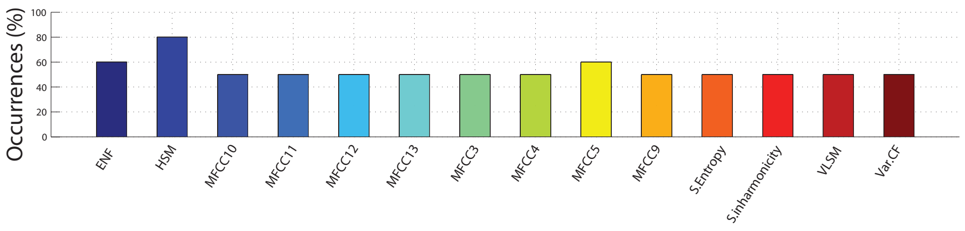
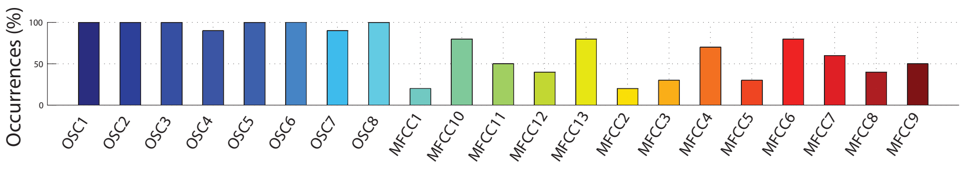


Figure 4.8: Percentage of occurrences of Frame feature referring to Forward + Cross Validation feature selection in All Dataset category, averaged on the 30 *test performed.*

As we said, some features have been extracted only for the Mono signal. We can analyse these features. Figure 4.9 shows the Global and Frame features selected from the Mono signal with their occurrences.



(a) Global Mono feature occurrences



(b) Frame Mono feature occurrences

Figure 4.9: Global and Frame feature occurrences referring to Forward feature selection in All Dataset category. These graphs refer to the features extracted only for the Mono.

We have also said the CVS assign more significance only to three Bands each time. Figure 4.10 shows the average weights assigned to each Band by the CVS. Bands 9 and 10 are the most significant.

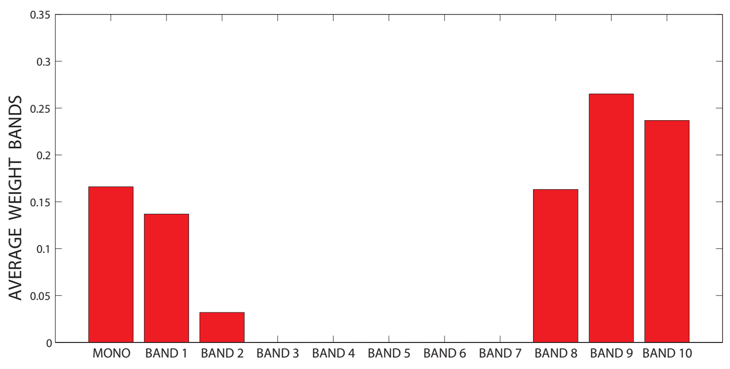


Figure 4.10: Percentage of weight values assigned to each Band and to the Mono signal by the Cross Validation Selection in All Dataset category.

Considering only the most significant Bands, we can see that there are features that in some Bands are more selected than in others. E.g., we can consider the Zero Crossing Rate, that has been selected all the time in the 10-th Band. We expected the ZCR value to be higher in Bootleg files due to some noise components. Referring to the ZCR extracted from frames of the 10-th Band, we can analyse why this feature have been selected always by the Forward feature selection.

In Figure 4.11 the distribution of ZCR values is represented for bootleg e not-bootleg files.

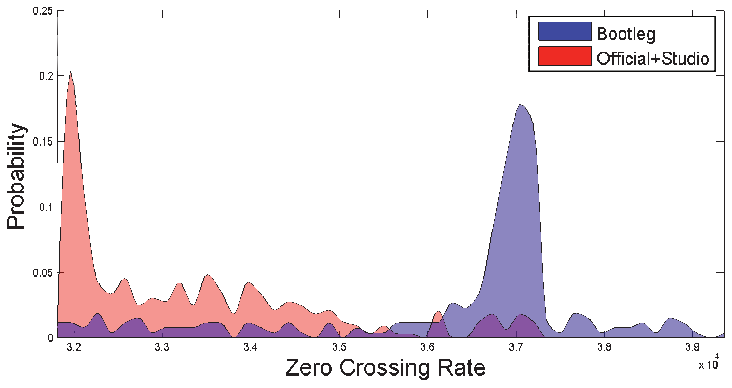


Figure 4.11: Band 10, Frame, Zero Crossing Rate: distribution of ZCR values for Bootleg and not-Bootleg files.

As we can see, most of Bootleg files have a high ZCR value, while most of not-Bootleg files have a lower value. Figure 4.12 shows the values of the ZCR for each file and its mean value for Bootleg and not-Bootleg.

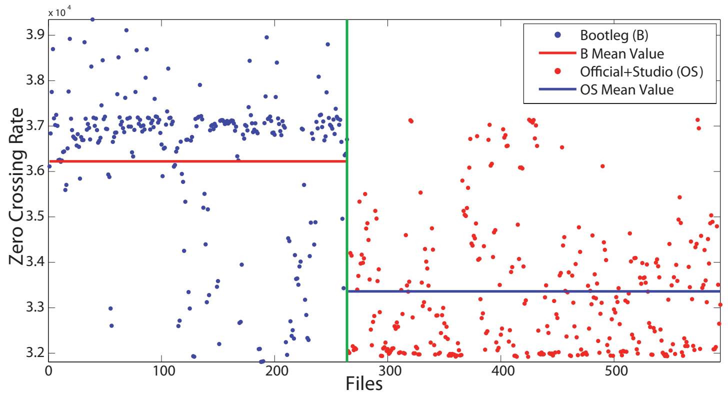


Figure 4.12: Band 10, Frame, Zero Crossing Rate: ZCR values for each file and value means for Bootleg and not-Bootleg files.

From these two figures is quite clear that the distribution of values of this feature is very different in the two classes. This means that the ZCR (especially for the considered Band) is very characterizing.

We can analyse also from the Mono signal one of the most significant feature. We show as example the Electrical Network Frequency, that is one of the feature added in Chapter 3 for the Bootleg Detection problem. The ENF shows a high value when some post-processing has been applied to a file. In Figure 4.13, we show the distribution of Electrical Network Frequency values. We make some considerations about the ENF distribution. In rare cases, Bootlegs are recorded with device connected to the electricity network, so the ENF value of Bootleg files is lower. Furthermore, is probable that the higher cleanness of Studio files permit to individuate more easily jitters (not necessarily bounded to the electrical network) around the 50 Hz, and so the ENF values of Studio files is higher.

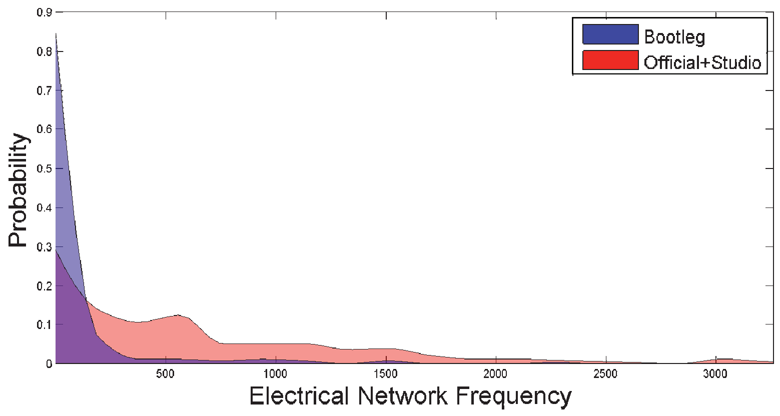


Figure 4.13: Mono, Global, Electrical Network Frequency: distribution of ENF values for Bootleg and not-Bootleg files.

As for the ZCR, in Figure 4.14 ENF values of each file and the means of the two separated classes are represented.

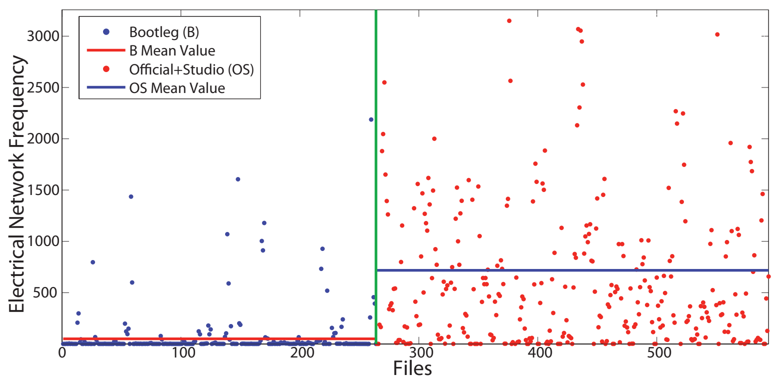


Figure 4.14: Mono, Global, Electrical Network Frequency: ENF values for each file and value means for Bootleg and not-Bootleg files.

4.3.3 Bootleg and Official

In the first category analysed, we have considered Bootleg and Studio files. The Studio files have, obviously, less noise both of the Bootleg and the Official ones. We have so performed these tests, to obtain results with only live excerpt, where there is the presence of ambient noise (clasp, scream, etc.). We expect to have results lower than the Bootleg and Official category. Anyway, we obtained an average accuracy percentage of 81.80% in the best case (Forward Feature Selection), that is only 3% percentage points less than the All Dataset category. In Table 4.4, as done for precedent categories, we show the different accuracies between Validation and Test phases.

Table 4.4: Combination rank in Bootleg and Official category. ***VP Pos*** *is the method position in the rank of the Validation Phase and* ***VP% Acc*** *is the respective accuracy.* ***Test Pos*** *and* ***Test% Acc*** *are the position and the accuracy of the methods combination after the Test Phase.* ***M/B*** *indicates if only Mono signal is taken or Mono+Bands.* ***Gr/Mcr*** *indicates features divided in Groups or taken as Macro-Set.* ***Feat-S*** *indicates the selection method applied and* ***Class*** *the classifier used. Only the first 10 and the last position are shown. The best combination chosen by the Validation Phase is highlighted in green, while the worst one is highlighted in red.*

VP	Combinations				VP%	Test	Test%
Pos	M/B	Gr/Mcr	Feat-S	Class	Acc	Pos	Acc
1	B	Mcr	FWD+CVS	SVM	83.70	3	81.80
2	B	Gr	PCA	SVM	83.30	2	82.00
3	B	Mcr	PCAgr	SVM	83.10	1	82.50
4	B	Gr	GA	GMM	82.90	9	81.30
5	B	Mcr	LDA	GMM	82.00	16	80.80
6	B	Mcr	SW	GMM	81.90	10	81.10
7	B	Gr	GA+CVS	GMM	81.80	18	80.60
8	B	Gr	LDA	SVM	81.70	6	81.60
9	B	Gr	SW+CVS	GMM	81.50	9	81.30
10	B	Mcr	SW+CVS	SVM	81.40	4	81.70
...							
152	M	Mcr	RE+FWD	SVM	49.90	152	50.80

We show the significant feature for this case in Figure 4.15 and Figure 4.16. The main consideration about specific features and bands weights are more or less the same that we have done before. Indeed, the most significant features (i.e., those with many occurrences) are those computed frame-wise and finally aggregated.

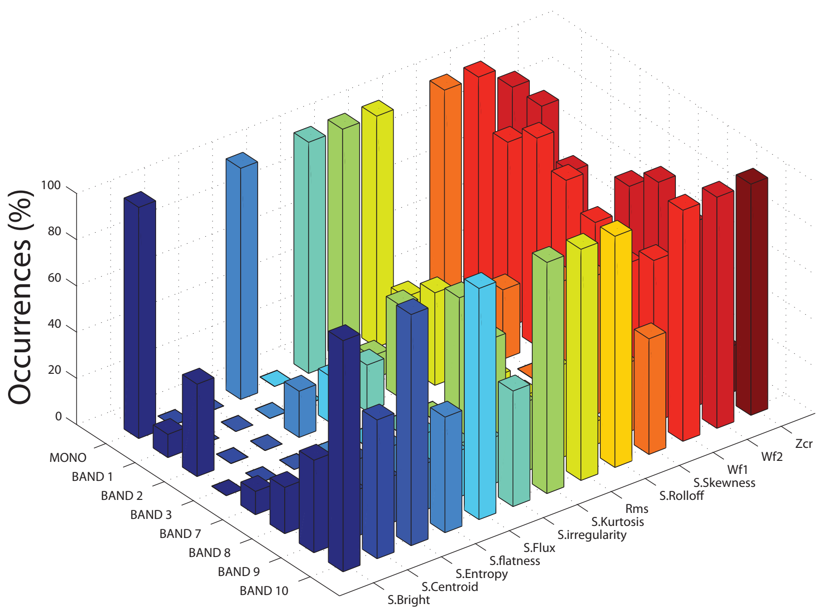


Figure 4.15: Frame feature occurrences referring to Forward + Cross Validation selection in Bootleg and Official category.

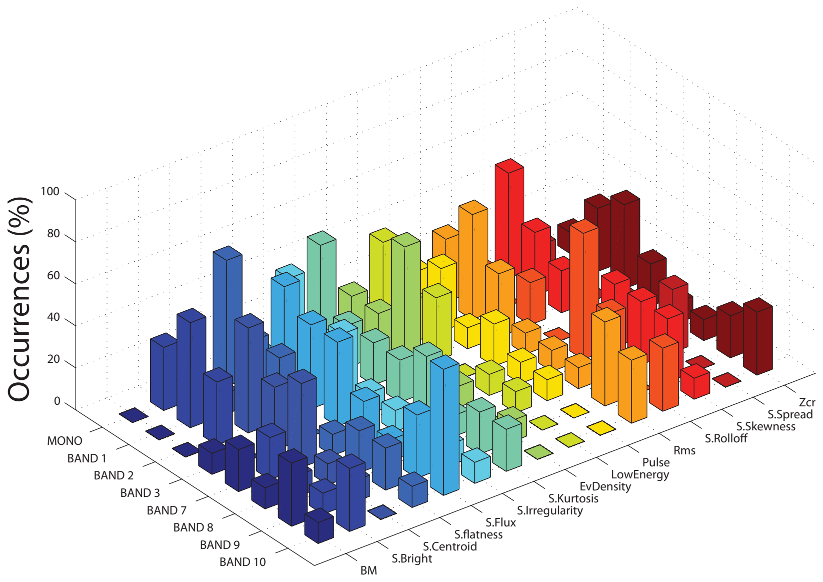


Figure 4.16: Global feature occurrences referring to Forward + Cross Validation selection in Bootleg and Official category.

Anyway, we can show an example of significant feature for these tests. In figure 4.17 we show the values of the Band Magnitude of each signal for the Band 9. As we can see, the Bootlegs have lower values of Band Magnitude respect to the Officials. This can be the consequences of a band-pass filter present in the integrated microphones, that cuts the higher frequencies.

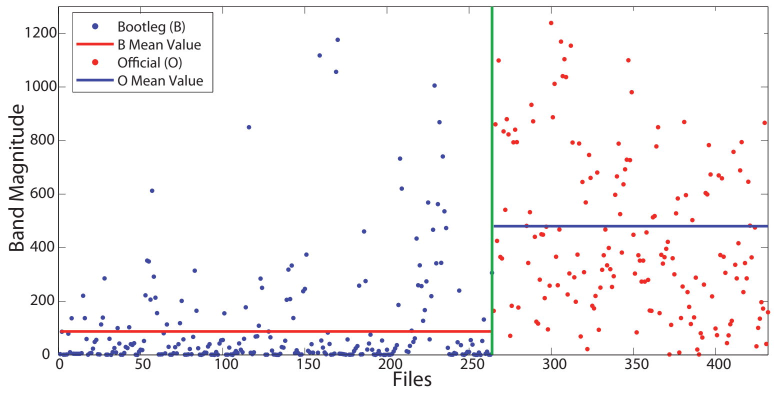
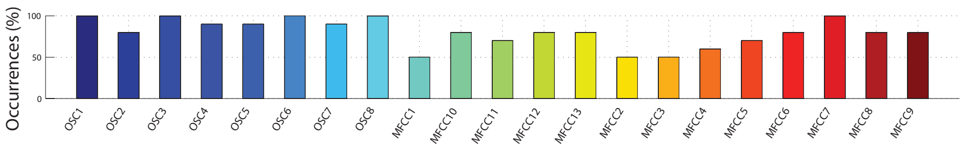
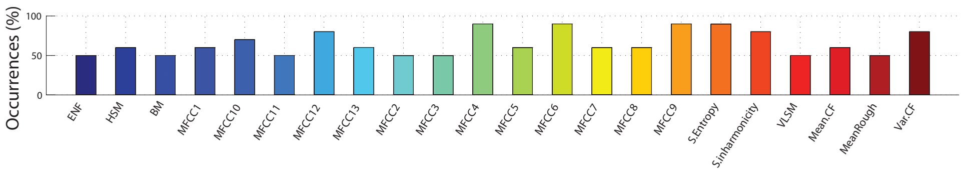


Figure 4.17: Values of the Band Magnitude of each file for Band 9 and relative average for Bootlegs and Officials.

As for the precedent categories, we can see in the end the feature occurrences for features extracted only from Mono signal (Figure 4.18).



(a) Frame features



(b) Global features

Figure 4.18: Global and Frame feature occurrences referring to Forward feature selection in Bootleg and Official category. These graphs refer to the features extracted only for the Mono.

4.3.4 Multi-class Results Example

We analyse now another significant category of tests. In this case we try a 4-class classification, utilising home-made bootlegs. We compare here three home-made categories with their corresponding studio versions. The best combination of method for these type of test is the Forward feature selection, with an accuracy of 97%. In this case all Bands are analysed. We can deduce that this test case is more oriented to microphone source detection.

In Table 4.5, we show the 10 best tests chosen in the Validation Phase and their corresponding rank once the Test Phase has been performed.

Table 4.5: Combination rank in Multi-class category. ***VP Pos*** *is the method position in the rank of the Validation Phase and* ***VP% Acc*** *is the respective accuracy.* ***Test Pos*** *and* ***Test% Acc*** *are the position and the accuracy of the methods combination after the Test Phase.* ***M/B*** *indicates if only Mono signal is taken or Mono+Bands.* ***Gr/Mcr*** *indicates features divided in Groups or taken as Macro-Set.* ***Feat-S*** *indicates the selection method applied and* ***Class*** *the classifier used. Only the first 10 and the last position are shown. The best combination chosen by the Validation Phase is highlighted in green, while the worst one is highlighted in red.*

VP	Combinations				VP%	Test	Test%
Pos	**M/B**	**Gr/Mcr**	**Feat-S**	**Class**	**Acc**	**Pos**	**Acc**
1	B	Mcr	FWD	GMM	95.83	1	95.83
2	B	Mcr	BWD	SVM	95.83	2	94.44
3	B	Mcr	PCAgr	SVM	95.83	3	94.44
4	B	Mcr	PCAgr+CVS	SVM	94.44	6	93.06
5	B	Mcr	SW	GMM	94.44	11	90.28
6	B	Mcr	LDA	GMM	94.44	7	93.06
7	B	Gr	BWD	SVM	93.06	4	94.44
8	B	Gr	LDA	SVM	93.06	5	94.44
9	B	Gr	SW	GMM	88.89	8	93.06
10	B	Mcr	FWD	GMM	88.89	16	88.89
...							
152	M	Mcr	RE*BWD	GMM	17.20	148	19.10

We can see from Figure 4.19 that also in the Multi-class category some features are quite different between classes, and so are significant.

As we can see in Figure 4.20 and in Figure 4.21, fewer features are selected. However, CVS is not used, so all Bands are considered. The reason is the need to analyse all bands in order to distinguish 4 classes.

In Figure 4.22 frame features extracted from Mono signal are shown.

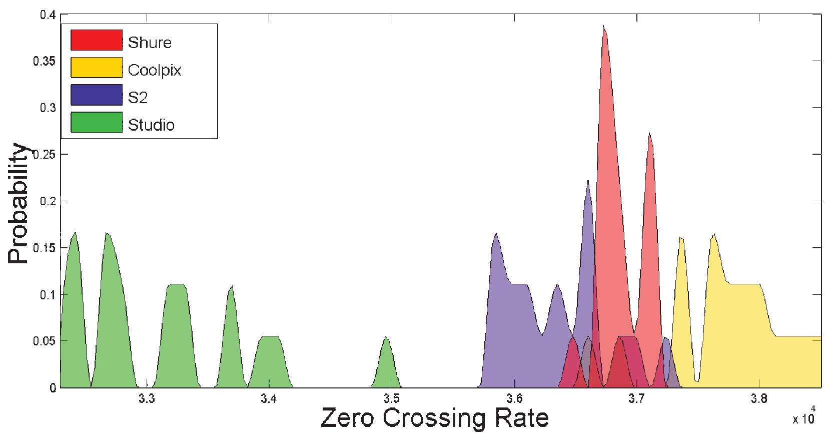


Figure 4.19: Distribution of ZCR values of Band 10 Multi-class example.

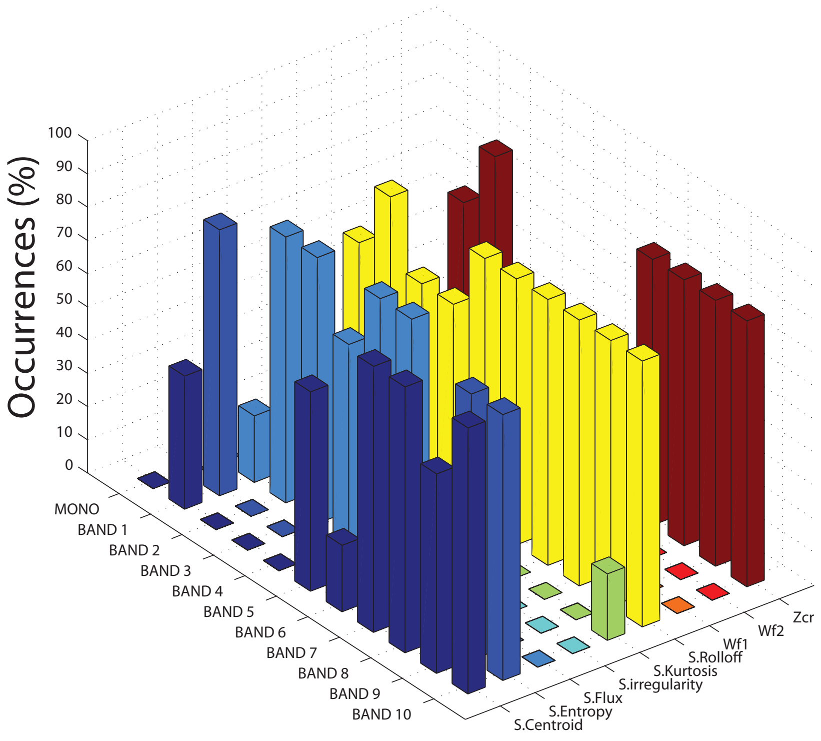


Figure 4.20: Frame feature occurrences referring to Forward plus Cross Validation Selection in Multi-class category.

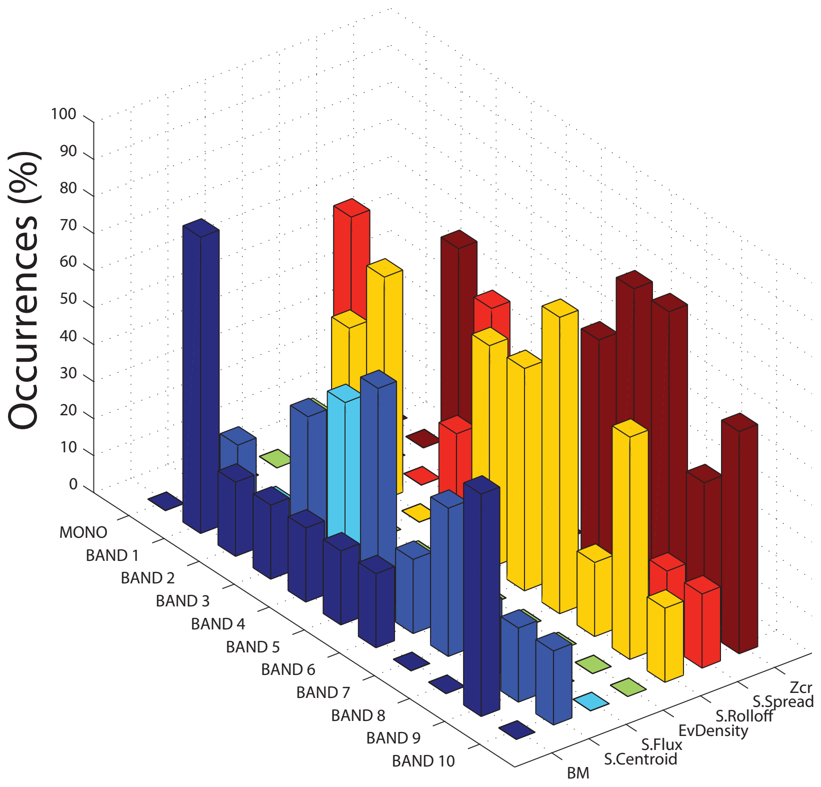


Figure 4.21: Global feature occurrences referring to Forward plus Cross Validation Selection in Multi-class category.

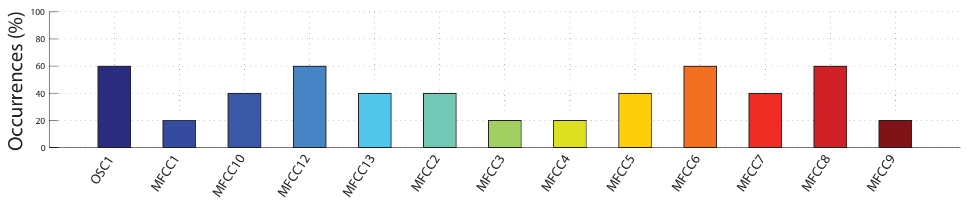


Figure 4.22: Frame feature occurrences referring to Forward feature selection in Multi-class category. These graphs refer to the features extracted only for the Mono.

4.3.5 Bootlegs Home Made and Corresponding Studio Files

In the end, since we have re-recorded some files at home, we have done some tests between the original excerpts and their re-captured version. As said in Section 4.1, we created the Home Made Bootlegs re-capturing with different microphones some Studio excerpts. We have performed tests considering only excerpts recorded by one microphone at time. We so expected to have an high accuracy, since one class contains only audio tracks recorded with the same device. Indeed, we can see from Table 4.6 that the accuracies are very high.

Table 4.6: Combination rank in Home-Made Bootlegs and Corresponding Studio Files. ***VP Pos*** *is the method position in the rank of the Validation Phase and* ***VP% Acc*** *is the respective accuracy.* ***Test Pos*** *and* ***Test% Acc*** *are the position and the accuracy of the methods combination after the Test Phase.* ***M/B*** *indicates if only Mono signal is taken or Mono+Bands.* ***Gr/Mcr*** *indicates features divided in Groups or taken as Macro-Set.* ***Feat-S*** *indicates the selection method applied and* ***Class*** *the classifier used. Only the first 10 and the last position are shown. The best combination chosen by the Validation Phase is highlighted in green, while the worst one is highlighted in red.*

VP Pos	Combinations				VP% Acc	Test Pos	Test% Acc
	M/B	Gr/Mcr	Feat-S	Class			
1	B	Gr	SW+CVS	GMM	97.22	1	97.22
2	B	Mcr	FWD+CVS	GMM	97.22	3	97.22
3	B	Gr	PCAgr+CVS	SVM	97.22	2	97.22
4	B	Gr	BWD+CVS	GMM	97.22	5	94.44
5	B	Gr	FWD+CVS	GMM	94.44	4	94.44
6	B	Mcr	LDA	GMM	94.44	3	94.44
7	B	Mcr	GA+CVS	GMM	94.44	7	94.44
8	B	Gr	GA+CVS	GMM	94.44	8	94.44
9	B	Mcr	SW+CVS	GMM	94.44	9	94.44
10	B	Gr	PCAgr	SVM	94.44	10	94.44
...							
152	M	Mcr	RE*FWD	GMM	43.80	148	65.40

Chapter Conclusions

In this Chapter we have shown the results related to our work. We can observe some constant and interesting conclusions.
First of all, the tests with the higher accuracies consider always both the

Mono signal and the Bands. This means that, for our specific purpose, information extracted from particular sections of frequencies are more relevant than information extracted from the not-processed file. Furthermore we can observe that not all the Bands carry relevant information. In-fact only some Bands are considered from our Cross Validation selection and, in general, features derived from the extreme bands have higher weights. The lower Bands (1 and 2) and the higher Bands (8, 9 and 10) are the most considered. The central Bands from 3 to 7 are never considered. This means that the central frequencies (from 230 Hz to 8 kHz) do not carry relevant information, or probably that the information carried by these Bands are the same retrieved from the Mono signal.

We have obtained a high accuracy of Bootleg detection in every category of test (i.e., higher than 80%). In particular, as we expected, experimental results show that some features characterize bootlegs much better than others. Among these, we found that features that capture noise characteristics (such as ZCR, ENF or features related to high-frequency bands) can be essential to solve the problem.

Analysing the results that we obtained, we can conclude that the lowest and the highest considered frequency bands are the most significant to solve the bootleg detection problem. The importance of the low frequencies analysis is explained by the rumbling phenomenon, i.e., an excess of low frequency noise that can be present in a recording environment. On the other hand, recording an audio track in a particularly crowdy place (typical of concert halls) may give rise to a high frequency absorption. This phenomenon is given by the reflections, refractions and diffractions due to the presence of the bodies of people that cause a sort of confusion in the registration. For this reason, high frequency components in a bootleg may result less clear than in studio songs.

Chapter 5

Conclusions and Future works

In this work we presented a method to solve the audio bootleg detection problem, which is a problem of interest in the forensic community. Indeed, with the increasing diffusion of portable recording devices, such as integrated microphones in photo-cameras, mp3 players and many more, it is nowadays easy for everyone to create and share bootlegs. For this reason, a tool that allows to automatically detect bootlegs may be helpful to prevent copyright infringements, e.g., on multimedia sharing platforms.

The detector that we propose starts from a classification tool that is as general and modular as possible. It is based on audio features extraction and classifiers such as GMMs and SVMs. However, additional features, features selection methods, and classifiers can be added at any moment. The classification procedure that we propose is then developed to automatically select the best combination of features and classifiers to maximize the classification accuracy using a small set of training data and comparing many different feature selection methods.

To tune this tool in order to solve the bootleg detection problem, we have considered an additional set of features and a feature selection method that allows fusing information from different frequency bands of the signal. To test the detector, we have built a Dataset of nearly 600 audio excerpts. We have divided the Dataset in Bootleg, Home Made Bootleg, Official and Studio excerpts. Bootlegs are files obtained mainly from the web, they are illegally distributed. Home Made Bootlegs are excerpts created on purpose re-capturing some original Studio-recorded audio. Officials and Studios are files officially release by artists, respectively recorded in live performances and in recording studios. By using such different audio excerpts, we have been able to test the tool in different situations, obtaining a high accuracy of Bootleg detection in every case (i.e., higher than 80%). In particular, as we expected, experimental results show that some features characterize bootlegs much better than others. Among these, we found that features that capture noise characteristics (such as ZCR or features related to high-frequency bands) can be essential to solve the problem.

Even if results are promising, the detector could still be improved. As an example, a set of high-level features could be inserted into the pool of tested features. Moreover, more in depth studies on the presence of characteristic reverberations on bootlegs could be carried on to improve the robustness of the detector. Another idea could be the texture analysis of the chromagram. Indeed, we used the chromagram as a feature without any processing. However, using it as a picture and compute a feature that characterizes its texture could be an interesting addition.

From a slightly different point of view, another interesting future work may be the study of an anti-forensic technique. Indeed, since it is now possible to discriminate between bootlegs and non-bootlegs, it would interesting to analyse the possibility of fooling this detector applying some kinds of audio post-processing operations aiming to remove bootlegs footprints without affecting the sound quality.

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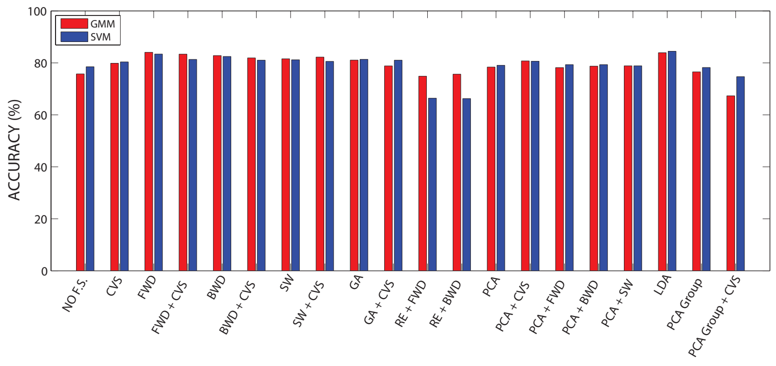
Appendix A

Other Test Results

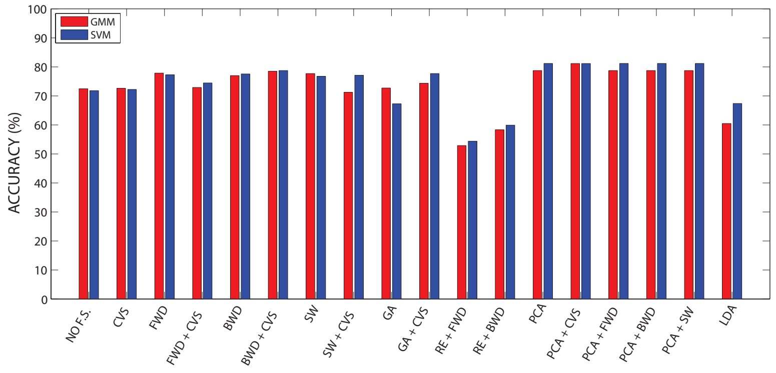
We show now some other graphs relative to tests described in Chapter 4. We can see, in the following histograms, the accuracies related to all the 152 combinations of methods for each category of test. For each category, the first two graphs indicate the case where only Mono signal in considered, and respectively where the features are analysed in Macro-set and in Groups. The last two indicate the case where Mono signal and Bands are considered, respectively with the features analysed in Macro-set and in Groups.

A.1 Bootleg and Studio

In this category of tests we consider Bootleg and Studio excerpts. We have Bootleg, that are recorded during live performances, with ambient noises as screams and claps from public, and Studio files, that are recorded in professional recording studios, with no background noises.

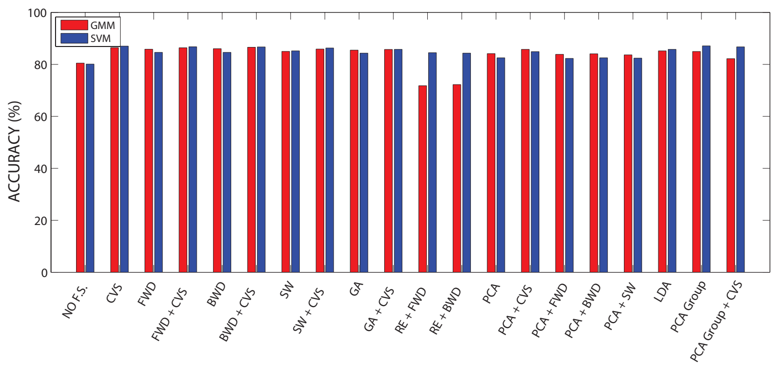


(a) Features divided in groups

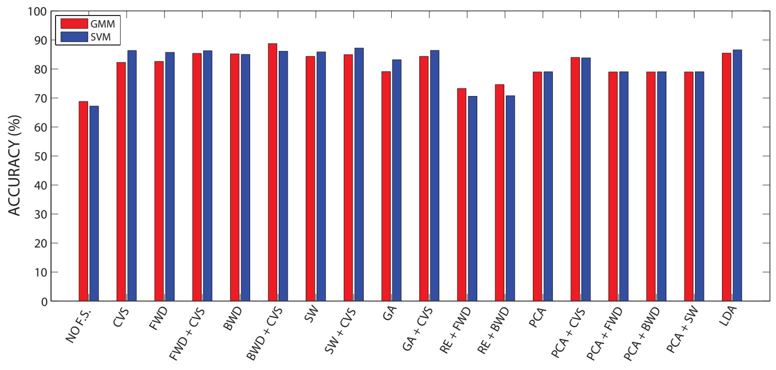


(b) Macro-set of features

Figure A.1: Test results for Bootleg and Studio category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Only features from the Mono signal are used.



(a) Features divided in groups

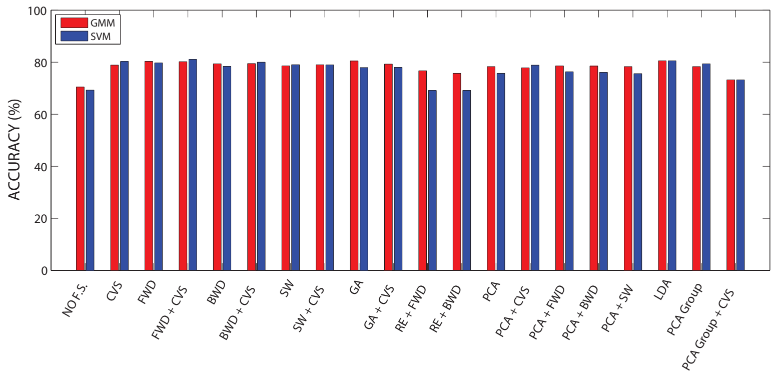


(b) Macro-set of features

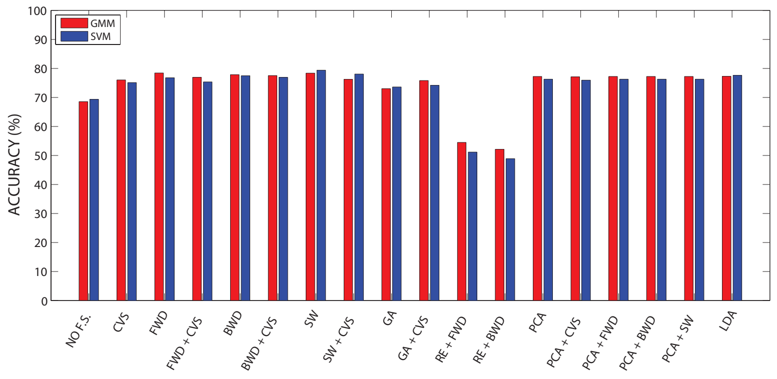
Figure A.2: Test results for Bootleg and Studio category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Features both from Band and Mono signal are used.

A.2 All Dataset

This test considers all the files in the Dataset, dividing them in two classes: Bootleg and Official+Studio.

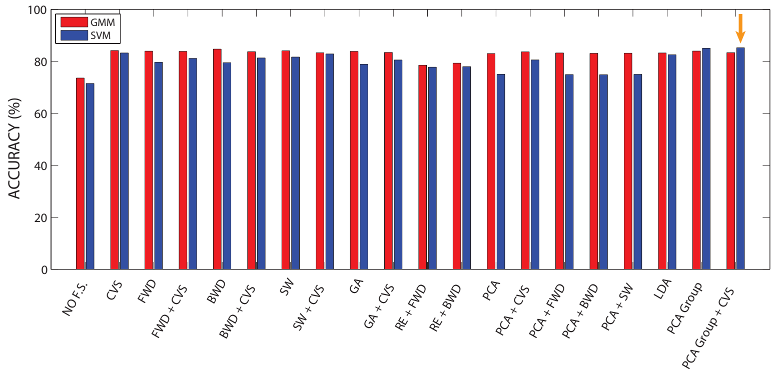


(a) Features divided in groups

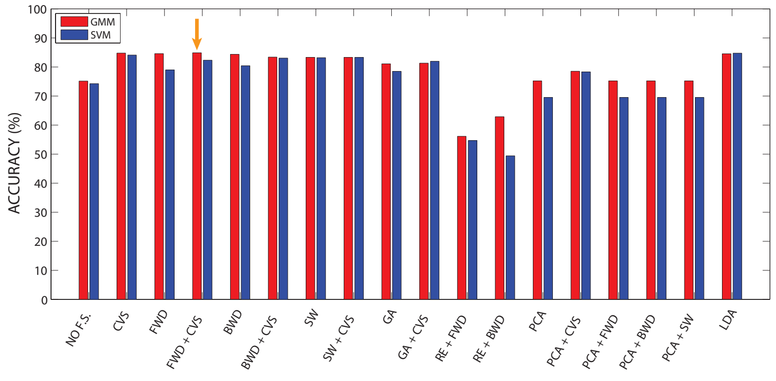


(b) Macro-set of features

Figure A.3: Test results for All Dataset category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Only features from the Mono signal are used.



(a) Features divided in groups

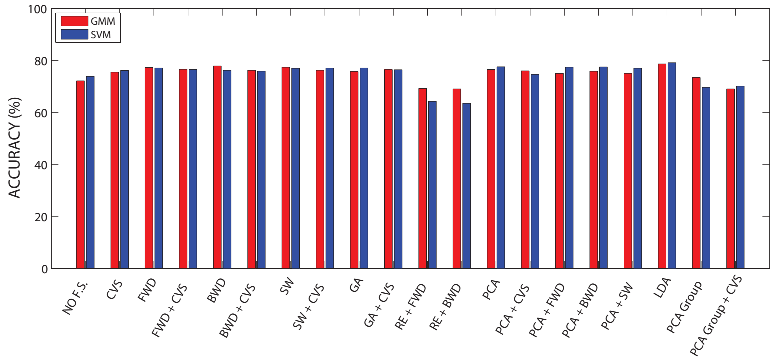


(b) Macro-set of features

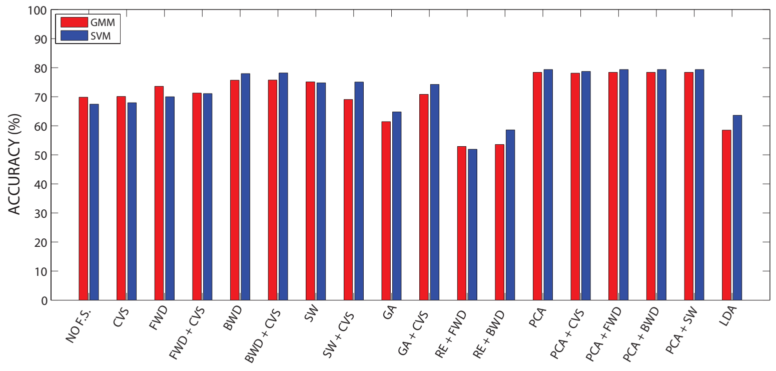
Figure A.4: Test results for All Dataset category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Features both from Band and Mono signal are used.

A.3 Bootleg and Official

We have performed these tests to obtain results with only live excerpt, where there is the presence of ambient noise (clasp, scream, etc.).

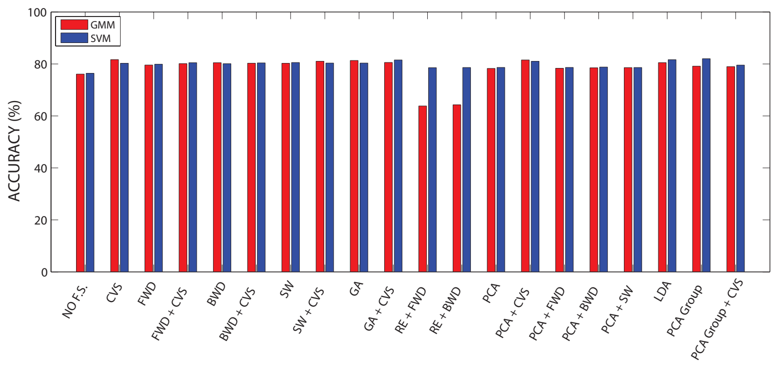


(a) Features divided in groups

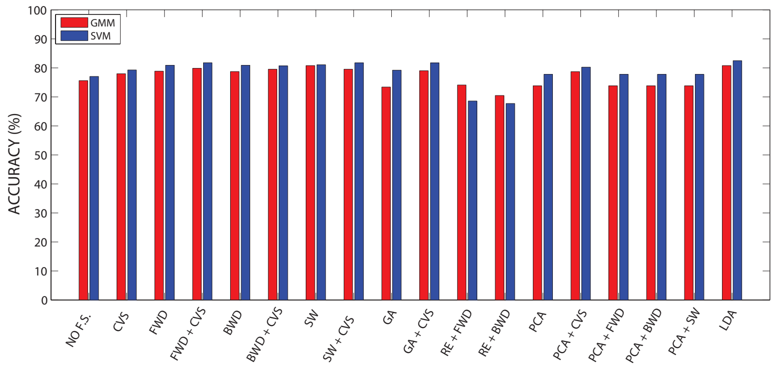


(b) Macro-set of features

Figure A.5: Test results for Bootleg and Official category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Only features from the Mono signal are used.



(a) Features divided in groups

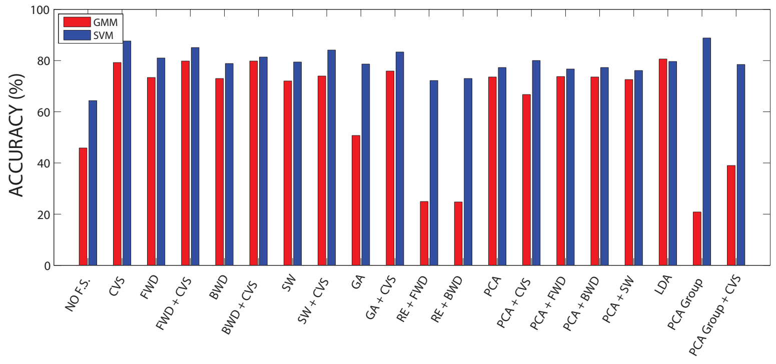


(b) Macro-set of features

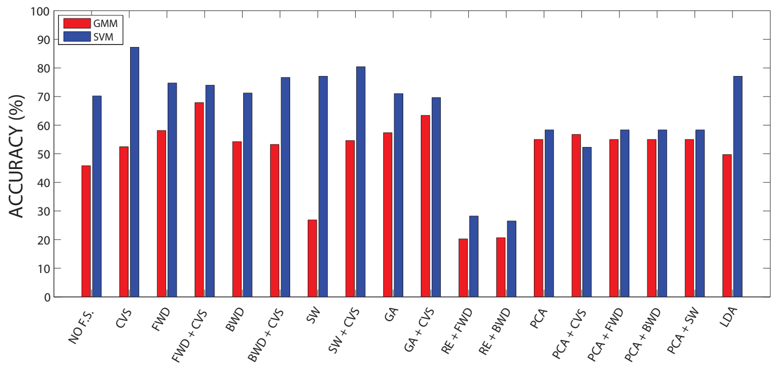
Figure A.6: Test results for Bootleg and Official category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Features both from Band and Mono signal are used.

A.4 Multi-class Result

In this category we analyse a 4-class classification, utilising home made bootlegs.

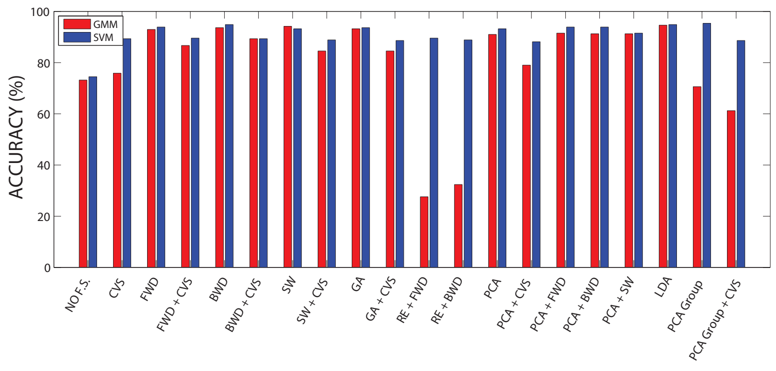


(a) Features divided in groups

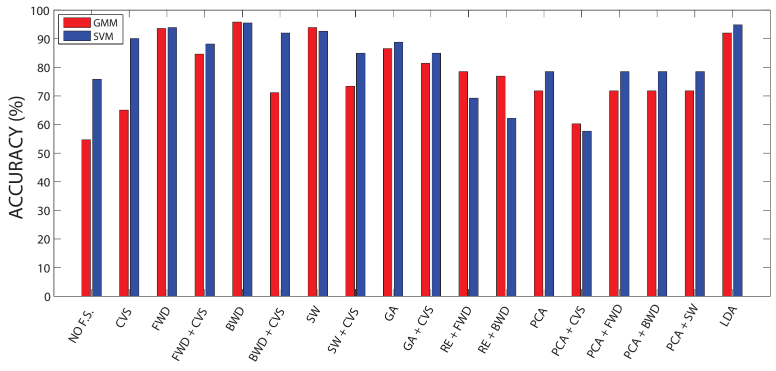


(b) Macro-set of features

Figure A.7: Test results for Multi-class category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Only features from the Mono signal are used.



(a) Features divided in groups



(b) Macro-set of features

Figure A.8: Test results for Multi-class category: accuracy for each (combination of) method of feature selection/reduction both for GMM and SVM classifiers. Features both from Band and Mono signal are used.