DOUBLE PSEUDO AFFINE PROJECTION ALGORITHM FOR SPEECH ENHANCEMENT AND ACOUSTIC NOISE REDUCTION

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ABSTRACT

In this paper, we consider the speech enhancement problem in a moving car through a blind source separation scheme involving two closely spaced microphones. We propose the use of a new double pseudo affine projection DPAP algorithm to estimate and suppress coherent noise components from speech. The proposed DPAP algorithm is applied to the forward blind source separation FBSS structure and combined with a new whitening scheme of its two inputs. In order to avoid the use of a manual voice activity detector in the new DPAP algorithm, we have adapted then applied the technique proposed in [1] *to the FBSS structure and for the new proposed algorithm. The simulation results show that the DPAP algorithm, when controlled by the proposed technique is able to fully cancel the correlated noise components from speech.*

1. INTRODUCTION

In the classical noise canceling structure with a noise reference sensor and when the primary and reference sensors are closely spaced, significant leakage of the primary signal can occur onto the noise reference. This reduces the effectiveness of the noise cancellation and also produces distortion of the signal components in the output [2, 3]. The maximum signal to noise ratio (SNR) obtained at the output of such a canceler is equal to the noise to signal ratio present on the reference input [4], [5]. Some improvement is possible if the primary signal is intermittent and the filter is adapted only during periods when the primary signal is absent, but this relies on an efficient primary signal detector. Furthermore, a post-processing stage may be required to reduce signal distortion [3], [4]. To overcome these problems, two suitable types of blind separation (BSS) structures, named forward and backward, are available. At the present, we focus our interest on the forward structure and we propose the use of a double pseudo affine projection (DPAP) algorithm to estimate and suppress coherent noise components from speech. We also propose to use an automatic voice activity detector (AVAD) system based on SNR estimation with the proposed DPAP algorithm. The paper is organized as follows: Section 2 presents the used mixing model for generating the test signals. In Section 3, we describe the FBSS structure and its optimal solution. In Section 4, we recall the formulation of two basic algorithms: the normalized least mean square (NLMS) and the pseudo affine projection (PAP) algorithms. In Section 5, we describe the proposed double pseudo affine projection (DPAP) algorithm. The AVAD system used in the proposed DPAP algorithm is presented in Section 6. In the last Section 7, we show the simulation results of the proposed algorithm and its performance comparison with the DNLMS one.

2. MODEL FORMULATION

The mixing model that we consider in this paper is described in Figure 1. It employs two convolutive mixtures of two uncorrelated point sources (s(n) and b(n)), with impulse responses $h_{11}(n)$, $h_{22}(n)$, $h_{12}(n)$ and $h_{21}(n)$. $n_1(n)$ and $n_2(n)$ represent the non-coherent parts of the diffuse acoustic noise in the vicinity of the microphones plus the electronic noise in the sensors circuits.

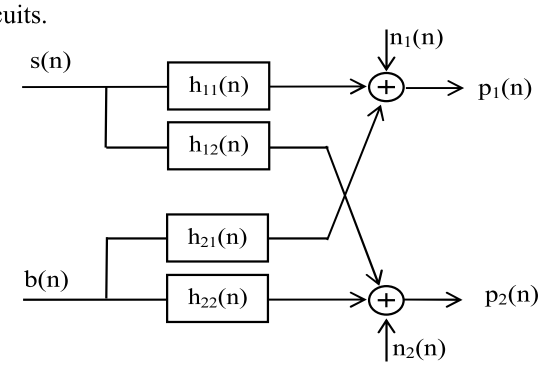

Figure 1: The mixing model.

The model is defined as follows in the frequency domain:

$$\begin{pmatrix} P_1(\omega) \\ P_2(\omega) \end{pmatrix} = \begin{pmatrix} H_{11}(\omega) & H_{21}(\omega) \\ H_{12}(\omega) & H_{22}(\omega) \end{pmatrix} \begin{pmatrix} S(\omega) \\ B(\omega) \end{pmatrix} + \begin{pmatrix} N_1(\omega) \\ N_2(\omega) \end{pmatrix} \quad (1)$$

One of the two point sources $S(\omega)$ is speech, and the second one $B(\omega)$ can represent either the car noise or far-end speech that we want to cancel. $H_{11}(\omega)$ and $H_{22}(\omega)$ represent the frequency responses of each direct channel separately, and $H_{12}(\omega)$ and $H_{21}(\omega)$ represent the cross-coupling effects between the channels. $N_1(\omega)$ and $N_2(\omega)$ represent the Fourier transforms of the diffuse noise components. In this work, $h_{11}(n)$ and $h_{22}(n)$ are assumed to be identity [4]. Moreover, we do not take into account the non-coherent components of the diffuse acoustic noise in the microphones vicinity (*i.e.* we assume $n_1(n) = n_2(n) = 0$).

3. FORWARD BSS STRUCTURE (FBSS)

The FBSS structure that we have investigated is shown in Figure 2. The theoretical solution of the problem is given by setting $w_{21}(n)=h_{21}(n)$ and $w_{12}(n)=h_{12}(n)$ [5]. The least squares (LS) solution to this problem is obtained by minimizing the mean square error MSE of $u_1(n)$ and $u_2(n)$, or equivalently in the Fourier domain:

$$\begin{pmatrix} U_1(\omega) \\ U_2(\omega) \end{pmatrix} = \begin{pmatrix} 1 & -W_{21}(\omega) \\ -W_{12}(\omega) & 1 \end{pmatrix} \begin{pmatrix} P_1(\omega) \\ P_2(\omega) \end{pmatrix} \tag{2}$$

where $W_{21}(\omega)$ and $W_{12}(\omega)$ represent the frequency responses of the separating filters $w_{12}(n)$ and $w_{21}(n)$ respectively. Inserting equation (1) in equation (2), we get the input-output relationship:

$$\begin{pmatrix} U_1(\omega) \\ U_2(\omega) \end{pmatrix} = \begin{pmatrix} F_1(\omega) & H_{21}(\omega)-W_{21}(n) \\ H_{12}(\omega)-W_{12}(n) & F_2(\omega) \end{pmatrix} \begin{pmatrix} S(\omega) \\ B(\omega) \end{pmatrix} \tag{3}$$

where

$$F_1(\omega)=1-H_{12}(\omega)W_{21}(\omega) \tag{4}$$

$$F_2(\omega)=1-H_{21}(\omega)W_{12}(\omega) \tag{5}$$

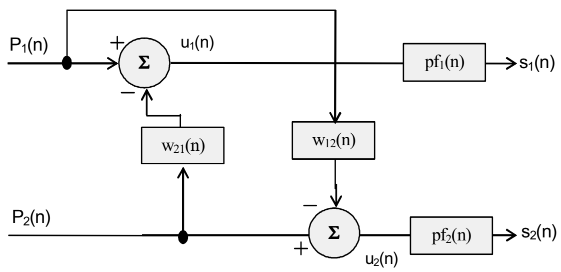

Figure 2: Forward BSS Structure with two post-filters.

3.1. Optimal Solution

To retrieve the original signals from $u_1(n)$ and u_2 (n) (minimum distortion solution) we should have:

$$\begin{pmatrix} S_1(\omega) \\ S_2(\omega) \end{pmatrix} = \begin{pmatrix} U_1(\omega)\left(1-H_{12}(\omega)W_{21}(\omega)\right)^{-1} \\ U_2(\omega)\left(1-H_{21}(\omega)W_{12}(\omega)\right)^{-1} \end{pmatrix} \tag{6}$$

Using post-filters at the output of the Forward BSS structure, as shown in Figure 2, we can approximate that solution. From (6), the two post-filters $PF1(\omega)$ and $PF2(\omega)$ are ideally given by:

$$\begin{pmatrix} PF1(\omega) \\ PF2(\omega) \end{pmatrix} = \begin{pmatrix} \left(1-H_{12}(\omega)W_{21}(\omega)\right)^{-1} \\ \left(1-H_{21}(\omega)W_{12}(\omega)\right)^{-1} \end{pmatrix} \tag{7}$$

In practice, the filters $w_{11}(n)$ and $w_{22}(n)$ are adjusted by using adaptive algorithms. Assuming that the two adaptive filters tend asymptotically to the theoretical solutions, the two post-filters $PF1(\omega)$ and $PF2(\omega)$ lead to the same ideal solution:

$$PF1^*(\omega)=PF2^*(\omega)=\left[1-H_{12}(\omega)H_{21}(\omega)\right]^{-1} \tag{8}$$

We have proposed in [4] techniques that estimate theses post-filters. Since we are interested in the reduction of the speech distortion, we focus our interest on the output $s_1(n)$ which corresponds to the denoised speech signal.

4. ADAPTIVE FILTERING ALGORITHMS

It has been proved in [5] that minimizing the correlation of the output is the same as in the least square (LS) case; hence we propose to use the DPAP and the DNLMS algorithms.

4.1. The NLMS Algorithm

The NLMS algorithm updates the coefficients of the impulse response $w(n)$ of a FIR filter so as to minimize the MSE between the filter output and a desired-response signal $d(n)$. The updating rule is [6]:

$$e(n)=d(n)-\mathbf{x}^T(n)\mathbf{w}(n) \tag{9}$$

$$\mathbf{w}(n)=\mathbf{w}(n-1)+\mu\, e(n)\,\mathbf{x}(n)\left[\mathbf{x}^T(n)\mathbf{x}(n)\right]^{-1} \tag{10}$$

where $\mathbf{x}(n)=[x(n),\ldots,x(n-L+1)]^T$ is the input signal vector of *L* samples, and μ is the step size, which must be chosen between 0 and 2 to achieve convergence.

4.2. The Pseudo Affine Projection PAP Algorithm

In the affine projection algorithm, of order *p* [7], the adaptive filter w(n) is adjusted according to the following update equations:

$$\mathbf{k}(n)=\mathbf{D}(n)-\mathbf{X}(n)\mathbf{w}(n-1) \tag{11}$$

$$\mathbf{w}(n)=\mathbf{w}(n-1)+\mu\,\mathbf{X}^+(n)\mathbf{k}(n) \tag{12}$$

where $\mathbf{k}(n)$ represents the *a priori* error vector. The scalar μ is chosen between 0 and 1 and controls stability and convergence rate. $\mathbf{D}(n)=[d(n),\ldots,d(n-p+1)]^T$ is a vector of the *p* last samples of the reference (microphone) signal, the matrix $\mathbf{X}(n)=[\mathbf{x}(n),\ldots,\mathbf{x}(n-p+1)]^T$ has dimension *pxL* and consists of the *p* last input vectors $\mathbf{x}(n)$. The matrix $\mathbf{X}^+(n)=\mathbf{X}^T(n)\left[\mathbf{X}(n)\mathbf{X}^T(n)\right]^T$ stands for the Moore Penrose pseudo-inverse of matrix $\mathbf{X}^T(n)$. We note that when *p* is set to one, the APA algorithm reduces to the NLMS one [9].

The main attractive properties of this algorithm are its good tracking behaviour and its good convergence rate, which is very close to the recursive LS (RLS) algorithm. Another important parameter is the vector $\boldsymbol{\varepsilon}(n)$ of the *K a posteriori* errors which is given by:

$$\boldsymbol{\varepsilon}(n)=\mathbf{D}(n)-\mathbf{X}(n)\mathbf{w}(n) \tag{13}$$

Combining (11) and (12) we find

$$\boldsymbol{\varepsilon}(n)=(1-\mu)\,\mathbf{k}(n) \tag{14}$$

Assuming in the following that μ=1, the relation (13) reduces to the zero vector and (11) may be rewritten as:

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \left[\mathbf{X}^T(n)\mathbf{X}(n) + \varepsilon\mathbf{I}\right]^{-1}\mathbf{X}(n)e(n) \quad (15)$$

Where $\varepsilon\mathbf{I}$ is an identity matrix used for regularization, and $e(n)$ is given by (9). By considering the additional assumption of stationary of the input signal, we get the following relation between the optimal forward linear prediction coefficient vector $\mathbf{A}_p = [1\ a_1\ a_2\ \ldots\ a_{p-1}]^T$ and the energy E_{p-1} of the prediction error:

$$\mathbf{A}_p = K^{-1}\left[\mathbf{X}(n)^T\mathbf{X}(n)\right]^{-1}\left[E_{p-1}\ 0 \ldots 0\right]^T \quad (16)$$

On the other hand, the optimum linear predicted error vector $\mathbf{m}(n) = [x(n)\ x(n-1) \ldots x(n-p+1)]\mathbf{A}_p$ is related to E_{p-1} through:

$$\mathbf{E}_{p-1} = \mathbf{m}^T(n)\,\mathbf{x}(n) \quad (17)$$

By substituting (16) and (17) into relation (15), we get for the update equation of the filter coefficients:

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \mu\left[\mathbf{m}^T(n)\mathbf{x}(n)\right]^{-1}\mathbf{m}(n)e(n) \quad (18)$$

4.2.1 The pre-whitened version of the PAP algorithm

In Figure 3, we show the new scheme for echo cancellation that we propose to use with the pseudo affine projection PAP algorithm. In this structure, the input signal is a non stationary signal (speech) that is filtered by a whitening filter A_P. The output of this filter is the prediction error vector written as:

$$m(n) = \mathbf{x}^T(n)\mathbf{A}_p \quad (19)$$

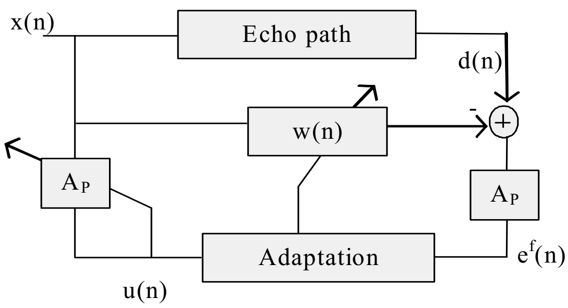

Figure 3: The used structure: Whitening of the input and the filtered error of the adaptation.

The filter $\mathbf{A}_P$ is applied to the adaptation error e(n). We can rewrite the update equation of the adaptive filter $\mathbf{w}(n)$ of the pseudo affine projection PAP algorithm as follows:

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \mu\frac{\mathbf{m}(n)}{\mathbf{m}^T(n)\mathbf{x}(n)}e^f(n) \quad (20)$$

Where $e^f(n)$ is the pre-whitened error, it is given by:

$$e^f(n) = \mathbf{A}_p^T\begin{bmatrix} d(n) - \mathbf{x}^T(n)\mathbf{w}(n-1) \\ \vdots \\ d(n-p+1) - \mathbf{x}^T(n-p+1)\mathbf{w}(n-p+2)\end{bmatrix} \quad (21)$$

5. THE PROPOSED DOUBLE DPAP ALGORITHM

In Figure 4, we show the proposed robust forward implementation of the noise canceller with a new proposed DPAP algorithm. In this Figure, the evident theoretical solution of the problem when $n_1(n)=n_2(n)=0$ is given by setting $\mathbf{w}_{21}(n) = \mathbf{h}_{21}$ and $\mathbf{w}_{12}(n) = \mathbf{h}_{12}$ [3]. The proposed DPAP algorithm minimizes the following *a priori* errors:

$$\mathbf{u}_1(n) = \mathbf{p}_1(n) - \mathbf{p}_2(n) * \mathbf{w}_{21}(n) \quad (22)$$

$$\mathbf{u}_2(n) = \mathbf{p}_2(n) - \mathbf{p}_1(n) * \mathbf{w}_{12}(n) \quad (23)$$

Where (*) represents the convolution operation.

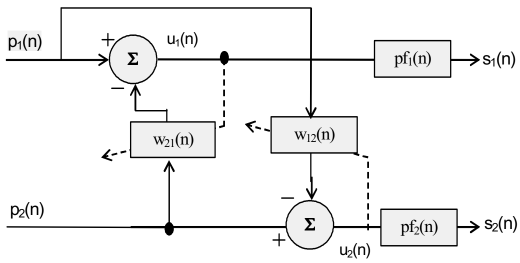

Figure 4: Forward implementation of the ANC with the new DPAP algorithm

For each input $p_1(n)$ and $p_2(n)$: i) we calculate the optimal forward linear prediction coefficient vectors $\mathbf{A}_{p1}(n)$ and $\mathbf{A}_{p2}(n)$, ii) we estimate the optimum linear predicted error vector $\mathbf{m}_1(n)$ and $\mathbf{m}_2(n)$ related to E_{p1-1} and E_{p2-1} through the following formulas:

$$\mathbf{m}_1(n) = [p_1(n),\ p_1(n-1), \ldots, p_1(n-p+1)]\mathbf{A}_{p1}(n) \quad (24)$$

$$\mathbf{m}_2(n) = [p_2(n),\ p_2(n-1), \ldots, p_2(n-p+1)]\mathbf{A}_{p2}(n) \quad (25)$$

Finally we get the update equations of the filter coefficients w_{12} and w_{21} as follows:

$$\mathbf{w}_{12}(n) = \mathbf{w}_{12}(n-1) + \mu_1 u_1^f(n)\frac{\mathbf{m}_1(n)}{\mathbf{m}_1^T(n)\mathbf{x}_1(n)} \quad (26)$$

$$\mathbf{w}_{21}(n) = \mathbf{w}_{21}(n-1) + \mu_2 u_2^f(n)\frac{\mathbf{m}_2(n)}{\mathbf{m}_2^T(n)\mathbf{x}_2(n)} \quad (27)$$

Where $u_1^f(n)$ and $u_2^f(n)$ are the filtering errors of the FBSS structure (see Figure 4) computed by (21). We also note that (26) and (27) are obtained by the use of the pre-whitening structure of Figure 3 combined with our proposed DPAP algorithm. This modification allows an improvement of the DPAP algorithm behaviour with non stationary signal such as speech.

6. AVAD-CONTROLLED ADAPTIVE SCHEME

It is well known that the signals at the outputs of the symmetric structure shown in Figure 2 are obtained within a permutation. Nevertheless, one can get the useful signal at the appropriate output by taking advantage of the non-stationary of speech, which is basically an intermittent signal [5], [3]. We have used an AVAD system to control the adaptation of the filters: i.e., the filter w_{21} is adapted during noise-only periods, whereas the filter w_{12} is adapted only during voice activity periods. This AVAD-controlled adaptive scheme yields de-noised speech at the output s_1, and achieves good convergence of the adaptive algorithms. During noise-only periods, the structure controlled by the AVAD behaves as an ANC, as described in [3].

6.1 description of the VAD technique based SNR

The AVAD controlled system that we consider and adapt to the forward BSS structure is shown on Figure 5.

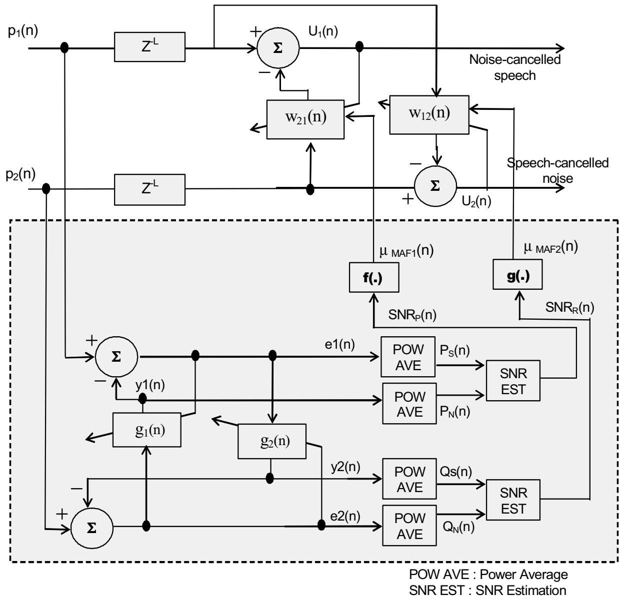

Figure 5: Robust Implementation of the forward BSS structure with a new DPAP algorithm and controlled stepsizes

This AVAD system has been proposed with the backward structure in [1]. This block-diagram corresponds to the ANC FBSS structure with variable step size sub-filters. Four adaptive filters, namely, the main adaptive filters ($\mathbf{w}_{12}$, $\mathbf{w}_{21}$) and the sub adaptive filters ($\mathbf{g}_1$, $\mathbf{g}_2$) generate noise and crosstalk replicas. Coefficients in the main adaptive filters are updated by the proposed DPAP algorithm; however, the sub adaptive filters are updated by the DNLMS algorithm. To reduce signal distortion in the output, the step sizes for coefficients adaptation in the w_{12} and w_{21} filters are controlled according to estimated SNRs of the input signal. This SNR estimation is carried out using $\mathbf{g}_1$ and $\mathbf{g}_2$ output signals. The g_1 output $y_1(n)$ and the subtraction result $e_1(n)$ are used to estimate a more precise SNR at the primary input. This error $e_1(n)$ serves as an approximation to the target speech, and $y_1(n)$ is used as that to the noise. The stepsize for w_{21} is controlled by the estimated SNR calculated from $\mathbf{g}_1$ output signals. The filter $\mathbf{g}_2$ works for crosstalk instead of the noise in a similar way to that of $\mathbf{g}_1$. The resulting SNR estimate from $\mathbf{g}_2$ output signals is used to control the $\mathbf{w}_{12}$ stepsize (we use $y_2(n)$ and $e_2(n)$ to estimate the SNR for the $\mathbf{g}_2$ filter). The details of the parameters of this technique based SNR (AVAD) are given in [1].

7. ANALYSIS OF SIMULATION RESULTS

In this section, we analyze the behaviour of the proposed DPAP algorithm that has been presented in the previous sections. Also, we compare our DPAP algorithm with the DNLMS one, in two cases. The first corresponds to the configuration when the microphones are loosely spaced and the second one is when the microphones are closely spaced. To represent appropriately the effect of the distance between the two microphones on the characteristics of the signals, we have used the specific model proposed in [8] which yields simulated impulse responses $\mathbf{h}_{12}(n)$ and $\mathbf{h}_{21}(n)$ [The sampling frequency is f_s = 8 kHz; the corresponding reverberation time is 30.8ms; the length of the impulse responses is $L = 100$]. The speech signal is a sentence of about 4s and the point-source noise signal is stationary white noise (USASI). The SNRs (speech-to-noise ratios) are chosen equal to 3dB at the input (p_1) and equal to 0dB at the other input (p_2). Note that in all the simulations carried out with this structure and with the DPAP algorithm, we have used post-filters of [4]. We note that this proposed specific model in [8] highlights the physical phenomenon of microphones spacing and allow representing the behaviour of the forward structure in real situations.

7.1. Simulations with loosely spaced microphones

In this simulation, the length of the adaptive filters $\mathbf{w}_{12}(n)$ and $\mathbf{w}_{21}(n)$, for DNLMS and DPAP algorithms, is selected to be equal to L=100 (L is the length of the generated impulse response). The impulse responses have been constructed with a random noise variance of 0.5. The simulation results in the case of loosely spaced microphones are shown in Figure.6.

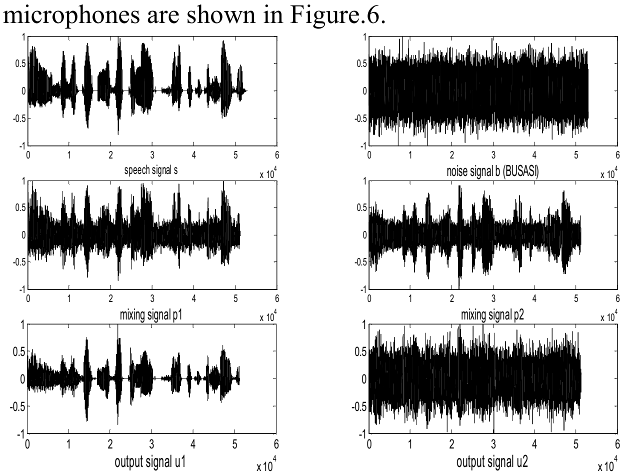

Figure 6: Source signals (top), mixtures (middle) and noise canceller outputs (bottom) obtained with the DPAP algorithm

One can see from inspection to Figure 6 that the proposed DPAP algorithm performs well with the feed-forward structure and that the speech output is completely de-noised. Note that this result was obtained thanks to the use of the AVAD system as explained before. Figure 7 shows the system mismatch which is evaluated according to the following expression:

$$SM_{dB} = 20\log 10\left(\frac{\|\mathbf{h}_{21} - \mathbf{w}_{21}\|}{\|\mathbf{h}_{21}\|}\right) \tag{28}$$

This criterion is evaluated for the proposed DPAP and DNLMS algorithms. The highly superior convergence speed of the DPAP appears clearly in Figure 7. This result comes from the spectral shaping of the noise, one can expect even higher differences in real cases.

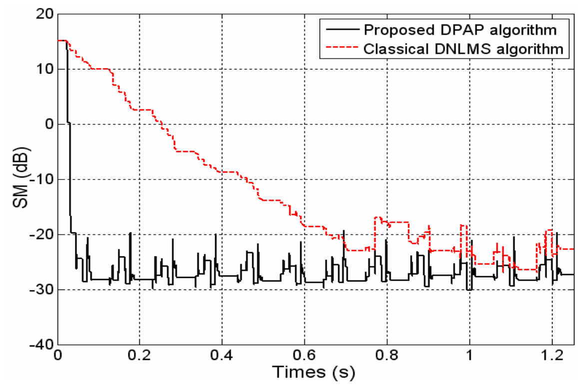

Figure 7: Comparison of system mismatches obtained by DNLMS (dotted in red) and DPAP (solid in black) algorithms. The periodic pattern comes from recycling the same speech file to achieve sufficient simulation length.

7.2. Simulations with closely spaced microphones

The impulse responses have been constructed with random noise variance of 0.0025. In this case, the two adaptive filters w_{12} and w_{21} are close to $\delta(n)$. The output signals are strongly attenuated when the post filters PF1 and PF2 given by (8) in the frequency domain were not used. In order to correct the amplitude attenuation of the output signal of the new DPAP algorithm, we propose to use and apply the post-filter described in [4] to the outputs signals $u_1(n)$ and $u_2(n)$.

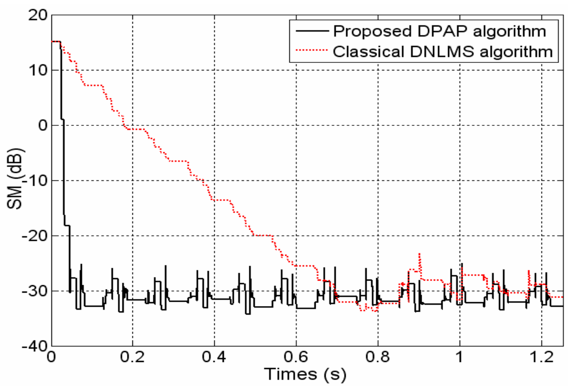

Figure 8: Comparison of system mismatches obtained by DNLMS (dotted in red) and DPAP (solid in black) algorithms. The periodic pattern comes from recycling the same speech file to achieve sufficient simulation length.

The proposed combination of the proposed DPAP algorithm with this adaptive post-filter provides the same outputs signals as in Figure 6. To prove the good performance of this proposed combination, we have shown on Figure 8, the obtained system mismatch values of the adaptive filter $w_{21}(n)$ in this case when the microphone are closely spaced for the two DPAP and DNLMS algorithms. Therefore, one can deduce that the source signal amplitudes can be recovered through the use of the post-filters, which take high gain values in the case of closely spaced sensors [4]. Similar results were obtained with the DNLMS algorithm. We have also noted that behaviour of the system mismatch similar to Figure 7 was obtained in these simulations with the DPAP and DNLMS algorithms. In the end, we have confirmed the better behaviour of the DPAP Algorithm of section 5 *vs.* the DNLMS algorithm through informal listening tests.

8. CONCLUSION

In this paper, we have proposed a new double pseudo affine projection DPAP algorithm. This algorithm is used to adapt the adaptive filters of the FBSS structure to extract the speech signal from noisy observations. This algorithm use two microphones either loosely (first case) or closely (second case) spaced. The DPAP algorithm has given good simulation results for the case of loosely and closely spaced microphones. The good performance of the proposed DPAP algorithm and its superiority over the DNLMS algorithm is validated by the system mismatch criterion values, obtained by (28), and by informal listening tests. We have also noted that the spectral distortion and the amplitude attenuation of the outputs when the microphones are closely spaced are fully corrected when the post-filter of [4] is used with the proposed DPAP algorithm. According to these obtained results, we recommend the DPAP algorithm to be used in practice with the post-filters proposed in [4].

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