Listening for Sirens: Locating and Classifying Acoustic Alarms in City Scenes

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Abstract—This paper is about acoustic event detection and sound source localisation in urban scenarios. Specifically, we are interested in detecting and localising horns and sirens of emergency vehicles. Urban scenarios, though, can be characterised by copious, unstructured and unpredictable traffic noise, which can severely compromise the performance and effectiveness of traditional filtering techniques. By analysing the spectrograms of incoming stereo signals as images, we can leverage image processing techniques and obtain a demonstrably robust system. Indeed, image processing methods, such as convolutional neural networks, which do not operate locally, offer interesting mechanisms for background foreground separation. When applied to spectrograms, those mechanisms allow using the entire context of the soundscape to discover and learn correlations both in the time and frequency domains, de facto implementing noise detection through semantic segmentation. In a multi-task learning scheme, together with signal denoising, we perform acoustic event classification to identify the nature of the alerting sound. Lastly, we use the denoised signals to localise the acoustic source on the ground plane, by regressing the direction of arrival of the sound. Our experimental evaluation shows an average classification rate of 94\%, and a median absolute error on the localisation of 7.5\(^\circ\) when operating on audio frames of 0.5 s, and of 2.5\(^\circ\) when operating on frames of 2.5 s. The system offers excellent performance in particularly challenging scenarios, where the noise level is remarkably high.

Index Terms—Acoustic event classification, siren detection, semantic segmentation, smart vehicles, deep learning.

I. INTRODUCTION

Our autonomous vehicles / cars are largely deaf. They typically make little if any use of auditory inputs and this paper starts to address that shortcoming. Here we approach the problem of using auditory perception in intelligent transportation to spot the presence of, and localise “alerting events” which carry crucial information to enable safe navigation in urban areas, and which, in some cases (e.g. a car honking) could not be perceived by different sensing means. Specifically, we aim to detect and recognise anomalous sounds, such as car horns and sirens of emergency vehicles, and localise the respective acoustic sources. Autonomous vehicles would clearly benefit from the ability to identify and interpret those signals. An emergency vehicle approaching an intersection could be detectable long before it reaches the crossing point and despite occlusions. The possibility of having advance information of this kind would considerably increase the time frame allowed for a safe response from the driver, as well as the probability of successfully implementing an emergency plan for an autonomous car [1] (e.g. park aside to let the emergency vehicle pass); in a smart vehicle working in semi-autonomous “L3” regime, it could also be used to trigger manual intervention. Furthermore, people with hearing impairments are potentially more prone to accidents which could be avoided if these cues could be perceived [2].

One of the greatest challenges in the identification of auditory events lies in the copious and unstructured traffic noise which characterises the acoustic urban scene, and, against which, filtering techniques, traditionally used in signal processing literature, struggle to perform well. In one of our previous works [3] we introduced the idea of treating tempo-spectral representations of the incoming audio signals (e.g. spectrograms) as images, applying segmentation techniques for signal denoising. Identification of the various sound types was, then, performed on the filtered clean signals, obtaining a high level of accuracy. Further analysis of the behaviour of the system when operating on the gammatonegrams of the unclean signals is also carried out, yielding to a much lower identification rate. This direct comparison serves as proof of the efficacy of the segmentation as a denoising method.

Building on the analysis and the results of [3], we extend that contribution in three directions. Firstly, rather than relying on the use of \textit{k-means} to perform image segmentation, we now employ deep learning, in the form of a \textit{U-Net} architecture [4], [5] in a multi-task learning scheme, to simultaneously identify the nature of the acoustic event, and extract the corresponding target signal from the background noise. The conspicuous advantage that this kind of approach offers over other filtering techniques is its extreme flexibility. Traditional signal processing methods need to estimate the behaviour and the characteristics of the background noise to be able to discard it, which might be extremely challenging in urban scenarios, where the traffic noise is of a diverse nature, does not present a clear structure, and the geometry of the sound sources is unknown and unpredictable. The use of the \textit{U-Net} makes noise modelling unnecessary, as it attempts to retrieve the target signals directly. Furthermore, this method overcomes the limitations and constraints of [3], where the segmentation procedure was purely based on the energy characterising the stimuli in the audio mixture, and assumptions on their relationships were required. A \textit{U-Net} architecture, as described in more details in Section III-B, builds on the use of Convolutional Neural Networks, which do not operate locally, offering interesting mechanisms for background foreground separation. Indeed, image processing methods, such as convolutional neural networks, which do not operate locally, offer interesting mechanisms for background foreground separation. When applied to spectrograms, those mechanisms allow using the entire context of the soundscape to discover and learn correlations both in the time and frequency domains, de facto implementing noise detection through semantic segmentation.

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Networks (CNNs). CNNs offer the possibility to analyse the full soundscape fingerprint, and can be trained to discover time-frequency correlations. Those correlations allow to learn the characteristics of the target signal, independently of the competing noise, overcoming the limitations suffered by traditional filtering methods. We are now able to robustly address scenarios where the noise is particularly powerful compared to the target signal, and where earlier work was having major difficulties in recovering the shape of the sound of interest. Additionally, thanks to the multi-task learning scheme, the segmentation, and the consequent signal extraction, are now tailored to the class of the signal analysed.

Secondly, while in [3] sound source localisation is not directly addressed, in this work, we exploit the potential of CNNs for time-frequency pattern retrieval, and utilise a CNN-based architecture to localise the acoustic source. Specifically, from a stereo combination (i.e. as perceived by two different microphones, separated in space) of the recovered target signals, we estimate the direction of arrival (DoA) of the sound on the horizon plane, also known as Horizontal Localisation (HL). Horizontal sound source localisation techniques rely on the analysis of two main auditory cues to establish differences between the two signals in the stereo combination [6]. Those differences are expressed as the Interaural Time Difference (ITD) and the Interaural Level Difference (ILD). The former refers to the difference in the time necessary for the acoustic wave to reach the two channels. The latter refers to the difference in the intensity of the signals in the two channels. For this kind of analysis to be successful, the sound should not be corrupted by noise. Intuitively, the cleaner the two signals are, the more accurate the resulting localisation will be; which is why spectrogram segmentation plays such a crucial role in this context. Nevertheless, small inaccuracies in the segmentation can lead to further inaccuracies in the estimation of the ITD and the ILD, which, in turn, can lead to important errors in the computation of the sound source position. In order to avoid this risk, rather than recovering the DoA of the sound from the extracted signals, we opt for learning a direct, and more robust to interference, mapping between those and the location of the sound source, through the use of CNNs.

Thirdly, as noise represents a really challenging constraint when dealing with auditory perception in urban scenes (e.g. [7]), we here perform a thorough analysis of the behaviour of our system at different SNR levels.

II. RELATED WORK

The literature reports few attempts to detect siren, and more generally, alerting urban sounds [8]–[14]. The least recent of those attempts follow two main strategies to spot the presence of the sound of interest in the acoustic scene: they either model the characteristics of the background noise [8], [11], or the ones of the target signal [9], [10], [15]. In the case of the former, adaptive filtering techniques (e.g. [16]) are applied. In the case of the latter, peak searching and spectral analysis, respectively, are employed to detect the siren in the background noise. In most recent works ([10], [12], [13], [17], [14], [18]), instead, alarms are detected through more traditional machine learning paradigms. Our work is closer in spirit to those, as it aims to learn the characteristics of the sound of interest independently of the nature and the features of any kind of noise potentially present. Yet, with respect the aforementioned studies, we are able to successfully address extremely challenging scenarios characterised by a remarkably low Signal-to-Noise Ratio (SNR) (−40dB ≤ SNR ≤ 10 dB). Scenarios which in previous studies, instead, are either not directly examined [9], [12], [17], [15], [18], [14] or yield to a substantial degrade in the classification performance [10], even at a relatively high SNR (SNR = −5 dB). In [13], the authors intend to detect alarming sounds in different noisy scenarios, but the SNR of those scenarios is not mentioned.

Semantic segmentation has been widely investigated both in robotics and computer vision literature. Recent advancements in deep learning [19], [20], [4], [5], especially, have determined tremendous improvements in the performance of segmentation algorithms in a wide range of application domains. Audio analysis and understanding, on the other hand, has only partially benefited from such improvements in image processing. Indeed, the idea of exploiting image processing techniques operating on tempo-spectral representations of acoustic signals (e.g. spectrograms) is still in its infancy, with only few works (e.g. [21]–[23]) exploring this path for speaker, birds, and music classification purposes. In [3], we investigated the possibility of utilising image segmentation as a noise cancelling method, obtaining promising results. We now enhance that approach, which relied on the use of k-means [24], by employing a more powerful segmentation method, based on a Unet architecture [4], [5]. As already discussed in Section I, this allows us to extract the sound of interest from a noisy background, even when this noise is extremely powerful, SNR at −40dB, where [3] was not able to work properly with SNRs lower than −15dB. Lately, [25] proposed the use of sub-spectrogram segmentation for the classification of acoustic events in domestic environments (e.g. bag opening, dishwasher, flatware sorting). Yet, the authors do not apply any image processing technique to obtain the segmentation, but rather Singular Value Decomposition (SVD) to discriminate between low and high-energy spectral components.

Sound source localisation in robotics has been mainly concerned with human-robot interaction applications. Recently, more traditional geometry-based methods [26], [27], have been replaced by deep learning techniques [28]–[33]. In [28] and [29], the authors employ cross-correlation information to model the sound source location, while [30] and [31] propose end-to-end localisation. Different perspectives are analysed in [32] and [34], where the former discusses the possibility of relying on domain adaptation techniques to exploit models built in simulation in real-world acoustic scenes, and the latter introduces the concept of regional localisation. This work is close in spirit to all those studies, and, in particular to [28], [29]. Yet, with respect to those, which focus on indoor environments and multi-speaker localisation, and the noise is either low (SNR ≥ −5dB) or structured in the form of competing speakers, we analyse and are able to cope with outdoor scenarios characterised by the presence of a variety of
unknown sources of noise of a different nature, and where the SNR can be significantly lower. Outdoor sound source localisation has been analysed in the past mainly for underwater vehicle navigation (e.g. [35], [36]). Only few investigations have been carried out in urban scenarios (e.g. [37]), mainly focusing on the analysis of sound propagation in cluttered environments, whose map is known, and where urban noise is not present. Sound source localisation in wide-range outdoor environments employing wireless sensor networks has been approached in [38]. Yet, also in this case, environmental noise is not present (i.e. experimental evaluation is carried out at 34 dB). Outdoor scenarios and lower SNRs are investigated in [30], but, in that instance, the system is tuned to work only on a known target speaker.

III. TECHNICAL APPROACH

In this paper, we employ two different learning schemes to detect the acoustic events and localise the respective sound sources. A full representation of the framework is provided in Fig. 1. The network we use to perform segmentation and event classification is reported in the blue area of the figure (cf. Sound event Classification, SeC), while the one used to regress the direction of arrival of the sound is reported in the pink area (cf. Source Localisation, SL). The acoustic events we are interested in analysing are sirens of emergency vehicles and horns. Specifically, we consider three types of sirens: “yelp”, “wail” and “hi-low” [39], [40], which are the ones adopted in most countries. A description of the features employed is presented in Section III-A, while a detailed illustration of the deep architectures used is delineated in Sections III-B and IV-D.

A. Feature Representation

Traditionally, audio classification relies on the use of Mel-Frequency Cepstrum Coefficients (MFCCs) [34]. Recent works [3], [41], demonstrated that MFCCs do not provide an acoustic signature which is robust to interference, leading to a deterioration in the classification performance, when operating in noisy scenarios. Given the potentially high level of noise we might encounter in traffic scenes, we here choose a different signal representation, based on the use of gammatone filterbanks [42]. Gammatone filterbanks have been originally introduced in [43], as an approximation to the human cochlear frequency response, and, as such, can be used to generate a tempo-spectral representation of audio signals, where the frequency range is parsed in a human-like fashion. The sounds we are interested in spotting are explicitly designed to be heard by humans, even in the presence of conspicuous traffic noise. Exploiting features mimicking human auditory perception, then, can be particularly convenient, as it is able to provide an additional pre-filtering of the signals. The impulse response of a gammatone filter centred at frequency \( f_c \) is:

\[
g(t, f_c) = \begin{cases} a^{t-1}e^{-2\pi bt} \cos 2\pi f_c t & \text{if } t \geq 0 \\ 0 & \text{otherwise} \end{cases}
\]

where \( a \) indicates the order of the filter, and \( b \) is the bandwidth. The bandwidth increases as the centre frequency \( f_c \) increases, generating narrower filters at low frequencies and broader filters at high frequencies. Following [44], we utilise fourth-order filters (i.e. \( a = 4 \)), and approximate \( b \) as:

\[
b = 1.09 (f_c / 9.26449 + 24.7)
\]

The centre frequencies are selected by applying the Equivalent Rectangular Bandwidth (ERB) scale [45]. Let \( x(t) \) be the original waveform audio signal, the output response \( y(t, f_c) \) of a filter characterised by the centre frequency \( f_c \) can, then, be computed as:

\[
y(t, f_c) = x(t) \ast g(t, f_c)
\]

Extending the filtering to the entire bank, across overlapping time frames, we obtain a gammatone-like spectrogram, also known as gammatonegram. The gammatonegrams of a stereo combination (corresponding to two different receivers, i.e. two different channels) of the original signals are computed and used in the semantic segmentation and event classification.

![Fig. 1. The figure illustrates the entire framework, based on a two-stage approach, indicated by the blue (sound event classification, SeC) and pink (source localisation, SL) areas. The gammatonegrams (cf. Section III-A) of the incoming stereo sound are fed to a multi-task learning architecture (SeC, SL), where both segmentation and event classification are applied. The resulting segmented gammatonegrams are, then, used as masks against the original noisy ones, channel by channel (darker pink area of the SL architecture). Lastly, the cross-correlation of the clean gammatonegrams is computed and employed to regress the direction of arrival of the sound (DoA).](image-url)
network, as well as in the acoustic source localisation network. Examples of gammatonegrams are provided in Fig. 2.

B. Acoustic Event Classification and Signal Denoising

As mentioned in Section I, in our previous work [3], we perform gammatonegram segmentation employing \( k\)-means. \( k\)-means has the advantage to operate in a completely unsupervised manner (i.e. no training or labelling necessary). Nevertheless, some parameters still need to be predefined, such as the number of clusters (i.e. parts we want the image to be segmented into), which is not a trivial choice to make in this particular scenario, where the noise is of a variegated structure and nature. Furthermore, it also necessary to make assumptions to decide which of the clusters actually corresponds to the target signal. In our previous framework, we assume the cluster corresponding to the most powerful time-frequency slots in the gammatonegrams to be the target signal. Yet, this assumption cannot hold in really low SNRs, where the most powerful time-frequency slots in the gammatonegrams might actually belong to the background noise. One might argue that cluster assignment could be based on the frequency range where the target signal lies. However, while this could be, perhaps, applied in the case of sirens, where the frequency content is clearly defined, the same cannot be said about horns, for instance. Additionally, in our previous system, the segmentation phase precedes the classification one. This entails that, when assigning clusters, we would not be able to look for the frequency content of a specific signal, as we would not know yet which signal to target. All of the shortcomings, described above, greatly worsen when dealing with scenarios characterised by really low SNRs. Fig. 3 shows qualitative examples of the change in the performance of the \( k\)-means approach, at various levels of background noise.

In this work, we perform acoustic event classification and signal denoising utilising a multi-task learning (MTL) scheme. Multi-task learning has been successfully employed following various implementation strategies, and in several domains applications, such as language processing [46] and traffic flow forecasting [47]. By taking advantage of information in training samples of related tasks, MTL has proved to be a valuable tool for reducing overfitting and, consequently, improving the models’ generalisation capabilities. In this work, we opt for hard parameter sharing, which was first introduced in [48], having the tasks directly share some of the architecture.

We implement noise removal, by treating the gammatonegrams of the incoming sound as intensity images, and feeding them to a Unet [4], to carry out semantic segmentation. Specifically, we rely on an architecture similar to the one defined in [5]. As the result of the segmentation will later be used to localise the sound source, we use as input to the network a concatenation of the gammatonegrams of the two signals in the stereo combination, rather than analysing one channel at a time. We make this choice, as we hypothesise it will help capture inter-channel information, and allow us to obtain a more stereo-aware segmentation. The Unet can be seen as an autoencoder, relying on two main processing phases: encoding, and following decoding. The encoding generates a more compact representation of the input (i.e. the code), while the decoding attempts to reconstruct the original input, filtered depending on the specific task. In this case, the output of the decoding step will be a segmented version of the original gammatonegrams. In order to perform acoustic event classification, the network is augmented by fully connected layers, which, operating on the code generated in the encoding step, assign the input signal to one of three classes of interest: siren of an emergency vehicle, horn, and any other kind of traffic noise. The MTL scheme aims to simultaneously assign a label (i.e. siren, horn, other sound) to each pixel (corresponding to a time-frequency slot of the gammatonegrams) of the input image (i.e. segmentation), and to the entire image (i.e. event classification).

The complete structure of the network is reported in Fig. 1. The encoding part of the network (i.e. left side of the network) consists of three layers, where each layer presents the application of two successive \( 3 \times 3 \) convolutions, followed by a \( 2 \times 2 \) max pooling operation, with stride 2 for downsampling. The first layer is characterised by 64 feature channels, which double at each layer. The decoding part of the network (i.e. right side of the network), instead, presents a \( 2 \times 2 \) upsampling step, which reduces in half the number of feature channels, followed by the application of two successive \( 3 \times 3 \) convolutions. After each upsampling operation, the resulting feature map is concatenated to the respective one from the left side of the network. All convolutions occur with an Exponential Linear Unit (ELU) [49]. A final \( 1 \times 1 \) convolution is applied to assign a label to each pixel. Acoustic event classification is obtained by adding two fully connected layers at the bottom of the Unet (cf. yellow area in Fig. 1). We train the multi-task learning architecture by minimising the loss \( L_{\text{sec}} \), defined as:

\[
L_{\text{sec}} = L_S + L_C
\]
where $L_S$ and $L_C$ refer to the loss related to the segmentation and classification tasks, respectively, and are computed by applying a soft-max combined with a cross-entropy loss function. In the case of $L_S$, the soft-max is applied over the final feature map, and defined as:

$$p_{i,k} = \frac{\exp(a_{i,k})}{\sum_{n=1}^{N} \exp(a_{i,n})}$$

where $a_{i,k}$ indicates the activation in feature map $k$ at pixel $i$, and $N$ is the number of classes. Training is performed by minimising the loss $L_{S\alpha C}$ with $l1$ regularisation, using back-propagation.

One of the reasons for which the $k$-means approach results to be less resilient to greater amount of background noise is that, in that case, the segmentation is merely based on the energy content of each time-frequency slot of the gammatonegram, while, when applying a $Unet$, as we operate in a supervised manner, we are actually able to learn, look for, and retrieve the particular shape of the signal of interest. As we are now operating in a MTL scheme, the segmentation is also augmented by information given by the classification task, lessening some of the issues induced by performing a blind segmentation (i.e. we first segment the spectrogram and then classify the signal; the segmentation cannot make use of any signal-specific information), as mentioned earlier. Fig. 4 reports a qualitative comparison between the $k$-means approach and the $Unet$ one, when applied to a scenario characterised by an SNR of $-35$dB. We can observe that even if the deep learning-based system does not recover perfectly the original target signal, the segmentation is still much more accurate and reliable than the one provided by $k$-means [3].

### C. Sound Source Localisation

In this work, we are interested in horizontal acoustic source localisation, relying on a stereo composition of the sound (i.e. as perceived by two different, spatially separated, microphones). Specifically, we are interested in learning a direct mapping between the clean gammatonegrams of the stereo signal and the direction of arrival of the sound. Once the segmentation has been performed, as described in Section III-B, the gammatonegrams of two channels of the target signal are recovered by applying the output of the segmentation as a mask on the original gammatonegrams. The cross-correlation between the resulting clean gammatonegrams, the cross-gammatonegram is then used as input to a CNN to regress the DoA. If $G_{N_1}$ and $G_{N_2}$ are the noisy gammatonegrams for the first and second channel of the stereo signal, and $S_1$ and $S_2$ the respective segmented images, the input to the network is given by:

$$(G_{C_1} \star G_{C_2})(p,l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} G_{C_1}(m,n) \cdot \tilde{G}_{C_2}(m-p,n-l),$$

$$-M + 1 \leq p \leq M - 1,$n

$$-N + 1 \leq l \leq N - 1$$

(6)

where $G_{C_j} = G_{N_j} S_j / \max \left( G_{N_j}^2 S_j \right)$, $j \in \{1, 2\}$ and $\tilde{G}_{C_j}$ denotes the complex conjugate. The CNN consists of two $6 \times 6$ convolutional layers, followed by a $2 \times 2$ max pool, and two fully connected layers. All layers are equipped with an ELU. We employ the network to regress the direction of arrival of the sound as the respective angle on the horizon plane, and define our loss function $L_{SL}$ as $L_{SL} = \| \alpha - \hat{\alpha} \|_2$, where $\alpha$ and $\hat{\alpha}$ are the ground truth values, and the predictions of the network. Training is performed by minimising the Euclidean loss $L_{SL}$ with $l1$ regularisation, using back-propagation.

### IV. EXPERIMENTAL EVALUATION

We evaluate our framework, analysing the performance of both networks, comparing their behaviour with other two different architectures. We show that the particular configuration chosen in this work, while providing comparable performance in the acoustic event classification task, yields significantly greater performance in the sound source localisation one compared to the other architectures analysed. Specifically, we evaluate two alternative networks:
We obtain when regressing the DoA from the gammatonegrams of the stereo sound as a denoising approach. As such, we are not interested in the performance of the segmentation per se, but rather in the accuracy we obtain when regressing the DoA from the gammatonegrams which have been cleaned by the segmentation. Thus, in this context, we will focus on the performance of the SL network and the classification task of the SeC one, and discuss the performance of the semantic segmentation only through the impact this has on the following DoA estimation.

\section*{A. The Dataset}

To evaluate the performance of our framework, we collected four hours of data by driving around Oxford, UK, on different kinds of road, and at different times of the day (i.e. different traffic conditions). The data was gathered using two Knowles omnidirectional boom microphones mounted on the roof of the car and an ALESIS IO4 audio interface. The data was recorded at a sampling frequency $f_s$ of 44100 Hz at a resolution of 16 bits. Furthermore, to obtain accurate ground truth values in the sound source localisation task against various levels of masking noise, we corrupted a stereo composition of specific target signals with the traffic noise recorded, generating samples at various SNRs. This kind of approach is commonly used in acoustics literature (e.g. \cite{10} and \cite{50}–\cite{52} among others), especially when the impact of noise on classification and identification tasks has to be isolated and accurately quantified. Lastly, it allows us to address scenarios where no other sensors can be used to provide ground truth, as either the target sound is purely acoustic (e.g. horns), or the sound source is too far away and, thus, out of the field of view of additional sensors potentially present (situation which would, indeed, match the low SNR levels analysed in this work). This additional data used has been extracted from the Urban Sound Dataset \cite{12}, and from other publicly available databases, such as \url{www.freesound.org}. We are interested in clean signals, as these will represent our ground truth data. Thus, we select only samples, where any background noise is either absent or can be easily removed through traditional filtering. The clean signals obtained are then mixed with the recorded traffic noise, simulating different direction of arrival of the sound, with the acoustic source moving at different velocities, following different paths. Frequency shifts, due to the Doppler effect, are applied accordingly. The simulation also takes into account additional propagation effects, such as echoes (i.e. delayed, less powerful copies of the original signal), and small perturbations (i.e. variation in the power of the perceived signal depending on the direction of arrival) to consider potential reflections, and different kinds of microphone response patterns. A schematic representation of the microphone configuration is given in Fig. 5. The direction of arrival of the sound, computed as the angle between the sound source and the vehicle, is denoted by $\alpha$.

\begin{itemize}
  \item \textbf{Full-Sharing (FS):} the two tasks in the MTL scheme share both the encoding and decoding side of the network. Classification does not take place at the bottom of the \textit{Unet}, as in Fig. 1, but at the last decoding layer.
  \item \textbf{Mono:} the multi-task learning scheme is identical to the one of the SeC network, but, in this case, it does not operate on the gammatonegrams of the stereo sound, but gammatonegrams of different channels are considered as separate samples.
\end{itemize}

We remind the reader that we apply semantic segmentation to the gammatonegrams of the stereo sound as a denoising technique, which allows us to recover the target signal from the background noise. As such, we are not interested in the performance of the segmentation per se, but rather in the accuracy we obtain when regressing the DoA from the gammatonegrams which have been cleaned by the segmentation. Thus, in this context, we will focus on the performance of the SL network and the classification task of the SeC one, and discuss the performance of the semantic segmentation only through the impact this has on the following DoA estimation.

\subsection*{B. Implementation Details}

We trained the networks using mini-batch gradient descent based on back propagation, employing the Adam optimisation algorithm \cite{53}. We applied dropout \cite{54} to each non-shared layer for both tasks’ architectures with a keeping probability of 0.9. The models were implemented using the Tensorflow \cite{55}.
libraries. We confine our frequency analysis to a range between 50 Hz and \( f_s/2 = 22050 \text{ Hz} \), corresponding to the maximum reliable frequency resolution available, and utilise 64 frequency channels in the gammatone filterbank. The filtering is computed on time domain frames of 0.5s with 10ms overlap, after applying a Hamming window to avoid spectral leakage. Similarly to previous works on deep learning in the auditory domain (cf. [56], [57]), we randomly split our dataset into training set (90%) and test set (10%).

C. Acoustic Event Classification

Table I reports the confusion matrix obtained by employing the SeC network. The average classification rate for all classes is shown along the diagonal of the matrix. Fig. 6 shows the accuracy obtained in the classification, averaged over the three classes, at various SNR levels, when applying the SeC network, and the two benchmarks: the FS, and the Mono networks. (The figure also includes results that will be discussed in Section IV-E.) The results suggest that all three architectures are able to provide a great classification accuracy, despite the presence of copious noise in the original gammatonegrams. Specifically, SeC provides an average accuracy of 94%, while FS and Mono provide an accuracy of 98% and 96%, respectively. Furthermore, Table I confirms that this accuracy is stable among the different classes.

D. Sound Source Localisation

Table II reports the median absolute error obtained in the regression of the DoA, when the preliminary segmentation is carried out through the SeC network (cf. \( \hat{E}_{SeC} \)), and through the two benchmarks: the FS (cf. \( \hat{E}_{FS} \)), and the Mono networks (cf. \( \hat{E}_{Mono} \)). The correspondent normalised histograms of the absolute error are shown in Fig. 7. In all three cases, the DoA estimation relies on the SL network. We observe that our framework is able to accurately localise the acoustic sound source, successfully coping with scenes characterised by extremely low SNRs (\(-40 \text{ dB} \leq \text{SNR} \leq 10 \text{ dB}\)). Furthermore, it is the one yielding the greatest performance, when compared to the FS and the Mono networks. In particular, while losing only 4%, and 2% in the event classification task accuracy, we obtain a 46% improvement on \( \hat{E}_{FS} \) and 42% on \( \hat{E}_{Mono} \) in the DoA estimation, when considering both sirens and horns. We conclude that:

- **SeC vs FS**: performing classification at the bottom of the Unet allows the segmentation to learn more task-specific patterns, yielding an increase in the DoA estimation accuracy.
- **SeC vs Mono**: performing segmentation on the stereo gammatonegrams, rather than on the one of each channel independently, allows us to learn a more stereo-aware representation of the sound, which makes the DoA regression more robust and accurate.

We also observe that, in all the frameworks, the estimation process is more accurate with the sirens, than with the horns. This is as expected, as horns have characteristics similar to the ones of pure tones, and consist of a dominant frequency component, whose patterns tend to variate, only slightly, over time. Such characteristics reduce the ability of the system to detect the auditory cues necessary to correctly regress the direction of arrival of the sound, which are based on the difference between the gammatonegrams of the two signals in the stereo combination. From Table II, we see that, in the case of the horns, employing SeC for segmentation provides a 53% improvement on \( \hat{E}_{FS} \) and 57% on \( \hat{E}_{Mono} \).

In our previous work [3] we demonstrated that spectrogram segmentation greatly improves the accuracy in the classification of the various acoustic events. Similarly, we here investigate the impact of the segmentation on sound source localisation. Specifically, we evaluate the behaviour of two additional CNN architectures, which implement end-to-end regression, i.e. from the generalised cross-correlation of the
noisy original gammatonegrams of the signals to the direction of arrival of the sound. The structure of the CNN is the same as for the SL network, where the input is given by the generalised cross-correlation of the noisy gammatonegrams of the signals without applying any pre-processing and segmentation. The only difference in the two architectures is in the datasets used for training. The first network is trained using a dataset of noisy and clean gammatonegrams, while the second one is trained using a dataset of only noisy gammatonegrams. We tried both approaches to also verify whether by exposing the network to clean gammatonomagrams could help it learn how to implicitly discard the noise. Testing is always performed on noisy signals. Furthermore, we analyse the behaviour of an additional framework where no segmentation is performed, but event classification and sound source localisation are carried out in a multi-task learning fashion, which we call MTL Regression. In particular, this MTL scheme combines the SL network where neither pre-processing or segmentation are applied and a CNN structure similar to the one used for class prediction in the SeC architecture. The goal was to investigate whether supplying the network with information about the class of the signal could ease the regression task. Fig. 8 reports the normalised histograms of the absolute error obtained in all three scenarios, together with the corresponding median error. We can conclude that gammatonegram segmentation is, indeed, beneficial to sound source localisation as well; our proposed method (cf. Table II) provides \( E_{\text{SeC}} = 7.5^\circ \), in contrast to 11.02\(^\circ\), 16.98\(^\circ\) and 10.1\(^\circ\), respectively (corresponding to 31\%, 56\%, and 25\% improvement).

All the experiments considered so far, rely on a random split of the dataset into training and test sets. This scenario, however, is particularly challenging, and does not adhere faithfully to the reality, where the testing frames will be part of the same data stream and additional processing can be applied. In this last experiment, we build an additional test dataset, consisting of 600 consecutive audio frames and apply median filters of different orders to the DoA estimates to remove potential outliers. Results are shown in Fig. 9. We observe that the system becomes extremely reliable: we provide, for instance, estimates with a median absolute error of 2.5\(^\circ\) when employing audio frames of 2.5\(s\), which is an acceptable time frame in our scenario, as our system works properly also at really low SNRs, which implies that the sound source is still at a considerable distance from the microphones.

### E. Comparison With Related Work and Discussion

In order to also have a means of comparing the performance of our system to other related works, Table III shows the accuracy achieved by those works, together with some of the corresponding experimental settings, as reported by the authors in the original publications. Even though a direct comparison is not feasible, all works rely on different datasets and experimental conditions, we can observe that, operating on a more extensive dataset, in much harsher noisy scenarios, and while carrying out multi-class classification rather than detection (as almost all the other works used in the comparison do), the performance reached by our framework is comparable, when not greater, than what achieved by other methods. As an additional measure of comparison, we adapt the methods proposed in [12] to operate on our dataset and analyse their performance. Specifically, we investigate the behaviour of a system relying on Support Vector Machines (SVMs) and one relying on Random Forests (RFs), both acting on MFCC-based feature vectors, adjusted to execute the three-class classification task of our framework. Figure 6 reports the results of this comparison. We can observe that our framework outperforms both the SVM system and the RF one, and that this difference increases with the amount of noise. Indeed, while the performance of our framework is only mildly affected by the lowering of the SNR, the recognition rate obtained by the SVM and RF drop dramatically at lower SNRs until reaching less than 50\% when \( SNR = -35dB \).

We would also like to draw to the attention of the reader that in all the deep learning architectures analysed in this work, all convolutions occur with Exponential Linear Unit (ELU). The reason for this choice is to be attributed to some preliminary experiments we have performed and which demonstrated that
the use of ELUs in these scenarios led to higher performance with respect to other activation functions. In particular, in the case of Rectified Linear Units (ReLUs), while no significant differences in the performance were observed in the event classification task (cf. SeC network), the regression task (cf. SL network) was characterised by a median error of 10°, compared to the $\tilde{E}_\text{SeC} = 7.5°$, obtained with the use of ELUs. Further investigations seem to suggest that the reason behind this behaviour is due to a better segmentation mask generated by the SeC network when using ELUs. One example is shown in Fig. 10 where it is possible to observe that the segmentation mask generated by employing RELUs is less resilient to noise.

We did not directly analyse the real-time performance of the system, as we do not anticipate that this would be a challenge. Indeed, we do not foresee additional delays with respect to the offline experiments we carried out, considering that the system runs roughly at 2 Hz (frequency dictated by the length of the audio frames we employ). Indeed, while the training is time consuming, the execution time of sensing, gammatonegram creation and inference (through the deep network) is insignificant with respect to the 2 Hz (0.5s window).

V. CONCLUSION

In this paper we proposed a framework to detect alerting sound events in urban environments, and localise the respective sound source. As traffic scenarios are characterised by copious, unstructured and unpredictable noise, we proposed a new denoising method based on semantic segmentation of the stereo gammatonegram of the signals in a multi-task learning scheme, to simultaneously recover the original clean sound, and identify its nature. The direction of arrival of the sound is, then, obtained by training a CNN with the cross-gammatonegrams of the denoised signals. Our experimental evaluation, which includes challenging scenarios characterised by extremely low SNRs ($-40 \text{dB} \leq \text{SNR} \leq 10 \text{ dB}$), showed an average classification rate of 94%, and a median absolute error of 7.5° when operating on audio frames of 0.5s, and of 2.5° when operating with a median filter on longer frames of 2.5s. Further work can investigate the detection of audio events against other noise sources, and the occurrence of simultaneous acoustic alarms of a different nature.

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