Audio Surveillance: a Systematic Review

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Abstract

Despite surveillance systems are becoming increasingly ubiquitous in our living environment, automated surveillance, currently based on video sensory modality and machine intelligence, lacks most of the time the robustness and reliability required in several real applications. To tackle this issue, audio sensory devices have been taken into account, both alone or in combination with video, giving birth, in the last decade, to a considerable amount of research. In this paper audio-based automated surveillance methods are organized into a comprehensive survey: a general taxonomy, inspired by the more widespread video surveillance field, is proposed in order to systematically describe the methods covering background subtraction, event classification, object tracking and situation analysis. For each of these tasks, all the significant works are reviewed, detailing their pros and cons and the context for which they have been proposed. Moreover, a specific section is devoted to audio features, discussing their expressiveness and their employment in the above described tasks. Differently, from other surveys on audio processing and analysis, the present one is specifically targeted to automated surveillance, highlighting the target applications of each described methods and providing the reader tables and schemes useful to retrieve the most suited algorithms for a specific requirement.

1 Introduction

The monitoring of human activities has never been as ubiquitous and massive as today, with million of sensors deployed in almost every urban area, industrial facility and critical environment, increasing rapidly in terms of both amount and scope. In consequence of this, studies on automated surveillance have grown at a fast pace, with hundreds of algorithms embedded in various commercial systems. In general, surveillance systems are based on one or more sensors able to acquire information from the surrounding environment. While the first generation of surveillance systems [Raty, 2010] implied a monitoring activity by a human operator in order to detect anomalous situations or events, recently developed automated systems try to perform this task by computer vision and pattern recognition methodologies. The advantages of this perspective lie essentially in cost saving, especially with the decreasing price of sensors and processing units, and the ability to cope with huge amount of data (e.g. from tens
or even hundreds of different sensors per surveillance system) which cannot be handled by human operators, not even for a short time.

The early automated surveillance systems were based on one or more video cameras, such sensor typology being the most widespread also at the present days. Anyway, reasoning solely on visual data brings in considerable fallacies: among the others, the scarce performance of video cameras in adverse weather conditions, and their sensitivity to sudden light switching, reflections, shadows [Valera and Velastin, 2005]. Moreover, standard video cameras are almost useless during nighttime, due to the scarce illumination and car flashlights.

To overcome these drawbacks, other kinds of sensors have been designed, exploiting them either alone or jointly with the video signal. In particular, near infrared or far infrared (thermal) cameras can substitute video cameras during nighttime or assist them, considerably improving the overall performance; in particular, thermal cameras are suited for the detection of hot objects against a colder background, such as people or moving vehicles [Dai et al., 2005]. At the same time, infrared technology is highly dependent from the temperature, and the separation between background entities and foreground items can be problematic.

In this paper, we focus on the use of the audio information for surveillance purposes. This mean is less popular than the other modalities, especially in public surveillance systems, likely due to privacy issues, but it has been considered in many prototypical and research approaches [Pham and Cousin, 2013].

Recording of audio stream provides a rich and informative alternative sensory modality both in indoor and outdoor environments. Among them, home interiors [Zieger et al., 2009; Vacher et al., 2004], offices [Harma et al., 2005; Atrey et al., 2006b], banks [Kotus et al., 2013], elevators [Radhakrishnan et al., 2005b; Chua et al., 2014], public transport vehicles [Pham et al., 2010; Rouas et al., 2006; Vu et al., 2006], railway stations [Zajdel et al., 2007], public squares [Valenzise et al., 2007], farms [Chung et al., 2013] or car parkings can by cited as particularly relevant for surveillance tasks, where audio can contribute consistently.

With respect to video sensors, audio sensors (as microphones) bear several appealing features:

- Audio stream is generally much less onerous than video stream and this fact encourages both the deployment of an higher number of audio sensors (also thanks to a lower unitary cost) and a more complex signal processing stage
- While standard cameras have a limited angular field of view, microphones can be omnidirectional, i.e., with a spherical field of view
- Due to the bigger involved wavelenght, many surfaces allow specular reflections of the acoustic wave, permitting to acquire audio events also when obstacles are present along the direct path (even if this fact can be a drawback for sound localization task)
- Illumination and temperature are not issues for the audio processing
- Several audio events important for surveillance task like shouts or gunshots have little or no video counterpart
- From the psychological point of view, audio monitoring is experienced as less invasive than video monitoring, and can be a valid substitute in all situations in which privacy concerns are stressed [Chen et al., 2005]. To this end, it is important to remark that audio surveillance does not usually include automatic speech detection and recognition.

Despite automated audio surveillance is at its early steps, in the last decade a consistent amount of works have been published, and this paper contributes in providing the first systematic review. Several different taxonomies
can be proposed to organize all the approaches, based either on the algorithmic nature of a method or its particular applicative scenario. In this paper, we organize the review by considering the different tasks where audio information can be exploited, in a typical surveillance framework. Borrowing from the more established and widespread video surveillance literature, which organizes the processing starting from low-level to high-level processing, four typical tasks have been identified: background subtraction, event classification, object tracking and situation analysis, see Fig. 1.

Background subtraction is usually the first stage in a surveillance system, which aims at filtering the raw data, pruning away useless information, and separating expected data (the background) for interesting/unexpected items (the foreground). In video surveillance, background subtraction usually highlights moving objects, suppressing the visual content of the scene [Cristani et al., 2010]. The goal of audio background subtraction is analogous: to discard the expected audio signal, highlighting interesting audio events, that can be successively modeled and categorized [Cristani et al., 2004a].

While in video surveillance the background is often mostly static or slowly varying, the audio background exhibits an higher degree of variability due to the intrinsic time-varying nature of many sounds. Moreover, the audio signal is more complex due to the superimposition of multiple audio sources and to the multi-path propagation resulting in echo and reverberation effects. Whereas in the video analysis the background subtraction is limited to marking some pixels values, producing foreground masks, here the task is much more complex, incorporating source separation and filtering issues. Furthermore, the signal to noise ratio (SNR) is typically lower in an audio signal than in a video one, especially if the microphone is not very close to the acoustic source. All these issues make the audio background subtraction problem a challenging task.

Once the foreground is detected, the second stage in a surveillance system consists in characterizing the atomic entities lying therein. In the video analysis, this operation consists in the classification of objects of interests into a set of predefined categories, like pedestrians, vehicles, animals and so on. This happens usually by employing heterogeneous set of features, fed into statistical classifiers. In the audio realm, basic entities of interests are
called *events*, defined by temporal windows and characterized by a particular spectral blueprint. Apart from the surveillance context, classification and separation of audio signals in a given environment is mainly labeled as Computational Auditory Signal Analysis (CASA) [Bregman, 2005].

The third typical task in video surveillance is localization and tracking of a moving object or person in a scene, producing spatial trajectories that can be employed afterwards for analyzing structured activities. In the audio context, the spatial tracking can be carried out only if spatialization is performed: actually, the use of multiple microphones placed in different locations allows to spatially sample the audio wavefield so recovering spatial information about the direction of arrival of an audio wavefront [Choi et al., 2005], the location of an audio source [Huang et al., 2001] or even an acoustic map of the environment. In the latter case, the microphone array is used as an acoustic camera in order to obtain two or even three dimensional images of the acoustic intensity [O’Donovan et al., 2007].

In this way, the tracking problem can be decomposed in a sequence of spatial localization tasks, in which a particular sound source is localized over a short temporal window. Alternatively, localization can be considered as an input for a standard tracking algorithm, like Kalman filter or Particle filter, which relies on an underlying model of the source location dynamic and measurement noise. Multipath propagation and low SNR make the localization and tracking problem harder than the related video counterpart and the spatial resolution usually achieved can not reach the video one.

Finally, once multiple significant sounds are detected, classified and possibly tracked, all the information can be used together and combined into a higher analysis stage, in order to understand the nature of the scenario monitored. In video surveillance, this step is characterized by activity analysis: once objects have been characterized and tracked, this step provides a global characterization of what is happening in the monitored scene.

In the audio counterpart, this step is strictly linked to the so called Computational Auditory Scene Recognition (CASR) [Peltonen et al., 2002], [Cowling and Sitte, 2003], aimed at the overall interpretation of an acoustic scene rather than the analysis of single sounds: this task is usually known as situation analysis. The situation analysis, due to its inherent complexity, has been addressed by relatively few approaches in literature, but it represents the final goal for an automatic surveillance system able to extract semantic information from the monitored scene.

The choice of a proper set of audio features is a crucial step, affecting all the four tasks above described. The complex nature of audio signal has encouraged the use of more sophisticated features in comparison to the video case. This led to a proliferation of cues mostly targeted to specific sounds or acoustic environments, but up to now it is not clearly established what set of features is the most performing in a general case. This fact is due partly to the lack of audio datasets taken as benchmarks by the audio community on which features can be tested, and partly to the fragmentation of the topic in the scientific literature among different fields as acoustic signal processing, pattern recognition, multimedia, etc.

As the information brought by audio sensors is in large measure complementary to the other modalities, a multimodal surveillance system can provide a more accurate and reliable performance. In this paper, in addition to audio-only surveillance tasks, we will also address multimodal, mostly audio-video, surveillance applications.

Multimodal tasks will be presented exploiting the taxonomy above introduced, since crossmodal fusion can also happen at different processing levels, low and high. In addition, different sensory modalities can be generally fused at three different stages [Atrey et al., 2010]: raw data-level, feature-level or decision-level. Our taxonomy will take into account this categorization too, in order to give the reader a precise snapshot of how the audio information interact with the other modalities. Nevertheless, it is worth noting that in the audio and video fusion,
the raw data-level fusion is very rarely addressed due to the extreme difference in the two signals properties, while
the other two hold sistematically.

The present paper is structured as follows: after the Introduction, Sections from 2 to 5 describe the methods
devoted to background subtraction (Section 2), audio event classification (Section 3), audio source localization and
tracking (Section 4) and situation analysis (Section 5). In Section 6 audio features, often common to the above
tasks, are classified in a general taxonomy and described in detail. Finally, in Section 7 some conclusions are
drawn.

2 Background subtraction

Analogously to video [Cristani et al., 2010], audio background can be identified by the recurring and persistent audio
feature that dominates the portion of signal. Foreground sounds can be defined by the departure from the typical
background features.

The background subtraction approaches can be divided into those techniques which operate a simple thresh-
olding on the energy signal, implying that the distribution of audio features assumed as background is monomodal,
and those approaches which perform a multimodal analysis, assuming that the audio background could be formed
by different audio patterns that are repeated over time (see Fig. 2).

Figure 2: General taxonomy of the audio background subtraction methods, with pros and cons added for each
category of approach.

2.1 Background subtraction by monomodal analysis

The most simple and intuitive parameter that can be used to discriminate a foreground sound is the signal energy.
Many sounds of interest, especially the impulsive ones like gunshots, door slams, cries cause an abrupt change
in audio volume with respect to the typical auditory scenarios. Following this principle, some works proposed
to segment the audio stream into fixed-length windows and discard all the windows whose energy is below a
predefined threshold [Azlan et al., 2005] [Smeaton and McHugh, 2005]. Obviously, a criterion is needed to fix
such threshold. The simplest way consists in analyzing a long portion of audio stream containing only background
and fixing the threshold so as to capture louder sound signals [Azlan et al., 2005], or, alternatively, fixing the threshold proportionally to the average energy level [Smeaton and McHugh, 2005].

If the background average energy is known to vary deterministically, e.g. during nighttime or daytime, the threshold can be tuned accordingly [Smeaton and McHugh, 2005].

On the contrary, if the background energy variation in time is not predictable it is necessary to adopt an adaptive threshold. In [Dufaux et al., 2000], the signal energy, estimated over a number of temporal windows, is median-filtered, and the output of the filter is subtracted from the energy. The result is normalised, emphasizing the relevant energy pulses. Finally an adaptive thresholding, depending on the standard deviation of a past long-term windowed energy sequence, is applied. A scheme summarizing the BG subtraction by thresholding is reported in Fig. 3.

To cope with foreground signals of variable duration and bandwidth, in [Moragues et al., 2011] energy thresholding is applied in the time-frequency domain, that is, in parallel at different time scales and on different frequency bands. A foreground signal is considered to be detected if in at least one of the scale-frequency bins the energy is higher than the threshold.

The previous methods adopt a signal segmentation in block of fixed length: this fact may chop a significant audio event into two adjacent blocks so making more difficult the subsequent processing stages. To avoid this drawback, in [Rouas et al., 2006] an Autoregressive Gaussian model is employed to predict the current audio sample on the base of the previous ones: if the prediction error is higher than a certain value it is assumed that around that sample a different sound arose and the temporal window boundary is fixed. Subsequently, each temporal window is classified into background or foreground on the base of an adaptive threshold.

The segmentation problem is extensively treated in [Kemp et al., 2000], where three different approaches...
are compared: energy-based, model-based and metric-based segmentation. Energy-based segmentation, the less performing one, puts simply a boundary every time a silence period between two audio events is detected.

Model-based segmentation trains a statistical model for every predefined class of audio sound and puts a boundary every time adjacent audio segments are classified into different classes.

Metric-based segmentation evaluates the distance between two adjacent segments by means of a pseudo-metric like Kullback-Leibler divergence, putting a boundary if the distance is higher than a threshold. Interestingly, the threshold can be determined by an information theoretical measure like Minimum Description Length or Bayesian Information Criterion.

Finally, in [Kemp et al., 2000] a hybrid strategy, which outperforms the previous methods is proposed: first a metric based clustering of short segments is performed; secondly, each cluster is considered as an audio class, whose segments are employed to train a statistical model, which is subsequently used to segment the audio stream.

Energy thresholding yields in general limited performance in complex environments where high energy sounds may periodically appear yet being part of the background, e.g. car engines in a car parking. In these cases, to improve the background subtraction it is useful to extract other features from the signal, besides the energy, and examining the departure of their values from the typical ones in order to detect foreground events. A comprehensive exposition of acoustic features employed in audio surveillance can be found in Section 6. Differently, in Table 1 features employed in background subtraction, classified according to the taxonomy described in Section 6, and the corresponding references are reported. Similar tables are reported in subsequent sections for the other tasks.

In [Istrate et al., 2006], wavelet coefficients are extracted from the signal and the energy of the upper coefficients, corresponding to the higher frequencies, is compared with an adaptive threshold. The rationale is that background noise has mostly low frequency components whereas foreground tends to be more impulsive.

In [Harma et al., 2005], the differences between the frequency bins of the Fourier transform of the current window and the mean Fourier Transform are calculated. Then, in order to improve the detection of narrow band audio events, the difference between the maximum peak and the variance of the incremental frequency bins is evaluated and compared to a threshold.

In [Couvreur et al., 2008], the selected features are mainly drawn from psycho-acoustical findings on the human auditory attention system; three alternative normalization methods are proposed and a final threshold is adaptively determined by minimizing the sum of the intra-class variance over a given temporal window, where the two classes represents background and foreground sounds.

### 2.2 Background subtraction by multimodal analysis

In highly complex audio environments, the assumption that features values related to background are spread around a single value, i.e. that background feature values can be modeled as a unimodal distribution, may not hold anymore. In such a case, background modeling with multimodal distributions may provide better results in term of background/foreground discrimination.

A widely used multimodal model is the so called Gaussian Mixture Model (GMM). Given a vector of feature extracted from the signal their joint probability density function can be modeled as a sum of multidimensional gaussian functions with different mean vectors and covariance matrices. The underlying idea is that each sound source corresponds to a Gaussian distribution of the mixture. Usually, in order to cope with an adaptive background, the mixture parameters are updated at each iteration using the current feature vector. Different criteria have been proposed to both update the mixture parameters and to discriminate between background and foreground given the mixture model.

In [Radhakrishnan et al., 2005a], the GMM is trained over a background audio sequence using the Minimum Description Length method; subsequently, the probability of the current feature vector conditioned to the back-
ground GMM is calculated and compared to a predefined probability threshold. If the probability is lower than this threshold the observation is judged to be generated from a different probability distribution and so classified as foreground. Instead, if the current observation is classified as background, the GMM is updated by building a second GMM on the base of the most recent observations and fusing together the two GMMs by pairing and merging the most similar mixture components.

In [Cristani et al., 2004b], the most likely mixture component that matches the current observation is found, choosing among a set of Gaussian components which are ranked in descending order with respect to their weight and divided by their variance. If the sum of the weights until the matched component is higher than a threshold the observation is labeled as foreground. If no match is found, as the observation is too far from every component, a new component is created substituting the one with the lowest weight. The parameters of the matched component, and all the weights are then updated, irrespective of the BG/FG classification. Differently from [Radhakrishnan et al., 2005a], the GMM in [Cristani et al., 2004b] models explicitly both the background and the foreground. Another difference is that in [Cristani et al., 2004b] a uni-dimensional GMM is used for each feature (in that case the energy in a given frequency band) and the background/foreground classification is carried out independently for each feature. This choice allows a computational advantage but assumes the features to be independent from each other, which is typically a strict assumption.

In [Moncrieff et al., 2007], a multidimensional GMM is employed analogously to [Radhakrishnan et al., 2005a], but some solutions are proposed to deal with quite complex background environments. First, fragmented background states are unified by means of an entropy-based approach in order to avoid erroneous foreground classifications. Then the number of states is adaptively tuned according to the background complexity, and finally a cache is introduced to retain in memory the background components related to rapidly changing sounds. In [Ito et al., 2009], the problem of rarely occurring background events is faced by means of a multi-stage GMM approach. In the training phase, the first stage GMM is trained over all the background samples available: the samples with resulting lower likelihood are used to train the second stage GMM and so on. In the testing phase a sample is definitely classified as foreground only if it is classified as foreground in each of the GMM stages.

A problem not addressed by the previous methods is the case of slowly varying and gradual foreground, like a plane passing overhead. To overcome this drawback, in [Chu et al., 2009b] a semi-supervised method is adopted. First, both background and foreground are trained offline exploiting previous knowledge of specific foreground sounds; secondly, a separate model detects the changes in the background and it is finally integrated with the offline audio prediction models, that act as prior probabilities, to decide on the final foreground/background discrimination.

A different semi-supervised model, which specifically addresses the problem of detecting rare and unexpected foreground audio events, is proposed in [Zhang et al., 2005]. Usual events, i.e. the background, are used to train offline an Hidden Markov Model (HMM); unusual event are learned online iteratively adapting the usual event model to unusual events by means of Bayesian Adaptation Technique. In this way it is possible to supply to the scarcity of unusual events in the offline training phase.

A more challenging situation is faced in [Ntalampiras et al., 2011], where the class of anomalous events is assumed to be unbounded and only normal events, i.e. the background, are available in the training phase. Under the hypothesis that anomalous events are significantly different from the normal ones, this approach does not model explicitly the formers but labels as abnormal each event whose likelihood is lower than the lowest likelihood of
**Problem:** Background subtraction by multimodal analysis

The normal events belonging to the training set. Modeling of the normal event class is performed by means of three methods: GMM, HMM and GMM clustering. In the latter, several GMMs, each one corresponding to an audio recording of normal events, are modeled. A matrix of distances between the GMMs is computed using Kullback-Leibler similarity measure, and the GMM with the minimum distance from all the others is chosen as representative of the whole class of normal events. This approach showed better performance in case of complex environments with many different normal sounds in respect to standard GMM and HMM.

The same scenario of [Ntalampiras et al., 2011] is faced in [Lecomte et al., 2011], where One-Class Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel is adopted to model the background sound scene and to detect the onset of anomalous events. One-Class SVM builds an hyperplane separating the feature space into background and foreground regions. Since only background is available in the learning phase, the optimization criterion consists in the trade-off between the empirical classification error on the background class and the volume of the feature space corresponding to the background. The smaller the volume the simpler the background model and the lower the structural risk of false background classifications. As GMM before, One-Class-SVM with RBF models the PDF over the feature space related to background class as a mixture of Gaussian functions, but has better generalization properties thanks to the volume penalty, automatically learns from data the proper number of mixtures and does not suffer from local minima in the learning phase. However, if online learning is required
One-Class-SVM is less suited than GMM, mainly due to the higher computational load.

See Fig. 4 for a graphical summarization of the models assuming the BG is multimodal.

Besides energy changes, audio events deserving attention are often characterized by a rapid movement of the sound source location, whereas audio background has a more static spatial characterization. Based on this principle, in [Hang and Hu, 2010] sound source location is estimated by looking at interaural Level Difference (ILD) between a couple of microphones, followed by sound source velocity is estimation as the difference of ILDs between subsequent audio frames (ΔILD). To cope with multiple objects moving in different directions the ΔILD is evaluated at several frequency bands and a final threshold is set multiplying the ΔILD mean by the ΔILD variance.

3 Audio events classification

The recognition of audio events depends usually on a classification strategy: first, features are extracted from class-labeled audio signals to learn a specific classifier in an off-line fashion; second, the trained classifier is employed to recognize unseen audio samples. A simple taxonomy, displayed in Fig. 5, subdivides classification methods in generative and discriminative; in the former case, each class of audio events has its own classifier, trained on samples of the same class. Usually, generative classifiers are defined into a Bayesian context, so that the classification score assigned to a test sample is a posterior probability. Given a test sample, multiple classifiers are evaluated (one for each class), and the highest a posteriori probability determines the chosen classifier, and thus the chosen class. Among generative models Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM) are the most widespread in the audio classification field. In particular, HMMs are suited to model the

<table>
<thead>
<tr>
<th>Class</th>
<th>Short Description</th>
<th>Reference</th>
</tr>
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<tbody>
<tr>
<td>Time</td>
<td>Zero-crossing rate</td>
<td>[Couvreur et al., 2008; Moncrieff et al., 2007].</td>
</tr>
<tr>
<td></td>
<td>Waveform minimum and maximum</td>
<td>[Ntalampiras et al., 2011].</td>
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<tr>
<td></td>
<td>Autocorrelation coefficients</td>
<td>[Couvreur et al., 2008].</td>
</tr>
<tr>
<td>Frequency</td>
<td>Fourier coefficients</td>
<td>[Harma et al., 2005].</td>
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<tr>
<td></td>
<td>Fundamental frequency</td>
<td>[Ntalampiras et al., 2011].</td>
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<tr>
<td></td>
<td>Spectral flatness</td>
<td>[Ntalampiras et al., 2011].</td>
</tr>
<tr>
<td>Cepstrum</td>
<td>MFCC</td>
<td>[Kadhakrishnan et al., 2005a; Moncrieff et al., 2007; Ito et al., 2009; Ntalampiras et al., 2011; Chu et al., 2009b; Zhang et al., 2005].</td>
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<tr>
<td></td>
<td>MFCC derivatives</td>
<td>[Moncrieff et al., 2007].</td>
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<tr>
<td>Time-frequency</td>
<td>Wavelet coefficients</td>
<td>[Istrate et al., 2006; Moncrieff et al., 2007].</td>
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<tr>
<td></td>
<td>Mean and Std of frequency and scale of Gabor atoms selected by Matching Pursuit</td>
<td>[Chu et al., 2009b].</td>
</tr>
<tr>
<td>Energy</td>
<td>Signal energy over a fixed window</td>
<td>[Azlan et al., 2005; Smeaton and McHugh, 2005; Dufaux et al., 2000; Kemp et al., 2000; Cristani et al., 2004b; Rouas et al., 2006; Ito et al., 2009; Moncrieff et al., 2007]. [Hang and Hu, 2010], [Hu et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Interaural Level Difference</td>
<td></td>
</tr>
<tr>
<td>Biologically or</td>
<td>Spectral features based on Gammatone filter bank: spectral moments, slope,</td>
<td>[Couvreur et al., 2008].</td>
</tr>
<tr>
<td>perceptually driven</td>
<td>decrease, roll-off, variation, flatness etc.</td>
<td></td>
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<tr>
<td></td>
<td>Intonation and Teager Energy Operator (TEO) based features</td>
<td>[Kemp et al., 2000].</td>
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<tr>
<td></td>
<td>High-order Local Auto-Correlation (HLAC)</td>
<td>[Ntalampiras et al., 2011].</td>
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<td></td>
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<td>[Sasou, 2011].</td>
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Table 1: Features employed in background subtraction: first column indicates the feature class according to the taxonomy defined in Section 6, second column reports feature names and third column reports references of works where they are employed.
temporal variation of the feature vector over consecutive frames, allowing a more accurate modeling of each sound class. Transient sounds, such as gunshots or screams have typical temporal signatures which can be captured with left-right HMMs [Rabaoui et al., 2009], whereas stationary sounds can be efficiently modeled by ergodic HMMs.

On the other hand, discriminative models try to directly construct the best hyper-surface of separation in the feature space, dividing it into subspaces segregating the most training samples for each class. Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are the most common discriminative models employed in the audio classification task.

Concerning audio event classification, the state of the art is far from conclusive toward a common framework as, for example, for speech/speaker recognition where the classifier and the feature extraction process is rather established (i.e., GMMs and HMMs as classifiers and variations of spectral features as input [Ntalampiras et al., 2009b]). In fact, the direct application of state-of-art techniques for speaker or musical instrument recognition to environmental sounds provides in general poor performance [Cowling and Sitte, 2003]. The challenge lies here on the fact that it is difficult to foresee all the kinds of sounds which could be present in a given environment, and often very little samples of unusual sounds are available to properly train a classifier.

Furthermore, differently from speech, generic sound events may have very different characteristics including duration, spectral content and volume with respect to background noise. Finally, the microphone(s) can be located far from the acoustic source, therefore implying strong echoes and reverberations (especially in indoor environments) and low SNR at the received signal. For these reasons, the findings from works not explicitly devoted to surveillance tasks [Guo and Li, 2003; Lin et al., 2005; Lu et al., 2002; Li, 2000] cannot be straightforward extended

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Figure 5: Taxonomy for the classification methods, with pros and cons added for each category of approach.
to the audio surveillance field, despite useful ideas can certainly be borrowed.

In audio surveillance, several works recently presented dealt with a limited set of sound classes. In [Ellis, 2001], an ANN is used to detect the presence of several alarm sounds, treated as a single class, against generic ambient noise. In such a case, audio classification closely resembles background subtraction, where foreground is predefined offline and encompasses a specific sound type.

A similar task was faced by [Clavel et al., 2005], in which the audio events of interest are gun shots. Two approaches are adopted: in the first one, a couple of GMMs is trained offline so as to model shot class and “normal” audio class; in the second one, several GMMs, one for each kind of shot (e.g. gun shot, rifle shot etc.), are trained offline and used to implement a series of binary classifiers (normal sound vs. specific shot) and the final decision on shot is taken if at least one of the classifiers detects a kind of shot. The latter approach allows to significantly improve the recall at the expense of a slight decrease in the precision. In [Gerosa et al., 2007], two classifiers based on GMMs run in parallel in order to detect respectively scream and gun shot against normal sound and the decision that an harmful event (either scream or gunshot) has occurred is taken computing the logical OR of the classifiers.

A comparative analysis of several classifiers, including Learning Vector Quantization, GMM, ANN, Dynamic Time Warping and Long-Term Statistics, coupled with different features, was performed in [Cowling and Sitte, 2003]. The best results with a 70% of samples correctly classified were obtained with Dynamic Time Warping, but the small size of training and test sets does not allow to draw a general conclusion.

If the number of classes increases, a hierarchical classification scheme, composed of different levels of binary classifiers, generally achieves higher performance than a single level multiclass classifier. Following this principle, in [Atrey et al., 2006b] five sound classes (talk, cry, knock, walk, run) are discriminated by a GMM classification tree whose intermediate nodes comprehend vocal events, non vocal events and footsteps. A similar approach was used in [Ntalampiras et al., 2009a].

Moving to the discriminative classifiers, hierarchical approaches were followed in [Zhao et al., 2010] using binary SVMs, and in [Abu-El-Quran et al., 2006] using ANN. The same hierarchical scheme is employed in [Rouas et al., 2006], but in this case only two final classes shout/non-shout are considered. The tree is aimed at progressively excluding background noise, non-voice sound and non-shout voice, so yielding a consistent improvement in precision (lower false alarm rate) with respect to a single level classification. In [Choi et al., 2012], the first-level classifier subdivides sounds into harmonic ones and non-harmonic ones. The former are subsequently classified into voice and non-voice, and the latter are classified into low brightness (like glass breaking) and high brightness (like gunshots).

As SVM classification was originally developed for binary discrimination, the extension to multi-class classification has been achieved by a set of one-against-one or one against-all strategies: in the former case \( N \cdot (N - 1)/2 \) SVMs, \( N \) being the number of classes, are trained with data related to each couple of classes, while in the latter case \( N \) SVMs are trained taking into account all the data available. In both cases, the final classification is achieved by a voting procedure. An interesting alternative is reported in [Rabaoui et al., 2008], where \( N \) One-Class SVMs are trained with data belonging to just one class for each SVM. In the testing phase, a dissimilarity measure is calculated between the current data sample and each 1-class SVM, and the sample is assigned to the class yielding the lowest dissimilarity value. Other than the computational advantage in the training phase, this approach provides a natural way to classify as unknown a given data. If the dissimilarity measure is higher than a predefined threshold for all One-Class SVMs, the data is classified as not belonging to anyone of the predefined classes.

The complementary strengths of generative and discriminative models can be exploited by hybrid strategies.
For example, in [Zieger and Omologo, 2008] a GMM-SVM couple is instantiated for each class. Given a data sample a combined score is produced by each GMM-SVM couple by a weighted sum of normalized scores related to GMM and SVM, with weights inversely proportional to the classification error rate. Finally, the classification is performed on the basis of the highest combined score. A more elaborate scheme is proposed in [Zhuang et al., 2010] for joint segmentation and classification of an audio stream. The first stage, composed of an ANN and an HMM in cascade, provides segment boundaries and Maximum a Posteriori (MAP) probabilities for each class. The probabilities are used to train a GMM model whose parameters are finally fed to an SVM that provides a refined estimation of the class labels for each segment.

The recorded sounds of interest are normally superimposed to environmental and electronic noise which determines a given SNR. If the classification is aimed at distinguishing between background noise and a given sound type, the SNR in training phase can affect the trade-off between precision and recall in the testing phase: high SNR yields a statistically better precision at the expense of recall and vice-versa as shown in [Clavel et al., 2005]. Moreover, the change of SNR between training and testing phase can negatively impact on the overall classification performance. To overcome this drawback in [Dufaux et al., 2000] several noise levels were superimposed to the training sound samples to build an array of classifiers (GMM or HMM), each one targeted to a particular SNR. In the testing phase, after a coarse SNR estimation the classifiers with the nearest SNR level was applied. A similar approach to the problem was pursued in [Rabaoui et al., 2009] and [Choi et al., 2012], where a single classifier was trained replicating the data with different SNRs (the so called multi-style training). On Table 2, a summarizing scheme which focuses on the several different audio events (so far described), and related classification methods is reported. Moreover on Table 3 features employed for audio event classification and related references are displayed.

4 Source localization and tracking

4.1 Audio Source Localization

When localizing a sound source, a single microphone samples the whole propagating wavefield in the scene, producing a one-dimensional electric signal as output. Therefore, differently from a video sensor, the spatial location of the source emitting the sound can not be inferred, unless knowing a priori the emitted signal, the environment characteristics, and the relation between the source location and the cues of the acquired signal, e.g. energy and spectral distribution. As an example, knowing the energy of the emitted sound and supposing to be in free space, one could estimate the source distance from the microphone by measuring the energy of the acquired signal. Moreover, if the microphone is not omnidirectional, also the sound direction of arrival could be in line of principle estimated. However, in a general case, the information on the spatial environment and the audio scene is quite limited or not available at all. Therefore, it is mandatory to rely on multiple sensors, either homogeneous or heterogeneous. In the first case, a number of microphones is deployed in a given spatial configuration, obtaining a microphone array or a microphone network, in order to spatially sample the acoustic wavefield. From the set of acquired signals, a panoply of techniques [Van Trees, 2002; Johnson and Dudgeon, 1992] based on array signal processing can be applied to estimate the source location. In the latter case, the single microphone is associated to a natively spatial sensor, typically a video camera, trying to infer the sound source spatial location by exploiting temporal correlations between pixel changes in the visual image, likely caused by the object emitting sound, and sound cues. The two previous approaches can be combined together, fusing the spatial information provided by

1Recently Acoustic Vector Sensors (AVS) have been employed in a surveillance context [Kotus et al., 2014]: differently from microphones a single AVS is able to measure the sound direction of arrival; however the diffusion of such kind of devices is to date quite limited.
<table>
<thead>
<tr>
<th>Event Typology</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alarms, sirens, klaxons</td>
<td>Left-right HMM [Li and Ma, 2009], discriminative GMM [Kim and Ko, 2011], discriminative GMM [Kim and Ko, 2011], ANN [Ellis, 2001]</td>
</tr>
<tr>
<td>Ambient</td>
<td>Discriminative GMM [Kim and Ko, 2011], GMM [Vu et al., 2006]</td>
</tr>
<tr>
<td>Applauding</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008], left-right HMM [Li and Ma, 2009]</td>
</tr>
<tr>
<td>Beating (light)</td>
<td>Bayesian networks + KNN [Giannakopoulos et al., 2010]</td>
</tr>
<tr>
<td>Car braking</td>
<td>Left-right HMM [Li and Ma, 2009]</td>
</tr>
<tr>
<td>Car engine, bus engine</td>
<td>Left-right HMM [Li and Ma, 2009]</td>
</tr>
<tr>
<td>Chair moving</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Cheer</td>
<td>Left-right HMM [Li and Ma, 2009]</td>
</tr>
<tr>
<td>Coins dropping</td>
<td>GMM, HMM, [Cowling and Sitte, 2003], Learning vector quantization, ANN, SOM [Cowling and Sitte, 2003]</td>
</tr>
<tr>
<td>Coughing</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Crashing</td>
<td>GMM classification tree [Atrey et al., 2006b] GMM [Ntalampiras et al., 2009b], [Pham et al., 2010], Binary SVM [Zhao et al., 2010], ANN [Abu-El-Quran et al., 2006], Discriminative GMM [Kim and Ko, 2011]</td>
</tr>
<tr>
<td>Crying</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008], discriminative GMM [Kim and Ko, 2011]</td>
</tr>
<tr>
<td>Door opening/slamming</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008], GMM, HMM, [Cowling and Sitte, 2003], [Menegatti et al., 2004] GMM classification tree [Atrey et al., 2006b], [Ntalampiras et al., 2009b], hybrid GMM/SVM [Zieger and Omologo, 2008], discriminative GMM [Kim and Ko, 2011], Learning vector quantization [Cowling and Sitte, 2003], SVM [Atrey et al., 2006b], ANN, SOM [Cowling and Sitte, 2003], [Abu-El-Quran et al., 2006]</td>
</tr>
<tr>
<td>Footsteps</td>
<td>GMM, HMM, [Cowling and Sitte, 2003], [Atrey et al., 2006b], [Menegatti et al., 2004] GMM classification tree [Atrey et al., 2006b], [Ntalampiras et al., 2009b], hybrid GMM/SVM [Zieger and Omologo, 2008], discriminative GMM [Kim and Ko, 2011], Learning vector quantization [Cowling and Sitte, 2003]</td>
</tr>
<tr>
<td>Glass breaking</td>
<td>GMM, HMM, [Cowling and Sitte, 2003], Learning vector quantization, ANN, SOM [Cowling and Sitte, 2003]</td>
</tr>
<tr>
<td>Gunshots</td>
<td>GMM [Clavel et al., 2005], [Gerosa et al., 2007], Bayesian networks + KNN [Giannakopoulos et al., 2010]</td>
</tr>
<tr>
<td>Jangling keys</td>
<td>GMM, HMM, [Cowling and Sitte, 2003], Hybrid GMM/SVM [Zieger and Omologo, 2008], Learning vector quantization [Cowling and Sitte, 2003], ANN, SOM [Cowling and Sitte, 2003]</td>
</tr>
<tr>
<td>Keyboard typing</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Knock</td>
<td>GMM classification tree [Atrey et al., 2006b] GMM [Ntalampiras et al., 2009b], Atrey et al 2006, hybrid GMM/SVM [Zieger and Omologo, 2008], Binary SVM [Zhao et al., 2010], ANN [Abu-El-Quran et al., 2006]</td>
</tr>
<tr>
<td>Laughing</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008], left-right HMM [Li and Ma, 2009]</td>
</tr>
<tr>
<td>Music</td>
<td>Left-right HMM [Li and Ma, 2009], Bayesian networks + KNN [Giannakopoulos et al., 2010]</td>
</tr>
<tr>
<td>Paper rustling</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Phone ringing</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Running</td>
<td>GMM [Atrey et al., 2006b]</td>
</tr>
<tr>
<td>Scream, Shouting</td>
<td>GMM [Gerosa et al., 2007], [Atrey et al., 2006b] [Vu et al., 2006], hierarchical GMM [Rouas et al., 2006]</td>
</tr>
<tr>
<td>Spoon/cup jingling</td>
<td>Hybrid GMM/SVM [Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Tag ticket</td>
<td>GMM [Vu et al., 2006]</td>
</tr>
<tr>
<td>Talk, voice</td>
<td>GMM classification tree [Atrey et al., 2006b] GMM [Ntalampiras et al., 2009b], Bayesian networks + KNN [Giannakopoulos et al., 2010], Binary SVM [Choi et al., 2012], one-class SVM [Rabaoui et al., 2008]</td>
</tr>
<tr>
<td>Walk</td>
<td>GMM classification tree [Atrey et al., 2006b] GMM [Ntalampiras et al., 2009b], [Atrey et al., 2006b], left-right HMM [Li and Ma, 2009], Binary SVM [Zhao et al., 2010], ANN [Abu-El-Quran et al., 2006]</td>
</tr>
<tr>
<td>Wood snapping</td>
<td>GMM, HMM, [Cowling and Sitte, 2003], Learning vector quantization, ANN, SOM [Cowling and Sitte, 2003]</td>
</tr>
</tbody>
</table>

Table 2: Events typologies and related classification strategies adopted in the literature.
<table>
<thead>
<tr>
<th>Class</th>
<th>Short Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Zero Crossing Rate (ZCR)</td>
<td>[Valenzise et al., 2007; Vacher et al., 2004; Rabaoui et al., 2009, 2008; Istrate et al., 2006; Gerosa et al., 2007; Atrey et al., 2006b; Choi et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Correlation-based features: Periodicity, correlation slope, decrease and roll-off</td>
<td>[Valenzise et al., 2007; Gerosa et al., 2007].</td>
</tr>
<tr>
<td></td>
<td>Pitch range features: calculated from short time autocorrelation function</td>
<td>[Uzkent et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Waveform minimum and maximum</td>
<td>[Ntalampiras et al., 2009a].</td>
</tr>
<tr>
<td>Frequency</td>
<td>Fourier coefficients</td>
<td>[Zhu et al., 2010; Cowling and Sitte, 2003].</td>
</tr>
<tr>
<td></td>
<td>Spectral moments</td>
<td>[Valenzise et al., 2007; Gerosa et al., 2007; Clavel et al., 2005; Choi et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Spectral slope and decrease</td>
<td>[Valenzise et al., 2007; Gerosa et al., 2007].</td>
</tr>
<tr>
<td></td>
<td>Spectral roll-off</td>
<td>[Valenzise et al., 2007; Vacher et al., 2004; Rabaoui et al., 2009, 2008; Istrate et al., 2006; Gerosa et al., 2007; Choi et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Spectral flatness</td>
<td>[Ntalampiras et al., 2009a; Choi et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Spectral centroid</td>
<td>[Valcher et al., 2004; Rabaoui et al., 2009, 2008; Istrate et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>Pitch Ratio</td>
<td>[Abu-El-Quran et al., 2006]</td>
</tr>
<tr>
<td>Cepstrum</td>
<td>MFCC</td>
<td>[Ramos et al., 2010; Lee et al., 2010; Kim and Ko, 2011; Zieger and Omologo, 2008; Zhuang et al., 2010; Zhou et al., 2008; Zhao et al., 2010; Valenzise et al., 2007; Vacher et al., 2004; Rouas et al., 2006; Rabaoui et al., 2009, 2008; Istrate et al., 2006; Cowling and Sitte, 2003; Clavel et al., 2005; Chu et al., 2009a; Choi et al., 2012; Abu-El-Quran et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>MFCC derivatives</td>
<td>[Zieger and Omologo, 2008; Kim and Ko, 2011; Zhou et al., 2008; Rouas et al., 2006; Istrate et al., 2006; Gerosa et al., 2007; Choi et al., 2012; Abu-El-Quran et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>Homomorphic Cepstral Coefficients</td>
<td>[Cowling and Sitte, 2003].</td>
</tr>
<tr>
<td></td>
<td>Linear Prediction Cepstral Coefficients (LPCC)</td>
<td>[Rabaoui et al., 2009, 2008; Atrey et al., 2006b].</td>
</tr>
<tr>
<td>Time-frequency</td>
<td>Wavelet coefficients</td>
<td>[Rabaoui et al., 2009, 2008; Cowling and Sitte, 2003].</td>
</tr>
<tr>
<td></td>
<td>Discrete Wavelet Transform Coefficients (DWTC)</td>
<td>[Istrate et al., 2006; Vacher et al., 2004].</td>
</tr>
<tr>
<td></td>
<td>Mel Frequency Discrete Wavelet Coefficients (MFDWC)</td>
<td>[Rabaoui et al., 2008].</td>
</tr>
<tr>
<td></td>
<td>Gabor Atoms</td>
<td>[Chu et al., 2009a].</td>
</tr>
<tr>
<td></td>
<td>Short Time Fourier Transform</td>
<td>[Hoyn et al., 2005; Cowling and Sitte, 2003].</td>
</tr>
<tr>
<td></td>
<td>Trace transform applied to spectrogram</td>
<td>[Gonzalez, 2007].</td>
</tr>
<tr>
<td></td>
<td>Visual features applied to spectrogram</td>
<td>[Souli and Lachiri, 2011].</td>
</tr>
<tr>
<td></td>
<td>Local Autocorrelation of Complex Fourier Values (FLAC)</td>
<td>[Ye et al., 2010].</td>
</tr>
<tr>
<td>Energy</td>
<td>Signal energy</td>
<td>[Rouas et al., 2006; Clavel et al., 2005].</td>
</tr>
<tr>
<td></td>
<td>Log energy first and second derivatives</td>
<td>[Zieger and Omologo, 2008]</td>
</tr>
<tr>
<td>Biologically or perceptually</td>
<td>Log frequency filterbank</td>
<td>[Zhuang et al., 2010; Zhou et al., 2008].</td>
</tr>
<tr>
<td>driven</td>
<td>Narrow Band Autocorrelation Features</td>
<td>[Valero and Alias, 2012a].</td>
</tr>
<tr>
<td></td>
<td>Gammatone Cepstral Coefficients (GTCC)</td>
<td>[Valero and Alias, 2012b].</td>
</tr>
<tr>
<td></td>
<td>Linear Prediction Coefficients and derivatives (LPC)</td>
<td>[Rouas et al., 2006; Cowling and Sitte, 2003; Atrey et al., 2006b; Choi et al., 2012].</td>
</tr>
<tr>
<td></td>
<td>Perceptual Linear Prediction Coefficients and derivatives (PLP)</td>
<td>[Rouas et al., 2006; Rabaoui et al., 2009, 2008; Cowling and Sitte, 2003].</td>
</tr>
<tr>
<td></td>
<td>Intonation and Teager Energy Operator (TEO) based features</td>
<td>[Rabaoui et al., 2009, 2008].</td>
</tr>
<tr>
<td></td>
<td>Relative Spectral (RASTA) Perceptual Linear Prediction</td>
<td>[Ntalampiras et al., 2009a].</td>
</tr>
</tbody>
</table>

Table 3: Summary features for audio event classification: first column indicates the feature class according to the taxonomy defined in Section 6, second column reports feature names and third column reports references of works where they are employed.
microphone arrays and video cameras to achieve an increased robustness and performance. A general taxonomy of source localization methods is summarized in Fig. 6.

**Problem: Source localization and tracking**

![Diagram of source localization methods](image)

**Time delay**
- Pros: High spatial resolution
- Cons: Strict requirements: synchronized and calibrated microphones

**Energy ratio**
- Pros: Robust towards synchronization mismatch, Low sample rate, Suited for large scale microphone networks
- Cons: Sensitive to reverberation, Low spatial resolution

**Learning**
- Pros: Suited for complex audio environments, Do not require microphone geometric calibration
- Cons: Cumbersome training phase, Prone to local minima (depending on the algorithm)

**Multiple homogeneous sensors (microphones)**

**Multiple heterogeneous sensors**

**Microphone + Video camera**
- Pros: Exploits audio-video complementary cues
- Cons: Robust toward occlusions, sound interferences etc.

**Microphone array + Video camera**

Figure 6: General taxonomy of source localization: pros and cons are referred to energy-based (on the left) and learning-based methods (on the right).

Concerning sound source location estimation by a microphone array, an essential taxonomy is reported here, describing the pros and cons of each methodology. A first partition individuates the time-delay, energy-ratio and learning based methods. The first class, by far the richest and most investigated, exploits the fact that signal delay of arrival is proportional, in free space, to the distance between each microphone and the sound source. The second one relies on signal energy attenuation which is inversely proportional to the square of the distance from the source. Finally, the last one does not assume a particular propagation model but tries to extract features from the set of audio signals in order to learn a regression function linking the feature vector and the sound location. Time-delay-based methods can be in turn subdivided into three categories, as summarized in Fig. 7: Steered Beam-
• **Steered Beamforming.** A beamformer or beamforming algorithm denotes a technique devoted to spatially filter a wavefield originating from one or multiple sources. More specifically, the beamformer tries to attenuate as much as possible all the signals coming from different directions, while letting unaltered the signal coming from the direction of interest, known as **pointing or steering direction.** In its simplest version [Van Trees, 2002], known as delay-and-sum beamforming, the signal at each microphone is delayed in order to compensate for the propagation delay related to a given steering direction; after that, all the signals are summed together producing the beam signal, i.e. the beamformer output. The signal components related to the source in the steering direction will sum coherently, due to the delay compensation, while all the other components will sum uncoherently. Therefore, the beam signal will be representative of the signal of interest plus a residual sum of all the other signals attenuated. Steered Beamformer based methods evaluate the beam signal energy on a grid of directions covering all the space of interest and search for the maxima which should correspond to the direction of arrival of the sounds. With linear microphone array, the more widespread one, localization is limited to a single angle, e.g. elevation, while with planar or volumetric arrays the direction of arrival can be estimated in terms of both azimuth and elevation. If sources are located in the near field of the array also their distance from the array can be estimated, allowing a complete 3D localization. A set of variants to this method have been proposed, including Filter-and-Sum beamforming [Crocco and Trucco, 2014], where each signal is filtered by a predefined FIR filter, Phase Transform (PHAT) [DiBiase et al., 2001], consisting in a sort of frequency whitening aimed at improving robustness toward reverberation, and Maximum Likelihood reformulations [Zhang et al., 2008]. The main advantage of Steered Beamformer-based method is the robustness against environmental noise and reverberation, allowing acceptable performance even in complex scenes. The main drawbacks are the relatively poor spatial resolution and the significant computational cost, especially working with big arrays (50 – 100 microphones) and fine grid discretization.

• **High Resolution Spectral Estimation.** This class of methods [Choi et al., 2005; Chen et al., 2002] takes as input the cross-correlation matrix of the signals acquired by the array and directly extracts the directions of arrival or location of the signals, via autoregressive (AR), minimum variance (MV) or eigen-analysis techniques [Johnson and Dudgeon, 1992]. The main advantage of these methods is the high spatial resolution achieved in comparison with the Steered Beamforming techniques. However, a series of drawbacks, including the sensitivity to reverberation, the limited number of sources that can be localized at the same time and the need for long time windows over which the signals should be statistically stationary, make their use in the surveillance scenario quite limited.

• **Time Difference of Arrival Based.** In this class of methods [Huang et al., 2001; Brandstein and Silverman, 1997] the procedure is split in two steps. First, the Time Differences of Arrival (TDOA) at each couple of microphones are estimated, typically by peak search in cross-correlation functions; second, such TDOA are employed to infer the source positions, typically by geometric methods based on curve intersections or rank constraints of the matrix of microphone - sources distances. TDOA-based method are computationally not-demanding since the first step can be accomplished just on a subset of microphone couples, while the second one is intrinsically lightweight. Moreover just the estimated TDOAs have to be sent to a central processing unit, while the first step can be performed in a distributed manner close to each microphone couple. Finally, TDOA method can be adapted to work in complex environments, where a subset of microphones...
may be occluded with respect to the source, due to architectural barriers [Crocco et al., 2012; Gaubitch et al., 2013]. Such features make TDOA-based methods particularly suited for microphone networks, i.e. a set of microphones deployed at considerable distance each other and without a predefined geometric layout. In a surveillance scenario microphone networks represent often a more practical and cost saving solution in respect to microphone arrays, where microphones are densely packed in a costly, ad-hoc built, single device with a specific geometric structure. One issue related with microphone networks is the network geometric calibration: to this end, recent approaches have been developed, that allow joint source localization and network calibration [Crocco et al., 2012]. The main drawback of TDOA methods is however the information loss intrinsic to the two-step procedure, which may result in a sub-optimal solution. Moreover, some of the previous methods are based on the minimization of nonlinear functions that are prone to local minima. In addition, some methods are sensitive to reverberation, especially in presence of multiple sources.

Figure 7: Taxonomy for time-delay based localization methods

- **Energy ratio based methods.** These methods [Blatt and Hero, 2006; Sheng and Hu, 2005] are conceptually similar to the TDOA-based methods. In a first step, the signal energy ratio at each couple of microphones is evaluated; secondly the source location is estimated exploiting the relation between energy ratios and relative distances between microphones and source. Such techniques are generally adopted with microphone networks where the inter-microphone distances are sufficiently broad to allow substantial differences in the signal energies. Though their precision is generally inferior as compared to the three classes above based on
propagation delays, and despite they are sensitivity to reverberation, some practical advantages make their use quite common in the surveillance context: energy evaluation does not require high sampling rates, so decreasing the burden of data transfer in wireless sensor networks, and is robust toward synchronization mismatch. Moreover, if sounds are narrowband, energy-ratio-based method can consistently improve the performance of TDOA-based methods [Ho and Sun, 2008].

- **Learning Based methods.** This class of methods is based on a learning stage in which a set of features is extracted from the sound collected by the microphones and a classifier is trained in order to estimate the sound location. Such methods are comparatively less diffuse due to the difficulty in acquiring and annotating a reliable database of sounds encompassing all the range of possible locations, especially in uncontrolled environments. Moreover, the training phase needs to be repeated whenever the microphone array is moved in a different location. Nevertheless, learning-based methods allow to cope with complex environments implying strong reverberations, occlusions, nonlinear effects, deviations from the nominal parameters of the microphones, and in general all the deviations from the simple propagation and transduction model assumed by all the other methods. Moreover, local minima problems, arising in many of the previous methods, can be avoided by a learning strategy. The most common features adopted are Interaural Level Difference (ILD) and Interaural Time Difference (ITD), corresponding to energy ratio and TDOA among couple of microphones [Weng and Guentchev, 2001]. A common approach [Youssef et al., 2012; Willert et al., 2006; May et al., 2011], inspired by the human auditory system, consists in preprocessing the signals with a gammatone filter bank, or cochleogram, mimicking the human cochlea frequency response, and subsequently extracting ITD, ILD and IPD (Interaural Phase Difference) on each single output of the filter bank. Such bio-inspired approaches typically work with just a couple of microphones and consequently limit the localization to the horizontal plane [May et al., 2011], unless elevation-dependent frequency distortion induced by the reflections of a synthetic human head is taken into account [Youssef et al., 2012; Willert et al., 2006].

In Fig. 8 a 2D diagram illustrates the optimal working conditions for each class of localization methods based on microphone arrays above described. Finally, in Table 4 the set of features employed for audio localization is reported together with the related references.

### 4.2 Audio-visual source localization

Single microphone localization techniques work in synergy with an optical imaging device: many environmental sounds (including voice, car engines, glass breaks, dog barks) have a visual counterpart, i.e. the image region depicting the sound source usually experience pixel changes that are temporally correlated with the sound emission (a clear example is given by a moving car). Exploiting such correlation it is possible to filter out the image background and the foreground not associated to the acquired sound, localizing in this way on the image the target sound source. A widely used methodology is Canonical Correlation Analysis (CCA) aimed at projecting audio and video signal onto a common subspace in which their correlation is maximized, while by inverting the process it is possible to recover the pixels associated to the sound source. CCA has been improved by imposing sparsity constraints [Kidron et al., 2007] or working on intermediate feature representations [Izadinia et al., 2013] (MFCC for audio and pixel velocity and acceleration for video), rather than raw audio samples and image pixels.

In [Hershey and Movellan, 2000], sound location is performed by looking at the image regions for which the mutual information between video stream and audio signal is maximized. In [Smaragdis, 2003] Principal Component Analysis and Independent Component Analysis are applied in sequence to a compound vector of pixels and
audio power spectra, so that the audio-video stream is segmented into independent components, each one corresponding to a different sound source. Another approach performs sparse-coding using joint audio-visual kernels [Monaci et al., 2009] in order to learn bimodal informative structures from which the sound target location can be inferred. Finally, in [Barzelay and Schechner, 2010] a matching pursuit procedure is devised to localize multiple audio-video events: the adopted criterion is the temporal coincidence of audio and video onsets, the latter being evaluated by means of audio-visual features capturing strong temporal variations. The main limitation of these approaches is the audio-video matching ambiguity when multiple sounds and multiple moving objects occur at the same time. Moreover, they are unfeasible when no visual counterpart is present (e.g., a pipeline loss or a phone ring). It is interesting to note that the approaches above described can be considered as a particular kind of audio-video raw data fusion: the output of the fusion process is a pixel mask, function of time, selecting the “sounding” pixels.

<table>
<thead>
<tr>
<th>Class</th>
<th>Short Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Interaural Time difference</td>
<td>[Weng and Guentchev, 2001; Youssef et al., 2012; Willert et al., 2006; May et al., 2011].</td>
</tr>
<tr>
<td>Frequency</td>
<td>Interaural Phase difference</td>
<td>[Youssef et al., 2012].</td>
</tr>
<tr>
<td>Energy</td>
<td>Interaural Level difference</td>
<td>[Weng and Guentchev, 2001; Youssef et al., 2012; Willert et al., 2006; May et al., 2011].</td>
</tr>
</tbody>
</table>

Table 4: Features for audio localization: first column indicates the feature class according to the taxonomy defined in Section 6, second column reports feature names and third column reports references of works where they are employed.

### 4.3 Audio source tracking

Tracking of an audio target can be performed in a naive way, simply updating the target position detected at each audio frame, according to the output of the localization algorithm. Such procedure is obviously not robust with respect to localization errors due to interfering sounds and is adopted only in the context of audio-visual tracking.
Differently, standard tracking algorithms take into account the dynamic of the source and recursively estimate the source location on the basis of the previous and current measurements or observations [Arulampalam et al., 2002]. In particular, at frame $t$ the source location is predicted according to the evolution of the state dynamic, taking as initial condition the estimation at frame $t - 1$ (prediction step). Subsequently, the predicted location is updated with the observation at frame $t$ (update step).

The most simple tracking algorithm is the Kalman Filter, which, under assumptions of Gaussian noise and linear functions wrt to the state for both dynamic and measurement, provides statistically optimal estimations. Unfortunately, such conditions are rarely fulfilled in the audio context. For example, in [Strobel et al., 2001] the observation is given by the estimated azimuth angle and range provided by a microphone array, which are clearly nonlinear with the respect to the cartesian coordinates of the source location. For this reason, it is suggested to switch to the Extended Kalman Filter, based on local linearization of the observation function [Strobel et al., 2001].

In strong reverberation conditions, or in presence of impulsive disturbing sounds, the Gaussian assumption on the measurement noise does not hold anymore. In fact the observation function, given by a localization algorithm, will likely return a location quite far from the real source in a significant number of frames. In such a case, it is necessary to move to other algorithms able to handle arbitrary PDFs of the measurement noise. Among them, the Particle Filtering [Arulampalam et al., 2002] has been widely used in the audio localization context [Zotkin et al., 2002; Ward et al., 2003; Levy et al., 2011]. The underlying principle is to approximate the likelihood function, defined as the probability of obtaining the current observation from a given state, by a Monte Carlo simulation of a set of samples or particles. Each particle at time $t$ is weighted according to the observation, and the weights determine how many particles at time $t + 1$ will be generated around each particle at time $t$. Finally, the estimated position is taken as the centroid of the particles. In this way particles are forced to crowd around the coordinates which are more likely to be close to the true target position. Moreover, if a measurement is quite far from the previous estimation, probably it will fall in a particle-free zone and will not be taken into account in the update stage, so naturally filtering out reverberations and disturbing sounds.

### 4.4 Audio-visual source tracking

Despite the encouraging results demonstrated in ad-hoc and controlled setups, audio-only tracking methods have till now rarely been implemented in surveillance systems in real environments, due to the lack of robustness in complex sound scenarios. In such context, joining audio and visual devices allows each modality to compensate for the weaknesses of the other one, yielding a determinant boosting in the overall performance. For example, whereas a visual tracker may mistake the background for the target or lose it due to occlusion, an audio-visual tracker could continue focusing on the target by following its sound pattern. Conversely, an audio-visual tracker could help where an audio-only tracker may lose the target as it interrupts emitting sound or is masked by background noise.

The main issue to be faced in audio-visual localization and tracking is the fusion of information of the single devices, which can take place at different processing levels: at the feature extraction level, simply feature level, or at the decision level. In the former case, a single tracker, typically a particle filter is instantiated and the fusion occurs when building the likelihood function. In particular in [Aarabi and Zaky, 2001] the final likelihood function is proportional to the sum of the two likelihood functions related to audio and video measurements, whereas in [Zotkin et al., 2002] and [D’Arca et al., 2013] the final likelihood function is proportional to the product. These two fusion strategies can be extended to multiple cameras and multiple microphone arrays [Kushwaha et al., 2008]. More advanced fusion policies for the likelihood function are weighted sum [Gerlach et al., 2012] or exponentiation of the two likelihoods with different coefficients prior to sum [Gerlach et al., 2012], in order to take into account
the different reliability of the two modalities. In [Beal et al., 2003], fusion is implicitly achieved by a Bayesian
Graphical Model in which observed variables, here two microphones signals and the video pixels, are modeled as
depending from hidden variables denoting the target positions and the audio and video noise (feature fusion level).
Considering the decision level fusion scheme, in [Strobel et al., 2001], audio and video data are processed sepa-
ately by two independent Kalman filters; next the two localization outputs are fed to a fusion stage which provides
a final joint estimation. Interestingly, the fusion stage can be conceptually divided into two inverse Kalman filters,
recovering the audio and video measurements, and a joint Kalman filter that takes as input the audio-video mea-
surement vectors and yields the final estimation. In [Megherbi et al., 2005], audio and video localization output
are fused together using Belief Theory [Ayoun and Smets, 2001]. Moreover, Belief Theory has the advantage to
be able to handle the problem of associating multiple audio and video data to multiple targets.

Another issue raising in multimodal localization is the mutual geometric calibration of the different devices. In
[O’Donovan et al., 2007], it is demonstrated that spherical microphone arrays can be considered as central projec-
tion cameras; therefore, calibration algorithms based on epipolar geometry, usually employed to calibrate a couple
of video cameras, can be easily adapted to the problem of camera-microphone array calibration. In other works,
the mutual calibration problem is jointly solved with the localization. In [Beal et al., 2003], calibration param-
eters and target locations are modeled together as hidden variables in a Bayesian framework, and inferred from
the observations through Expectation-Maximization. In [Zotkin et al., 2002], calibration parameters are added to
the state vector and tracked jointly with the target location, allowing to cope with unforeseen movements of the
acquisition devices.

Beyond collaborative modality, audio and video devices can be exploited also in in a master-slave configura-
tion. When the master role is played by the microphone array, the slave is usually a Pan Tilt and Zoom (PTZ)
camera which is rotated and focused on the location from which an interesting or alarming sound has been emitted
[Chen et al., 2013; Kotus et al., 2013; Viet et al., 2013]. On the contrary, when the interest is focalized in hear-
ing toward the direction where visual activity has been detected, the slave role is played by a microphone array
[Menegatti et al., 2004] which is electronically pointed, or simply a single directional microphone mechanically
moved analogously to the PTZ camera.

5 Situation analysis

In respect to the previously described tasks, situation analysis, also known as scene analysis, deals with audio
data at higher level of abstraction, trying to extract complex semantic concepts from the previous intermediate
processing stages. Situation analysis generally involves the temporal and spatial integration of multiple data, often
acquired from several heterogeneous sensors. As an example, a relevant situation for surveillance such as human
aggression involves several agents, at least an aggressor and an attacked subject, holding anomalous behaviors
(e.g., running, hitting, shouting), whose cues can be detected through audio and video modalities.

5.1 One-layer systems

Though conceptually different from sound classification or foreground extraction, situation analysis can be faced
using similar statistical approaches. The most straightforward one consists in defining a finite set of states charac-
terizing a given environment, e.g. normal traffic, queue or accident on a road, or normal activity and aggression in
Figure 9: Taxonomy for the situation analysis methods, with pros and cons added for each category of approach.

a public space, and infer such states directly from a set of features extracted from the audio stream or audio-video stream through machine learning algorithms. According to this strategy, situation analysis is formally treated as a sound classification problem, where single sounds signals are substituted with more general scene descriptions. The approach was firstly addressed in the context of Computational Scene Recognition (CASR) [Peltonen et al., 2002] and [Eronen et al., 2006]. Differently from the typical CASR application, i.e. a moving device recognizing the different environments crossed, in situation analysis each state is defined by a different situation related to a single environment where fixed sensors are deployed (e.g. normal traffic or car crash in the same route). The complexity of audio signatures related to each situation or environment is by far increased with respect to single sound sources, as very different sound may characterize alternatively or jointly a single situation (e.g., siren and crashing in a car accident), and the same sound can be shared by different scenes (e.g., sound of running people can occur either in a normal situation or in a threatening one). For these reasons performance is generally worse in comparison to sound classification task.
5.2 Hierarchical systems

A different approach exploits the inherent hierarchical structure of a scene, detecting at first time the single elements composing the scene, notably the single sound sources or the individual objects in the video case, and subsequently trying to fuse them in a second time according to a given policy. The fusion stage can be addressed either by 1) explicit rules incorporating human knowledge about the relationship among single sound events in a given scene, or 2) a machine learning approach.

An example of the first strategy can be found in [Li and Ma, 2009]: first, basic audio events are modeled by a set of HMMs; second, audio events that are likely to occur simultaneously in an audio frame are grouped together defining a priori the transition probabilities among them, and assuming that each basic audio event can belong to multiple groups, each one identifying a different structured audio scene.

In [Atrey et al., 2006a], the detection of compound events is addressed fusing information coming from multiple sensors. In particular, three fusion levels are defined: media stream level, atomic event level and compound event level. In the first one, features extracted from the data stream related to each sensor are stacked together (feature fusion level) and fed into a classifier in order to detect atomic events (e.g., walking, shouting, etc.). Second, each detector, related to just one sensor, yields a probability of detection for each atomic event. Such probabilities are fused together (decision fusion level) with a policy which takes into account both the different confidence of each sensor and the average level agreement of different sensors with respect to each atomic event. Third, probabilities of each compound event (e.g., a person running, while another one shouts) are estimated by fusing the probabilities of the subset of atomic events which define a priori the given compound event (decision level fusion). Detection of compound events is performed by a thresholding operation on the final probabilities. Such late thresholding policy allows to achieve higher accuracy, exploiting all the information available, in comparison to early thresholding which discards atomic events with low probability or sensors with low confidence.

An example of the second strategy, which does not incorporate prior knowledge, can be found in [Xiaoling and Layuan, 2008], where situation recognition is performed by a hierarchical Dynamic Bayesian Network (DBN), whose three hidden levels correspond, in descending order, to Situation event, Group event and Single events, and the visible layer corresponds to audio and video cues. Since events at a given level can be regarded as the cues of the events at higher levels, all the statistical dependencies among different levels can be learned by a training procedure.

An hybrid approach, in which learned inferences are tuned according to prior knowledge, can be found in [Li et al., 2009]. In this work, scene semantic content is extracted by means of a two-layer neural network. Single sound events are detected through HMMs, their duration and frequency in the audio sequence is used to calculate an input vector feeding the first layer of the neural network, corresponding to the single event level. Then the weighted sum of the inputs gives the probability of occurrence of each scene in the second layer. Finally, weights are adjusted on the base of the a priori judged importance of the related events for the given scene.

Differently from the vast majority of CASR applications where multiple audio contexts have to be recognized, scene analysis in the surveillance field is often devoted to distinguish among a normal situation and a specific relevant situation strongly related to a single environment. For example, detection of aggression in a public space [Zajdel et al., 2007], [Andersson et al., 2010] or human intrusion in an private indoor space [Menegatti et al., 2004], [Zieger et al., 2009] have been addressed in the literature.

More in detail, in [Zajdel et al., 2007] an aggression detection system in a railway station has been devised based on a combined audio-video system. The audio part distinguishes normal speech from speech under strong stressing emotions, analyzing the pitch and the spectral tilt of the audio sequence. The video part tracks pedestrians
and calculates their body articulation energy, which is used as a visual feature of aggression. A separate system detects passing trains in order to exclude false alarms. Audio and video cues of aggression are subsequently fed into a DBN which encodes the probabilistic dependency between the aggression level of the scene and the aggression cues (feature level fusion). The output of the DBN is the estimated time-dependent aggression level in the scene.

In [Andersson et al., 2010], a sensor set including two video cameras, a thermal camera and an array of microphones is employed to detect fights in outdoor urban environments. Audio and video stream are first processed separately: two HMMs modeling normal and abnormal audio events, together with audio features specifically targeted for abnormal vocalic reactions, are employed to reveal human sound associated to panic or aggression. Conversely, video streams, both visual and thermal, are used to estimate crowd size and activity. Information on crowd state and human voice are used as observations of a further HMM whose states model calm motions, or slightly increased activities (i.e., normal situations). Hence, low likelihood values for a given observation set denote abnormal, aggression-like situations.

In [Giannakopoulos et al., 2010], audio and video features are extracted and fed separately into two Bayesian networks, whose outputs give the probability associated to two video classes (normal and high activity) and seven audio classes (including violent and non violent ones). Subsequently, such probabilities are considered as higher level features and fed into a nearest neighbor classifier, which yields to the final classification between violent and non violent activity. The fusion strategy in [Andersson et al., 2010] and [Giannakopoulos et al., 2010] can be considered halfway between feature and decision level fusion, since the output of the first stage classification represents both the decision related to a given class (semantically different from the final ones) and the higher level features for the final classifier.

In [Menegatti et al., 2004], intruder detection in a dynamic indoor environment, e.g. the storage room of a shipping company, is addressed by means of audio and video static sensors and a mobile robot. The static cameras detect a moving object in the image communicating its position to the robot and the static microphone arrays. Microphones arrays are electronically steered toward the moving object and footsteps of the likely person are recorded and analyzed by a set of HMMs aimed at distinguishing between several known persons or an unknown one. The person is then tracked by microphone arrays and the information on the person location from both audio and video static sensors are fused together (feature fusion) and used to guide the robot toward the target person.

In [Zieger et al., 2009], an heuristic strategy is devised to distinguish an actual intrusion in a room from false alarms generated by both ground noise coming from outside the room (road traffic, trains) or noise generated by static objects in the room (fridge pump, heating system). A network of microphones pairs is deployed in the room; each couple is able to measure the sound direction of arrival into a limited range. If a sound energy increase is detected, but no definite direction of arrival can be measured by any of the microphone pair, the sound is discarded as it is likely to be diffused from outside the room. On the contrary, if a clear direction of arrival is measured, a counter is incremented. Each microphone couple can increment the counter just once, so that a sound produced by a static object in the pairs range causes just one increment of the counter. When the counter exceeds a predefined threshold, becoming higher than the maximum number of noisy objects in the room, an intrusion is detected.

Intrusion detection is also addressed in [Castro et al., 2011] using an heterogeneous sensor network composed by microphones, video cameras and proximity sensors. The focus of this work is on the integration of mid-level single sensor output, such as people tracking, glass breaking detection, etc., by means of ontologies, fuzzy logic and expert systems, in order to get a semantic interpretation of the scene and trigger an alarm which also notifies its degree of confidence and other useful cues.

Other environment-specific methods concern security in public transportation, in particular small vehicles [Kim
and Ko, 2011] and trains [Pham et al., 2010; Vu et al., 2006]. In [Kim and Ko, 2011], a system for detection of abnormal situations in small vehicular environments is proposed. A first processing stage classifies each audio frame into a given class drawn from two subsets of normal and abnormal events. Next, an abnormal situation is detected if the ratio of abnormal events in the whole audio sequence is higher than a predefined threshold.

The method proposed in [Pham et al., 2010] is aimed not only at detecting an alarming event occurrence but also at identifying the person causing the event to happen. To this end, an audio-video sensor network is deployed in a train coach: a set of microphones located along the ceiling of the coach detects and locates alarming audio events such as shouts or spray bombs sending a warning to the human operator together with the image of the video camera closest to the audio event. After the human operator has selected the suspected person in the image, it is automatically tracked from video. When such person approaches a frontal camera, a further image is sent to the operator in order to allow face identification. A priori knowledge on the geometry of the environment is exploited for both audio localization and video tracking. As a matter of fact, the system involves the interaction with a human operator to identify the person to be tracked and cannot be considered truly automated.

<table>
<thead>
<tr>
<th>Event Typology</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Celebration</td>
<td>HMM combination [Li and Ma, 2009], [Li et al., 2009], Two-layer neural network [Li et al., 2009]</td>
</tr>
<tr>
<td>Excitement</td>
<td>HMM combination [Li and Ma, 2009], [Li et al., 2009] Dynamic Bayesian Network [Zajdel et al., 2007], Two-layer neural network [Li et al., 2009]</td>
</tr>
<tr>
<td>Greetings</td>
<td>Dynamic Bayesian Network [Zajdel et al., 2007]</td>
</tr>
<tr>
<td>HOME: bathroom</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006], K-NN [Peltonen et al., 2002]</td>
</tr>
<tr>
<td>Normal VS abnormal</td>
<td>Discriminative GMM [Kumar and Mittal, 2005]</td>
</tr>
<tr>
<td>OFFICES/MEETING ROOMS/QUIET PLACES: Office, lecture, meeting, library, multi-person motion activity, multi-person speaking activity, using the projector, human presence activity, intrusion</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006], HMM combination [Li and Ma, 2009], [Li et al., 2009], K-NN [Peltonen et al., 2002], Two-layer neural network [Li et al., 2009]</td>
</tr>
<tr>
<td>OUTDOORS: street, road, nature, construction site</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006], HMM combination [Li and Ma, 2009], [Li et al., 2009], K-NN [Peltonen et al., 2002], Two-layer neural network [Li et al., 2009]</td>
</tr>
<tr>
<td>PUBLIC/SOCIAL PLACES: restaurant, café, supermarket</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006], K-NN [Peltonen et al., 2002]</td>
</tr>
<tr>
<td>REVERBERANT: church, railway station, subway station</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006], K-NN [Peltonen et al., 2002]</td>
</tr>
<tr>
<td>VEHICLES: car, bus, train, subway train, traffic accident</td>
<td>GMM [Peltonen et al., 2002], HMM [Eronen et al., 2006] HMM combination [Li and Ma, 2009], [Li et al., 2009], K-NN [Peltonen et al., 2002], Two-layer neural network [Li et al., 2009]</td>
</tr>
<tr>
<td>VIOLENCE: Aggression, fight</td>
<td>Dynamic Bayesian Network [Zajdel et al., 2007], HMM Anderson et al 2010, Bayesian Network [Giannakopoulos et al., 2010], K-NN [Giannakopoulos et al., 2010]</td>
</tr>
<tr>
<td>Vocal events VS non vocal event</td>
<td>GMM for basic events + aggregation and thresholding [Atrey et al., 2006b]</td>
</tr>
</tbody>
</table>

Table 5: Situation typologies and related classification strategies adopted in the literature. Names in capital letters indicate scenarios where multiple situations have been taken into account with the same framework.

On the contrary, in [Vu et al., 2006] a fully automatic surveillance system based on audio-video sensor networks is proposed. The audio module detects alarming audio events, while the video module identifies and tracks all people and moving objects in the scene. The situation analysis is performed heavily relying on a priori knowledge of the environment, including 3D geometry, static objects positions, physical properties and functionalities. Furthermore, a set of composite events is explicitly defined including the physical objects involved, the sub-events
<table>
<thead>
<tr>
<th>Class</th>
<th>Short Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Zero Crossing Rate</td>
<td>[Li et al., 2009; Eronen et al., 2006; Giannakopoulos et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Waveform minimum and maximum</td>
<td>[Andersson et al., 2010].</td>
</tr>
<tr>
<td>Frequency</td>
<td>Spectral centroid</td>
<td>[Li et al., 2009; Eronen et al., 2006; Clavel et al., 2008].</td>
</tr>
<tr>
<td></td>
<td>Spectral Roll-off</td>
<td>[Eronen et al., 2006; Giannakopoulos et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Band energy ratio(BER)</td>
<td>[Li et al., 2009; Eronen et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>Bandwidth</td>
<td>[Li et al., 2009; Eronen et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>Spectral Flatness</td>
<td>[Andersson et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Pitch Ratio</td>
<td>[Giannakopoulos et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Fundamental frequency</td>
<td>[Andersson et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Spectral Variation</td>
<td>[Zieger et al., 2009].</td>
</tr>
<tr>
<td></td>
<td>Spectral Flux</td>
<td>[Eronen et al., 2006].</td>
</tr>
<tr>
<td>Cepstrum</td>
<td>MFCC</td>
<td>[Vu et al., 2006; Li et al., 2009; Li and Ma, 2009; Kumar and Mittal, 2005; Eronen et al., 2006; Andersson et al., 2010; Clavel et al., 2008; Giannakopoulos et al., 2010; Kim and Ko, 2011; Pham et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>MFCC derivatives</td>
<td>[Vu et al., 2006; Eronen et al., 2006; Kim and Ko, 2011].</td>
</tr>
<tr>
<td></td>
<td>Linear Prediction</td>
<td>Cepstral Coefficients and derivatives (LPCC) [Eronen et al., 2006].</td>
</tr>
<tr>
<td>Energy</td>
<td>Signal Energy</td>
<td>[Li et al., 2009; Zieger et al., 2009].</td>
</tr>
<tr>
<td></td>
<td>Energy Entropy</td>
<td>[Giannakopoulos et al., 2010].</td>
</tr>
<tr>
<td>Biologically-Perceptually driven</td>
<td>Pitch and spectral tilt extracted from filtered and thresholded cochleogram</td>
<td>[Zajdel et al., 2007].</td>
</tr>
<tr>
<td></td>
<td>Intonation and Teager Energy Operator (TEO) based features</td>
<td>[Andersson et al., 2010].</td>
</tr>
<tr>
<td></td>
<td>Linear Prediction Coefficients and derivatives (LPC)</td>
<td>[Eronen et al., 2006].</td>
</tr>
<tr>
<td></td>
<td>Prosodic group and Voice quality group</td>
<td>[Clavel et al., 2008].</td>
</tr>
</tbody>
</table>

Table 6: Summary of features for situation analysis: first column indicates the feature class according to the taxonomy defined in Section FIXME, second column reports feature names and third column reports references of works where they are employed.

constituting the compound event, the sub-events not allowed during the compound event and a set of logical, spatial and temporal constraints among all events. Compound event detection is achieved by searching all the possible combinations of objects and sub-events detected, and checking whether the given combinations satisfy the above defined constraints. However, to avoid computationally unfeasible combinatorial explosion of sub-events, compound events are limited to the combination of at most two sub-events, this fact representing the major limitation of this promising approach.

A very specific task is addressed in [Kotus et al., 2013], i.e. the detection of kidnapping from a vehicle of a given person (supposed to be a “Very Important Person”). The framework is very preliminary and implies an extended network of heterogeneous sensors, including a bluetooth wearable device which triggers the alarm when removed from the car, thermal and video cameras monitoring the scene and acoustic devices which detect and localize shout and abrupt impulsive sounds like gunshots. An alarm is finally delivered to a human operator joining all the multimodal cues (decision level).

Another ambitious work, presented as a proof of concept, is described in [Kumar and Mittal, 2005]. Here microphones, video cameras and thermal cameras are jointly employed to infer several threatening situations. Video and thermal cameras perform segmentation and tracking of moving person/object; audio stream from a microphone is classified into a set of predefined classes, and finally semantic rules are applied to discover threatening situations like intrusion, theft, abandoned object (decision level). However, quantitative results are displayed only for single system modules.
6 Audio Features

As mentioned in the introduction, a plethora of audio features has been devised in the last decades in the field of sound detection and classification. A large part of them was developed for specific tasks such as speech recognition [Hunt et al., 1980], speaker recognition [Reynolds, 1994], music classification [Tzanetakis and Cook, 2002] or music/speech discrimination [Scheirer and Slaney, 1997], and a relevant subset has been later transferred in the audio surveillance context. To guide the reader in such vast feature landscape, we rely on the comprehensive survey recently proposed in [Mitrovic et al., 2010]. In this survey, a taxonomy is devised to describe audio features in a task-independent manner. Here, we focus on the feature subset actually employed in audio surveillance, detailing their use in the four macro-tasks so far discusses (background subtraction, audio events classification, source localization and tracking, situation analysis), and discussing several related issues such as computational load, expressivity, redundancy, robustness to noise, and others.

Generally speaking, audio features are aimed at encoding a high dimensional signal (typically an audio frame is made of hundreds or even thousands samples) into a small set of values that encapsulate the information useful for the detection or classification task, while discarding noise and redundancies. The taxonomy adopted in this survey subdivides audio features into six classes, namely temporal, spectral, time-frequency-based, cepstrum-based, energy based and biologically or perceptually driven.

The classification criterion for the first four classes is based on the intermediate signal representation from which features are extracted. In particular, temporal features are directly extracted from the signal samples, or more generally from a time domain representation of the signal, like the autocorrelation function. Spectral features are extracted from the signal spectrum, typically from its power modulus. Time-frequency features are extracted from a bidimensional representation function of time and frequency, like spectrogram, or time and scale, like wavelets. The 2D representation provides a rich amount of structure, useful for example to look at the spectral variation along time. Moreover, the 2D representation of the signal has recently encouraged the application of features borrowed from the image analysis domain. Cepstrum-based features are grounded on cepstrum, a nonlinear transformation of the spectrum which allows to compactly represent the spectrum envelope, discarding fine variations across close frequency bins (for example, the exact location of the harmonics in a periodic signal). Energy-based features deserve a separate class since their calculation is typically not associated to a given signal representation (energy can be extracted from time signal, spectrum, cepstrum and so on). Energy-based features are more involved in foreground extraction or tracking task, whereas they tend to be discarded for classification since generally they cause an increase in intra-class variation. Finally, biologically or perceptually driven features represent a class orthogonal to the previous ones: they can be grounded on temporal, spectral, time-frequency or cepstral representations but share a common inspiration from the psychophysiology of the human auditory and/or vocal apparatus. In particular, they can be subdivided in three subclasses: 1) features mimicking the processing of the human auditory system, in particular the cochlear filtering; 2) features reproducing the psychological perception of auditory cues and 3) features built according to the physical behavior of the human vocal tract, the latter being limited to encode vocal sounds. Since the same audio features are often shared by the four macro tasks defined in the previous sections, we preferred to unify their description in the following. However, a set of four tables is
displayed for each of the four tasks in the corresponding paper section. In each table, just the features employed for the specific task are reported, organizing them by the taxonomy above defined and reporting for each item the related references.

Finally, a large amount of the features here described have been previously gathered into two large corpora of audio features aimed at encoding generic sounds: the two corpora are related MPEG-7 standard [Chang et al., 2001] and CUIDADO project [Vinet et al., 2002] respectively. In this review the possible inclusion of each feature in these corpora will be highlighted.

6.1 Time

- **Zero Crossing Rate (ZCR):** number of times the sign of the signal changes in a given frame. It captures information about the dominant frequency within the frame. Strongly correlated with the spectral centroid. Used in combination with more complex features (e.g. MFCC, Wavelets). Size = 1.

- **Autocorrelation coefficients:** temporal samples of the autocorrelation function calculated convolving the signal by itself. Autocorrelation is often employed as an intermediate representation from which other features can be extracted (see below). Size depends on the autocorrelation window.

- **Correlation-based features:** Periodicity, correlation slope, decrease and roll-off. Periodicity is calculated as the maximum local peak of normalized signal autocorrelation. Useful to discriminate between periodic signals (e.g. periodicity of a sinus wave = 1) and aperiodic signals (e.g. periodicity of white noise = 0). Slope, decrease and roll-off are similar to the corresponding spectral features but calculated from the autocorrelation rather than the spectrum. They are suited for describing the energy distribution over different time lags. For impulsive noises, like gunshots, much of the energy is concentrated in the first time lags, while for harmonic sounds, like screams, the energy is spread over a wider range of time lags. Size of each feature = 1.

- **Pitch range Features:** features extracted from the autocorrelation function evaluated on subsequent time windows. From each autocorrelation function, the pitch is estimated as the inverse of the delay between the first and second highest positive peaks. Pitch range is then calculated as the ratio between the maximum and minimum pitch or the ratio between pitch standard deviation and pitch mean value. Pitch information is complementary to MFCC that encodes spectrum envelope: therefore their joint use seems to boost considerably the performance, especially on non-speech sound classification [Uzkent et al., 2012]. Size = 2;

- **Waveform minimum and maximum:** maximum and minimum value of the signal waveform. Included in MPEG-7 audio standards. Size = 2.

- **Interaural Time Difference (ITD):** difference in the time of arrival of an acoustic signal at a couple of microphones. Used mainly for localization and tracking tasks. Size = 1.

6.2 Frequency

- **Fourier coefficients:** coefficients of the signal DFT typically averaged in squared modulus over subbands. Baseline feature in the spectral domain. Computationally efficient using Fast Fourier Transform. Size = number of subbands.

- **Band Energy Ratio (BER):** energy of the frequency subbands normalized by the total signal energy. Size = number of subbands.
- **Spectral moments**: statistical moments of the power spectrum, this last considered as a probability density function: spectral centroid or mean value (strongly correlated with ZCR), spectral spread (variance), spectral skewness, spectral kurtosis. Size of each one = 1.

- **Bandwidth**: signal bandwidth, typically estimated as the frequency range in which a certain percentage of energy lies. Similar to spectral roll-off. Size = 1.

- **Spectral slope, spectral decrease and spectral tilt**: spectral slope is defined as the amount of decreasing of the spectral amplitude with frequency. Computed by linear regression of spectral amplitude. Spectral decrease is the perceptual version of spectral slope. Spectral tilt is similar to spectral slope but is calculated as the ratio of energies in the spectrum lower portion (e.g. above 500 Hz) and higher portion [Zajdel et al., 2007]. Included in CUIDADO corpus. Size = 1.

- **Spectral roll-off**: frequency below which a certain amount of the power spectrum lies (typically 95% percentile). Useful to discriminate between voiced and unvoiced speech. Size = 1.

- **Spectral flatness**: measure of noisiness/sinusoidality of the signal. Calculated as the ratio of the geometric mean to the arithmetic mean of the spectrum energy. Size = 1.

- **Pitch Ratio or Harmonicity**: in a fully periodic signal the spectrum energy is located at the fundamental frequency (the pitch) and its multiples (the harmonics), whereas in an aperiodic signal energy is spread over all the signal band. Such feature measures the degree of periodicity in a signal. Size = 1.

- **Fundamental Frequency**: in a periodic signal corresponds to the inverse of the signal period. For a general signal is correlated with spectral centroid and ZCR. Included in MPEG-7 corpus. Size = 1.

- **Interaural Phase Difference (IPD)**: difference in the phase of the spectra of two signals acquired by a couple of microphones. If the two signals are generated from a single audio source, phase difference is proportional to the delay in the sound time of arrival at the two microphones. Mainly used for localization and tracking tasks. Size = number of frequency bins.

Most of the previous spectral features, modeling spectrum shape, are used in combination with higher size features (e.g. MFCC, DWT). Poor performance if taken alone due to intrinsic low dimensionality.

### 6.3 Cepstrum

- **Mel Frequency Cepstral Coefficients (MFCC)**: the Cepstrum is the Discrete Cosine Transform of the log-magnitude of the signal spectrum. The Mel-cepstrum is calculated on the outputs of a Mel-frequency filter bank rather than directly on the spectrum. Mel-frequency filter bank is built according to the Mel scale, a nonlinear frequency scale corresponding to perceptually linear pitch scale, and characterized by a linear portion at low frequencies and a logarithmic portion at high frequencies. MFCC are the first coefficients of the Mel-cepstrum (typically excluding the first one that accounts for the signal energy). MFCC provide a compact representation of the spectral envelope (formant structure), discarding fine cues like positions of the spectral peaks (harmonic structure). Originally proposed in the context of speech-speaker recognition and successfully adapted to environmental sound recognition. Not suited for modeling noise-like flat spectrum sounds, like rain or insects. Higher order coefficients such as above 12 are believed to contain more information about environmental sound sources other than speech [Kim and Ko, 2011]. Often used in combination
with simpler spectral and temporal features (ZCR, spectral centroid, roll-off etc.). Low robustness to narrowband noise due to DCT transform that spreads noise over all the coefficients. Moderate computational complexity. Size = number of selected coefficients; typically from 3 to 15.

- **MFCC derivatives**: derivatives of MFCC across adjacent temporal frames. Size = like MFCC.

- **Homomorphic cepstral coefficients**: like MFCC but logarithm and discrete cosine transform are applied directly to the spectrum coefficients, without applying Mel filter-bank. Performance seems to be generally inferior to MFCC [Cowling and Sitte, 2003]. Size: like MFCC.

- **Linear Prediction Cepstral Coefficients (LPCC)**: representation of Linear Prediction Coefficients (LPC) in the cepstral domain (see LPC). Size: like MFCC.

### 6.4 Time-frequency

- **Short Time Fourier Transform or Spectrogram** [Hoiem et al., 2005; Cowling and Sitte, 2003]. Fourier transform applied to subsequent (possibly overlapped frames). PCA is used in [Cowling and Sitte, 2003] to reduce feature space dimensionality. In [Hoiem et al., 2005] STFT is used as intermediate representation in order to extract more synthetic features (e.g. mean std of each frequency channel, bandwidth, most powerful frequency channel, number of peaks over time etc.).

- **Wavelet coefficients**: Wavelet transform produces a joint time-frequency representation of the signal, allowing frequency dependent time resolution. This allows frequency to be identified as occurring in a particular area of the signal, aiding understanding of the signal. Wavelet coefficients as well as the other time-frequency features have in general high cardinality. To reduce the feature space PCA is usually applied [Cowling and Sitte, 2003] [Rabaoui et al., 2008] or coefficients are pooled over time (e.g. extracting mean, std, number of peaks) discarding in this way the temporal structure of the signal [Rabaoui et al., 2008, 2009].

- **Discrete Wavelet Transform Coefficients (DWTC)**: logarithm of the energies of last wavelets is evaluated and Inverse DWT is applied. Conceptually similar to MFCC but DFT and DCT are substituted with DWT and Inverse DWT. The final representation is not time-frequency. Wavelet is used as intermediate transformation. Better performance in respect to MFCC for low SNR conditions. Size = number of wavelet bases considered (typically six [Istrate et al., 2006; Vacher et al., 2004]).

- **Mel Frequency Discrete Wavelet Coefficients (MFDWC)**: like MFCC with the final DCT substituted with a Discrete Wavelet Transform. (wavelet transform applied to log magnitude of Mel filterbank). More robust to narrowband noise in respect to MFCC as only a subset of the final DWT coefficients is affected by noise.

- **Mean and Standard Deviation of Gabor Atoms** Signal is approximated with a combination of Gabor functions via Matching Pursuit. Frequency and scale of each atom is evaluated and mean and standard deviation of frequency and scale are finally extracted. Size = 4 [Rabaoui et al., 2009]

- **Spectral Variation and Spectral Flux**: amount of variation in the spectrum across two adjacent time windows. Calculated as the generalized cosine (spectral variation) or the $L^2$ norm of the difference (spectral flux) between the two vectors representing the two spectra. Size = number of time windows couples taken into account.
• **Trace transform applied to spectrogram**: spectrogram is treated as an image and Trace Transform is applied calculating integrals over lines parametrized by angle and distance from the image center. Final features are extracted calculating line integrals over diagonals of the transformed image. It seems to improve over MFCC [Gonzalez, 2007] in general sound classification task. Trace transform is usually applied to affine invariant images therefore it could be useful to remove differences due to temporal or pitch translations.

• **Visual features applied to spectrogram**: spectrogram is considered as a texture image on which visual features are extracted. In particular, scale and translation invariant wavelet transform is applied to the spectrogram; next, after a local max pooling a patch transform is applied and followed by a further max pooling [Souli and Lachiri, 2011].

• **High-order Local Auto-Correlation (HLAC)**: two dimensional autocorrelations calculated on the amplitude values of the spectrogram. Only local correlations (3 x 3 time-frequency lags) are taken into account. Feature borrowed from image classification field. Better results in respect to cepstrum based features in abnormal sound detection [Sasou, 2011].

• **Local Autocorrelation of Complex Fourier Values (FLAC)**: similar to HLAC but complex values of the spectrogram, instead of amplitude only are taken into account. Complex values allow to retain sound phase information. Definitely better performance in respect to MFCC in a classification task related to health monitoring [Ye et al., 2010].

6.5 **Energy**

• **Signal energy**: signal energy over a frame. Size = 1.

• **Log energy first and second derivatives**: Size = 1.

• **Energy Entropy**: Entropy calculated over the energy values extracted from a set of audio frames. Useful to detect abrupt energy changes. Size = 1 [Giannakopoulos et al., 2010]

• **Interaural Level Difference (ILD) or Gain Ratio Of Arrival (GROA)**: ratio of the energies related to the signal acquired by a couple of microphones. Used mainly for localization and tracking tasks. Size = 1.

6.6 **Biologically/perceptually driven**

• **Log frequency coefficients**: outputs of a set of band-pass filters whose central frequencies and bandwidths are scaled according to a logarithmic scale. The logarithmic scale roughly reproduces the filter-bank response of the human ear. Typically used in combination with some feature selection process (e.g. Adaboost). Size = number of filters.

• **Mel frequency coefficients**: similar to Log Frequency Coefficients, but the filters central frequencies are spaced according to Mel scale that reproduces the psycho-acoustical perception of the pitch. Mel scale is linear at the lowest frequencies and logarithmic at the highest ones. Mel scale is also adopted in several frequency, time-frequency or cepstral features. Size = number of filters.

• **Spectral features based on Gammatone filter bank**: this filter-bank aims at modeling the frequency analysis of the cochlea in the inner ear. Each filter has constant unitary bandwidth on an ERB frequency scale (Equivalent Rectangular Bandwidth). The energies of the filter outputs can be seen as a biologically driven version of the power spectrum from which spectral features are extracted. Size = number of filters.
• **Gammatone Cepstral Coefficients (GTCC)** variation of the MFCC in which the triangular filter bank spaced on the Mel scale is substituted with a Gammatone filter bank [Valero and Alias, 2012b], achieving better resolution at the lowest frequencies and tighter model of the human cochlea response. Performance comparable to MFCC (when used with SVM) or significantly higher (when used with K-nearest neighbor) on non-speech classification task. Size: like MFCC.

• **Cochleogram**: biologically inspired version of the spectrogram. It is based on modeling of basilar membrane oscillations in human ear cochlea. The short time spectrum is calculated by a leaky integration of the squared membrane displacements [Zajdel et al., 2007]. As for the spectrogram, it is normally employed as an intermediate time-frequency representation from which more synthetic features are extracted.

• **Linear Prediction Coefficients and derivatives (LPC)**: filter coefficients in an all-pole model approximating the audio signal. Originally devised to model the response of the human vocal tract (also known as Vocoder). Mainly targeted to speech vocal signals. Not suited for impulsive environmental sounds. Information captured is similar to MFCC. Size = typically some tens of coefficients.

• **Perceptual Linear Prediction Coefficients and derivatives (PLP)**: mapping of LPC to the nonlinear frequency scale of the human ear. Information captured is similar to MFCC. Size = typically some tens of coefficients.

• **Relative Spectral (RASTA) Perceptual Linear Prediction**: variation of PLP robust to background noise. The idea is to filter out stationary or slowly varying spectral components before the calculation of the all pole model (human auditory system pay little attention to steady state noise). [Hermansky and Morgan, 1994]. Size = like PLP.

• **Intonation and Teager Energy Operator (TEO) based features**: nonlinear operators, based on combination of signal derivatives, that capture the variations that the vocal tract airflow exhibits when it comes to abnormal circumstances. Useful to distinguish threatening from normal situations on the base of human voice.

• **Prosodic Group and Voice Quality Group**: a feature set tailored to human voice salient cues [Clavel et al., 2008]. Prosodic Group includes Pitch, Intensity Contour and Duration of Voiced Trajectory; Voice Quality Group includes jitter (pitch modulation), shimmer (amplitude modulation), unvoiced rate (proportion of unvoiced frames in a sequence), and Harmonic to Noise Ratio (HNR) (proportion of periodic vs non-periodic signal).

• **Narrow Band Autocorrelation Features**: Features extracted from narrow band autocorrelation functions. Signal is firstly filtered by a filter bank whose central frequencies are spaced according to the Mel scale (mimicking the perceptual pitch). An autocorrelation function is calculated for each filter output and four features are extracted from each autocorrelation. The four features are the intensity of the first positive peak, the time delay between first and second peak, the intensity of the second positive peak and the duration of the envelope at $-10$ dB. They are related to four primary perceptual qualities of the sound, respectively loudness, pitch, timbre and duration. Overcomes both MFCC and DWT features on a small scale classification task of non-speech signals [Valero and Alias, 2012a]. Size = 4 times size of filterbank.

### 6.7 Feature selection and feature learning

The current state-of-art in audio surveillance, and more in general in pattern recognition problems applied to audio signals, does not allow to draw an ultimate conclusion on the best feature or the best feature set to be used
in detection and classification task irrespective of the kind of audio sources involved. The naive idea of stacking together as much features as possible, in order to boost the performance, clashes against the well known curse of dimensionality problem. To solve this issue the dimensionality of the feature space can be reduced with standard techniques like PCA or Independent Component Analysis [Cowling and Sitte, 2003], or a feature selection process can be instantiated. To this end, in [Zhou et al., 2008; Zhuang et al., 2010; Hoiem et al., 2005] AdaBoost meta-algorithm is employed to select an optimal subset of features. In detail, each single feature is associated to a weak-learner, and the final strong-learner output is given by a weighted sum of the weak-learners outputs. After the training phase, selection of the best $N$ features is performed simply looking at the highest $N$ weights. The rationale is that if a weak learner is associated to a high weight, the corresponding feature will play an important role in the classification or detection task. With respect to feature space reduction techniques like PCA and ICA, feature selection has the advantage of being a supervised method which takes into account the labels of the data.

Beyond reduction and selection a more principled way to optimize the feature set consists in learning features from scratch directly from the data. Concerning the audio data, it has been noticed that audio events with a semantic meaning, e.g. human voice, are often composed of a sequence of non-semantic atomic units with a stable and well defined acoustic signature. In practice, atomic units are easier to be classified but do not correspond to meaningful classes from a human-interpretative point of view. Moreover audio events are much harder to be classified due to the fact that audio units generally do not occur in a predefined order (think at the phonemes in a human voice). An interesting way to cope with this issue is to learn audio units from the data, for example by some clustering procedure, and subsequently evaluate the number of occurrences in the audio stream for each audio unit and using such number as a high-level feature. The approach is very similar to the Bag-of-Words [Grauman and Darrell, 2005] method, widely adopted in computer vision, where a codebook of visual words is learned by clustering the set of image patches extracted from the image dataset. Next, an histogram of word occurrences is calculated by increasing, for each patch, the histogram bin of the word closest to the patch itself and finally the histogram is fed to a standard classifier.

The bag-of-word approach is directly translated into bag-of-aural-word in [Carletti et al., 2013] where the role of the patches is played by audio segments, allowing to cope with complex audio sequences made of multiple distinct audio units whose order is unknown. Moreover, robustness is achieved in presence of background noise, since the classifier can learn to ignore the corresponding words. The study is focused on a limited set of classes of interest in an audio surveillance context (scream, gunshot, glass break) mixed with background noise. A more complex approach is devised in [Kumar et al., 2012], where also the inner temporal structure of each audio segment is taken into account. In particular, a set of audio units is modeled in an unsupervised way by a set of HMMs able to translate the audio stream into a sequence of audio units whose histogram is fed to a random forest classifier.

In [Conte et al., 2012], each audio segment is directly classified into a predefined set of classes by the Learning Vector Quantization (LVQ) algorithm and the degree of confidence is estimated for each classification. At the sequence level, only the frames with a high confidence are taken into account and the final label is assigned on the base of the majority voting among the high-confidence frames. Moreover, if the winning class is close to the second winning the whole sequence is classified as uncertain. Unlike the previous approaches, here each audio segment is associated to the same set of semantic concepts (the classes) under which the whole audio sequence is classified.

A completely unsupervised approach suited for event detection is devised in [Chin and Burred, 2012]. The audio sequence is transformed into a multidimensional sequence of symbols extracted by a dictionary learning procedure (either by PCA or Nonnegative Matrix Factorization). From such sequence, audio events, represented as recurring onsets of audio structures immersed in background, are detected adopting a Motif Discovery algorithm.

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borrowed from analysis of DNA sequences.

Finally, in some approaches the codebook is not learned from the data but fixed a priori, typically as a set of time-frequency-scale bases. For example, in [Rabaoui et al., 2009] the dictionary is composed of Gabor atoms: for each audio sequence the atom subset best approximating the signal is found by matching pursuit. Final, features are then extracted as the mean and variance of frequency and scale of the atom subset. Fixed dictionary provides better generalization properties with respect to learned dictionary at the cost of an overcomplete dictionary of higher size.

7 Conclusions

In this paper, we presented an essay of automated surveillance methods based on, or including, audio devices. It has two important features that make it different and appealing with respect to the other literature reviews on similar topics. First, it proposes a global taxonomy encompassing all the typical tasks of a surveillance systems, from the low-level ones, like background subtraction, to the semantic analysis of a whole scene. This has never been done before for the audio sensory modality. Second, it is application oriented, i.e., for each proposed method, pros and cons are discussed with respect to the needs and challenges that characterize a surveillance scenario. Moreover, though the majority of the described methods was originally proposed for surveillance and monitoring applications, the reviews includes also more general works that may likely have an impact on future developments of the field. Beyond the general taxonomy, a set of tables and diagrams is provided to the reader in order to have quick hints concerning the best methods to be adopted for very specific tasks or operative conditions. In conclusion, we hope that this application-oriented analysis may help in speeding up the advancement in audio-based automated surveillance, leading to the design of complete systems, able to face all the above described tasks at once, and providing at the same time convincing and robust performance.

References


