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A method for environmental acoustic analysis improvement based on individual evaluation of common sources in urban areas

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HIGHLIGHTS

- This work allows the identification and evaluation of estimated individual sources.
- The method based on MBLMS and BSS achieves a successful separation of predominant noise sources.
- The method was applied to recorded measurements in semi-controlled environments.
- The evaluation results are based on recorded signals from a permanent monitoring system.
- The use of estimated predominant sources allows identifying successfully masked sources in noisy areas.

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ABSTRACT

Noise levels of common sources such as vehicles, whistles, sirens, car horns and crowd sounds are mixed in urban soundscapes. Nowadays, environmental acoustic analysis is performed based on mixture signals recorded by monitoring systems. These mixed signals make it difficult for individual analysis which is useful in taking actions to reduce and control environmental noise. This paper aims at separating, individually, the noise source from recorded mixtures in order to evaluate the noise level of each estimated source. A method based on blind deconvolution and blind source separation in the wavelet domain is proposed. This approach provides a basis to improve results obtained in monitoring and analysis of common noise sources in urban areas. The method validation is through experiments based on knowledge of the predominant noise sources in urban soundscapes. Actual recordings of common noise sources are used to acquire mixture signals using a microphone array in semi-controlled environments. The developed method has demonstrated great performance improvements in identification, analysis and evaluation of common urban sources.

1. Introduction

In general, noise present in an urban area could be characterized by the contribution of common sources, such as: vehicles, whistles, sirens, car horns and crowd sounds. The individual acoustic evaluation of each source is complicated, because typical source levels are mixed in the environment. This condition makes it difficult to take actions for the control or elimination of a specific noise source. A signal processing method to identify and analyze individual sources that disrupt the urban soundscape is needed in order to assist in controlling or reducing the sound level generated by those sources which are negatively perceived by exposed population. This issue takes great relevance because exposure to high noise levels for long periods of time causes serious damage to the health and comfort of people (WHO, 2009).

Nowadays the environmental acoustic analysis is performed based on measurements taken with sound level meters. The recorded signals are mixtures of all noise sources present simultaneously over a time period. The mixture analysis avoids evaluating the real acoustic contribution of each source. The common control actions for noise reduction are the motivation of this research, due to the fact that they are aimed to control or remove an individual source that produces noise.

Because of the need to evaluate noise sources individually, a method for separating common urban sources from recorded mixtures in semi-controlled environments is presented. The semi-controlled environments consider that both the sources and the microphones are fixed. A microphone array of four directional sensors and recordings of real sources was used. Also the results of a comparison study between the noise levels of mixed and separated sources are shown.

Since road traffic noise is considered the greatest contribution to urban noise pollution, there are several investigations dedicated to assess acoustic level and health damage of the vehicle types (Abo-

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Qudais and Abu-Qdais, 2005; Filho et al., 2004; Pandya, 2001; Paviotti and Vogiatzis, 2012; Zannin et al., 2006). As known by reviewing the state of the art, the papers related to analyze, identify or evaluate sources individually are based directly on mixture recordings and recent research results show grouped sources in classes. For instance, a classifier based on BSS of instantaneous mixtures identifies the road traffic noise into six categories in order to predict the road traffic noise using noise maps (Miedema, 2004). In order to detect and reduce or eliminate sudden increase of sound pressure level in instantaneous time intervals called noticed sound events (NSE), statistical descriptors are used in time domain and frequency to classify into three categories the road traffic. It is noteworthy that each class corresponds to a source mixture (Torija et al., 2012). An acoustic analysis in an area dedicated to leisure where road traffic is controlled was performed on the sources divided into frequency bands, which is affected by the simultaneity of noise sources in the recorded signals (Morillas et al., 2013).

The proposed method consists mainly of two stages: (1) blind deconvolution for eliminating or reducing the convolutional effect (Caron, 2004; Torkkola, 1999; Zhang et al., 2011) and (2) blind source separation using the linear mixture model Fast-ICA (Hyvärinen, 1999a; Hyvärinen and Oja, 1997) in the wavelet domain to improve the separation results. Fast-ICA algorithm has very fast convergence and there is no learning rate or other adjustable parameters in the algorithm. The mixtures recorded by microphone array are previously conditioned through a pre-processing stage. This approach helps to improve the acoustic analysis because it allows separate sources and thus individually evaluate them.

Ordinary noise cancelling methods such as low-pass filtering and nonlinear filtering can be used to separate just one of the sources from the rest; nevertheless they are satisfactory only if the noise signal has spectral characteristics that are clearly different from those of the interest source. Other noise canceling techniques cannot separate audio signals due to complexity of sources and the convolution effect in the mixtures, such as principal component analysis (PCA) (Nadal et al., 2000), wavelets (Mallat, 1989) and sparse code shrinkage (Donoho et al., 1995; Hyvärinen, 1999b).

Independent component analysis (ICA) is the most used technique to achieve blind source separation (BSS). The original ICA technique is useful for sources that can be assumed statistically independent, with non-Gaussian distributions and considering that the unknown mixing matrix is square. Therefore a microphone array of four sensors can separate a maximum of four sources. Because the common urban source spectrum is mainly concentrated in low frequencies, wavelets have the property to increase the resolution in this frequency range improving the separation performance (Popescu et al., 2009).

BSS method for linear mixing models cannot be applied directly to mixtures recorded in environments where there is a convolution effect between the sources due to reverberation. In this case, it is necessary to apply a blind deconvolution method where the number of mixtures and the characteristics of the mixing matrix are unknown. The convolutive model is considered for source signals that have different time delays in each observed signal due to the finite propagation speed in the medium. The convolutive BSS methods are difficult to apply through the large number of parameters to estimate in the methods proposed (Torkkola, 2000).

Blind deconvolution is a signal processing problem where the objective is to estimate the source signal from only the mixture signals recorded without knowing the convolving system. Several methods for handling these problems have been proposed, using different techniques such as cumulant-based methods (Nandi, 1999; Shalvi and Weinstein, 1990), blind deconvolution using linear ICA (Kaplan and Ulrych, 2003) and Bussgang methods that are widely used because of their good performance, in the sense that they are robust and have small mean square error after convergence (Bellini, 1994; Mathis and Douglas, 2003).

As will be shown in the following sections, our approach shows successful improvements in performance due to the combination of blind deconvolution with ICA in the wavelet domain. This method was validated using mixture signals recorded in semi-controlled environments. This work is divided into five sections. Section 2 shows the deconvolution and separation methodology of noise sources from mixtures recorded in semi-controlled environments. Section 3 describes how mixed signals were recorded and pre-processed and the final performance of the system is presented. A comparison study between the noise levels of mixed and separated sources is shown in Section 4. The results are discussed in Section 5. Promising results in identification and separation are offered and they demonstrate that it is possible to achieve a high accuracy level with a mixing process approximate model in real environments under controlled conditions.

2. Methodology

2.1. Blind source separation method

The methodology for BSS of convolutive mixtures consists of the following steps: a) blind deconvolution using Multichannel Blind Least Mean Squares (*MBLS*) technique; b) ICA in the wavelet domain; and c) evaluation of separate estimated sources. A pre-processing stage is necessary for sound mixture conditioning. Fig. 1 shows a block diagram of the proposed methodology.

Recorded sound mixtures are processed by whitening filter in order to remove frequencies below 80 Hz. The use of A-weighted descriptors could minimize the effects generated by low frequencies on annoyance and population health problems. So, non-weighted descriptors are recommended to evaluate the effects of environmental noise. These mixtures have noise sounds with the following characteristics: non-Gaussian signals, statistically independent and the separate source number equal the number of recorded mixtures. These are restrictions set by the ICA techniques.

The ICA problem is greatly simplified if recorded mixtures are first whitened or sphered. A signal is said to be white if it has zero-mean, its elements are uncorrelated and has unit variance. Because of whitening which is essentially decorrelation and scaling of the recorded sounds, this implies that whitening can be made with a linear operation. So the problem is to find a linear transformation z into another vector z as shown in Eq. (1).

$$\mathbf{z} = \mathbf{V}\mathbf{x} \tag{1}$$

where $\mathbf{x}$ is the input signal and $\mathbf{z}$ is the whitened signal. The linear whitening transform $\mathbf{V}$ is given by the matrix $\mathbf{E} = (\mathrm{e}_1, \ldots, \mathrm{e}_n)$, whose columns are the unit-norm eigenvectors of the covariance matrix $\mathbf{C}_x = \mathbf{E}\left\{\mathrm{x}\mathrm{x}^T\right\}$ and $\mathbf{D} = \mathrm{diag}(\mathrm{d}_1, \ldots, \mathrm{d}_n)$ is a diagonal matrix containing the respective eigenvalues d_i of matrix $\mathbf{C}$. The linear transform $\mathbf{V}$ is calculated by Eq. (2).

$$\mathbf{V} = \mathbf{D}^{-1/2}\mathbf{E}^T \tag{2}$$

Whitening is a useful pre-processing technique used by ICA, because it transforms from a mixing matrix to an orthogonal one. It restricts the search for mixing matrix to the space of orthogonal matrices, thus reducing the complexity of the source separation problem. The whitening procedure reduces the number of free parameters, considerably increases the performance of BSS methods and allows faster convergence in the blind deconvolution process (Hyvärinen et al., 2004).

The blind separation of convolution mixtures can be seen as a combined blind deconvolution and an instantaneous BSS problem. After whitening signals, blind deconvolution is performed using the MLBS approach. This technique reverses the reverberation effect in