Echo Cancellation in Telecommunications Using Variable Step-Size, Dynamic Selection, Affine Projection Algorithm.

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Abstract- *This paper focuses on how to improve the performance of Acoustic Echo Cancellation AEC in voice communication systems. A variable step-size, dynamic affine projection algorithm named as DSVSSAPA is devised for this purpose. The proposed version combines the merits of the variable step size APA as well as uses dynamic selection of the input vectors to reduce its computational power, which has not been found in literature elsewhere. The version proposed in this paper overcomes drawbacks incorporated with the standard AP algorithm. These drawbacks are convergence speed-misalignment trade off problem and the high computational complexity of the algorithm. The proposed algorithm reduces the computational complexity by carrying the update after satisfying a specific criterion. Performance of the proposed echo canceller is evaluated and compared with those obtained from the same echo canceller but based on conventional algorithms such as the normalized least mean square algorithm NLMS and the original affine projection algorithm APA. The performance is measured in terms of misalignment and echo return loss enhancement ERLE. Simulation results showed superior ERL performance of the DSVSSAPA compared to other algorithms. It also achieves 17.73% reduction in computational complexity compared with conventional APA which is useful in portable communication applications.*

I. INTRODUCTION

The use of acoustic echo cancellers is required in applications such as mobile phones, hand free telephony, speaker-phones and other voice communication systems. The purpose is to reduce or cancel the echoes which worsen the quality of voice communications [1]. The echo canceller identifies the room echo path and then subtracts an estimated replica of the echo from the near speaker voice signal as shown in Fig. 1.

In the aforementioned setup, adaptive filters are employed to identify the echo path. The output of the adaptive filter is a close replica of the echo signal which is used to reduce the unwanted voice echo [2]. The adaptive filter continuously updates its weight coefficients to cope with the time varying characteristic of the echo path which resulted from moving objects or any other changes in room conditions [3]. One of the popular methods used for weight update is normalized least mean square NLMS algorithm which has been used widely in adaptive filters for its simplicity and robustness. However, this algorithm has a slow asymptotic convergence in colored and non-stationary signals like speech and acoustic echo [4]. On the other hand, the original affine projection algorithm APA provides a much improved convergence speed compared to stochastic gradient algorithms such as the NLMS. It

Received 4 may 2017; Accepted 2 November 2017
 ISSN 1811-9212

possesses a performance that approaches the highly complex recursive least mean square RLS algorithm in many situations [5].

Referring to Figure 1, the aim of the echo canceller is identifying the unknown system i.e. the echo path, using an adaptive filter. The far-end speech signal $x(k)$ goes through the echo path resulting in the echo signal $y(k)$. This signal is received by the microphone plus the near-end signal $n(K)$ resulting in the desired microphone signal $d(k)$. The output of adaptive filter $\hat{y}(k)$ is a replica of the echo which is subtracted from the microphone signal [6]. The problems of the echo canceller AEC are challenging due to the fact that the echo path can be very long depending on the size and shape of the place where the communication occurs, such as small rooms or large halls. This means that a long transversal filter is needed to simulate the impulse response of the echo path.

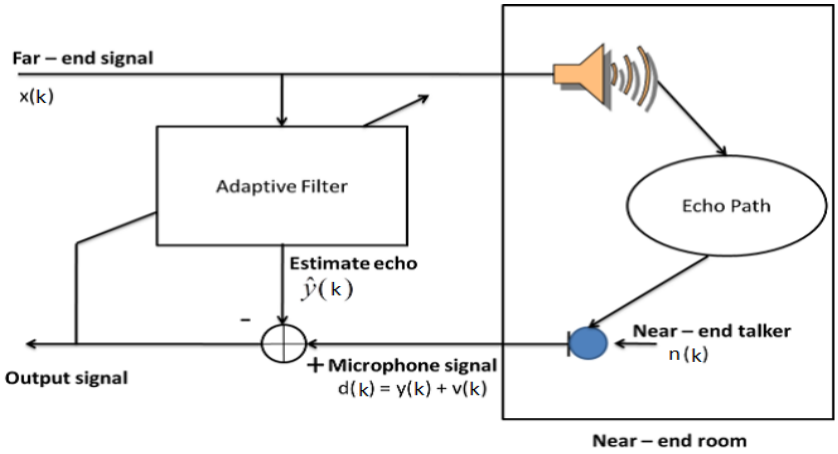

FIG. 1: ACOUSTIC ECHO CANCELLATION SETUP

Furthermore, the far-end microphone signal is normally a highly correlated speech signal which adversely affects the convergence rate of the adaptive filter. The echo path or the room impulse response can change rapidly by little movement of the near-end speaker's head or by change of objects in the room which can have a large effect on the impulse response of echo path. For these reasons, the convergence of the adaptive filter should be fast enough to keep tracking of the changes. These contradicting conditions brought up the use of the APA which is the best choice for such application [7]. The convergence speed of APA is increased as its projection order is increased. However, this has another adverse effect on its computational cost and its final residual error which gets worse at the same time. The original version of APA uses a fixed step size in filter coefficients update which governs the stability as well as the convergence rate and misalignment of the algorithm. As a result, a tradeoff has to be established between fast convergence and low final residual error. Variable step size version of the APA has been proposed in literature to mitigate these extreme requirements and therefore to get a better performance of the algorithm [7-10]. Although these techniques lead to a better performance, the computational cost of algorithm remains high, therefore an APA with evolving projection order has been proposed in order to reduce computational cost and achieve lower final error than these variable step-size methods [11-14]. The use of evolving projection order technique uses a combination of analytical and algorithmic procedures which turned out to be complex and require a lot of empirical testing before running the final version.

For the aforementioned reasons, this paper introduces a new version of the APA algorithm which combines between the variable step size method and the dynamic selection of input vectors to the adaptive filter in order to enhance the performance and reduce the computational complexity of the APA. The paper is organized as follows: after this introductory section, section 2 presents details of the derivation of the new version of the algorithm. Section 3 gives the simulation setup of the AEC under

Received 4 may 2017; Accepted 2 November 2017
 ISSN 1811-9212

the new algorithm, showing the results of the simulations. Finally Section 4 concludes the paper with main remarks of the results.

II. ECHO CANCELLATION BASED ON THE PROPOSED AP ALGORITHM

Referring to Fig. 1, the controlling core of the proposed echo canceller is the version of the APA devised in this paper named as variable step size dynamic selection affine projection algorithm VSSDSAPA, the derivation of which is given as follows. Based on the work in [12], the idea of the dynamic selection algorithm is that the input vectors are dynamically selected according to some specified criterion. The optimum selection of input vectors is derived by the largest decrease of the mean square deviation. The update equation of the dynamic selection algorithm is written as follows.

$$\boldsymbol{w}(k) = \begin{cases} \boldsymbol{w}(k-1) & if R(k) = 0 \\ \boldsymbol{w}(k-1) + \mu \boldsymbol{X}^t_{\mathrm{T}_R}(k)\left(\boldsymbol{X}_{\mathrm{T}_R}\boldsymbol{X}^t_{\mathrm{T}_R}\right)^{-1}\boldsymbol{e}_{\mathrm{T}_R}(k) & otherwise \end{cases} \tag{1}$$

where $T_{R(k)}(k) = \{t_1, t_2, \dots t_{R(k)}(k)\}$ is a subset, with $R(k)$ are members of the set $\{0,1,\dots,L-1\}$, L is the maximum number of input vectors.

t_R is the delay, and $R(k)$ is the number of selected input vectors at iteration *k*.

$$\boldsymbol{e}_{\mathrm{T}_{R(k)}}(k) = \begin{bmatrix} e_{t_1}(k) \\ e_{t_2}(k) \\ \vdots \\ e_{\mathrm{T}_{R(k)}}(k) \end{bmatrix} \tag{2}$$

$$\boldsymbol{X}_{\mathrm{T}_{R(k)}}(k) = \begin{bmatrix} x_{k-t_1} \\ x_{k-t_2} \\ \vdots \\ x_{k-t_{R(k)}} \end{bmatrix} \tag{3}$$

$$\left|e_{t(k)}(k)\right| \quad > \quad \sqrt{2/2-\mu}\,\sigma_v \tag{4}$$

$(r = 1,2 \dots R(k))$,$0 \le R(K) \le L$, L is the max number of input vectors, and σ_v is the variance of noise. The criterion that the dynamic step size affine projection algorithm DSAPA carries out to make the update is by selecting the input vectors that satisfy the following:

$$|e_l(k)| \quad > \quad \sqrt{2/2-\mu}\,\sigma_v \qquad , \; l = \{1,2 \dots L-1\} \tag{5}$$

Hence the update equation is controlled by the step size and a threshold value which also depends on the step size. It is used to control the step size to meet the conflicting requirements of fast convergence rate and low misalignment. Thus the threshold value will vary with the step size. The step size value in the update equation becomes variable. The update equation is now rewritten as:

$$\boldsymbol{w}(k) = \begin{cases} \boldsymbol{w}(k-1) & if \;\; R(k) = 0 \\ \boldsymbol{w}(k-1) + \mu(k)\, \boldsymbol{X}^t_{\mathrm{T}_k}(k)\left(\boldsymbol{w}_{\mathrm{T}_k}\boldsymbol{X}^t_{\mathrm{T}_k}\right)^{-1}\boldsymbol{e}_{\mathrm{T}_k}(k) & otherwise \end{cases} \tag{6}$$

and the condition is rewritten as:

$$|e_l(k)| \quad > \quad \sqrt{2/2-\mu(k)}\,\sigma_v \quad l = \{1,2 \dots L-1\} \tag{7}$$

where the step size varies as given by

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

$$\mu(k) = k_{max} \frac{\|\hat{p}(k)\|^2}{\|\hat{p}(k)\|^2 + c} \tag{8}$$

where

$$\hat{p}(k) = \alpha\hat{p}(k-1) + (1-\alpha)X^{\boldsymbol{t}} \left(X(k)X^t(k)\right)^{-1} e(k) \tag{9}$$

α is a smoothing factor $(0 < \alpha < 1)$.

μ_{max} is chosen less than 2 to guarantee the stability of the filter. In the same way as it is used in the LMS algorithm and c is a small constant to avoid division by zero.

The threshold is set so as not to take all input vectors to carry out the update, instead, only the input vectors that satisfy the criterion in equation (7) will be chosen for update. This makes a reduction in the number of computations required to perform the adaptation and hence a reduction in the overall computational power is achieved. Furthermore, the property of the variable step-size (VSS) overcomes the compromise between the fast convergence and small misalignment. Therefore, the problems of the APA are solved this way i.e. the compromise between convergence rate and miss-adjustment is mitigated by the use of variable step size, at the same time the computational complexity is reduced by using dynamic selection of input vectors for the adaptive filter update.

III. SIMULATION AND RESULTS

The simulations presented in this section were conducted in an acoustic echo cancellation AEC setup, as shown in Fig. 1. The near-end speaker of the AEC consists of a microphone and the loudspeaker is assumed to be located in a small room. The adaptive filter uses the far-end signal as an input; its output is subtracted from the microphone signal to produce the signal free from echo. The set of simulations is performed in an exact AEC modeling scenario in which the length of the adaptive filter and echo path is set to 400 which simulates a small room impulse response. The echo path's impulse response is sampled at 8 kHz and plotted in Fig. 2. The far-end signal is a speech signal shown in Fig. 3. Additive White Gaussian Noise is added to the echo signal representing the environmental noise. The performance is measured in terms of the normalized misalignment in dBs, which is defined as:

$$10log_{10} \frac{\|\boldsymbol{w}(k) - \boldsymbol{h}\|^2}{\|\boldsymbol{h}\|^2} \tag{10}$$

and in terms of echo return loss enhancement ERLE which is defined as:

$$ERLE = 10\log\left(\frac{E[(y^2(k))]}{E[(e^2(k))]}\right) dB. \tag{11}$$

The performance of the proposed DSVSSAPA is evaluated for three different values of projection order 4, 8 and 16. Comparison is made with conventional APA using three different orders similar to the proposed ones. A comparison has also been made with an NLMS as a bench mark to prove the validity of the method. The step size of the conventional APA is set to 0.01. The parameters for the variable step size equation are α which equals to 0.98, μ_{max} which equals to 1, and c which equals to 0.00009. The choice of these parameter values has been taken from previous literature works to achieve better performances for both the proposed and the original APA, also to make a fair judgment for the proposed DSVSSAP algorithm. The noise variance σ_v is assumed to be known.

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

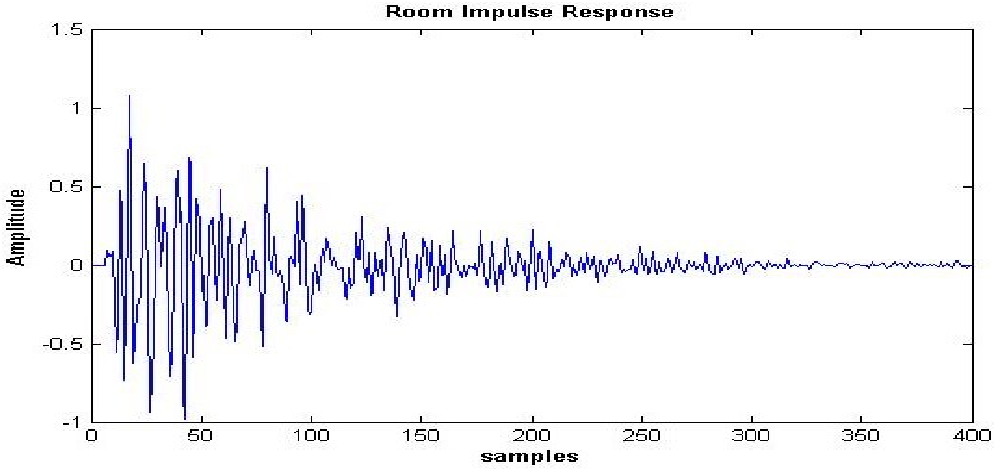

FIG. 2. ROOM IMPULSE RESPONSE

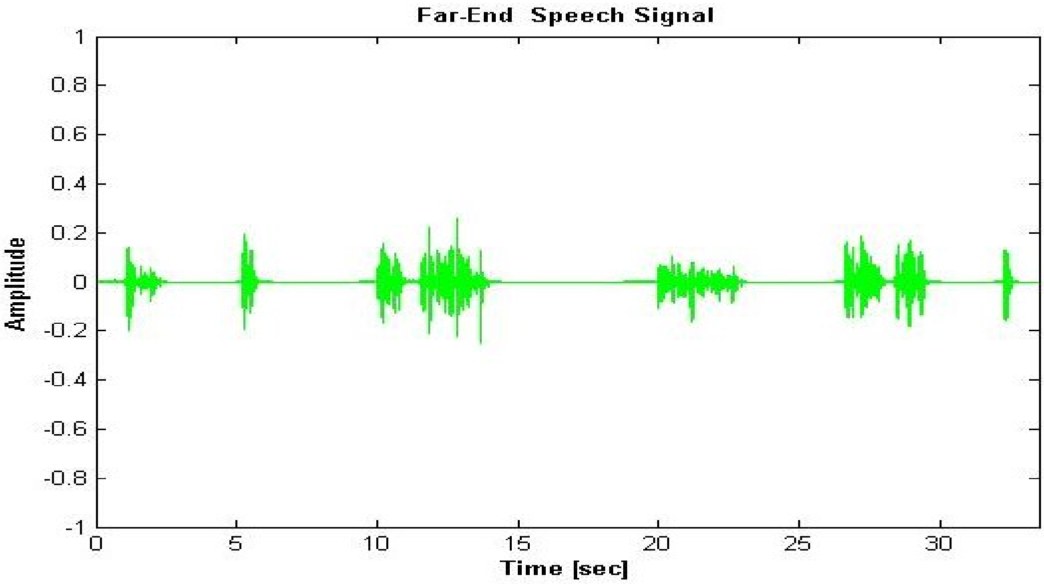

FIG. 3. FAR-END SPEECH SIGNAL

Fig. 4(a) shows the misalignment plot while Fig. 4(b) shows ERLE for conventional APA and the proposed DSVSSAPA algorithm when projection order is set to 4. As shown in Fig. 4(a), the proposed algorithm shows faster convergence rate and lower misalignment than the conventional APA. In addition to that, the improved performance was achieved with less computational complexity compared with the original APA. It is also clear from Fig. 4(b) the faster removal of echo compared to the APA.

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

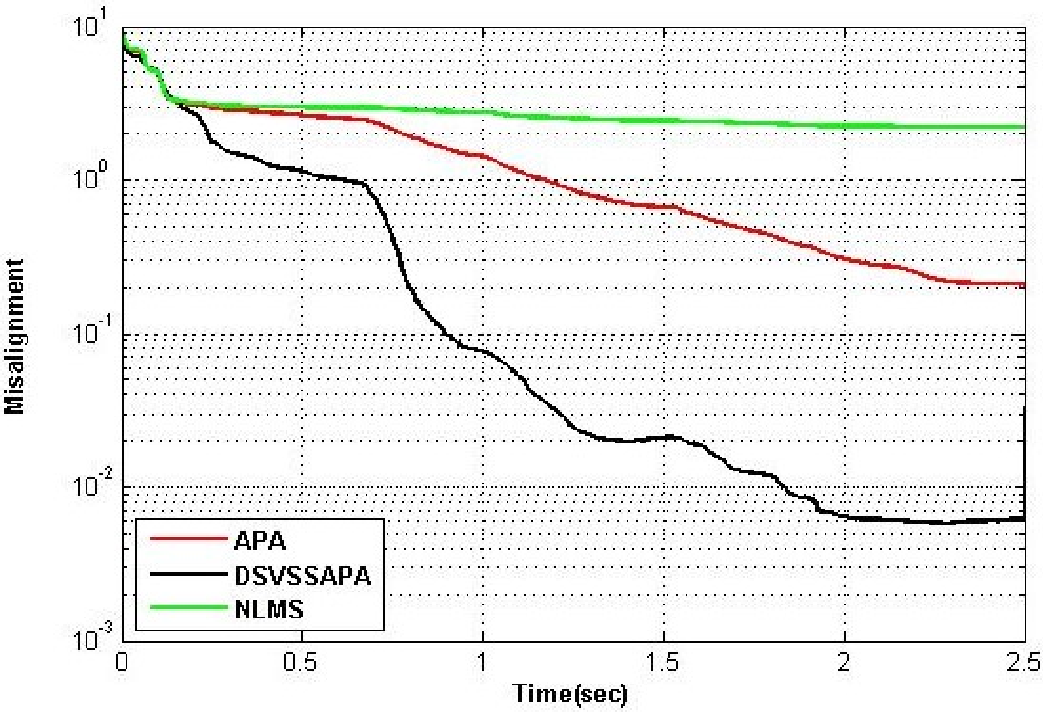

FIG. 4(A). MISALIGNMENT CURVE DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL TO 4.

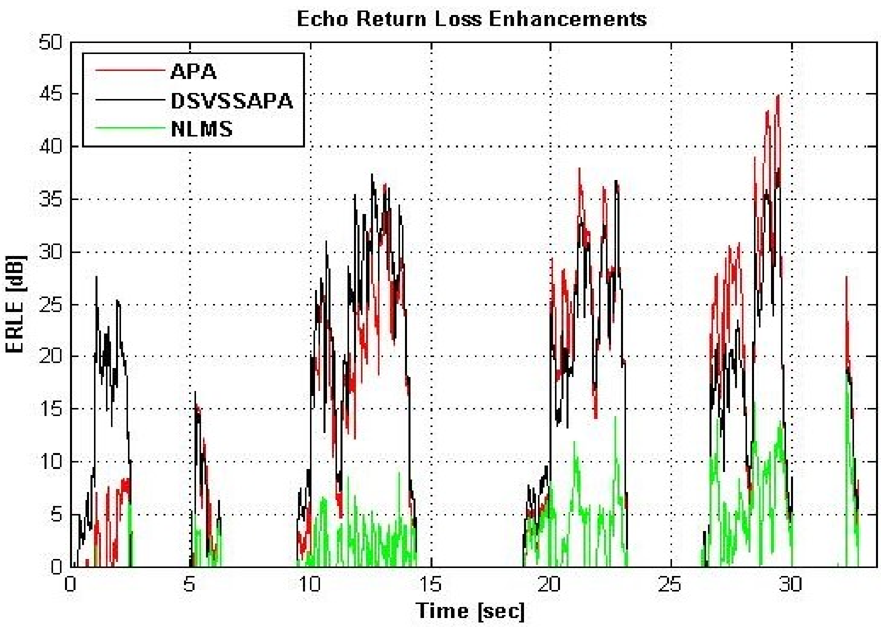

FIG. 4(B). ERLE PLOT FOR DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL TO 4.

The same simulation experiments were repeated but with projection orders of 8 and 16 for both the proposed DSVSSAPA and the conventional APA. The results are depicted in Fig. 5 and 6 in the same way as before.

As it is shown in Fig. 5 (a) and (b), the DSVSSAPA still shows a faster convergence and lower level of misalignment than conventional APA. However, at the beginning of the adaptation process the misalignment shows comparable performance to that of the APA, while it improves greatly towards the

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

end of the process. Furthermore, the ERLE plot for DSVSSAPA has a better performance than the original APA. The same argument applies to Fig. 6.

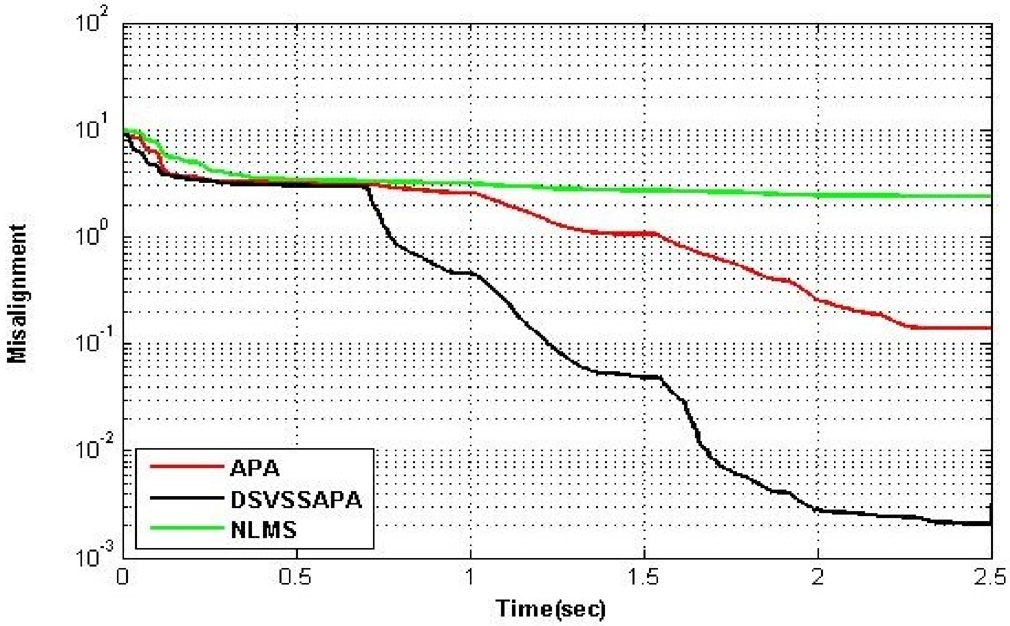

FIG. 5 (A) MISALIGNMENT PLOT DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL TO 8.

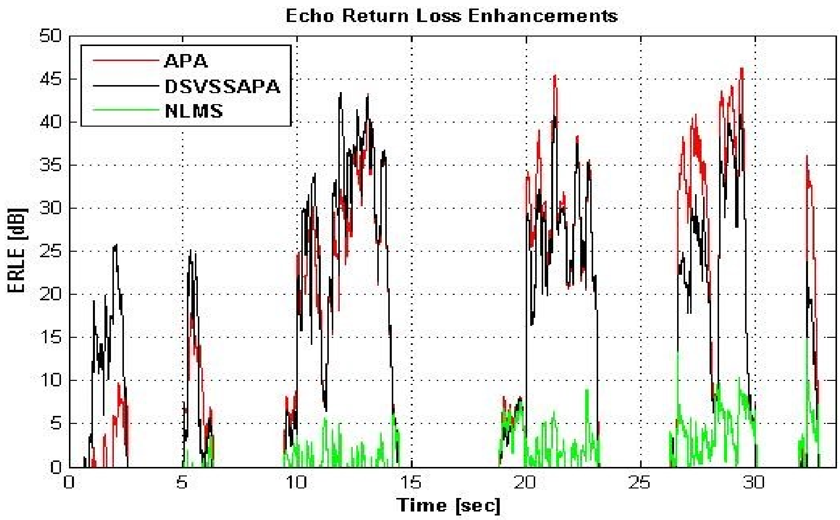

FIG. 5(B). ERLE FOR DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL TO 8.

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

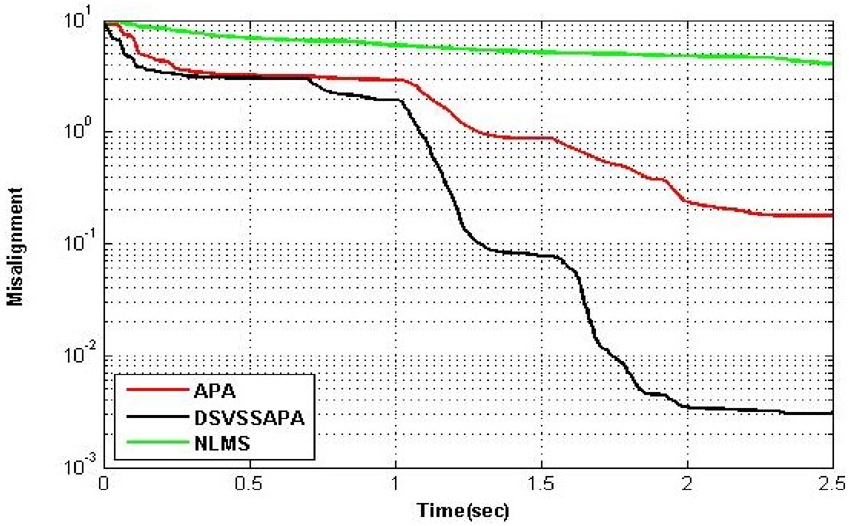

FIG. 6(A). MISALIGNMENT PLOT FOR DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL to 16.

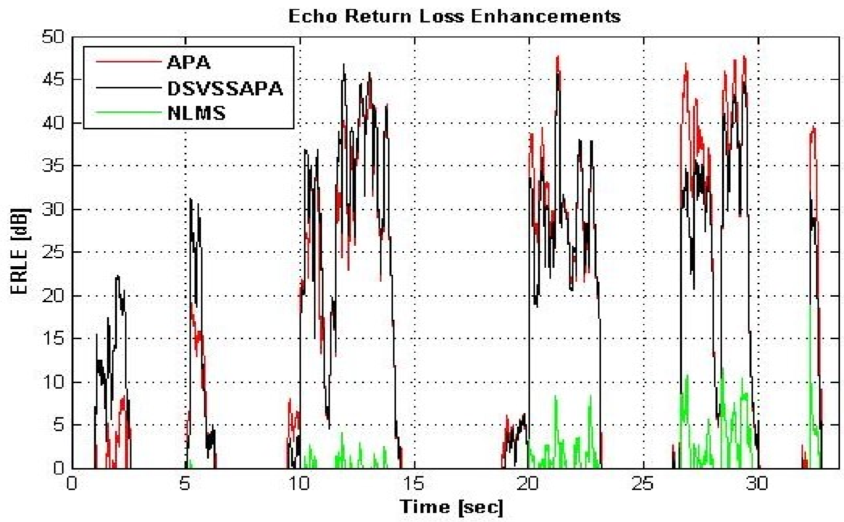

FIG. 6(B). ERLE PLOT FOR DSVSSAPA AND CONVENTIONAL APA WHEN PROJECTION ORDER IS EQUAL TO 16.

From these results, it’s clear that the performance of the proposed algorithms is superior to that of the conventional APA for all projection orders. The dynamic selection of the input vectors allows a reduction in computational complexity of 17% compared to the original algorithm i.e. only about 83% of the input vectors are required to achieve good results. This was calculated by counting the number of vectors that are actually processed by the adaptive filter. However the increase of projection order will increase the computational cost and this is usually avoided in case of limited resources such as low battery life and small capacity DSP processors. Finally, the processed output speech by the DSVSSAPA is displayed in Fig. 7. The Figure also shows the original microphone signal as well as those processed by APA and NLMS algorithms. It is clear that with the use of the proposed algorithm, the echo has been removed quickly and effectively from the near-end speaker microphone signal which proves the success of the proposed DSVSSAPA. The displayed case is for the order of 16.

Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212

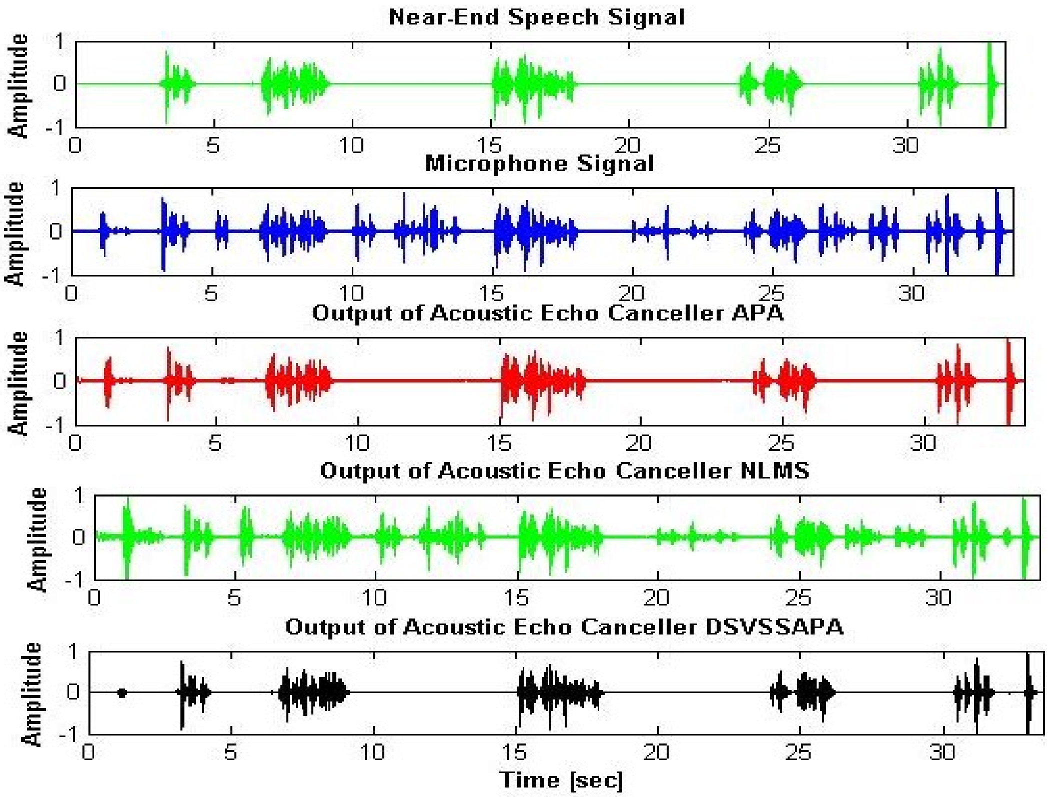

FIG. 7. PROCESSED SPEECH SIGNALS AFTER PROCESSING BY THE PROPOSED AND OTHER CONVENTIONAL ALGORITHMS.

IV. CONCLUSION

Both the variable step size APA and the dynamic selection APA methods are combined to present the proposed algorithm DSVSSAPA in order to improve the performance of the echo canceller by mitigating the convergence- speed problem and reducing the computational complexity problem. The performance of the proposed DSVSSAPA is evaluated and compared to conventional NLMS and APA algorithms. The DSVSSAPA has better echo reduction performance and converges earlier than other conventional algorithms. The DSVSSAPA has lower computational complexity than the APA by a percent of approximately 18%. When projection order increases, the DSVSSAPA performs with efficiency equivalent to APA, tacking the consideration of the reduction in computational complexity, this is considered as an advantage.

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Received 4 may 2017; Accepted 2 November 2017

ISSN 1811-9212