Efficient Sparse Blind Source Separation Algorithm for two-Channel Acoustic Noise Reduction

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ABSTRACT

Recently, the acoustic noise reduction problem is treated by two-channel forward blind source separation (BSS) techniques combined with normalized least mean square algorithm (T-FNLMS). The T-FNLMS algorithm shows good performances in two-channel convoluted dispersive mixture. In this paper, we propose new BSS structure based on the two-channel sparse normalized least mean square algorithm (TS-NLMS). The TS-NLMS algorithm is proposed exactly when the convoluted mixing system is characterized by sparse impulse responses. To confirm the good performance of this proposed algorithm, intensive experiments are done in acoustic noise reduction.

I. Introduction

Acoustic noise reduction (ANR) and speech quality enhancement (SQE) are often used in many applications in telecommunication systems such as hand-free telephony. In order to improve the robustness of ANR and SQE systems in such noisy environments, we can use different approaches [1─2]. Several one-, two- and multi-channel sensors techniques are proposed to resolve this problem [3─5]. Recently, blind source separation (BSS) technique has been used to separate the speech and acoustic noise signal in convolutive mixing.

Adaptive filtering algorithms are frequently employed in signal processing, telecommunications and many other applications because of its simplicity and robustness [6─7]. Recently, a very important amount of papers have investigated in ANR and SQE by using different adaptive filtering algorithms combined with the two-channel blind source separation structures (BSS) [8─11]. These approaches are proposed to improve the behavior of ANR and SQE systems in terms of speed convergence, steady state (misadjustment).

In two-channel BSS algorithms, we can use forward-and-backward structures which are simples and efficient [8, 11]. We note that, the two-channel forward BSS is important structure used to enhance the speech signal but with a distortion. Full analyses of this method with and without post-filters are well described in [8─17]. We note also that, all of these structures/algorithms require manual-or-automatic voice activity detector system (VAD) to cancel the acoustic noise components at the outputs [10─17].

In this paper, we consider a two-channel convolutive mixing system. Several forward-and-backward adaptive fultering algorithms have been proposed in time and frequency domains [8, 10]. These adaptive filtering BSS algorithms are used to identify the dispersive impulse responses (IRs) of two-channel convolutive mixture. It has been proven that the adaptive identification of unknown dispersive IR is equivalent to the problem of BSS technique [8─17]. In [14─18], the subband BSS algorithms have been proposed to improve the convergence rate. Recently, it was proposed efficient subband implementation and new variables step-sizes approaches of the two forward-and-backward BSS structures to improve their performances [14─19].

The two-channel forward NLMS algorithm is important solution to separate speech signal from noisy observations. This algorithm showed a good performance in two-channel convolutive mixing model with dispersive IRs. However, the main drawback of this algorithm is their poor performance when the IRs are sparse. This inconvenience is well observed in transient phase. To overcomes these problems, this algorithm has to consider the following notes, (i) need to adapt a relatively long filter and (ii) unavoidable adaptation noise occur at the inactive region of the tap weights [20]. In this paper, the sparse version of two-channel forward Sign-Sign NLMS algorithm is proposed. The proposed algorithm based on normalized step-sizes and proportionate techniques. This algorithm allows improving the convergence speed and the misadjustement performances.

This paper is presented as follows: in section 2, the two-channel mixing and separating system is detailed. In section 3, we present the proposed two-channel sparse forward NLMS algorithm (TS-FNLMS). The simulation results are presented in section 4 and finally the conclusion of this paper is presented in section 5.

II. Two-Channel Mixing and Separating Systems

In this section, we present the two-channel convoluted mixing model that is considered as the problem in this study. After, we will present the two-channel forward NLMS algorithm.

II.1. Two-Channel Convolute Mixing System

The two-channel convoluted mixing model is shown in Fig. 1 [6-13].

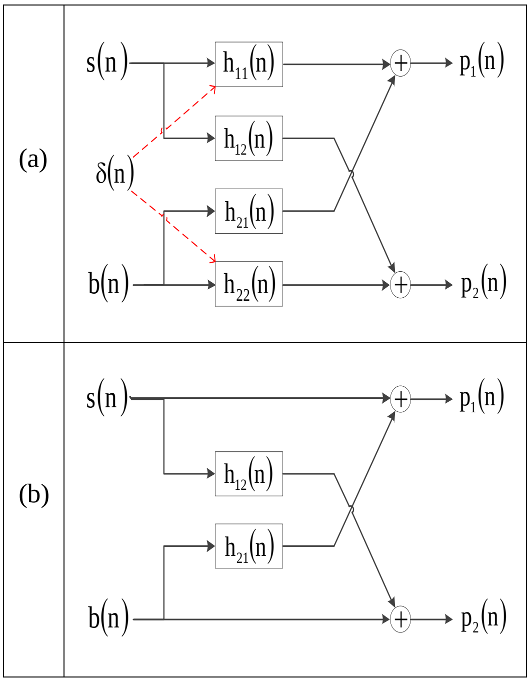

Figure 1. Two-channel convolutive mixture,
(a) full model and
(b) simplified model [6-13]

In model presented in Fig. 1 (a), we consider a first source of speech s(n) and a second of the noise b(n). At the output of this model, we observe two convolutive mixture signals of these two point sources with impulse responses $h_{11}(n)$, $h_{22}(n)$, $h_{12}(n)$ and $h_{21}(n)$. The observed signals are given by:

$$p_1(n)=s(n)*h_{11}(n)+b(n)*h_{21}(n) \qquad (1)$$

$$p_2(n)=b(n)*h_{22}(n)+s(n)*h_{12}(n) \qquad (2)$$

where (*) is the convolution operation, $h_{11}(n)$ and $h_{22}(n)$ are assumed to be identity; which represents the direct acoustic path of each direct channel separately ($h_{11}(n)=h_{22}(n)=\delta(n)$) and $h_{12}(n)$ and $h_{21}(n)$ are the cross-coupling effects between the channels [6-13]. In the case of simplified model Fig. 1 (b), the two equations (1) and (2) can be rewritten as follows:

$$p_1(n) = s(n) + b(n) * h_{21}(n) \quad (3)$$

$$p_2(n) = b(n) + s(n) * h_{12}(n) \quad (4)$$

II.2. Two-Channel Forward Structure

In this section, we present the forward blind source separation (BSS) structure and we give its full formulation and optimal solutions in the time-domain. This structure is intensively used in acoustic noise cancellation [10, 16-19]. The two-channel forward BSS structure is presented in Figure 2.At the output of this structure, the estimated speech signal $u_1(n)$ and $u_2(n)$ are estimated by the following relation:

$$u_1(n) = p_1(n) - p_2(n) * w_{21}(n) \quad (5)$$

$$u_2(n) = p_2(n) - p_1(n) * w_{12}(n) \quad (6)$$

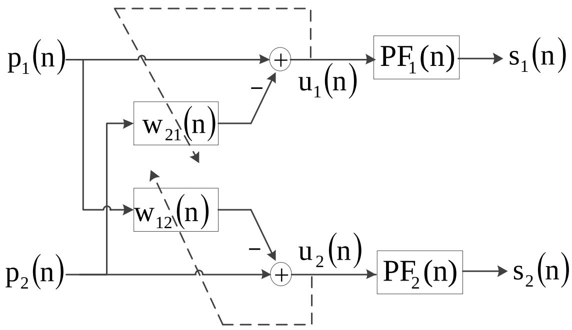

Figure 2. Two-channel Forward structure.

The optimal solutions for the two adaptive filters are given as

$$w_{21}^{opt}(n) = h_{21}(n) \quad (7)$$

$$w_{12}^{opt}(n) = h_{12}(n) \quad (8)$$

By inserting (3) and (4) in (5) and (6) respectively and considering the optimal solutions for the two adaptive filters, see (7) and (8). The output signals relations of this structure can be rewritten as follows:

$$u_1(n) = s(n) * [\delta(n) - h_{12}(n) * h_{21}(n)] \quad (9)$$

$$u_2(n) = b(n) * [\delta(n) - h_{21}(n) * h_{12}(n)] \quad (10)$$

The FBSS structure presents the disadvantage of distorting the output signals. It was shown theoretically that the correction of the distortions is possible thanks to the equalization of the output signals by post-filtering [10, 11], therefore, we can use the two post-filtering $PF_1(n)$ and $PF_2(n)$ in the output of this structure to compensate this distortion and these PFs are ideally given by:

$$PF_1(n) = PF_2(n) = \frac{1}{\delta(n) - h_{12}(n) * h_{21}(n)} \quad (11)$$

In this paper, we do not interest on the post-filters estimation and theirs introduced distortion on the output signal.

A. Two-channel forward NLMS algorithm (T-FNLMS)

In this study, we note that the coefficients of both separation filters $w_{12}(n)$ and $w_{21}(n)$ are adapted from the Normalized Least Mean Square algorithm (NLMS). The adaptation relations of both adaptive filter $w_{12}(n)$ and $w_{21}(n)$ are given by the following expressions:

$$\mathbf{w}_{12}(n) = \mathbf{w}_{12}(n-1) + \mu_{12} \frac{\mathbf{p}_1(n)u_2(n)}{\mathbf{p}_1^T(n)\mathbf{p}_1(n) + \xi_{nlms}} \qquad (12)$$

$$\mathbf{w}_{21}(n) = \mathbf{w}_{21}(n-1) + \mu_{21} \frac{\mathbf{p}_2(n)u_1(n)}{\mathbf{p}_2^T(n)\mathbf{p}_2(n) + \xi_{nlms}} \qquad (13)$$

where $\mathbf{p}_1(n) = [p_1(n), p_1(n-1), \ldots, p_1(n-L+1)]^T$ and $\mathbf{p}_2(n) = [p_2(n), p_2(n-1), \ldots, p_2(n-L+1)]^T$ are two vectors that contains the noisy observation sample $p_1(n)$ and $p_2(n)$ respectively. The two parameters μ_{12} and μ_{21} are the step sizes of both adaptive filters $w_{12}(n)$ and $w_{21}(n)$ respectively, which must be chosen between 0 and 2 to achieve convergence of adaptive filters [10]. We can notice that the forward structure, which has been described previously, use an optimal assumption.

$w_{21}^{opt}(n) = h_{21}(n)$ and $w_{12}^{opt}(n) = h_{12}(n)$)

This optimal solution is got in practice thanks to the adaptation control of both adaptive filters ($w_{21}(n)$ and $w_{12}(n)$). This adaptation is often a voice activity detector (VAD) system. This adaptation is controlled as follows: the adaptive filter $w_{21}(n)$ is adapted only during the noise presence periods, while the filter $w_{12}(n)$ is adapted only during the voice activity presence periods.

III. Proposed Two-Channel Sparse FNLMS Algorithm

In proposed algorithm, the adaptive step-sizes are calculated from the last estimate of the filter coefficients in an efficient way that step-size is proportional to the size of the filter coefficients. This is resulted to adjust the active coefficients faster than the non-active ones. This algorithm is proposed to improve the convergence rate of the adaptive filters tend their optimal solutions, exactly in sparse impulse responses system [20].

In this section, we present the proposed sparse version of two-channel forward NLMS algorithm. The general of the proposed TS-FNLMS algorithm is presented in figure 3.

The TS-FNLMS algorithm assigns an individual step-size to each filter coefficient. The larger coefficient receives a larger increment, thus increasing the convergence rate of coefficient. The active coefficients are adjusted faster than non-active coefficients (small or zero coefficients), so that proposed TS-FNLMS algorithm converges faster than non-proportionate version (T-FNLMS) for sparse impulse responses, when only a small percentage of coefficients is significant [20].

In the proposed TS-FNLMS algorithm, we propose to use the same updating formulas of two adaptive filters $\mathbf{w}_{12}(n)$ and $\mathbf{w}_{21}(n)$ obtained by T-FNLMS algorithm but modified as following:

$$\mathbf{w}_{12}(n) = \mathbf{w}_{12}(n-1) + \mu_{12} \frac{\mathbf{Q}_{12}(n-1)\ \mathrm{Sign}[\mathbf{p}_1(n)]\mathrm{Sign}\ [u_2(n)]}{\mathbf{p}_1^T(n)\mathbf{Q}_{12}(n-1)\ \mathbf{p}_1(n) + \xi} \qquad (14)$$

$$\mathbf{w}_{21}(n) = \mathbf{w}_{21}(n-1) + \mu_{21} \frac{\mathbf{Q}_{21}(n-1)\mathrm{Sign}\ [\mathbf{p}_2(n)]\ \mathrm{Sign}\ [u_1(n)]}{\mathbf{p}_2^T(n)\ \mathbf{Q}_{21}(n-1)\ \mathbf{p}_2(n) + \xi} \qquad (15)$$

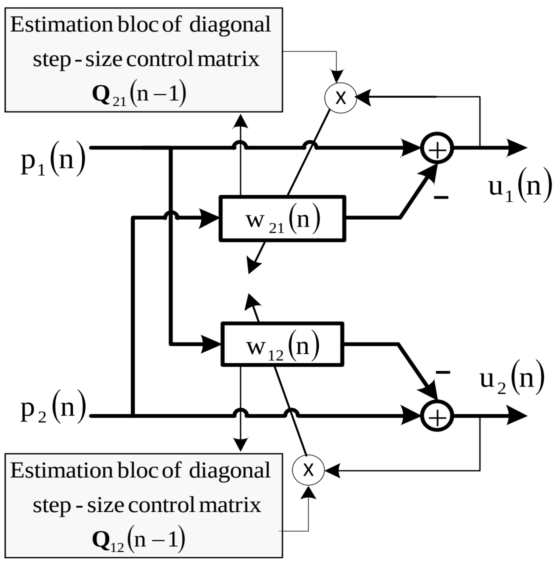

Figure 3 . General diagram of two-channel sparseforward NLMS algorithm (TS-FNLMS)

Where $\mathbf{Q}_{12}(n)$ and $\mathbf{Q}_{21}(n)$ represent the diagonals step-size control matrix (L x L) that are introduced here to determine the step-sizes of each filter coefficient and are dependents on the specific algorithm. The two diagonals step-size control matrix $\mathbf{Q}_{12}(n)$ and $\mathbf{Q}_{21}(n)$ are given by

$$\mathbf{Q}_{12}(n) = \mathrm{diag}\{q_{12,0}(n) \; q_{12,1}(n) \; \cdots \; q_{12,L\text{-}1}(n)\} = \begin{bmatrix} q_{12,0}(n) & 0 & \cdots & 0 \\ 0 & q_{12,1}(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_{12,L\text{-}1}(n) \end{bmatrix} \tag{16}$$

$$\mathbf{Q}_{21}(n) = \mathrm{diag}\{q_{21,0}(n) \; q_{21,1}(n) \; \cdots \; q_{21,L\text{-}1}(n)\} = \begin{bmatrix} q_{21,0}(n) & 0 & \cdots & 0 \\ 0 & q_{21,1}(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & q_{21,L\text{-}1}(n) \end{bmatrix} \tag{17}$$

The diagonals elements of

$$\mathbf{Q}_{12}(n) = \mathrm{diag}\{q_{12,0}(n) \; \cdots \; q_{12,L\text{-}1}(n)\}$$

and $\mathbf{Q}_{21}(n) = \mathrm{diag}\{q_{21,0}(n) \; \cdots \; q_{21,L\text{-}1}(n)\}$

are updated as follows :

$$q_{12,l}(n) = \frac{(1-\alpha)}{2L} + (1+\alpha)\frac{\left|w_{12,l}(n)\right|}{2\left\|\mathbf{w}_{12}(n)\right\|_1 + \varphi} \quad 0 \le l \le L-1 \tag{18}$$

$$q_{21,l}(n) = \frac{(1-\alpha)}{2L} + (1+\alpha)\frac{\left|w_{21,l}(n)\right|}{2\left\|\mathbf{w}_{21}(n)\right\|_1 + \varphi} \quad 0 \le l \le L-1 \tag{19}$$

Where α is small number take its values between –1 and 1, and φ is a very small positive number to avoid division by zero, especially at the beginning of adaptation where all the taps of the filter are initialized to zero.

$\|\mathbf{w}_{12}(n)\|_1$ and $\|\mathbf{w}_{12}(n)\|_1$ represents the 1-norms of the adaptive filters $\mathbf{w}_{12}(n)$ and $\mathbf{w}_{21}(n)$ respectively, which are defined as,

$$\|\mathbf{w}_{12}(n)\|_1 = \sum_{i=0}^{L-1} w_{12,i}(n) \tag{20}$$

$$\|\mathbf{w}_{21}(n)\|_1 = \sum_{i=0}^{L-1} w_{21,i}(n) \tag{21}$$

At initialization, since all the taps of the filters start with zeros, vectors $\mathbf{p}_2(n)$ and $\mathbf{p}_1(n)$ are multiplied by a quantity equal $(1-\alpha)/2L$. This later implies and suggests that the regularization parameter for the TS-FNLMS algorithm should be taken as: $\xi = ((1-\alpha)/2L)\xi_{nlms}$. It can be noticed that, the proposed TS-FNLMS algorithm is the same as non-proportionate T-FNLMS algorithm when α = -1.

Basing on update equations of the two adaptive filters and the diagonal elements presented in (16) and (17), when $\mathbf{Q}_{12}(n) = \mathbf{Q}_{21}(n) = \mathbf{I}_{L\times L}$, i.e. (L×L) identity matrix, we obtain the T-FNLMS algorithm. In comparison to the T-FNLMS algorithm when the IRs are sparse, the proposed algorithm has very fast initial convergence.

IV. Analysis of Simulation Results

In this section, the simulation results of classical T-FNLMS and proposed TS-FNLMS algorithms described previously are presented. In order to qualify the performance of all proposed algorithms, we are only interested on the estimated speech signal that we get in the first output (i.e. $u_1(n)$) of the second adaptive filter (i.e. $\mathbf{w}_{21}(n)$).In this simulations part, we consider the simplified two-channel convolutive mixing model presented in Figure 1-b-, and the two statistically independent source signals to generate the two noisy signals at the output [10-19]. These two-point sources are specified as: $s(n)$is a speech signal phonetically equilibrated, and $b(n)$is a punctual noise. With sampling frequency $Fs = 8\,kHz$

In the two-channel mixing model, we have used two sparse impulse responses $h_{12}(n)$and $h_{21}(n)$ that are convoluted with the original signals to generate the two noisy signals $p_1(n)$ and $p_2(n)$. The length of sparse impulse responses is L=512. The noisy signals $p_1(n)$ and $p_2(n)$ are generated by this model, with input SNR equal -6 dB in the mixing signals $p_1(n)$ and $p_2(n)$. In table 1, we have summarized all selected optimal parameters of classical and proposed algorithms.

In order to evaluate the convergence time and SM values properties of proposed TS-FNLMS algorithm in comparison with T-FNLMS algorithm, we have reported in Figures 4, 5 and 6, the SM evolution in the same simulation.

(i) This SM criterion is evaluated according to the following expression:

$$SM(n)_{dB} = 20\log_{10}\left[\frac{\|\mathbf{h}_{21}(n) - \mathbf{w}_{21}(n)\|}{\|\mathbf{h}_{21}(n)\|}\right] \tag{22}$$

Each point of this figure corresponds to a smoothing of 256 consecutive frames.

Table 1: Simulation parameters values of algorithms, with $\mu_{12} = \mu_{21} = 0.9$, L=512 and $SNR_1 = SNR_2 = -6\,dB$.

Algorithms	Classical T-FNLMS	Proposed TS-FNLMS
Parameters values	$\xi_{nlms} = 10^{-6}$	$\xi = ((1-\alpha)/2L)\xi_{nlms}$

	$\varphi = 10^{-6}$, α = -0.5

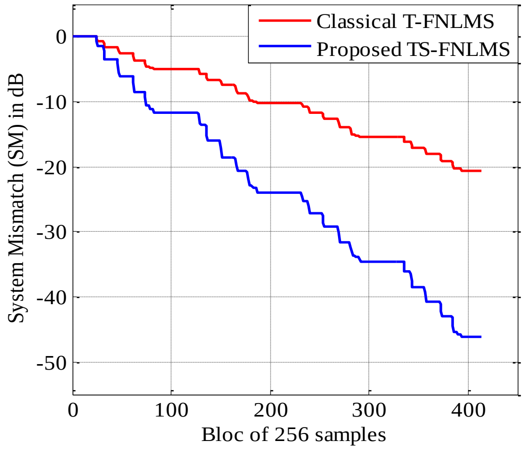

Figure 4 . SM evaluation of adaptive filter $\mathbf{w}_{21}(n)$ obtained by T-FNLMS and proposed TS-FNLMS algorithms with $\mu_{12} = \mu_{21} = 0.2$.

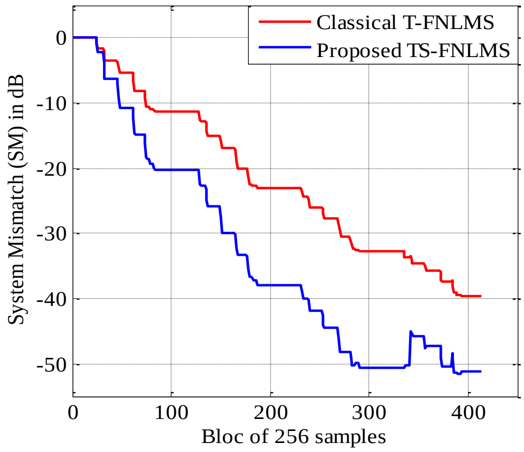

Figure 5. SM evaluation of adaptive filter $\mathbf{w}_{21}(n)$ obtained by T-FNLMS and proposed TS-FNLMS algorithms with $\mu_{12} = \mu_{21} = 0.5$.

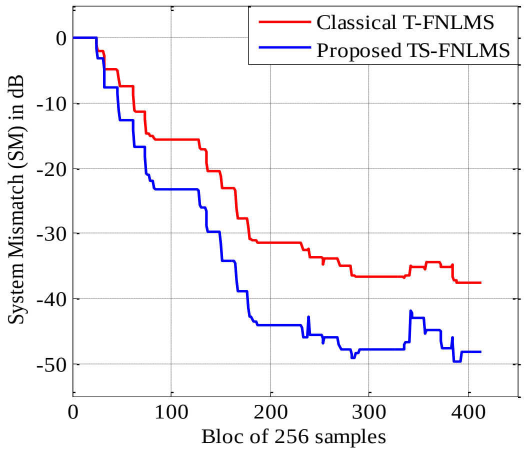

Figure 6 . SM evaluation of adaptive filter $\mathbf{w}_{21}(n)$ obtained by T-FNLMS and proposed TS-FNLMS algorithms with $\mu_{12} = \mu_{21} = 0.9$.

Table 2: Final SM values and convergence time obtained by: T-FNLMS and proposed TS-FNLMS algorithms with $\mu_{12} = \mu_{21} = 0.9$. The bold values represent the best ones.

Algorithms	Classical T-FNLMS	Proposed TS-FNLMS
SM average values (dB)	-38.52	**-50**
Convergence time (s)	10,1	**5,4**

From Figures 4, 5 and 6, we note the good convergence speed performance of the proposed TS-FNLMS algorithm compared with classical version. According to the averages results of Table 2, we observe a fast convergence time of proposed algorithm (**5,4** seconds). However, the other T-FNLMS algorithm suffer from slow convergence time especially in the very noisy observations with sparse impulse (12,1 seconds). Basing on the same results of Table 2, we note that the proposedTS-FNLMS algorithm keeps the good convergence speed time and small steady-staes values (**-50 dB**) in comparison with otheralgorithm (-38.52 dB).

For evaluate the quality of estimated speech signal, we have done other simulations based on cepstral distance (CD) and Segmental signal-to-noise ratio (SegSNR) criteria.

(ii) The CD criterion is evaluated according to the following expression

$$CD_{dB} = \sum_{p=1}^{U} ISFT\left[\log(|S(\omega,p)|) - \log(|U_1(\omega,p)|)\right]^2 \quad (23)$$

where $ISFT[\cdot]$ denote the inverse-short-Fourier-transform. $S(\omega,p)$ and $U_1(\omega,p)$ are, respectively, the short-Fourier-transform (SFT) of the original speech signal $s(n)$ and the enhanced output $u_1(n)$.

(i) The Segmental SNR criterion is given by the following relation:

$$\left(SegSNR_{\lambda}\right)_{dB} = 10\ \log_{10}\left(\frac{\sum_{i=0}^{U-1}|s(i)|^2}{\sum_{i=0}^{U-1}|s(i)-u_1(i)|^2} VAD_{\lambda}\right) \quad (24)$$

The parameter U represents the number of sample needed to obtain the average values of the output SNR. The $\{VAD_{\lambda}\}$is a voice activity detector that detects the presence/absence of only speech- and noise-sequences.

We have done several experiments according to the input SNR (SNR = -6, 0 and 6), the type of noise (white, USASI, babble and street) with L=512. We note that the obtained results of CD and SegSNR criteria are reported on Tables3 and 4.

Table 3: Output SNR evaluation for T-FNLMS and proposed TS-FNLMS algorithms. The bold values represent the best ones

Noise type	Input SNR (dB)	CD values in dB	
		Classical T-FNLMS	Proposed TS-FNLMS
White	-6	-6,8	**-7,3**
	0	-7,01	**-7,47**
	6	-7,75	**-8,69**
USASI	-6	-5,95	**-7,14**
	0	-6,51	**-7,22**
	6	-6,96	**-8,33**
Babble	-6	-6,61	**-7,45**
	0	-6,69	**-7,52**
	6	-7,7	**-8,86**
Street	-6	-6,42	**-7,19**
	0	-7,09	**-8**
	6	-7,33	**-8,56**

Table 4: Overall CD evaluation for T-FNLMS and proposed TS-FNLMS algorithms. The bold values represent the best ones

Noise type	Input SNR (dB)	SegSNR in dB	
		Classical T-T-FNLMS	Proposed TS-FNLMS
White	-6	46,75	**49**
	0	48,22	**50**
	6	50,02	**53**
USASI	-6	45,38	**48**
	0	48,69	**50**
	6	49,79	**52**
Babble	-6	44,01	**48**
	0	45,08	**51**
	6	48,89	**52**
Street	-6	45,03	**48**
	0	46,93	**50**
	6	49,25	**52**

From the obtained results presented in Table3, we have well observed the equality in the convergence to the optimum of classical and proposed algorithms in different cases. We note the good behavior of proposed TS-FNLMS algorithm compared with other ones. This behavior is noted with different situations, noisy types (i.e. white, USASI, babble and street noises) and different input SNR (i.e. SNR = -6, 0 and 6 dB). We conclude that the proposed TS-FNLMS algorithm had given the smaller CD values, which means less distortion on the estimated speech signal.

Basing on the presented results in Table4, firstly we can see that the output SNR characteristics are directly proportional with the input SNR (i.e. the output SNR decreases/increase with the input SNR). We have also observed the weak output SNR values of the classical algorithm in comparison with TS-FNLMS algorithm. Finally, we conclude that the segmental SNR criterion proves the good performance of the proposed TS-FNLMS algorithm compared whit classical for acoustic noise reduction and speech quality enhancement.

V. Conclusion

In this study, we have proposed the two-channel sparse forward NLMS algorithm (noted: TS-FNLMS) which allows extracting the speech signal from very noisy observed signals. This algorithm is mainly proposed exactly to improve the convergence speed in initial phase, when the two-channel convolutive mixing model is characterized by sparse impulses responses. Intensive simulations are carried out to validate the performance of the new proposed algorithm. Basing on the SM values and convergence time results obtained by SM criterion, we have noted the fast convergence speed in initial phase of proposed TS-FNLMSalgorithm compared to the non-proportionate algorithm. The superiority of proposed algorithm in term of estimated speech quality is proven by CD and SegSNR. Finally, all these objective results have proven the efficiency and the superiority of the proposed algorithm in terms of convergence rate and output speech quality compared with classical algorithm in two-channel sparse system.

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