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A dual fast NLMS adaptive filtering algorithm for blind speech quality enhancement

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ABSTRACT

This paper addresses the problem of acoustic noise reduction and speech enhancement in new telecommunications systems by adaptive filtering algorithms. Recently, a particular attention has been made to the blind source separation (BSS) approach applied for the separation of speech and noise components. The BSS application has inherits the good properties of the adaptive filtering algorithm to give more intelligible enhanced speech signal in term of quality. In this paper, we propose a new dual forward BSS algorithm that is based on signal prediction to give an automatic algorithm with a very fine behavior at the output. This algorithm is called the dual fast normalized least mean square (DFNLMS) algorithm. This algorithm has been tested in various noisy conditions and has shown its superiority in terms of the following objective criteria: cepstral distance (CD), segmental signal-to-noise-ratio (SegSNR), segmental mean square error (SegMSE), and system mismatch (SM). A comparison with other competitive and state-of-the-art algorithms is also presented in this paper.

1. Introduction

The integration of new services and applications in wireless telecommunication systems has led to several digital signal processing techniques that have been developed for different applications such as hand-free cell phone, hearing aids and teleconferencing systems. In these applications, the desired signal is often corrupted by noise and useless signals. The goal is to improve the quality and intelligibility of speech signals corrupted by the acoustic noise components. Due to the important of this field of research, it has been actively researched and several techniques and algorithms were proposed over the past several decades [1–3]. For example in [4], the additive acoustic noise components are eliminated by subtracting an estimate of noise spectrum from noisy speech spectrum. The Wiener filtering based approach was proposed in the same year to improve the a posteriori signal to noise ratio (SNR) [5]. Another technique called the minimum mean square error (MMSE) technique which achieves non-linear estimation of short time spectral amplitude of speech signal is proposed to improve the speech enhancement applications. Another efficient version of the MMSE algorithm referred as Log-MMSE which minimizes the mean square-error (MSE) in the logspectral domain was proposed in [6,7]. We can also recall here that there are further well-known classic algorithms which are called signal-subspace based methods were proposed in [8–10]. Another adaptive approach was adopted in last decade to improve the behavior of the speech enhancement techniques when a speech signal is corrupted by non-stationary noise components. In the same thought, several adaptive algorithms were proposed to reduce noise and enhance the speech signal [11–13]. The most well-known algorithms are the recursive least square RLS [14–16], the least mean square LMS and its normalized version [17–19], and the affine projection algorithm family [20–22]. The NLMS algorithm is widely used in practice for its stability, ease implementation and less computational complexity in comparison with the RLS one that involves more complex mathematical operations and requires more computational resources. However the RLS converges faster than LMS and NLMS. Another approach that is widely used in literature to resolve the problem of corrupted speech signals is the blind source separation (BSS) techniques. In the literature, we find two widely used structures of BSS, the forward BSS (FBSS) [23] and the backward BSS (BBSS) [24]. The FBSS and BBSS structure are often combined with different adaptive algorithms and then used for numerous applications such as in speech enhancement and acoustic noise reduction [25–28]. In this paper we focus on the fast NLMS (FNLMS) algorithm combined with the FBSS structure. This proposed algorithm has shown best performance in comparison with the classical double forward NLMS (DNLMS) one. This paper is organized as follows: in Section 2 we present the mixing model, in Section 3 we describe the FBSS structure. In Section 4, we give the full mathematical formulation of the proposed dual fast FNLMS (DFNLMS) algorithm, and then in Section 5, we give the experimental results of the proposed algorithm in comparison with the classical DNLMS one. Finally the conclusion is

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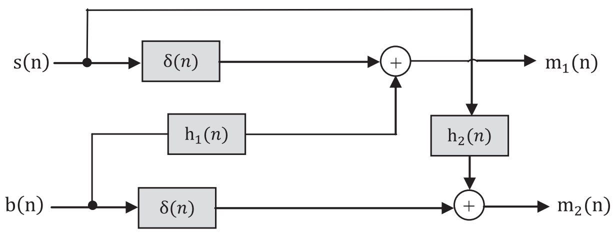

Fig. 1. Convolutive mixture model.

given in Section 6.

2. Mixture model

The convolutive mixing model that we consider in this paper is shown on Fig. 1. We consider two independent sources, a first source of speech signal s(n) and a second source of punctual noise b(n). At the output we observe two convolutive mixture signals of these two sources with two impulse responses $h_1(n)$, $h_2(n)$. In this model, we assume that the direct acoustic paths are equal to the unit impulse responses [3].

The observed signals at the output of the model of Fig. 1 are given by the following relations:

$$m_1(n) = s(n) + h_1(n)*b(n) \tag{1}$$

$$m_2(n) = b(n) + h_2(n)*s(n) \tag{2}$$

where (*) symbolizes the convolution operation and $h_1(n)$ and $h_2(n)$ represent the cross-coupling effects between the channels.

3. Forward BSS structure

The forward and backward BSS structures have been largely investigated in last ten years [3,17,27,28] for speech enhancement and acoustic noise reduction applications. The combination of these two structures with several types of adaptive filtering algorithms has given a new insight in telecommunication systems. In this paper, we focus on the forward BSS (FBSS) structure, which is presented in Fig. 2.

The objective of this approach of FBSS is to estimate two sources signals s(n) and b(n) by using only two noisy observations $m_1(n)$ and $m_2(n)$. The separation of speech and noise by the FBBS structure is based on statistic independent assumptions of the source signals. Furthermore, the FBSS needs an adaptive algorithm to recover the original signals. However, FBSS structure presents the disadvantage of distorting the output signals in the situation where the microphones are loosely spaced.

It was shown theoretically that the correction of the distortions is possible thanks to the equalization of the output signals by post-filtering [12], therefore, we can use two post-filters at the output of this FBSS structure to compensate this distortion. In this paper, we do not interest on the post-filters estimation which are useless in loosely spaced microphones situation that we are considering in this paper.

The two outputs signals of the FBSS structure are given by the following relations:

$$u_1(n) = m_1(n) - m_2(n)*w_1(n) \tag{3}$$

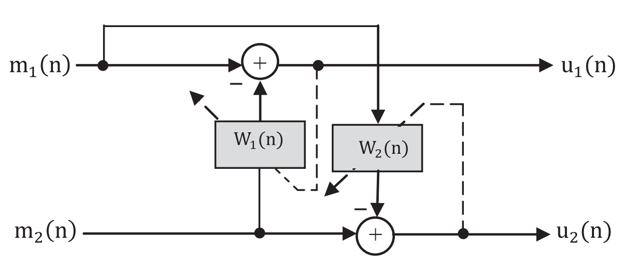

Fig. 2. Forward blind source separation (FBSS) structure.

$$u_2(n) = m_2(n) - m_1(n)*w_2(n) \tag{4}$$

The output of the FBSS structure can be obtained by inserting relations (1) and (2) in (3) and (4) respectively, and we get the following relations:

$$u_1(n) = b(n)*[h_1(n) - w_1(n)] + s(n)*[\delta(n) - h_2(n)*w_1(n)] \tag{5}$$

$$u_2(n) = s(n)*[h_2(n) - w_2(n)] + b(n)*[\delta(n) - h_1(n)*w_2(n)] \tag{6}$$

where '*' represents the convolution operation. The optimal solution of adaptive filters is obtained when $h_2(n) = w_2(n)$ and $h_1(n) = w_1(n)$ [12], so the outputs of this structure get the following forms:

$$u_1(n) = s(n)*\left(\frac{1}{\delta(n) - h_2(n)*h_1(n)}\right) \tag{7}$$

$$u_2(n) = b(n)*\left(\frac{1}{\delta(n) - h_1(n)*h_2(n)}\right) \tag{8}$$

based on relations (7) and (8), the outputs $u_1(n)$ and $u_2(n)$ of the FBSS structure are distorted by the post-filter $P_f(n) = \left(\frac{1}{\delta(n) - h_2(n)*h_1(n)}\right)$. To correct this distortion, post-filters are needed. An efficient way to compute this post-filter is to use the adaptive techniques that are described in [12]. This distortion takes place when the microphones are closely spaced. The problem of post-filters is beyond the scope of this paper, and the loosely spaced configuration that is considered in this paper allows us to avoid this problem.

4. Proposed algorithm

In this section, we present the mathematical formulation of the new dual forward blind source separation algorithm, based on the use of the Fast Normalized Least mean square (FNLMS) to update the two cross-filters of the forward structure as it is given in Fig. 3.

The Fast NLMS algorithm was firstly proposed in [29] for acoustic echo cancellation application. In this paper, we propose a new dual forward blind source separation structure based on two-channel Fast-NLMS algorithm. It is the result of a simplification of the fast transversal filter algorithm. The adaptation gains of this dual algorithm are obtained by discarding the backward and forward predictors from the fast transversal filter algorithm by using only the calculation structure of the dual Kalman variables and a simple decorrelating technique for the input signals. The output $u_1(n)$ and $u_2(n)$ of the proposed FBBS algorithm of Fig. 3 are given as:

$$u_1(n) = m_1(n) - \mathbf{W}_1^T(n)\mathbf{M}_2(n) \tag{9}$$

$$u_2(n) = m_2(n) - \mathbf{W}_2^T(n)\mathbf{M}_1(n) \tag{10}$$

where $\mathbf{M}_1(n) = [m_1(n), m_1(n-1), ..., m_1(n-L+1)]^T$, and $\mathbf{M}_2(n) = [m_2(n), m_2(n-1), ..., m_2(n-L+1)]^T$. The update relations of the adaptive filter $\mathbf{W}_1(n)$ and $\mathbf{W}_2(n)$ are given as follows:

$$\mathbf{W}_1(n+1) = \mathbf{W}_1(n) - \mu_1[u_1(n)\mathbf{C}_1(n)] \tag{11}$$

$$\mathbf{W}_2(n+1) = \mathbf{W}_2(n) - \mu_2[u_2(n)\mathbf{C}_2(n)] \tag{12}$$

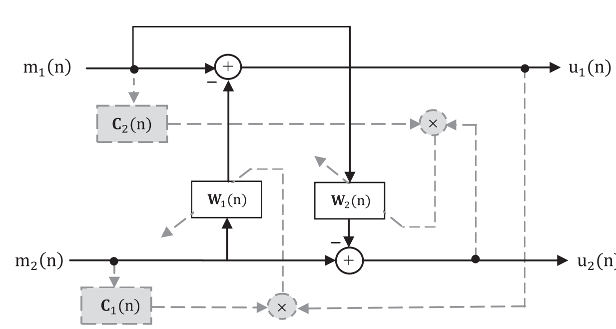

Fig. 3. Proposed dual forward FNLMS algorithm.

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