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Efficient subband fast adaptive algorithm based-backward blind source separation for speech intelligibility enhancement

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Abstract

This paper addresses the problem of speech intelligibility enhancement by subband adaptive filtering algorithms in a blind framework. Recently in Djendi and Sayoud (Int J Speech Technol 22:391–406, 2019), we have proposed a subband adaptive algorithm based on the forward blind source separation structure that is efficient for acoustic noise reduction and speech intelligibility enhancement applications. In this paper, we propose a novel subband domain implementation of the backward blind source separation structure combined with a modified version of the fast normalized least mean square (FNLMS) algorithm. The new proposed subband algorithm is efficient in improving the speech signal intelligibility without introducing any distortion at the output. A fair comparison of the proposed backward subband FNLMS algorithm with other fullband type algorithms is presented. This comparison is based on the evaluation of several objective criteria. The obtained results show the best performance of the proposed subband algorithm in terms of speed convergence.

Keywords BBSS · Speech enhancement · Subband adaptive filtering · NLMS algorithm · SNR

1 Introduction

In many modern speech communication systems, the presence of background noise causes degradation in the quality and intelligibility of the communications. For this reason, noise reduction plays an important role in ensuring high quality communication and is still an active research topic. Many techniques for noise reduction and speech enhancement applications have been developed in the literature depending on the number of sensors available for processing. These approaches can be classified into three basic categories which are: (i) the temporal filtering techniques using only single microphone such as optimal filtering (Benesty and Chen 2011) and spectral subtraction (Boll 1979), (ii) the adaptive noise cancellation based on a primary sensor that pick up the noisy signal and a reference sensor to measure the noise field (Widrow and Goodlin 1975), and (iii) the last approach is the beamforming techniques that used an sensor array (Habets et al. 2009).

Moreover, adaptive filtering algorithms have become more popular and have proven effectiveness in acoustic noise reduction and speech signal quality enhancement. The normalized least mean square (NLMS) is the most popular and widely used adaptive filtering algorithm because of its simplicity and robustness (Habets et al. 2009). In spite of these advantages, the use of the NLMS algorithm has been hampered by its slow convergence when the input signal is highly correlated (Sayed 2003). To tackle this issue, numerous algorithms have been proposed, such as the recursive least square algorithms and their fast versions (Slock and Kailath 1991), the affine projection algorithms and their fast versions (Ozeki and Umeda 1984; Bouchard 2003). In the same direction, adaptive filtering in subbands has been proposed to improve the convergence speed behavior of the conventional fullbband adaptive filtering algorithms (Pradhan and Reddy 1999; Lee and Gan 2004; Djendi and Bendoumia 2013). Subband adaptive filtering (SAF) employs multirate filter banks for signal decomposition and reconstruction. This technique leads to a fast convergence speed and less computational complexity (Lee et al. 2010; Gilloire et al. 1988). In this paper, we propose a new subband implementation of the

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backward blind source separation (BBSS) combined with a modified version of the fast normalized least mean square algorithm (FNLMS) for noise reduction and speech intelligibility enhancement applications.

The organization of this paper is as follows: in section II we present the adopted acoustic environment model. In section III we describe the principle of the proposed backward subband FNLMS algorithm. The simulation results of the comparative study between the proposed backward subband FNLMS algorithm and other fullband type algorithms are presented in section IV. Finally we conclude our work in section V.

1.1 Acoustical envirroment model presentation

In this paper, the acoustical environment is modeled by the two channel simplified convolutive mixture that was proposed in (Djendi and Zoulikha 2014), where two noisy observations $m_1(n)$ and $m_2(n)$ are generated by the propagation of two uncorrelated source signals of speech $s(n)$ and noise $b(n)$ as depicted in Fig. 1.

The two noisy observations $p_1(n)$ and $p_2(n)$ are modeled by these two equations:

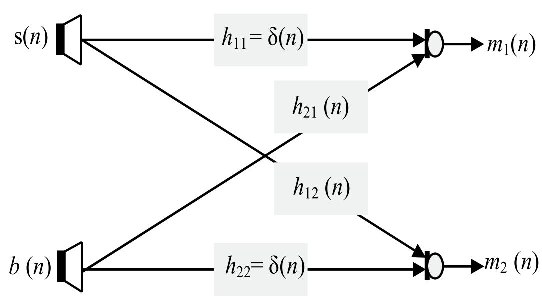

Fig. 1 Simplified convolutive mixture modeling

$$m_1(n) = s(n) + h_{21}(n) * b(n) \tag{1}$$

$$m_2(n) = b(n) + h_{12}(n) * s(n) \tag{2}$$

where $h_{12}(n)$ and $h_{21}(n)$ represent the acoustic coupling paths between the source signals and the microphones. We assume that the speech signal is close from the first microphone and the noise is close from the second microphone, hence the impulse responses $h_{11}(n)$ and $h_{22}(n)$ are equal to the Kronecker unit impulse $\delta(n)$ (Van Gerven and Van Compernolle 1995) (see Fig. 1).

2 Proposed subband backward algorithm descreption

In this section we describe the principle of the proposed backward subband FNLMS algorithm. The proposed algorithm is a subband implementation of the backward blind source separation (BBSS) structure combined with a modified version of the fast NLMS (FNLMS) algorithm. A general block diagram of the proposed backward subband FNLMS algorithm is presented in Fig. 2.

In this figure, we find the following signals:

- $m_1(n)$ and $m_2(n)$ are the fullband mixing signal.
- $m_{1i}(n)$ and $m_{2i}(n)$ are the subband signals of each fullband signals $m_1(n)$ and $m_2(n)$, respectively.
- $e_{1i,D}(p)$ and $e_{2i,D}(p)$ are the decimated output sub-signals.
- $\boldsymbol{E}_{1i}(n) = \left[e_{1i}(n), e_{1i}(n-1), \ldots, e_{1i}(n-l+1)\right]$ and $\boldsymbol{E}_{2i}(n) = \left[e_{2i}(n), e_{2i}(n-1), \ldots, e_{2i}(n-l+1)\right]$ are the vectors of the decimated output sub-signals $e_{1i,D}(p)$ and $e_{2i,D}(p)$
- $e_1(n)$ and $e_2(n)$ are the interpolated sub-signals into their fullband form.

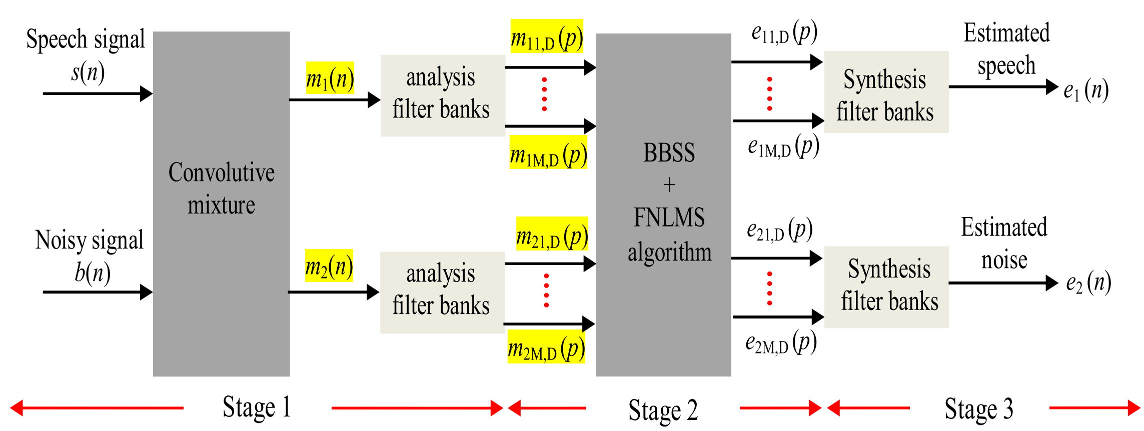

Fig. 2 General block diagram of the proposed backward subband FNLMS algorithm

All of these signals will be well detailed and explained by their mathematical derivation of the following analysis stage section.

2.1 Analysis stage

As shown in Fig. 2 (stage 1) the two noisy input signals $m_1(n)$ and $m_2(n)$ are split into M subband signals $m_{1i}(n)$ and $m_{2i}(n)$ by means of analysis filter banks $h_1(n), \ldots, h_M(n)$, and they are decimated by a factor $D = M$. The decimated mixing sub-signals are defined as follows:

$$m_{1i,D}(p) = m_{1i}(pM) \quad i = 1, \ldots, M. \tag{3}$$

$$m_{1i}(n) = \boldsymbol{h}_i^T(n)\boldsymbol{m}_1(n) \quad i = 1, \ldots, M. \tag{4}$$

$$m_{2i,D}(p) = m_{2i}(pM) \quad i = 1, \ldots, M. \tag{5}$$

$$m_{2i}(n) = \boldsymbol{h}_i^T(n)\boldsymbol{m}_2(n) \quad i = 1, \ldots, M. \tag{6}$$

where $\boldsymbol{m}_1(n) = [m_1(n), m_1(n-1\ldots, m_1(n-l+1]$, $\boldsymbol{m}_2(n) = [m_2(n), m_2(n-1\ldots, m_2(n-l+1)]$. l is the length of the analysis filters $h_i(n)$. The variable n is used for the time index of the original fullband signals, and p is used for the decimated sub-signals.

2.2 Adaptation prosses stage

In the second stage we applied the BBSS structure (Henni et al. 2019) to retrieve the original source signals $s(n)$ and $b(n)$ from only the decimated noisy observations $m_{1i,D}(p)$ and $m_{2i,D}(p)$. In this proposed structure, two symmetric adaptive filters are used to estimate the enhanced output signals. To update the coefficients of these adaptive filters, we use the modified FNLMS algorithm when combined with the BBSS structure. We note that the output signals of the proposed backward subband FNLMS algorithm are estimated in subbands, while the coefficients of the adaptive filters are adapted in their fullband forms. A detailed descriptive scheme of the adaptation process (stage 2) is given in Fig. 3.

2.3 Synthesis stage

In the last stage, the decimated output sub-signals $e_{1i,D}(p)$ and $e_{2i,D}(p)$ are interpolated by a factor $I = M$, subsequently a synthesis filter banks $g_1(n), \ldots, g_M(n)$ are used to merge these last interpolated sub-signals into their fullband form $e_1(n)$ and $e_2(n)$, which are given by the following relations:

$$e_1(n) = \sum_{i=1}^{M} \boldsymbol{g}_i^T(n)\boldsymbol{E}_{1i}(n) \tag{7}$$

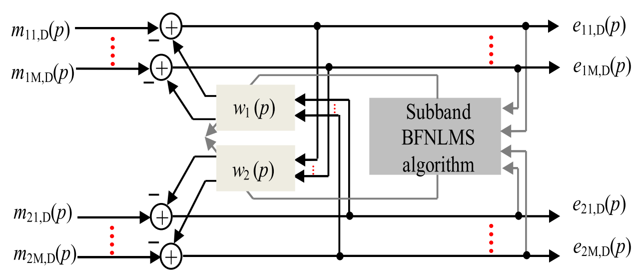

Fig. 3 Descriptive scheme of the adaptation process

$$e_2(n) = \sum_{i=1}^{M} \boldsymbol{g}_i^T(n)\boldsymbol{E}_{2i}(n) \tag{8}$$

where

$$e_{1i}(n) = \begin{cases} e_{1i,D}(p/I), & n = 0, \pm I, \pm 2I, \ldots \\ 0 \, otherwise & \end{cases} \quad For\ i = 1, \ldots, M. \tag{9}$$

$$e_{2i}(n) = \begin{cases} e_{2i,D}(p/I), & n = 0, \pm I, \pm 2I, \ldots \\ 0 \, otherwise & \end{cases} \quad For\ i = 1, \ldots, M. \tag{10}$$

and $\boldsymbol{E}_{1i}(n) = \left[e_{1i}(n), e_{1i}(n-1), \ldots, e_{1i}(n-l+1)\right]$, $\boldsymbol{E}_{2i}(n) = \left[e_{2i}(n), e_{2i}(n-1), \ldots, e_{2i}(n-l+1)\right]$.

2.4 Mathematical formulation of the processing algorithm

We have adopted the FNLMS algorithm to update the two cross-filters of the BBSS structure in a subband framework. In this subsection, we present the mathematical formulation of the proposed backward subband FNLMS algorithm.

The estimated signals for M subbands of the proposed backward subband FNLMS algorithm are given as follows:

$$e_{1i,D}(p) = m_{1i,D}(p) - \boldsymbol{w}_1^T(p)\boldsymbol{e}_{2i,D}(p) \quad i = 1, \ldots, M. \tag{11}$$

$$e_{2i,D}(p) = m_{2i,D}(p) - \boldsymbol{w}_2^T(p)\boldsymbol{e}_{1i,D}(p) \quad i = 1, \ldots, M. \tag{12}$$

where $\boldsymbol{e}_{1i,D}(p) = \left[e_{1i,D}(p), e_{1i,D}(p-1), \ldots, e_{1i,D}(p-L+1)\right]$ and $\boldsymbol{e}_{2i,D}(p) = \left[e_{2i,D}(p), e_{2i,D}(p-1), \ldots, e_{2i,D}(P-L+1)\right]$. L is the length of the adaptive filters. The vectors $\boldsymbol{w}_1(p)$ and $\boldsymbol{w}_2(p)$ are the two adaptive filters of the proposed backward subband FNLMS algorithm, which are updated as follows:

$$\boldsymbol{w}_1(p+1) = \boldsymbol{w}_1(p) - \mu_1 \sum_{i=1}^{M} \left[e_{1i,D}(p)\boldsymbol{c}_{1i,D}(p)\right] \tag{13}$$

$$\boldsymbol{w}_2(p+1) = \boldsymbol{w}_2(p) - \mu_2 \sum_{i=1}^{M} \left[e_{2i,D}(p)\boldsymbol{c}_{2i,D}(p)\right] \tag{14}$$

where $0 < \mu_1,\mu_2 < 2$ are defined as the step-size parameters which affects the convergence behavior of the filter weights, and $\boldsymbol{c}_{1i,D}(p)$, $\boldsymbol{c}_{2i,D}(p)$ are the decimated subbund adaptation gain vectors, which are given by the following relations:

$$\boldsymbol{c}_{1i,D}(p) = \gamma_{1i,D}(p)\boldsymbol{k}_{1i,D}(p) \quad i = 1, \dots, M. \tag{15}$$

$$\boldsymbol{c}_{2i,D}(p) = \gamma_{2i,D}(p)\boldsymbol{k}_{2i,D}(p) \quad i = 1, \dots, M. \tag{16}$$

where the scalars $\gamma_{1i,D}(p)$ and $\gamma_{2i,D}(p)$ are the decimated subband likelihood variables, which are defined as follows:

$$\gamma_{1i,D}(p) = \frac{1}{1 - \boldsymbol{k}^T_{1i,D}(p)\boldsymbol{e}_{2i,D}(p)} \quad i = 1, \dots, M. \tag{17}$$

$$\gamma_{2i,D}(p) = \frac{1}{1 - \boldsymbol{k}^T_{2i,D}(p)\boldsymbol{e}_{1i,D}(p)} \quad i = 1, \dots, M. \tag{18}$$

The decimated subband vectors $\boldsymbol{k}_{1i,D}(p)$ and $\boldsymbol{k}_{2i,D}(p)$ are the kalman gains, that are given by the following relations:

$$\begin{bmatrix} \boldsymbol{k}_{1i,D}(p) \\ * \end{bmatrix} = \begin{bmatrix} -\frac{\varepsilon_{1i,D}(p)}{\lambda\alpha_{1i,D}(p-1)+c_0} \\ \boldsymbol{k}_{1i,D}(p-1) \end{bmatrix} \quad i = 1, \dots, M. \tag{19}$$

$$\begin{bmatrix} \boldsymbol{k}_{2i,D}(p) \\ * \end{bmatrix} = \begin{bmatrix} -\frac{\varepsilon_{2i,D}(p)}{\lambda\alpha_{2i,D}(p-1)+c_0} \\ \boldsymbol{k}_{2i,D}(p-1) \end{bmatrix} \quad i = 1, \dots, M. \tag{20}$$

where the asterisk * represents the last unused element of the Kalman gains, λ $(0 < \lambda < 1)$ is an exponential forgetting factor and c_0 is a small positive constant used to avoid division by very small values in absence of the input signal. The decimated subband parameters $\alpha_{1i,D}$ and $\alpha_{2i,D}$ are the forward prediction errors variances, they are defined as follows:

$$\alpha_{1i,D}(p) = \lambda\alpha_{1i,D}(p-1) + \varepsilon^2_{1i,D}(p) \quad i = 1, \dots, M. \tag{21}$$

$$\alpha_{2i,D}(p) = \lambda\alpha_{2i,D}(p-1) + \varepsilon^2_{2i,D}(p) \quad i = 1, \dots, M. \tag{22}$$

The decimated subband prediction errors $\varepsilon_{1i,D}(p)$ and $\varepsilon_{2i,D}(p)$ that are used to evaluate the kalman gains can be calculated using a first-order prediction model as follows:

$$\varepsilon_{1i,D}(p) = e_{2i,D}(p) - a_{1i,D}e_{2i,D}(p-1) \quad i = 1, \dots, M. \tag{23}$$

$$\varepsilon_{2i,D}(p) = e_{1i,D}(p) - a_{2i,D}e_{1i,D}(p-1) \quad i = 1, \dots, M. \tag{24}$$

where $a_{1i,D}$ and $a_{2i,D}$ are the decimated subband prediction coefficients that are obtained by minimizing the functions $E\left[\varepsilon^2_{1i,D}(p)\right]$ and $E\left[\varepsilon^2_{2i,D}(p)\right]$. The derivative of these last functions with respect to $a_{1i,D}$ and $a_{2i,D}$ respectively leads to the following relations:

$$a_{1i,D}(p) = \frac{E\left[e_{2i,D}(p)e_{2i,D}(p-1)\right]}{E\left[e^2_{2i,D}(p-1)\right]} = \frac{r_{1i,D}(p)}{r_{2i,D}(p)} \quad i = 1, \dots, M. \tag{25}$$

$$a_{2i,D}(p) = \frac{E\left[e_{1i,D}(p)e_{1i,D}(p-1)\right]}{E\left[e^2_{1i,D}(p-1)\right]} = \frac{r_{3i,D}(p)}{r_{4i,D}(p)} \quad i = 1, \dots, M. \tag{26}$$

where $r_{1i,D}(p)$ and $r_{2i,D}(p)$ represent respectively, the first coefficient of the autocorrelation function of the decimated output sub-signals $e_{2i,D}(p)$ and the power of the decimated output sub-signals $e_{2i,D}(p)$. $r_{3i,D}(p)$ and $r_{4i,D}(p)$ represent respectively, the first coefficient of the autocorrelation function of the decimated output sub-signals $e_{1i,D}(p)$ and the power of the decimated output sub-signals $e_{1i,D}(p)$. An estimation of these last prediction coefficients for each subband can be performed as follows:

$$a_{1i,D}(p) = \frac{r_{1i,D}(p)}{r_{2i,D}(p) + c_a} \quad i = 1, \dots, M. \tag{27}$$

$$a_{2i,D}(p) = \frac{r_{3i,D}(p)}{r_{4i,D}(p) + c_a} \quad i = 1, \dots, M. \tag{28}$$

where $r_{1i,D}(p)$, $r_{2i,D}(p)$, $r_{3i,D}(p)$, and $r_{4i,D}(p)$ are estimated recursively by the following relations:

$$r_{1i,D}(p) = \lambda_a r_{1i,D}(p-1) + e_{2i,D}(p)e_{2i}(p-1) \quad i = 1, \dots, M. \tag{29}$$

$$r_{2i,D}(p) = \lambda_a r_{2i,D}(p-1) + e^2_{2i,D}(p) \quad i = 1, \dots, M. \tag{30}$$

$$r_{3i,D}(p) = \lambda_a r_{3i,D}(p-1) + e_{1i,D}(p)e_{1i,D}(p-1) \quad i = 1, \dots, M. \tag{31}$$

$$r_{4i,D}(p) = \lambda_a r_{4i,D}(p-1) + e^2_{1i,D}(p) \quad i = 1, \dots, M. \tag{32}$$

where λ_a is a forgetting factor and is c_a a small positive constant.

3 Simulation results

3.1 Descreption of the used signals

In this simulation, we consider that the mixing model of Fig. 1 generates two noisy observations $m_1(n)$ and $m_2(n)$, where the original speech signal $s(n)$ is a French male speaker of about 4 seconds length and the noisy disturbance source $b(n)$ is a USASI (United State of America Standard Institute now ANSI) noise taken from AURORA database (Sayoud et al. 2018). Fig. 4 shows the time evolution of the source signals $s(n)$ and $b(n)$. These source signals are sampled at $8kHz$ with 16 bit quantification. We have used the model proposed in (Djendi et al. 2006) to generate the two impulse responses $h_{12}(n)$ and $h_{21}(n)$. Figure 5 shows an example of the two simulated impulse responses with $L = 128$. In Fig. 6 we show the time evolution of the two noisy observation $m_1(n)$ and $m_2(n)$, the input SNR (signal-to-noise ratio) at the inputs of the two microphones is selected equal to $0dB$.

3.2 Time evolution of the enhanced output

Figure 7 presents the time evolution of the enhanced output signal $e_1(n)$ obtained by the proposed backward subband FNLMS algorithm with $M = 2$ and $M = 4$. As shown in Fig. 7, the enhanced output speech signal is completely denoised, this means that the proposed backward subband FNLMS algorithm can efficiently enhances noisy speech.

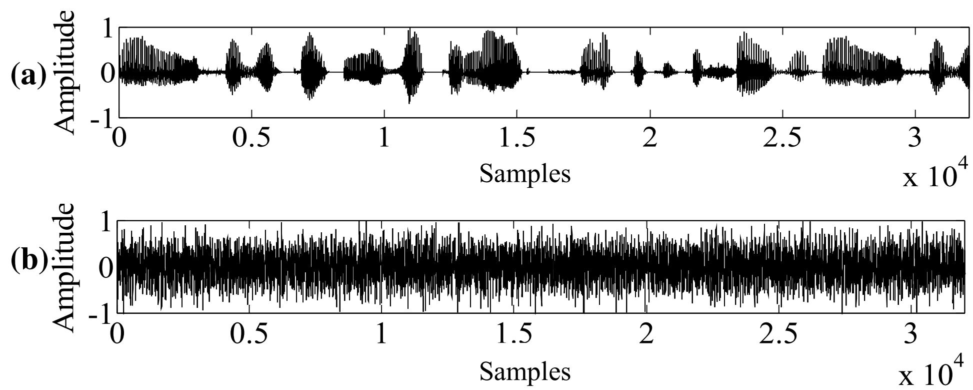

Fig. 4 Time evolution of the used signals: **a** original speech signal $s(n)$, **b** USASI noise signal $b(n)$

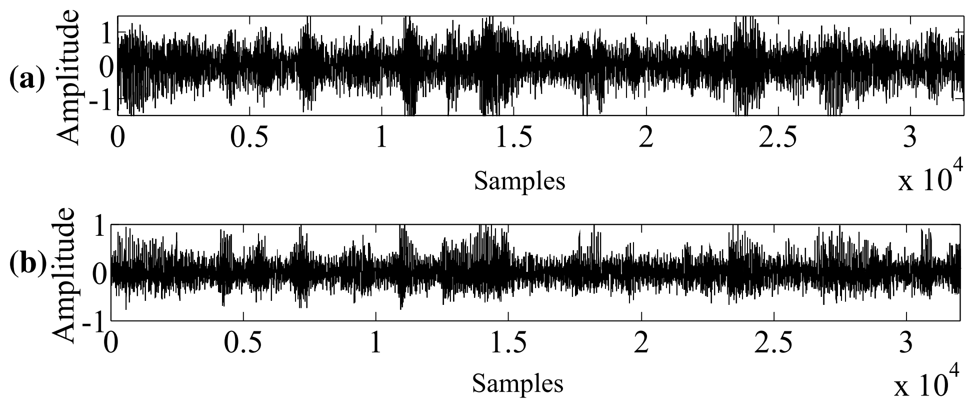

Fig. 5 Time evolution of the noisy observations: **a** $m_1(n)$, **b** $m_2(n)$

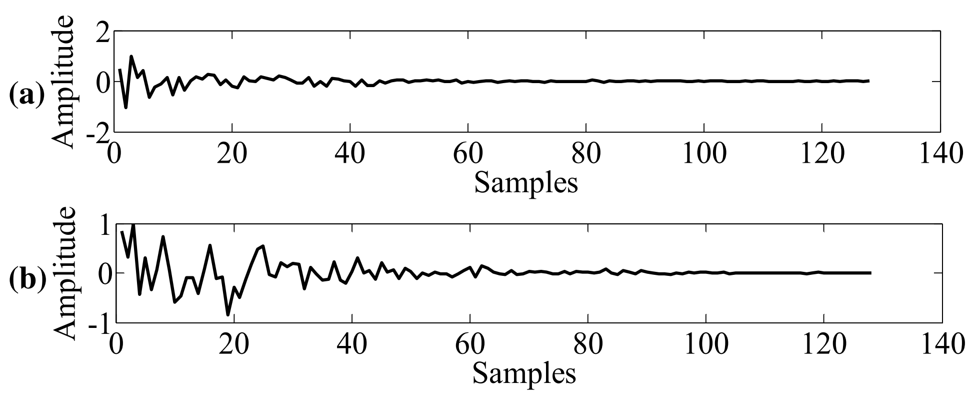

Fig. 6 Simulated impulse responses: **a** $h_{12}(n)$, **b** $h_{21}(n)$, with real filters length $L = 128$.

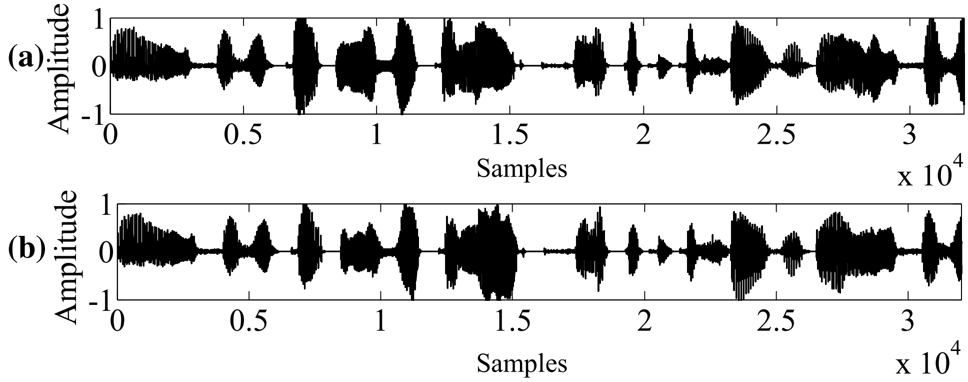

Fig. 7 Time evolution of the enhanced output signal $e_1(n)$ obtained by: **a** proposed backward subband algorithm with two subbands, **b** proposed backward subband algorithm with four subbands

3.3 Performance evaluations

This subsection, is reserved to evaluate the performance properties of the proposed backward subband FNLMS algorithm in comparison with the following adaptive fullband type algorithms: (i) the backward normalized least mean square (BNLMS) algorithm (Van Gerven and Van Compernolle 1992), which is based on the combination between the BBSS structure and the NLMS algorithm, (ii) the backward fast normalized least mean square algorithm (BFNLMS) proposed recently in our previous work (Sayoud et al. 2018). This algorithm is based on the combination between the BBSS structure and the FNLMS algorithm, which represents the fullband version of our proposed backward subband FNLMS algorithm. We recall here that all simulated algorithms are controlled by a manual activity voice detector (MAVD) to retrieve the speech signal at the first output $e_1(n)$. The simulation parameters of each algorithm are given in Table 1. This comparative study is based on the following objective criteria:

(i) System Mismatch (SM) criterion which is computed between the adaptive filter $w_1(n)$ and the real one $h_{21}(n)$ as follow (Hu and Loizou 2008):

$$SM_{dB} = 20log_{10}\left(\frac{\|\boldsymbol{h}_{21} - \boldsymbol{w}_1(n)\|}{\|\boldsymbol{h}_{21}\|}\right) \tag{33}$$

(ii) Segmental Mean Square Error (SegMSE) criterion is given by the following relation (Ghribi et al. 2016):

$$SegMSE_{dB} = \frac{10}{K}\sum_{m=0}^{K-1} log_{10}\left(\frac{1}{N}\sum_{n=Nm}^{Nm+N-1}\left|s(n) - e_1(n)\right|^2\right) \tag{34}$$

Where N is the segment length of the original signal s(n) and the enhanced one $e_1(n)$, and K is the number of segments in silence periods. We note that the SegMSE criterion is evaluated only in silence periods.

(iii) Segmental signal-to-noise-ratio (SegSNR) criterion is calculated using the following formula (Rabiner and Juang 1993):

$$SegSNR_{dB} = \frac{10}{K}\sum_{m=0}^{K-1} log_{10}\left(\frac{\sum_{n=Nm}^{Nm+N-1}|s(n)|^2}{\sum_{n=Nm}^{Nm+N-1}\left|s(n) - e_1(n)\right|^2}\right) \tag{35}$$

where $s(n)$ and $e_1(n)$ are the original and the enhanced speech signals, respectively. The parameters K and N are the number of segments and the segment length, respectively.

Table 1 Simulation parameters of the following algorithms i.e. proposed backward subband FNLMS algorithm, BNLMS algorithm and BFNLMS algorithm

Algorithms	Simulation parameters
BNLMS algorithm (Van Gerven and Van Compernolle 1992)	Adaptive filter length of w_1, w_2: $L = 128$. Fixed step-sizes: $\mu_1 = \mu_2 = 0.8$
BFNLMS algorithm (Sayoud et al. 2018)	Adaptive filter length of w_1, w_2: $L = 128$. Fixed step-sizes: $\mu_1 = \mu_2 = 0.8$ Exponential forgetting factor: $\lambda = 0.99$. Forgetting factor: $\lambda_a = 0.996$. Positive constant: $c_0 = 1, c_a = 0.001$. Initialisation constant: $E_0 = 0.5$
Proposed backward subband FNLMS algorithm [in this paper]	Adaptive filter length of w_1, w_2: $L = 128$. Subband filters length for $M = 2$, $M = 4$ are respectively: $l = 16$, $l = 32$. Fixed step-sizes: $\mu_1 = \mu_2 = 0.8$ Exponential forgetting factor: $\lambda = 0.99$. Forgetting factor: $\lambda_a = 0.996$. Positive constant: $c_0 = 1, c_a = 0.001$. Initialisation constant: $E_0 = 0.5$

3.4 System mismatch (SM) evaluation

We have used the SM criterion to evaluate the speed convergence performance of the proposed backward subband FNLMS algorithm in comparison with the fullband BNLMS and fullband BFNLMS ones. The simulation parameters of each simulated algorithm are given in Table 1. The obtained results for three inputs SNR (i.e. − 3dB, 0dB, 3dB) are shown in Fig. 8. From these results we can see clearly the superiority of the proposed backward subband algorithm in comparison with the other ones (i.e. BNLMS, BFNLMS) in terms of speed convergence performance for every case of input SNR.

3.5 Segmental mean square error (SegMSE) evaluation

The obtained results of the SegMSE criterion for the three algorithms i.e. proposed backward subband FNLMS algorithm, BNLMS and BFNLMS algorithms are reported on Fig. 9. The simulation parameters of each simulated algorithm are given in Table 1. From this experiment of Fig. 9 we can confirm again that the proposed backward subband FNLMS algorithm behaves more efficiently in terms of speed convergence than the other algorithms i.e. BNLMS and BFNLMS, especially when the number of subbands is selected high ($M = 4$).

3.6 Segmental (SegSNR) signal-to-noise-ratio evaluation

In order to evaluate the noise reduction performance of the proposed backward subband FNLMS algorithm, in the steady state, in comparison with the BNLMS and BFNLMS algorithms, we have used the SegSNR criterion to compute the final values of SNR and only in speech activity periods. We recall here that the simulation parameters of Table 1 are used for each simulated algorithm. In Fig. 10 we present the obtained results of the SegSNR evaluation for three inputs SNR (i.e. − 3dB, 0dB, 3dB). According to these results, we can see clearly that our proposed backward subband FNLMS algorithm has almost the same SegSNR values

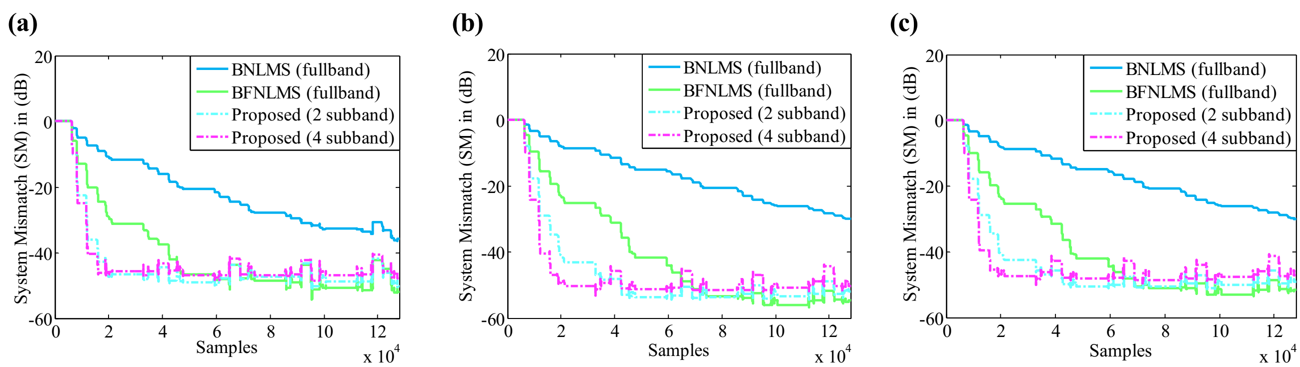

Fig. 8 SM evaluation of the proposed backward subband algorithm and the state-of-the-art algorithms (i.e. BNLMS, BFNLMS) for the input SNR at the two observations: **a** − 3 dB, **b** 0 dB, **c** 3 dB

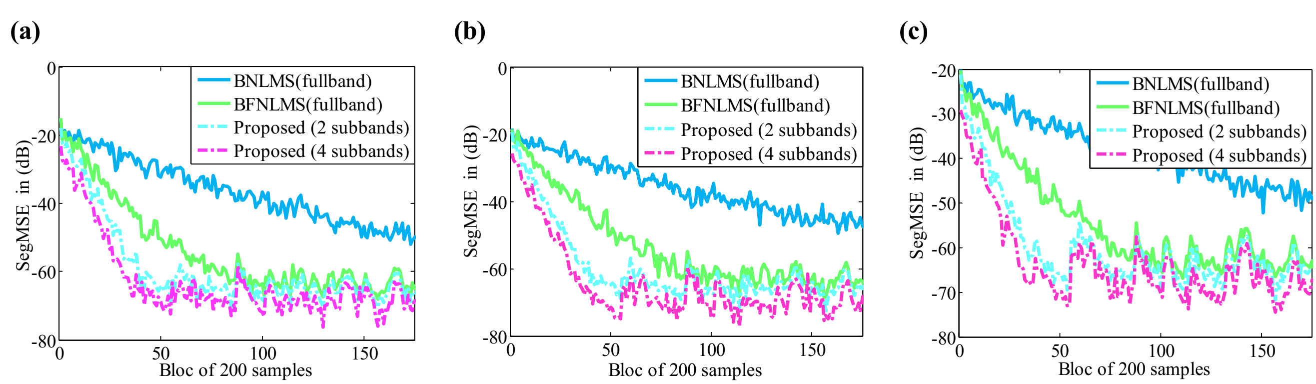

Fig. 9 SegMSE evaluation of the proposed backward subband algorithm and the state-of-the-art algorithms (i.e. BNLMS, BFNLMS) for the input SNR at the two observations: **a** − 3 dB, **b** 0 dB, **c** 3 dB

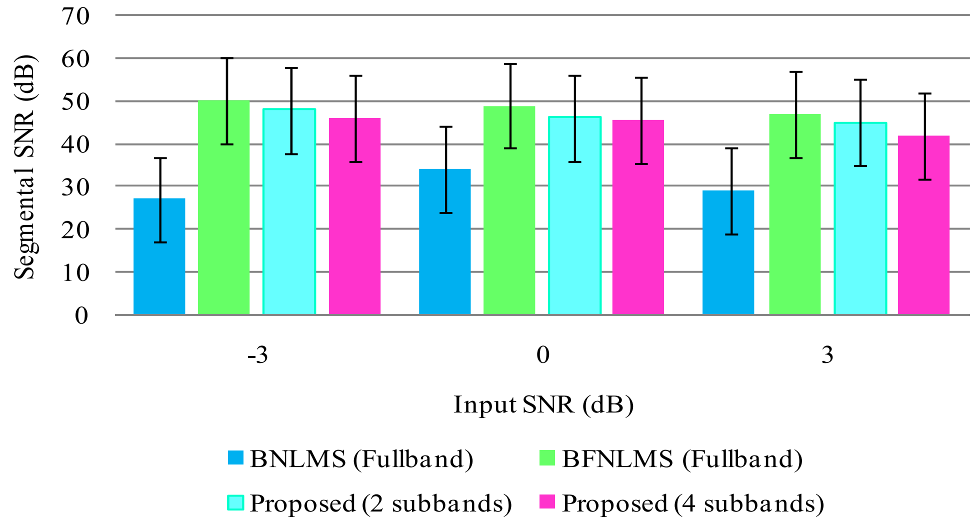

Fig. 10 SegSNR evaluation of the proposed backward subband algorithm and the state-of-the-art algorithms

with the fullband BFNLMS algorithm when the number of subbands is selected to $M = 2$. However, the output SegSNR values decrease when the number of subbands is high ($M = 4$). We have also noted that the output SegSNR values of the proposed backward subband FNLMS algorithm with 2 and 4 subbands are superior to 40 dB, which confirm the good behavior of the proposed backward subband FNLMS algorithm in reducing the acoustic noise components. A poor behavior of the BNLMS algorithm is noted.

4 Conclusion

In this paper, we have proposed a new backward subband FNLMS adaptive filtering algorithm for noise reduction and speech intelligibility enhancement application. The proposed backward subband FNLMS algorithm is a subband implementation of the BBSS structure based on the use of the modified FNLMS algorithm. The performances of the proposed backward subband FNLMS algorithm are compared with two fullband type algorithms i.e. BNLMS and BFNLMS. Therefore, intensive experiments were conducted in terms of three objective criteria, i.e. system mismatch (SM), segmental signal to-noise-ratio (SegSNR), and segmental mean square error (SegMSE). The obtained results with different noisy observations levels (i.e. highly and slightly noisy observations), have confirmed that the proposed backward subband FNLMS algorithm improves the speed convergence behavior in the transient phase especially when the number of subbands is selected high. We have also noted a degradation of the output SegSNR values when the number of subbands is selected high, however the proposed backward subband FNLMS algorithm reduces the acoustic noise components by about 40 dB at the output, with low and high selected subbands number. Finally we can say that the proposed backward subband FNLMS algorithm is an interesting candidate for acoustic noise reduction and speech enhancement applications.

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