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Research Article

MULTI-SOURCE ECHO CANCELLATION SYSTEM BY ADVANCED NORMALIZED SUBBAND ADAPTIVE FILTERING

Samuyelu B[1] and Rajesh Kumar P[2]

[1]Department of ECE, PVP Siddhartha Institute of Technology
Vijayawada, Andhra Pradesh, India
[2]Department of ECE, Andhra University College of Engineering
Visakhapatnam, Andhra Pradesh, India

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ABSTRACT

In current scenarios, a foremost crisis like echo in current communication network is brought to a solution using AEC. The major reason for this issue happens when the signals provided at input are the signals of speech which are recurrently colored more when distinguished with white noise. This paper implements a D-MVS-SNSAF technique for identifying the Echo Cancellation Systems (ECS) by deploying NSAF system. Here, the transition count in the input/output signals is evaluated for obtaining the polynomial order from three sets of audio signals such as speech, audio and song. In addition, the proposed technique is compared with traditional algorithms like NSAF, VS-NSAF, SS-NSAF, VS-SNSAF and MVS-SNSAF and improvements in the implemented technique is proved.

INTRODUCTION

AEC is measured as a renowned method to administrate the acoustic echoes formed by the mechanical audio terminals [1] [2] [3]. Based on this technique, the Adaptive Filter (AF) is engaged for identifying the path of echoes amongst the terminals of loudspeaker and microphone and consequently the resultant outcome of the filter is modelled in to an electronic design of the acoustic echo which is condensed for evading the acoustic echo from the microphone signal [4] [5]. Although AEC can be predicted as a chief application for identifying systems, modern hands-free telephones and systems for teleconferencing create several restrictions on the conventional adaptive filters [6] [7] [8].

The primary restriction is due to the input speech signals which are colored when compared with white noise; next one is the path of echo where the impulse response is long and sparse. This indicates that a lot of coefficients are adjacent to zero or equivalent to zero [9][10]. Therefore, the well-known Normalized least mean square (NLMS) technique is not suitable for AEC, because of its rate of convergence for Sparse Echo Paths (SEP) [5] [29]. The most excellent approach to suggest convergence is by Subband AF(SAF) method that relies on a sampling method which is almost equal to SAFs with significant structure [11] [12] [13]. In addition, NSAF has proposed that exposed improved performance, together with its complications that are adjacent to that of the NLMS technique [14] [15] [16].

Furthermore, an astonishing means to quicken the convergence is to exploit SAF, as it could whiten the colored input signals throughout the process of filter bank investigation [17] [18] [19]. The NSAF method involves enhanced convergence evaluation when distinguished with the colored input signals of NLMS [20] [21] [22]. Additionally, the complication of the NSAF is comparable with NLMS for an extended AF function. Consequently, to accomplish both quicker convergence rate and reduced steady-state error, several Variable step-size (VS-NSAF) techniques were implemented. Most recently, for initializing the convergence rate of SEP in NSAF, balanced

Corresponding author:* **Samuyelu B
Department of ECE, PVP Siddhartha Institute of Technology Vijayawada, Andhra Pradesh, India

family was suggested by broadening the traditional balanced details to the NSAF directly.

The foremost concept of the NSAF is to utilize the subband signals, created by their equivalent input variances of subband for altering the weights of tap in a full-band adaptive filter. This system paves the way for the decorrelating character of the NSAF. Nevertheless, as the real NSAF makes use of a predetermined step-size, it has to carry out a tradeoff between quicker rate of convergence and low mis-adjustments. For discovering a resolution to this concern, an improved NSAF version, known as the Set-membership NSAF (SM-NSAF), was created currently. On the other hand, the restrictions prevailing in the process of filtering paves the way for lessening the enhancement of performance in AEC [23] [24] [25].

This paper contributes a ECS identification improved NSAF technique known as D-MVS-SNSAF method. Here, the number of transitions in the input/output signals is measured for deriving the polynomial order by providing three audio signals as input. The implementation is made by determining the error bound and memorizing error. Subsequent to the execution, the implemented D-MVS-SNSAF technique is distinguished with the traditional methods like NSAF, VS-NSAF, VS-SNSAF, SS-NSAF and MVS-SNSAF techniques. The paper is contributed as follows. Section II discusses the related works and reviews done on this topic. Section III explains the Acoustic echo cancellation framework and section IV describes the modeling NSAF and its functioning. Section V demonstrates the proposed deterministic initialization. Section VI illustrates the results and discussions, and section VII concludes the paper.

LITERATURE SURVEY

Related works

In 2017, Yi Yu and Haiquan Zhao [1] have suggested modifications in sparseness by incorporating the pre determined sparseness into the MPNSAF and Proportionate Normalized Subband AF(PNSAF) methods that may perhaps adapt well to the alterations in sparseness residing in impulse responses. In addition, on the basis of the energy controversy, a unified formula to presume the SSMS computation of any PNSAF method is enhanced by experimentations. Investigational outcomes from the simulations of AEC have exposed that the suggested algorithms not only presents quick rate of convergence but also practice robustness to the alterations in the sparseness of impulse response.

In 2017, Zongsheng Zheng *et al.* [2] have presented an association of RSM-NSAF techniques for obtaining better AEC. A novel error bound with robust set-membership was adopted, so that the RSM-NSAF system attains an improved robustness in contrary to the lessened misalignment of steady-state and impulsive noises relative to the expected SM-NSAF scheme. Implementation in AEC application validates the improvements of the presented algorithms in computation.

In 2010, Jingen Ni *et al.* [3] implemented an adaptive alignment system to manage with the various kinds of trade-off. The alignment is made in subband region, and the combination factor that administrates the grouping was updated by means of a stochastic gradient method which exploits the calculation of errors in squared subbands as the computational operation. Experimental outcomes demonstrated that the aligning technique could attain both fast rate of convergence and reduced steady-state MSE.

In 2016, Yi Yu *et al.* [4] proposed a novel SAF system by minimizing the cost exploitation of Huber that was dynamic to unprompted noises. In general, this scheme assists the approach of the NSAF algorithm, when it computes like the SSAF algorithm on the occurrence of impulsive noises. Outcomes obtained from the simulation results, by adopting various colored input signals in both impulsive noise and free-impulsive surroundings, illustrated that the presented scheme had offered better results in terms of various measures when compared with several conventional algorithms.

In 2016, Yi Yu *et al.* [5] have proposed a model for achieving steady-state with reduced error and quicker convergence rate in AEC, a convex sorting technique of the improved NSAF algorithm. According to this system, the integration parameter was allowed to sort by deploying the normalized gradient method that makes this scheme more robust to the divergences of signals in the errors of subband.

In 2016, Mariane R. Petraglia *et al.* [6] accomplished a concerted complication subband adaptive scheme which can be employed to deploy subband for cost function of APA and a sparse subband filter. A VSS-NSAF system was established, thus providing a quicker convergence rate, simultaneously making sure regarding the mis-adjustments of small steady-state.

In 2010, Jingen Ni and Feng Li [7] have suggested a VSSM-NSAF from an additional observation, which was done by recovering the manipulation of the noises from subband scheme to further develop the computation of the NSAF technique. Results obtained from various experimental measures have exposed better performance of the implemented technique when distinguished with a variety of members prevailing in the NSAF family.

Model of Acoustic Echo Cancellation

A linear echo cancellation [26] is occurred because of the mechanism of coupling occurred between loudspeaker and microphone that are modeled by means of FIR signal. The objective of AEC is to estimate this coupling. The path of AEC $\hat{f}(n)$ is comprised with the loudspeaker signal $x(n)$ for attaining the signal of echo as shown in Eq. (1), in which the coefficients of AF are addressed by $\hat{f}(n)=\left[\hat{f}_0(n)\,\hat{f}_1(n)\cdots\hat{f}_{L-1}(n)\right]^T$, length of filter is addressed by L and the echo canceled signal is denoted by $\hat{r}$ and $X(n)=[x(n)\,x(n-1)\cdots x(n-L+1)]^T$ denotes the sample vectors of loudspeaker. The modified form of $\hat{f}(n)$ is executed by means of a feedback loop occurring on the estimation error $e_e(n)$ that is found similar to the gain addressed by $G(n)$ as shown by Eq. (2) and Eq. (3). Further, Eq. (3) is the customized model of an adaptive filter.

$$\hat{r}(n)=\left(\hat{f}*x\right)(n)=\hat{f}^T(n).X(n) \tag{1}$$

$$\hat{f}(n+1)=\hat{f}(n)-\hat{G}(n)e_e(n) \tag{2}$$

$$e_e(n)=g(n)-\hat{r}(n) \tag{3}$$

Behavior of NSAF model

Architecture

A linear ECS which is not recognized is predicted with the desired signal $r(n)$ as in Eq. (4), in which, V^o denotes the column vector which has to be detected by adopting an adaptive filter, $d(i)$ that provides the assessment of noise with zero variance and mean σ_v^2, $Y(n)$ is associated to the length W of input row vector that is portrayed as in Eq. (5),

$$r(n)=X(n)V^o+d(n) \tag{4}$$

$$X(n)=[x(n)\ x(n-1)\dots\ x(n-W+1)] \tag{5}$$

Both the best possible resulting signals are separated into N subbands, provided by $r_i(n)$ and $y_i(n): i=0,1,\dots,N-1$. The filters offered for these signals are suggested by $H_0(z),\dots,H_{N-1}(z)$ as given in Fig. 1.

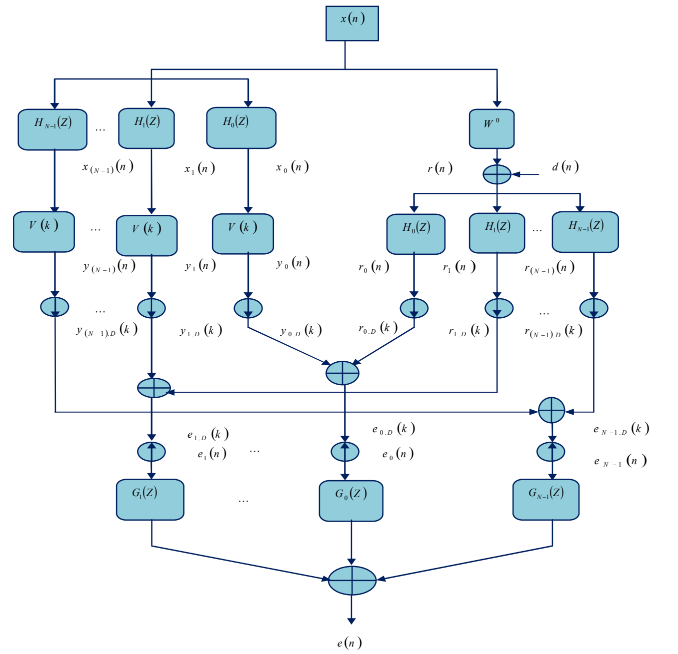

Fig 1 NSAF Architectural Model

The signals produced from subbands are assigned with related bandwidths and are converted to the reduced rate of sampling. Based on this model, the real sequences are indicated as n and k that addresses the evaluated sequences. The resulting decimated signal for the entire subband signals is given by Eq. (6), where, $X_i(k)$ is allotted with $1\times W$ row vector. As a result, Eq. (6) is configured as shown in Eq. (11). For demonstrating V^o with V, Eq. (8) has been formulated, in which V indicates the length. Eq. (9) and Eq. (10) are deployed to discover the fault signal of the overwhelmed subband, in which, $r_{i,D}(k)=r_i(kN)$ denotes the necessary signal occurring in the whole subbands. Therefore, Eq. (11) offers the NSAF filter in which the step-size is addressed by μ.

$$y_{i,D}(k)=Y_i(k)V(k) \tag{6}$$

$$Y_i(k)=[x_i(kN),x_i(kN-1),\dots,x_i(kN-W+1)]$$
(7)

$$V(k)=[v_o(k),v_1(k),\dots,v_{W-1}(k)]^T \tag{8}$$

$$e_{i,D}(k)=r_{i,D}(k)-y_{i,D}(k) \tag{9}$$

$$e_{i,D}(k)=r_{i,D}(k)-Y_i(k)V(k) \tag{10}$$

$$V(k+1)=V(k)+\mu\sum_{i=0}^{N-1}\frac{Y_i^T(k)}{\|Y_i(k)\|^2}e_{i,D}(k) \tag{11}$$

Subband selection for NSAF

The modified design for altering the step-size and mandatory subband of the implemented NSAF filter is revealed in Eq. (12), where, γ is enclosed by error, which is adjusted to one for the existing NSAFs and subbands that are preferred for matrix are signified by U_{T_M}. By adopting the factors of directions and step-size sequence $\{\mu_k\}$, developments in the SM-NLMS address the zero convergence as revealed in Eq. (19). As the magnitude $<\gamma$, the assumed error, Eq. (20) is attained.

$$\hat{V}_M(k+1)=\hat{V}(k)+\begin{cases}1-\dfrac{\gamma}{|e_i(k)|}Y(k)\tilde{Y}U_{T_M}e(k);\ if\ |e_i(k)|>\gamma\\ 0;\ otherwise\end{cases}$$
(12)

The time index is represented by k as given in Eq. (13) and Eq. (14), and it has the ability to expose the complete timing instance owing to Eq. (15).

$$\lim_{k\to\infty}\left\|\hat{V}_k-\hat{V}_{k-1}\right\|=\lim_{k\to\infty}\mu_k=0 \tag{13}$$

$$\limsup_{k\to\infty}\|e_i(k)\|\le\gamma \tag{14}$$

$$\left\|\hat{V}_k-\hat{V}_{k-1}\right\|=\mu_k=0\ otherwise \tag{15}$$

As the spheroid U_n is satisfied for the complete k, $\sigma_k^2>0$. σ_k^2 is generally monotonic and consequently, the sequence represented by $\{\sigma_k^2\}$ is convergent. Based on Eq. (11), modifications can be carried out as given in Eq. (16) and Eq. (17).

$$\frac{\mu_k^2\|e_i(k)\|^2}{\|x_k\|^2}\to 0 \tag{16}$$

$$\left\|\hat{V}_k-\hat{V}_{k-1}\right\|=\frac{\mu_k\|e_i(k)\|}{\|x_k\|}\to 0 \tag{17}$$

Assume that, $\|x_k\|$ is enclosed and the technique of modifications are carried out by deploying $\|e_i(k)\|>\gamma>0$. It is dependent upon $\mu_k\to 0$. Based on Eq. (11), $\|e_i(k)\|\to\gamma$ is detailed throughout the updating course and

$\left\| e\left(k\right)\right\| < \gamma$ *otherwise*, owing to which Eq. (18) is formed. The updating design dependent on NSAF through subband grouping matrix U_{T_M} is exposed by Eq. (18)

$$\hat{V}(k+1) = \hat{V}(k) + \mu_i(k) X(k) \left(Y^T(k) Y(k)\right)^{-1} U_{T_M} e(n) \tag{18}$$

Better correlation is attained amongst $Y_i(k)$ with μ_i and as a result, the obtained formula is revealed in Eq. (19) by which the modified design can be achieved as described in Eq. (20). On account of the achieved error, μ is differed as shown in Eq. (21) and consequently, the model is attained as in Eq. (21).

$$\left\| \hat{V}_M(k+1) - \hat{V}(k)\right\|^2 = \mu_i^2 \left(Y^T(k) Y(k)\right)^{-1} e^T(n) U_{T_M} e(n) \tag{19}$$

$$\hat{V}_M(k+1) = \hat{V}(k) + \mu_i(k)\, Y(k) \tilde{Y} U_{T_M} e(k) \tag{20}$$

$$\mu = \begin{cases} 1 - \dfrac{\gamma}{\left|e_i(k)\right|}; if \left|e_i(k)\right| > \gamma \\ 0; \ otherwise \end{cases} \tag{21}$$

Error Bound and Memorizing Error

The enclosed error denoted by γ is maintained at constant in which the NSAF filter enhances it to vary with respect to the iteration position. The suggested one to denote the error bound evaluation is provided by Eq. (22). In Eq. (22), the iteration taking place currently is implied by k and the maximum iterations allotted are $k_{\max}$ and $\gamma(\gamma_{\min}, \gamma_{\max})$ is the higher and smaller error bounds.

$$\gamma(k+1) = \gamma_{\min} + \frac{(\gamma_{\max} - \gamma_{\min})(k+1)}{k_{\max}} \tag{22}$$

In addition, the predicted error can be obtained based on the deviation among the original output and desired output as in Eq. (9) and Eq. (10). As the error is remembered until earlier iteration gets over, as in Eq. (23), the method of MVS-SNSAF concerns the earlier error and prevailing error.

$$e_{i,D}^M(k) = \frac{\left|r_{i,D}(k) - Y_i(k) V(k)\right| + e_{i,D}(k-1)}{2} \tag{23}$$

Concept behind Deterministic Initialization

The AF remains as a challenging design to regard the appropriate weight, as it generates output by raising a certain weight factor together with the input. Thus there is a possibility of obtaining improved filtering. In the conventional system, the initialization process is performed by concerning the zeros in the AEC system. Moreover, initialization is executed in the suggested D-MVS-SNSAF system based on depiction of the ECS. As a result, the ECS can attain improved convergence.

Assume an ECS with an input x and output $\hat{r}$. By deploying the model of D-MVS-SNSAF, weight for reliable ECS identification can be done for identifying the polynomial form. The transitions in the input-output characteristics have been adopted for portraying the polynomial order. Consequently, the amount of orders could be described by concerning the transition amounts as in Eq. (24), in which the amount of orders is given by N^{orders} and the quantity of transitions occurring in the input-output characteristics is indicated by $N^{transitions}$.

$$N^{orders} = N^{transitions} + 1 \tag{24}$$

Accordingly, the transitions of the curves can be sorted into six classifications namely, stable to high, stable to low, low to stable, high to stable, low to high and high to low which are denoted by Eq. (25), Eq. (26), Eq. (27), Eq. (28), Eq. (29) and Eq. (30). Eq. (31), respectively depicts the polynomial formula in which, $\hat{r}$ indicates the ECS's output. From Eq. (25) to (30), the preceding output of ECS's is given by $\hat{r}(n-1)$, the present output is indicated by $\hat{r}(n)$ and the subsequent output of ECS is given by $\hat{r}(n+1)$.

$$\hat{r}(n-1) = \hat{r}(n) < \hat{r}(n+1) \tag{25}$$

$$\hat{r}(n-1) = \hat{r}(n) > \hat{r}(n+1) \tag{26}$$

$$\hat{r}(n-1) > \hat{r}(n) < \hat{r}(n+1) \tag{27}$$

$$\hat{r}(n-1) < \hat{r}(n) = \hat{r}(n+1) \tag{28}$$

$$\hat{r}(n-1) > \hat{r}(n) = \hat{r}(n+1) \tag{29}$$

$$\hat{r}(n-1) < \hat{r}(n) > \hat{r}(n+1) \tag{30}$$

$$\hat{r} = a_0 + a_1 x + a_2 x^2 + \ldots + a_{N^{orders}} x^{N^{orders}} \tag{31}$$

The total coefficients in Eq. (31) should be brought to a solution for defining the initial weighting factor. On the basis of the entire coefficients, weighting factor initialization happens. Thus, the initial weight ($V^0 = V(k=0)$) of the ECS is indicated in Eq. (32). Therefore, the enhanced system identification by means of ECS technique could be attained by suitable weight initialization with proposed D-MVS-SNSAF system and proper update.

$$V^0 = \sum_{i=0}^{N^{orders}} a_i \tag{32}$$

RESULTS AND DISCUSSIONS

Simulation procedure

The proposed D-MVS-SNSAF for identifying ECS is simulated in MATLAB [30], and the investigational outcomes are distinguished with the traditional NSAF [4], SS-NSAF [27], VS-NSAF [21], VS-SNSAF [28] and MVS-SNSAF [29]. Here, three audio signals namely, speech, audio, and song are used for experimentation. Moreover, the amount of subbands employed in VS-NSAF and NSAF is varied by 2, 4 and 8 to produce enhanced results. The considered mechanisms are executed for 1000 iterations when it is reciprocated for its up-sampling rate, and the down-sampling rate is set to 50%. The NSAF and SS-NSAF are allocated with a step-size 1. The implementation is done in the audio signals in a frequency range of 50 Hz to 50 kHz. The weight $\hat{V}$ is measured for the non-determined echo cancellation systems by exploiting NSAF algorithms. As noise spoils the real echo cancellation systems, complications of the methods to lessen the noise are noted by varying the SNR of the input signal from 0 dB to 25 dB. The accomplished results are observed based on convergence analysis, error analysis, and stability analysis. In addition, the complications of the algorithm in minimizing noise are also examined in the forthcoming sections.

Error analysis

The error analysis of the implemented D-MVS-SNSAF system based on identification of ECS is given by Fig.2 for speech signal. From Fig. 2(a), the 1st order of signal without varying step-size for the proposed method is 2.02% better than NSAF with 8 subbands, 1.8% better than NSAF with 2 subbands, 1.1% better than SS-NSAF methods. Similarly, from Fig. 2(b), the 2nd order of signal without varying step-size for the proposed method is 1.1% superior to NSAF with 8 subbands, 1.8% superior to NSAF with 2 subbands, 0.2% superior to SS-NSAF methods. Also, from Fig. 2(c), the 1st order signal with varying step-size for the proposed method is 1.14% better than VS-NSAF with 8 subbands and MVS-SNSAF methods, 0.2% better than VS-NSAF with 4 subbands, and 0.6% better than VS-NSAF with 2 subbands methods. Moreover, from Fig. 2(d), the 2nd order signal with varying step-size for the proposed method is 4.58% superior to MVS-SNSAF and 2.29% superior to all other compared methods.

Similarly, Fig. 3 reveals the implemented D-MVS-SNSAF system based on identification of ECS for audio signal. From Fig. 3(a), the 1st order of signal without varying step-size for the proposed method is 7.6% better than NSAF with 8 subbands, 0.3% better than NSAF with 2 subbands, 0.1% better than SS-NSAF methods. Similarly, from Fig. 3(b), the 2nd order of signal without varying step-size for the proposed method is 0.3% superior to NSAF with 8 subbands, 1% superior to NSAF with 2 subbands, 0.7% superior to SS-NSAF methods. Also, from Fig. 3(c), the 1st order of signal with varying step-size for the proposed method is 3.8% better than all other compared techniques. Moreover, from Fig. 3(d), the 2nd order of signal with varying step-size for the proposed method is 0.72% superior to all other compared methods.

Moreover, Fig. 4 shows the proposed D-MVS-SNSAF system based on identification of ECS for song signal. From Fig. 4(a), the 1st order of signal without varying step-size for the proposed method is 3.9% better than NSAF with 8 subbands, 0.3% better than NSAF with 2 subbands, and 7.9% better than SS-NSAF methods. Similarly, from Fig. 4(b), the 2nd order of signal without varying step-size for the proposed method is 0.37% superior to NSAF with 8 subbands, 0.74% superior to NSAF with 2 subbands, 0.37% superior to SS-NSAF methods. Also, from Fig. 4(c), the 1st order of signal with varying step-size for the proposed method is 0.39% better than all other compared techniques.

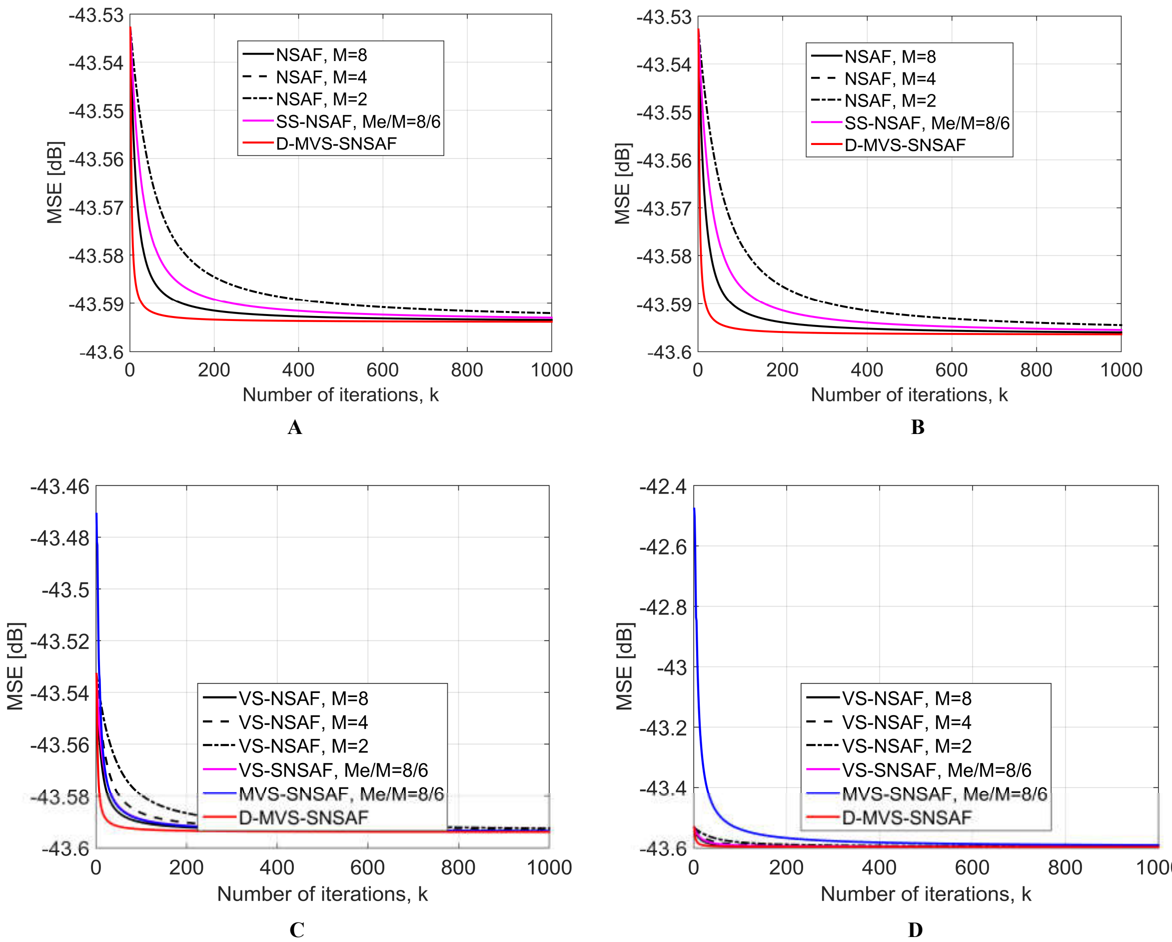

Fig 2 Error analysis for echo cancellation system for speech signal (a) Without varying step-size for 1st order of signal (b) Without varying step-size for 2nd of order signal (c) With varying step-size for 1st order signal (d) With varying step-size for 2nd order of signal

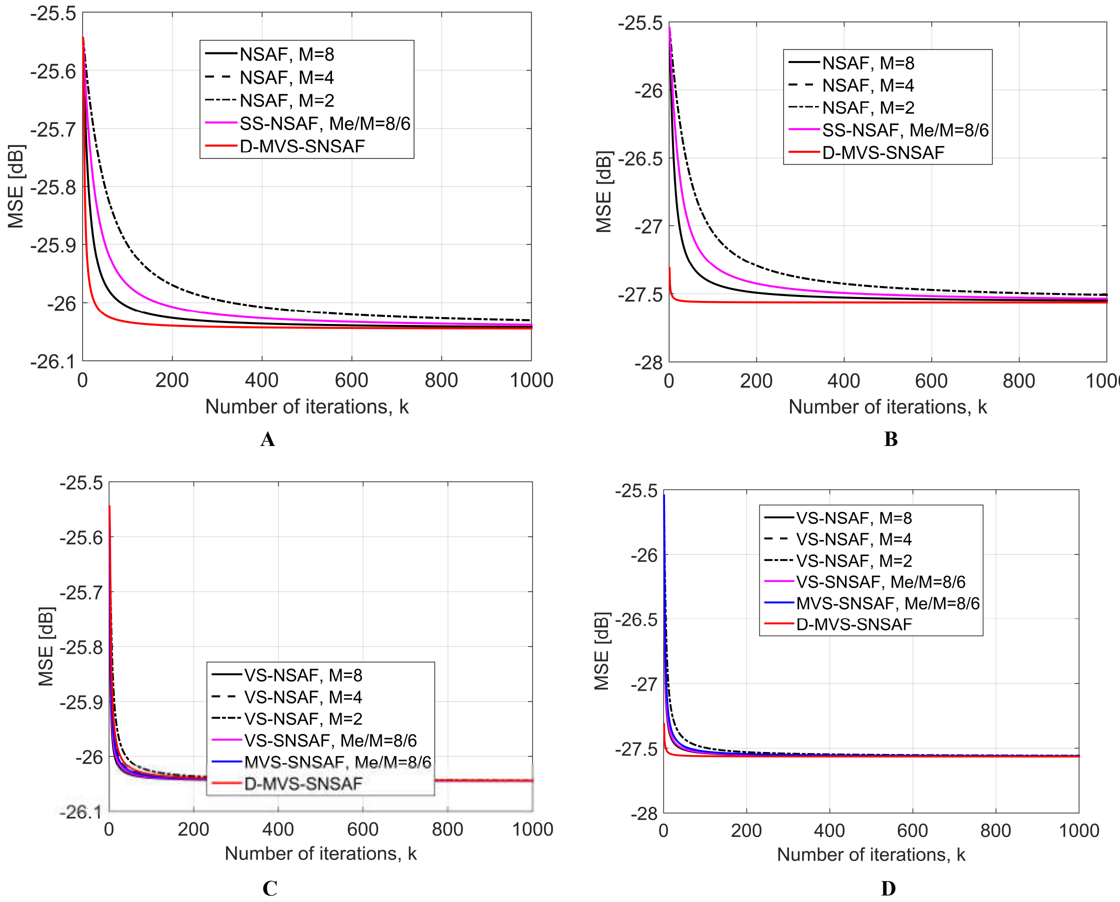

Fig 3 Error analysis for echo cancellation system for audio signal (a) Without varying step-size for 1st order of signal (b) Without varying step-size for 2nd of order signal (c) With varying step-size for 1st order signal (d) With varying step-size for 2nd order of signal

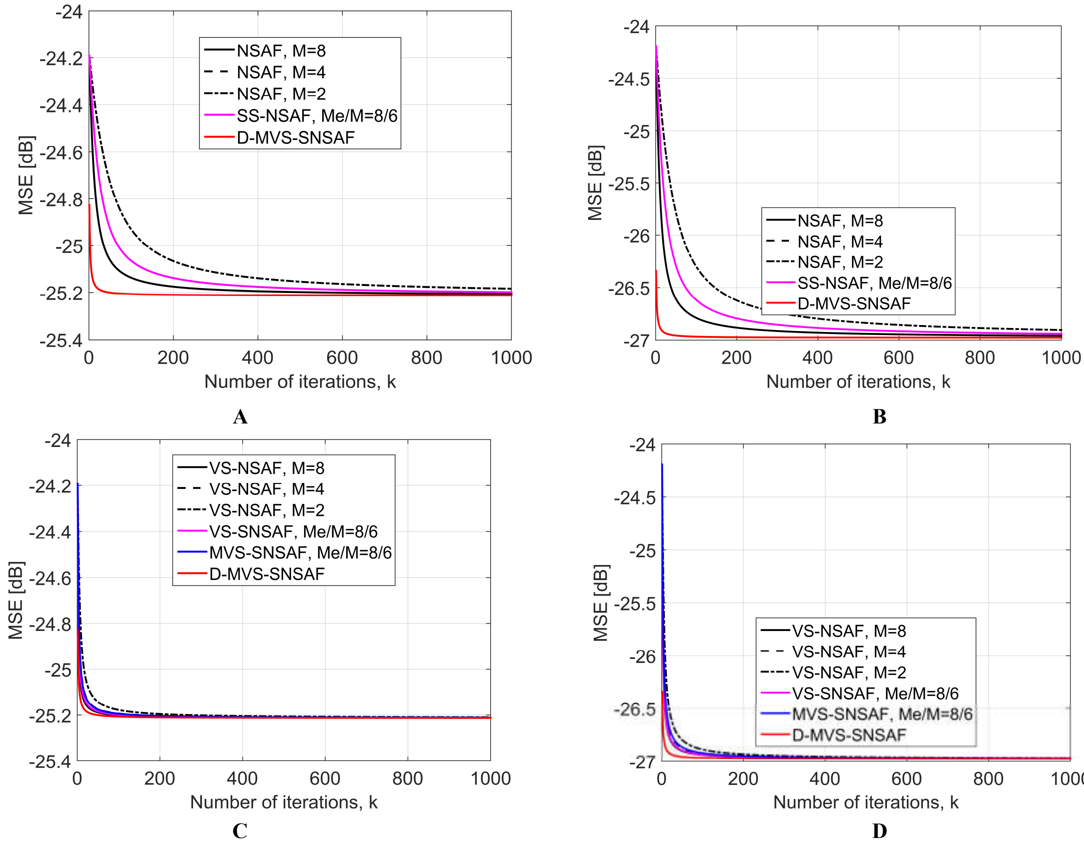

Fig 4 Error analysis for echo cancellation system for song signal (a) Without varying step-size for 1st order of signal (b) Without varying step-size for 2nd of order signal (c) With varying step-size for 1st order signal (d) With varying step-size for 2nd order of signal

Moreover, from Fig. 4(d), the 2nd order of signal with varying step-size for the proposed method is 0.74% superior to all other compared methods. Thus the proposed D-MVS-SNSAF system based on the identification of ECS is proved to have efficient performance when compared with the existing techniques.

CONCLUSION

This paper has presented improvements in identifying the ECS for three signals such as speech, audio and song by exploiting an enhanced NSAF technique known as the D-MVS-SNSAF scheme. According to this technique, the number of transitions in the input/output signals was measured for deriving the polynomial from three audio signals as input. Following the simulation, the proposed D-MVS-SNSAF method was distinguished with the existing techniques such as NSAF, VS-NSAF, SS-NSAF, VS-SNSAF and MVS-SNSAF methods. From the analysis, it was observed that for speech signal, the 1st order of signal without varying step-size for the proposed method is 2.02% superior to NSAF with 8 subbands, 1.8% superior to NSAF with 2 subbands, 1.1% superior to SS-NSAF methods. Similarly, the 2nd order of signal without varying step-size for the proposed method is 1.1% better than NSAF with 8 subbands, 1.8% better than NSAF with 2 subbands, 0.2% better than SS-NSAF methods. Also, the audio signal with varying step-size for the implemented technique is 1.14% better than VS-NSAF with 8 subbands and MVS-SNSAF methods, 0.2% better than VS-NSAF with 4 subbands, and 0.6% better than VS-NSAF with 2 subbands methods. Moreover, the 2nd order of signal with varying step-size for the proposed method is 4.58% better than MVS-SNSAF and 2.29% better than all other compared methods. Thus the proposed D-MVS-SNSAF system based on the identification of ECS is proved to have proficient performance when compared with the conventional methods.

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