14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006, copyright by EURASIP

AN EXTENDED NORMALIZED MULTICHANNEL FLMS ALGORITHM FOR BLIND CHANNEL IDENTIFICATION

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ABSTRACT

Blind channel estimation algorithms for acoustic channels have generated much interest in recent years due to the innovations in consumer products including, but not limited to, tele- and video-conferencing. The direct path constrained NMCFLMS algorithm was proposed to enhance noise robustness of the conventional NMCFLMS algorithm. In this paper, we propose to extend the direct path constrained NMCFLMS algorithm with the aim of achieving a higher rate of convergence. This objective is achieved by introducing a penalty component to the multichannel blind adaptive cost function and we further derive the proposed extended-NMCFLMS algorithm from first principles. Simulation results show an improvement, both in convergence rate *and* noise robustness, compared to existing NMCFLMS algorithms.

1. INTRODUCTION

Blind channel identification (BCI) for single-input multiple-output (SIMO) systems has become very important with the advent of wireless communications and multimedia signal processing systems. Increased demand and advanced research have motivated BCI algorithm development and therefore it has attracted a lot of attention for its promise recently. The identified channel can be utilized, after inversion, to remove the degradation introduced by the propagating channel. Techniques for BCI based upon second order statistics [1] [2] and higher order statistics [3] have been studied. Multichannel identification techniques are increasingly successful. The normalized multichannel frequency domain LMS (NMCFLMS) algorithm [4] has been shown to be effective in identifying room impulse responses which are of particular interest in acoustic dereverberation. However, NMCFLMS [5] [6] lacks robustness to additive noise and can suffer misconvergence even in moderate noise conditions.

For a SIMO system we propose an extended-NMCFLMS algorithm in which the BCI is formulated as a constrained minimization problem in such a manner that the cost function based upon the input signal is penalized whenever it violates a certain constraint. This constraint aims to improve noise robustness and is made an implicit part of the devised adaptive algorithm. The constraint is based upon assumed prior knowledge of one or more significant coefficients of the unknown channel impulse responses. The proposed extended-NMCFLMS algorithm thus achieves better performance over the NMCFLMS algorithm [4] by searching the solution within the subspace that satisfies the constraint.

This paper is organized as follows: Section 2 defines the problem and the variables used in the paper. Section 3 reviews the conventional NMCFLMS [4] and direct path constrained NMCFLMS [5] algorithms for acoustic room impulse responses. In Section 4, the proposed extended-NMCFLMS algorithm is developed from first principles by introducing a penalty into the cost function. Simulation results are presented in Section 5 with conclusions presented in Section 6.

2. STATEMENT OF THE PROBLEM

Consider a speech signal recorded inside a non-anechoic room using a linear array of microphones where received signals at the microphones can be modelled as convolutive mixtures of the speech signal and the impulse responses of the acoustic paths between source and microphones. With reference to Fig. 1 and defining $s(n)$ and $v_i(n)$ as the source signal and background noise respectively, the i^{th} channel output signal $x_i(n)$ is given by

$$x_i(n) = y_i(n) + v_i(n), \quad i = 1, 2, \ldots, M, \tag{1}$$

where M is the number of channels while

$$y_i(n) = \mathbf{h}_i^T(n)\mathbf{s}(n), \tag{2a}$$

$$\mathbf{h}_i(n) = [h_{i,0}(n) \;\; h_{i,1}(n) \;\; \ldots \;\; h_{i,L-1}(n)]^T, \tag{2b}$$

$$\mathbf{s}(n) = [s(n) \; s(n-1) \; \ldots \; s(n-L+1)]^T, \tag{2c}$$

such that $\mathbf{h}_i(n)$ is the i^{th} channel impulse response, L is the length of the longest channel impulse response and the superscript ^{T} denotes vector transposition. Defining $E\{\cdot\}$ as the expectation operator, we assume that the additive noise on M channels is uncorrelated, i.e., $E\{v_i(n)v_j(n)\} = 0$ for $i \neq j$ and $E\{v_i(n)v_i(n-n')\} = 0$ for $n \neq n'$ while additive noise $v_i(n)$ is uncorrelated with the input signal $s(n)$.

For channel identifiability [7], we also assume that

1. The channel transfer functions $H_i(z)$, $i = 1, 2, \ldots, M$, do not contain any common zeros.
2. The autocorrelation matrix of the source signal, $\mathbf{R}_{ss} = E\{\mathbf{s}(n)\mathbf{s}^T(n)\}$, is of full rank.

3. REVIEW OF EXISTING BCI ALGORITHMS

3.1 The NMCFLMS algorithm

A blind multichannel system identification algorithm estimates $\mathbf{h}_i(n)$, $i = 1, 2, \cdots, M$, from the signal observations $\mathbf{x}_i(n)$ that are given by

$$\mathbf{x}_i(n)=[x_i(n) \; x_i(n-1) \ldots x_i(n-L+1)]^T, \; i=1,2,\ldots,M. \tag{3}$$

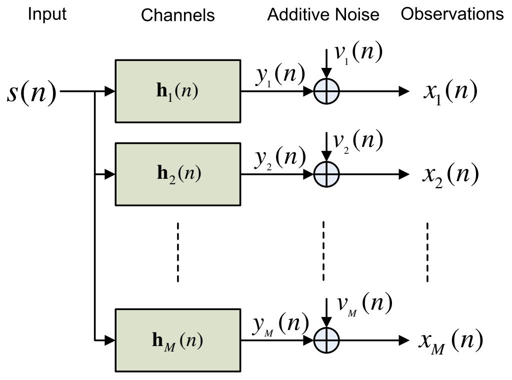

Figure 1: Relationship between input and output in a SIMO model.

For SIMO systems such as shown in Fig. 1, the observations are correlated since they are driven by the same input source. This correlation can be exploited for the derivation of blind identification algorithms. Consider, for simplicity, a noise-free case for which we can deduce the following relationship [8]

$$\mathbf{x}_i^T(n)\mathbf{h}_j(n) \quad = \quad \mathbf{x}_j^T(n)\mathbf{h}_i(n), \;\; i,j = 1,\ldots,M, \qquad (4)$$

An *a priori* error exists if noise is present, or the channels are estimated with error, given, for $i \neq j$, by

$$e_{ij}(n) = \mathbf{x}_i^T(n)\widehat{\mathbf{h}}_j(n) - \mathbf{x}_j^T(n)\widehat{\mathbf{h}}_i(n), \;\; i,j = 1,\ldots,M, \qquad (5)$$

where $\widehat{\mathbf{h}}_i(n)$ is the estimated i^{th} channel impulse response. The NMCFLMS [4] algorithm is a fast-converging and efficient algorithm for blind multichannel frequency-domain BCI. Using (5) and defining $\widehat{\mathbf{h}}(n) = \left[\widehat{\mathbf{h}}_1^T(n)\; \widehat{\mathbf{h}}_2^T(n)\; \ldots\; \widehat{\mathbf{h}}_M^T(n)\right]^T$, BCI algorithms such as NMCFLMS are derived by minimizing the cost function

$$J(n) = \frac{1}{\|\widehat{\mathbf{h}}(n)\|^2} \sum_{i=1}^{M-1} \sum_{j=i+1}^{M} e_{ij}^2(n) \qquad (6)$$

or its frequency domain equivalent [4] with respect to the estimated impulse response $\widehat{\mathbf{h}}_i(n)$ for $i = 1,\ldots,M$, where the normalization of $\|\widehat{\mathbf{h}}\|^2$ prevents the trivial solution $\widehat{\mathbf{h}}_i = \mathbf{0}_{L\times 1}$.

Defining $\mathbf{I}_{L\times L}$, $\mathbf{0}_{L\times L}$, and $\mathbf{F}_L$ as the identity, null and Fourier matrices each of dimension $L \times L$, the following matrices, for each m^{th} frame of samples, are defined as

$$\begin{aligned}
\mathbf{W}_{2L\times L}^{10} &= [\mathbf{I}_{L\times L}\; \mathbf{0}_{L\times L}]^T, \quad \mathbf{W}_{2L\times 2L}^{01} = \begin{bmatrix} \mathbf{0}_{L\times L} & \mathbf{0}_{L\times L} \\ \mathbf{0}_{L\times L} & \mathbf{I}_{L\times L} \end{bmatrix}, \\
\mathscr{W}_{2L\times 2L}^{01} &= \mathbf{F}_{2L}\mathbf{W}_{2L\times 2L}^{01}\mathbf{F}_{2L}^{-1}, \quad \mathscr{W}_{2L\times L}^{10} = \mathbf{F}_{2L}\mathbf{W}_{2L\times L}^{10}\mathbf{F}_{L}^{-1}, \\
\underline{\widehat{\mathbf{h}}}_i(m) &= \mathbf{F}_L\widehat{\mathbf{h}}_i(m), \\
\underline{\widehat{\mathbf{h}}}_i^{10}(m) &= \mathbf{F}_{2L}\begin{bmatrix} \widehat{\mathbf{h}}_i(m) \\ \mathbf{0}_{L\times 1} \end{bmatrix} = \mathbf{F}_{2L}\mathbf{W}_{2L\times L}^{10}\widehat{\mathbf{h}}_i(m), \\
\mathscr{D}_{x_j}(m) &= \operatorname{diag}\{\mathbf{F}_{2L}[x_j(mL-L)\;\; x_j(mL-L+1)\ldots \\
&\qquad x_j(mL+L-1)]^T\}\,.
\end{aligned}$$

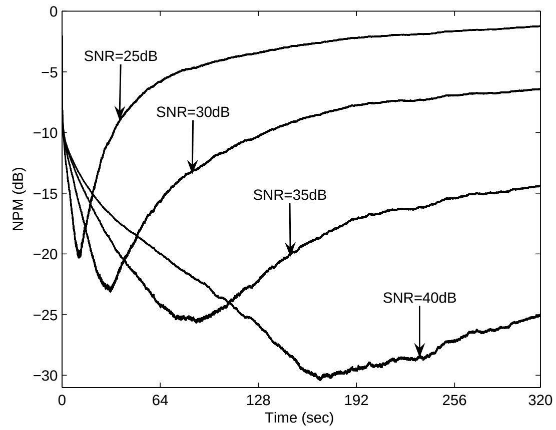

Figure 2: Effect of noise on normalized projection misalignment for the NMCFLMS algorithm.

The NMCFLMS algorithm is then given by

$$\begin{aligned}
\underline{\boldsymbol{\varepsilon}}_{ij}^{01}(m) &= \mathscr{W}_{2L\times 2L}^{01} \times \\
&\qquad \left[\mathscr{D}_{x_i}(m)\mathscr{W}_{2L\times L}^{10}\underline{\widehat{\mathbf{h}}}_j(m) - \mathscr{D}_{x_j}(m)\mathscr{W}_{2L\times L}^{10}\underline{\widehat{\mathbf{h}}}_i(m)\right], \quad (7) \\
\mathscr{P}_i(m+1) &= \lambda\mathscr{P}_i(m) + (1-\lambda)\sum_{j=1, j\neq i}^{M} \mathscr{D}_{x_j}^*(m)\mathscr{D}_{x_j}(m), \quad (8) \\
\underline{\widehat{\mathbf{h}}}_i^{10}(m+1) &= \underline{\widehat{\mathbf{h}}}_i^{10}(m) - \rho\left[\mathscr{P}_i(m) + \delta\mathbf{I}_{2L\times 2L}\right]^{-1} \times \\
&\qquad \sum_{j=1}^{M} \mathscr{D}_{x_j}^*(m)\underline{\boldsymbol{\varepsilon}}_{ji}^{01}(m), \;\; i = 1,\ldots,M, \quad (9)
\end{aligned}$$

where * denotes complex conjugate, ρ is the step-size, λ is the forgetting factor and δ is the regularization constant.

3.2 The direct path constrained NMCFLMS algorithm

As shown in Fig. 2 and explained in [5], the NMCFLMS algorithm lacks robustness to the additive noise. It can be seen from Fig. 2 that the NMCFLMS algorithm misconverges after achieving normalized projection misalignments (NPM) (c.f. (27)) −20 dB, −23 dB, −25 dB, and −30 dB for corresponding signal-to-noise ratios (SNR) 25 dB, 30 dB, 35 dB, and 40 dB, respectively. Hence, the problem of misconvergence in the NMCFLMS algorithms [4] increases with noise level. In [5], a modification was proposed in the NMCFLMS algorithm where the estimated direct path coefficient of each channel is constrained to match the actual direct path coefficient at each frame iteration. This constraint is of practical importance since one can assume the existence of robust estimation of the direct path using algorithms such as [9].

Defining $h_{i,dp}$ as the direct path component of the i^{th} channel and

$$\begin{aligned}
\Delta\widehat{\mathbf{h}}_i(m) &= \left[0\;\; 0\; \cdots\; 0\; h_{i,dp} - \widehat{h}_{i,dp}(m)\; 0\; \cdots\; 0\;\; 0\right]^T, \quad (10) \\
\widehat{\widehat{\mathbf{h}}}_i(m) &= \left[\widehat{h}_{i,0}(m)\;\; \widehat{h}_{i,1}(m)\; \cdots\; h_{i,dp}\; \cdots\; \widehat{h}_{i,L-1}(m)\right]^T \\
&= \widehat{\mathbf{h}}_i(m) + \Delta\widehat{\mathbf{h}}_i(m), \quad (11) \\
\underline{\widehat{\widehat{\mathbf{h}}}}_i^{10}(m) &= \mathbf{F}_{2L}\begin{bmatrix} \widehat{\widehat{\mathbf{h}}}_i(m) \\ \mathbf{0}_{L\times 1} \end{bmatrix} = \mathbf{F}_{2L}\mathbf{W}_{2L\times L}^{10}\widehat{\widehat{\mathbf{h}}}_i(m), \quad (12)
\end{aligned}$$

the impulse response estimates are computed recursively using

$$\underline{\widehat{\mathbf{h}}}_i^{10}(m+1) = \widehat{\underline{\widehat{\mathbf{h}}}}_i^{10}(m) - \rho_{\mathrm{I}}[\mathscr{P}_i(m)+\delta\mathbf{I}_{2L\times 2L}]^{-1} \times \sum_{j=1}^{M}\mathscr{D}_{x_j}^*(m)\underline{\varepsilon}_{ji}^{01}(m) - \rho_{\mathrm{I}}[\mathscr{P}_i(m)+\delta\mathbf{I}_{2L\times 2L}]^{-1} \times \sum_{j=1}^{M}\mathscr{D}_{x_j}^*(m)\Delta\underline{\varepsilon}_{ji}^{01}(m)\ , \quad (13)$$

where

$$\Delta\underline{\widehat{\mathbf{h}}}_i(m) = \mathbf{F}_L\Delta\widehat{\mathbf{h}}_i(m)\ ,$$
$$\Delta\underline{\varepsilon}_{ji}^{01}(m) = \mathscr{D}_{x_j}(m)\mathscr{W}_{2L\times L}^{10}\Delta\underline{\widehat{\mathbf{h}}}_i(m) - \mathscr{D}_{x_i}(m)\mathscr{W}_{2L\times L}^{10}\Delta\underline{\widehat{\mathbf{h}}}_j(m),$$

and ρ_{I} is the step-size. Hence the direct path constrained NMCFLMS algorithm improves noise robustness by replacing the estimated direct path component with the true direct path coefficient at each sample iteration.

4. THE EXTENDED-NMCFLMS ALGORITHM EMPLOYING PENALTY FUNCTION

We now develop the extended-NMCFLMS algorithm by introducing a penalty term to (6) and minimizing this new cost function with respect to $\widehat{\mathbf{h}}_i(n)$. The motivation for employing this methodology can be explained, using (1) and (3), by considering the output of the system such as shown in Fig. 1 such that

$$\mathbf{x}_i(n) = \mathbf{y}_i(n) + \mathbf{v}_i(n), \quad (14)$$

where

$$\mathbf{y}_i(n) = [y_i(n)\ y_i(n-1)\ \ldots\ y_i(n-L+1)]^T, \quad (15a)$$
$$\mathbf{v}_i(n) = [v_i(n)\ v_i(n-1)\ \ldots\ v_i(n-L+1)]^T. \quad (15b)$$

Using (5) and (14), the error to be minimized can then be expressed as

$$\begin{aligned} e_{ij}(n) &= \left[\mathbf{y}_i^T(n)\widehat{\mathbf{h}}_j(n) - \mathbf{y}_j^T(n)\widehat{\mathbf{h}}_i(n)\right] \\ &\quad + \left[\mathbf{v}_i^T(n)\widehat{\mathbf{h}}_j(n) - \mathbf{v}_j^T(n)\widehat{\mathbf{h}}_i(n)\right] \\ &= e_{ij}^y(n) + e_{ij}^v(n), \end{aligned} \quad (16)$$

where $e_{ij}^y(n)$ and $e_{ij}^v(n)$ are the errors due to signal and additive noise respectively. In this noisy case, the cost function can be described by

$$\begin{aligned} J(n) &= \frac{1}{\|\widehat{\mathbf{h}}(n)\|^2}\sum_{i=1}^{M-1}\sum_{j=i+1}^{M}\left\{\left[e_{ij}^y(n)\right]^2 + \left[e_{ij}^v(n)\right]^2\right\} \\ &= J_y(n) + J_v(n). \end{aligned} \quad (17)$$

If the problem in (17) is considered as a constrained minimization problem then it can be reformulated as

$$J(n) = J_y(n) \quad (18)$$

subject to the constraint

$$J_v(n) = 0. \quad (19)$$

Such that $J_v(n)$ is needed to be minimized as well to get an accurate channel estimate from the minimization of signal cost function $J_y(n)$. As evident, since $\mathbf{v}_i(n)$ is unknown, $J_v(n)$ is not controllable.

Hence we devise an alternative approach for BCI under noisy conditions. In contrast to the direct path constraint as discussed in Section 3.2, the new algorithm is formulated in terms of a penalty function in $J(n)$ by minimizing the constrained cost function which is defined as

$$J(n) = \frac{1}{\|\widehat{\mathbf{h}}(n)\|^2}\sum_{i=1}^{M-1}\sum_{j=i+1}^{M}\left[e_{ij}(n)\right]^2 \quad (20)$$

subject to the constraint

$$\widehat{h}_{i,dp}(n) = h_{i,dp}(n),\ \ i = 1,2,\cdots,M. \quad (21)$$

Employing the method of Lagrange multipliers [10], with β being the multiplier, the cost function can be reformulated as

$$\begin{aligned} \text{minimize } J(n) &= \frac{1}{\|\widehat{\mathbf{h}}(n)\|^2}\sum_{i=1}^{M-1}\sum_{j=i+1}^{M}e_{ij}^2(n) \\ &\quad + \beta\sum_{i=1}^{M}\left[h_{i,dp}(n) - \widehat{h}_{i,dp}(n)\right]^2. \end{aligned} \quad (22)$$

The gradient of the penalty term

$$J_p(n) = \sum_{i=1}^{M}\left[h_{i,dp}(n) - \widehat{h}_{i,dp}(n)\right]^2 \quad (23)$$

can be obtained as

$$\begin{aligned} \nabla J_p(n) &= \frac{\partial J_p(n)}{\partial\widehat{\mathbf{h}}_i(n)} \\ &= -2\left[h_{i,dp} - \widehat{h}_{i,dp}(n)\right]\widetilde{\mathbf{g}}, \end{aligned} \quad (24)$$

where the $L\times 1$ vector $\widetilde{\mathbf{g}} = \left[\mathbf{0}_{1\times l_{dp}-1}\quad 1\quad \mathbf{0}_{1\times L-l_{dp}}\right]^T$ while l_{dp} denotes the position of the direct path coefficient. With the gradient vector computed, we can now define the parameter update equation for the direct path constrained NMCFLMS algorithm. The update equation for the proposed algorithm will contain an additional term due to the penalty function as compared to the original one, and is given by

$$\begin{aligned} \underline{\widehat{\mathbf{h}}}_i^{10}(m+1) &= \underline{\widehat{\mathbf{h}}}_i^{10}(m) - \rho_{\mathrm{E}}[\mathscr{P}_i(m)+\delta\mathbf{I}_{2L\times 2L}]^{-1} \\ &\quad \times\sum_{j=1}^{M}\mathscr{D}_{x_j}^*(m)\underline{\varepsilon}_{ji}^{01}(m) \\ &\quad + 2\beta\rho_{\mathrm{E}}\mathbf{F}_{2L}\mathbf{W}_{2L\times L}^{10}\left\{\left[h_{i,dp} - \widehat{h}_{i,dp}(m)\right]\widetilde{\mathbf{g}}\right\}, \end{aligned} \quad (25)$$

where ρ_{E} is the step-size. Comparing (25) and (13), the proposed extended-NMCFLMS algorithm does not substitute the direct path component at each iteration. The direct path constrained NMCFLMS algorithm [5], as discussed in Section 3, searches for the solution within the whole subspace $\mathbf{h}_i \in \mathbb{R}^L$ and the estimated solution $\widehat{\mathbf{h}}_i(n)$ is then obtained by substituting $\widehat{h}_{i,dp} = h_{i,dp}$ at each sample iteration. In contrast, the proposed extended-NMCFLMS algorithm imposes a limiting constraint such that the search of solutions is within the

Table 1: The extended-NMCFLMS algorithm

$$\mathbf{W}^{10}_{2L\times L} = [\mathbf{I}_{L\times L}\ \mathbf{0}_{L\times L}]^T$$
$$\mathbf{W}^{01}_{L\times 2L} = [\mathbf{0}_{L\times L}\ \mathbf{I}_{L\times L}]$$
$$\mathscr{W}^{10}_{2L\times L} = \mathbf{F}_{2L}\mathbf{W}^{10}_{2L\times L}\mathbf{F}^{-1}_{L}$$
$$\mathscr{W}^{01}_{L\times 2L} = \mathbf{F}_{L}\mathbf{W}^{01}_{L\times 2L}\mathbf{F}^{-1}_{2L}$$
$$\widetilde{\mathbf{g}} = \left[\mathbf{0}_{1\times l_{dp}-1}\ \ 1\ \ \mathbf{0}_{1\times L-l_{dp}}\right]^T$$
$$\mathscr{D}_{x_j}(m) = \mathbf{F}_{2L}\left[x_j(mL-L)\ \ x_j(mL-L+1)\ldots x_j(mL+L-1)\right]^T$$
$$\underline{\varepsilon}^{01}_{ij}(m) = \mathscr{W}^{01}_{2L\times 2L}\times\left[\mathscr{D}_{x_i}(m)\mathscr{W}^{10}_{2L\times L}\underline{\widehat{\mathbf{h}}}_j(m) - \mathscr{D}_{x_j}(m)\mathscr{W}^{10}_{2L\times L}\underline{\widehat{\mathbf{h}}}_i(m)\right]$$
$$\mathscr{P}_i(m+1) = \lambda\mathscr{P}_i(m) + (1-\lambda)\sum_{j=1,j\neq i}^{M}\mathscr{D}^*_{x_j}(m)\mathscr{D}_{x_j}(m)$$
$$\underline{\widehat{\mathbf{h}}}^{10}_i(m+1) = \underline{\widehat{\mathbf{h}}}^{10}_i(m) - \rho_{\mathrm{E}}[\mathscr{P}_i(m)+\delta\mathbf{I}_{2L\times 2L}]^{-1}\times \sum_{j=1}^{M}\mathscr{D}^*_{x_j}(m)\underline{\varepsilon}^{01}_{ji}(m) + 2\beta\rho_{\mathrm{E}}\mathbf{F}_{2L}\mathbf{W}^{10}_{2L\times L}\left\{\left[h_{i,dp}-\widehat{h}_{i,dp}(m)\right]\widetilde{\mathbf{g}}\right\}$$

subspace containing $\widehat{h}_{i,dp} = h_{i,dp}$ and as a consequence the convergence rate of the extended-NMCFLMS algorithm is higher compared to that of the direct path constrained NMCFLMS algorithm as will be shown via simulation results in Section 5. The proposed extended-NMCFLMS algorithm is summarized in Table 1.

5. SIMULATION RESULTS

We now present simulation results to compare the performance of the proposed extended NMCFLMS algorithm for BCI against the NMCFLMS algorithms [4] and [5] in the context of acoustic room impulse response identification.

5.1 Experimental setup

The dimensions of the room are $(5\times 4\times 3)$ m and impulse responses are generated using the method of images [11] with reverberation time $T_{60} = 0.1$ s which are then truncated to length $L = 128$. A linear microphone array containing $M = 5$ microphones with uniform separation $d = 0.2$ m is used. The source and the first microphone are placed at $(1.0, 1.5, 1.6)$ m and $(2.0, 1.2, 1.6)$ m, respectively. The input signal is either white Gaussian noise (WGN) or a male speech signal while uncorrelated zero-mean additive WGN is added to achieve the SNR specified for each experiment. The sampling frequency is 8 kHz and the SNR is 20 dB unless otherwise specified. Defining $\mathbf{h} = [\mathbf{h}_1^T\ \mathbf{h}_2^T\ \ldots\ \mathbf{h}_M^T]^T$, the SNR for this BCI application is given [4] as

$$SNR \triangleq 10\log_{10}\left[\sigma_s^2\|\mathbf{h}\|^2/(M\sigma_v^2)\right], \tag{26}$$

where σ_s^2 and σ_v^2 are the signal and noise powers, respectively, while the following parameters are chosen for all simulations: $\lambda = [1-1/(3L)]^L$, $\mathscr{P}_i(0) = 0$ for all algorithms, $\widehat{\mathbf{h}}_i(0) = [1\ \ 0\ldots 0]^T/\sqrt{M}$ for $i = 1,\ldots,M$. , λ is $[1-1/(3L)]^L$ for WGN input but $[1-1/(10L)]^L$ for speech signal input and δ is set to one fifth of the total power over all channels at the first frame [4] while the value of β is inversely proportional to the adaptive step-size ρ_{E} as can been seen in Table 1. The NPM [4] is used as performance measure and is given by

$$\mathrm{NPM}(m) = 20\log_{10}\left(\left\|\mathbf{h} - \frac{\mathbf{h}^T\widehat{\mathbf{h}}(m)}{\widehat{\mathbf{h}}^T(m)\widehat{\mathbf{h}}(m)}\widehat{\mathbf{h}}(m)\right\|/\|\mathbf{h}\|\right)\ \mathrm{dB}, \tag{27}$$

where m is the frame index, $\|.\|$ is the l_2 norm and $\widehat{\mathbf{h}}(m) = [\widehat{\mathbf{h}}_1^T(m)\ \widehat{\mathbf{h}}_2^T(m)\ldots\widehat{\mathbf{h}}_M^T(m)]^T$.

5.2 Effect of variation in β on convergence rate

Fig. 3 shows the effect of variation of the penalty gain β on the convergence of the proposed extended NMCFLMS algorithm using WGN input signal at an SNR $= 20$ dB. An adaptive step-size $\rho_{\mathrm{E}} = 0.5$ is chosen. It can be seen that with increasing β misconvergence reduces while the convergence rate increases. Fig. 4 presents an additional result demonstrating that high β values are required at low SNRs to ensure stability of the proposed extended NMCFLMS algorithm. It can be seen that for lower SNR, relatively higher values of β are required to achieve the convergence. Hence under low SNR conditions a stronger penalty must be imposed on the cost function to cancel the effect of additive noise.

5.3 Comparison of the algorithms

Figure 5 shows a comparison of convergence between NMCFLMS [4], direct path constrained NMCFLMS [5] and the proposed extended NMCFLMS algorithms using a WGN input sequence at an SNR $= 20$ dB. The step-sizes for all algorithms are adjusted such that they reach same the asymptotic NPM. This corresponds to $\rho = 0.5$, $\rho_{\mathrm{I}} = 0.4$ and $\rho_{\mathrm{E}} = 1.1$ for NMCFLMS, direct path constrained NMCFLMS and extended NMCFLMS algorithms respectively while β is determined empirically as 6. It can be seen that the NMCFLMS algorithm misconverges after achieving an NPM of approximately -20 dB.The extended NMCFLMS algorithm exhibits higher rate of convergence compared to that of direct path constrained NMCFLMS algorithm. During convergence, extended NMCFLMS achieves more than 3 dB improvement in NPM over the NMCFLMS algorithm [5].

Figure 6 shows an additional result using a male speech input sequence with an SNR = 40 dB where step-sizes for the direct path constrained NMCFLMS and the proposed extended NMCFLMS algorithms are adjusted to achieve the same asymptotic NPM which correspond to $\rho_{\mathrm{I}} = 0.04$ and $\rho_{\mathrm{E}} = 0.04$ while β is found empirically as 20. The step-size ρ for the NMCFLMS algorithm is 0.04. It can be seen that the relative performance of all algorithms is similar to that obtained using WGN input. The NMCFLMS algorithm [4] misconverges after achieving an NPM of approximately -12 dB and the extended NMCFLMS algorithm achieves a higher rate of convergence than the NMCFLMS algorithm [5].

6. CONCLUSION

We have developed the extended NMCFLMS algorithm for multichannel frequency-domain BCI. The proposed extended NMCFLMS algorithm offers fast convergence in comparison with the NMCFLMS [4] and the direct path constrained NMCFLMS [5] algorithms. This has been achieved

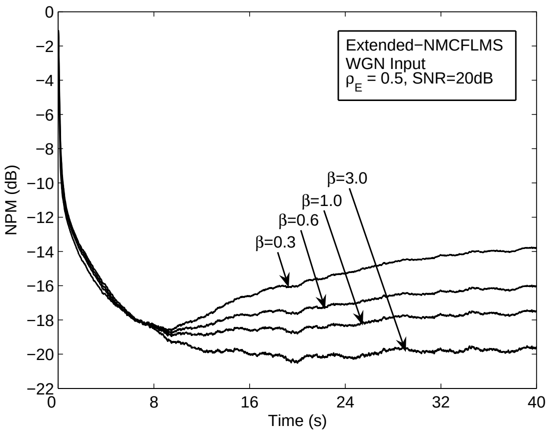

Figure 3: Effect of variation in β on convergence of the extended NMCFLMS algorithm.

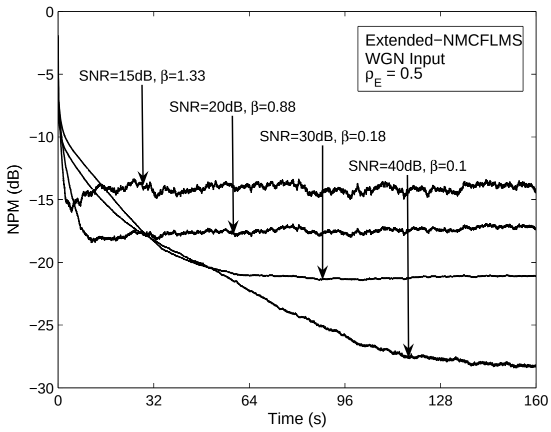

Figure 4: Relationship between the value of β and SNR of the system for the extended NMCFLMS algorithm.

by imposing a constraint on the cost function of the minimization problem. In addition the proposed algorithm offers noise robustness and converges at an SNR as low as 15 dB for the WGN input example. Simulation results show for both WGN and speech signal inputs that the proposed algorithm offers significantly better convergence behavior than NMCFLMS and an improvement in NPM by approximately 2 to 3 dB over the direct path constrained NMCFLMS algorithm [5].

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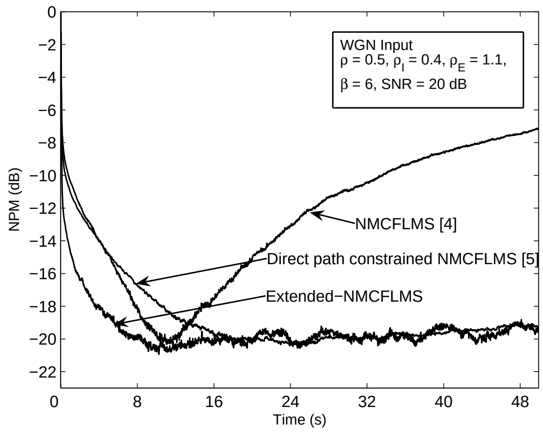

Figure 5: Comparison of the algorithm convergence for WGN input.

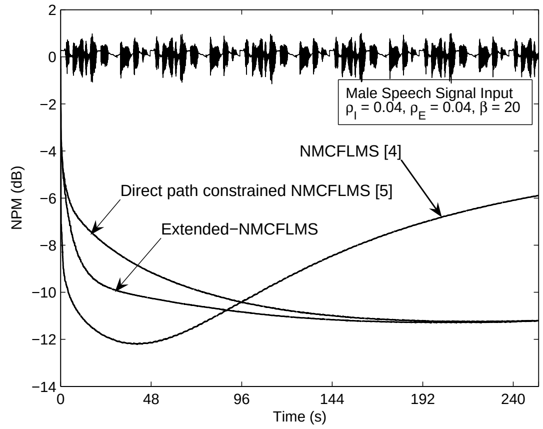

Figure 6: Comparison of the algorithm convergence for a male speech signal input.

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