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

TRACKING BEHAVIOUR OF ACOUSTIC ECHO CANCELLER USING MULTIPLE SUB-FILTERS

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ABSTRACT

An adaptive filter with large number of coefficients is required for acoustic echo cancellation. But a long length adaptive filter has slow convergence and poor tracking performance. In this paper a multipath acoustic echo model has been used as the basis for an adaptive echo canceller. The convergence and tracking performance of this new structure has been studied and compared with the conventional structure and found to be better.

1. INTRODUCTION

Acoustic echo is generally modelled as the response of a linear system whose impulse response is of the order of a few tens to hundreds of milliseconds. Acoustic echo cancellers (AEC) are usually realized by adaptive Finite Impulse Response (FIR) filters having thousands of coefficients and use the Least Mean Square (LMS) algorithm for adaptation [2]. Due to the long length of the filter and the usage of the LMS algorithm, the convergence speed of these adaptive filters is considerably slow. Further, this leads to degradation in the tracking performance also.

Several methods have been reported in the literature to improve the convergence speed of such long length adaptive filters [1, 4, 5, 6, 7]. But these methods do not try to exploit the multipath nature of acoustic echo. In [8] acoustic echo is modelled as a sum of signals propagating via different paths with a delay and filter associated with each path. Based on this model a Multiple Sub-Filter (MSF) structure for AEC has been proposed in [8]. To realize this AEC we need to estimate the delay and filter order associated with each path. In [9] an Autocorrelation based Estimator (AE) has been proposed for the estimation of the delay when the received signal is a delayed, attenuated and filtered version of the transmitted signal. A number of methods exist for the estimation of filters order [3]. In [8], however, the tracking behaviour of AEC was not studied.

In this paper we study the convergence and tracking behaviour of AEC. The performance of the new structure (MSF) is compared with the conventional Single Long Adaptive Filter (SLF) structure and found to be better.

The paper is divided into 5 sections. In section 2 the multipath model of acoustic echo is briefly described. Section 3 discusses about the adaptation of Multiple sub-filters based AEC. In section 4 we study the tracking performance of the AEC. Conclusions of the paper are presented in section 5.

2. MULTIPATH MODEL OF THE ACOUSTIC ECHO CHANNEL

When a loudspeaker and a microphone are placed within an enclosure, each reflection can be viewed as an image of a real source emanating energy proportional to the reflection coefficient of the surface and inversely proportional to the distance travelled. The resulting model is shown on the top left corner within Fig.1 as signal generation model. The output signal $d(n)$ of the signal generation model (in mixed notation) can be expressed as:

$$d(n) = \sum_{i=0}^{M} H_i(z)x(n-D_i) + \xi(n) \quad \text{for } n = 0,1,...,N-1 \quad (1)$$

where $x(n)$ is the transmitted signal, $\xi(n)$ is the ambient noise, $H_i(z)$ denotes the low-pass filter of order L_i corresponding to the i^{th} path and

$$H_i(z) = g_i \times \left(1 + \sum_{n=1}^{L_i-1} h_i(n)z^{-n}\right)$$

where g_i and $h_i(n)$ are the attenuation coefficient and impulse response respectively of the i^{th} path. Further, by $H_i(z)x(n-D_i)$ we mean $h_i(n) * x(n-D_i)$ where $'*'$ denotes convolution. Without loss of generality, in the sequel we assume that $g_0 = 1$ and $D_0 = 0$ (Direct Path). Hence, although there are $M+1$ paths, we need to estimate only M delays. The structure of the multipath model of the acoustic echo channel motivates a new structure for acoustic echo canceller as discussed in the next section. The idea is that each branch of the MSF can cancel the signal in the corresponding path of the echo signal.

3. MULTIPLE SUB-FILTER BASED ADAPTIVE ECHO CANCELLER

From the multipath model we see that $d(n)$ can be synthesized by using multiple filters. We refer to the filters within each path as sub-filters. In Fig.1 apart from signal generation model the overall scheme for AEC has also been shown. The scheme includes the delay and order estimation blocks as shown on the right side and MSF based AEC on the left side (lower portion) of Fig.1. Let the delay estimates and filter orders be denoted by $\widehat{D}_i$ and $\widehat{L}_i$ of the i^{th} path respectively. In the figure AF_i denotes the i^{th} adaptive sub-filter. We study the convergence and tracking behaviour of AEC using MSF.

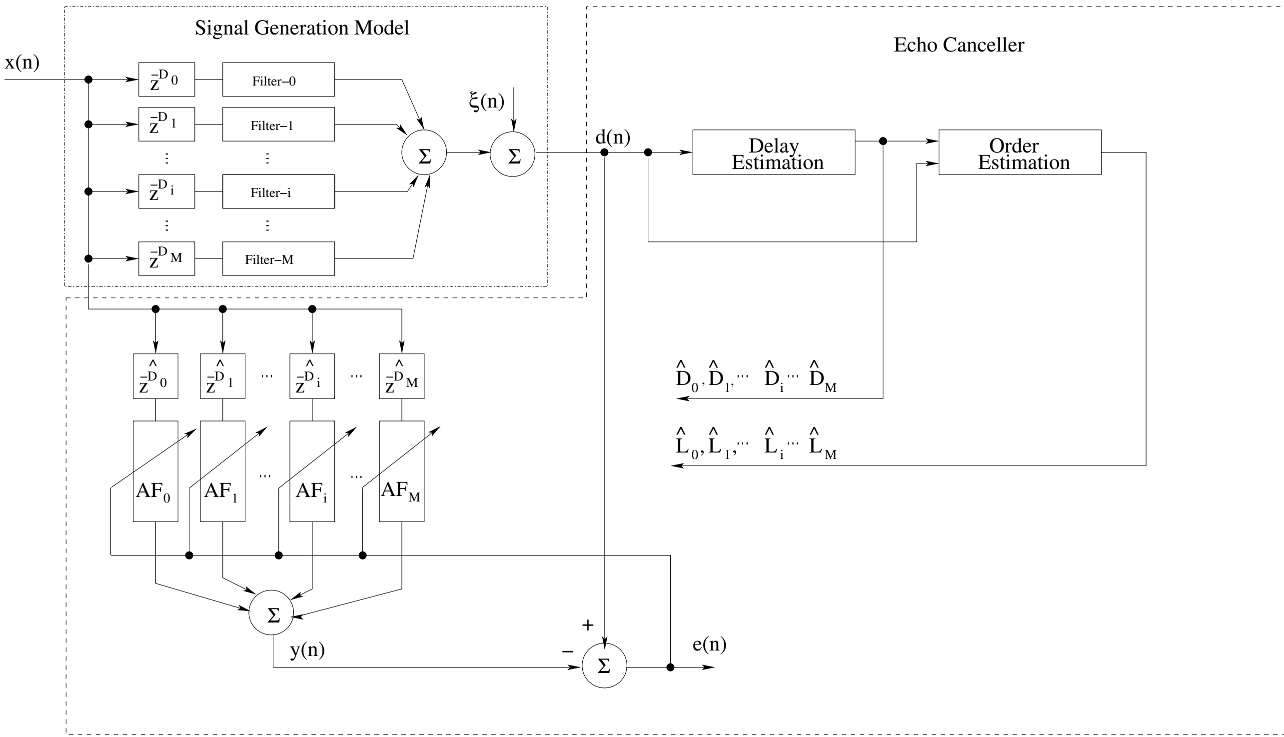

Figure 1: Multiple Sub-filter Based Scheme for Adaptive Echo Canceller

3.1 Adaptive Algorithm for Multiple Sub-filter

The error signal is obtained by subtracting the sum of all sub-filters output from the microphone signal $d(n)$ shown in Fig.1 and expressed as:

$$e(n) = d(n) - \sum_{i=0}^{M} W_i^T(n)\widehat{X}_i(n); \tag{2}$$

where $W_i(n) = [w_{i,1}(n), w_{i,2}(n), \ldots, w_{i,\widehat{L}_i}(n)]^T$, $\widehat{X}_i(n) = [x(n-(\widehat{D}_i)), x(n-(\widehat{D}_i+1)), \ldots x(n-(\widehat{D}_i+\widehat{L}_i-1))]^T$. The parameters $\widehat{L}_i$ and $\widehat{D}_i$ are the estimated order of the sub-filter and time delay associated with i^{th} path respectively. The LMS adaptation of each sub-filter $W_i(n)$ is given as

$$W_i(n+1) = W_i(n) + \mu_i \widehat{X}_i(n)e(n); \quad i = 0,1,2,\ldots,M \tag{3}$$

The output of the MSF shown in Fig.1 is given as:

$$y(n) = \sum_{i=0}^{M} W_i^T(n)\widehat{X}_i(n); \quad n = 0,1,2,\ldots,N-1 \tag{4}$$

Each sub-filter is updated by an individual adaptive algorithm as shown in Fig.1 and adaptation step size is chosen separately for each sub-filter. The procedure for adaptation of MSF is presented in Table-1.

Table-1

Adaptation Algorithm for Multiple sub-filter

1. Parameters: $\widehat{D}_i$, $\widehat{L}_i$ Estimates of i^{th} path delay and filter order
$$\forall\ i = 0,1,2,\ \ldots, M.$$
$$\mu_i = \text{Step size for } i^{th} \text{ sub-filter}$$
2. Data: $\widehat{X}_i(n) = \widehat{L}_i$-by-1 input vector at time n for i^{th} path.
$$d(n) = \text{Acoustic echo channel output at time } n.$$
3. Initialize: $W_i(0) = 0 \quad \forall\ i = 0,1,2,\ \ldots, M.$
4. Compute: For each instant of time n=1,2, ...
$$e(n) = d(n) - \sum_{i=0}^{M} W_i^T(n)\widehat{X}_i(n);$$
$$W_i(n+1) = W_i(n) + \mu_i \widehat{X}_i(n)e(n); \quad i = 0,1,2,\ldots,M$$

3.2 Simulation Results

With reference to Fig.1 each path (or branch) of the signal generation model is assumed to have the same low pass filter of order 12. The delays and attenuation coefficients in each of the three paths are assumed to be $D_0 = 0$, $D_1 = 115$, $D_2 = 200$ and $g_0 = 1$, $g_1 = 0.9$, $g_2 = 0.7$ respectively. The input to the multipath model is assumed to be white Gaussian with zero mean and unit variance. The observation length N is 2500. The longest delay is assumed to be at $D_2 = 200$ samples, therefore the conventional i.e. single long adaptive filter or SLF will have $(200+12) = 212$ coefficients. The adaptation step size has been chosen to be 0.3 for each branch of the MSF. For SLF the adaptation step size has been taken 1.0. These values of step size were found to be the largest possible values which did not lead to instability. The results have been obtained by averaging over 100 independent runs.

Simulation results for three different structures have been obtained. We denote SLF (LMS) as the single long filter adapted by the LMS algorithm. Further, we use the notations MSF (Estimated) to denote the case when the multiple sub-filter is adapted using the estimates of delays and sub-filter orders given in [9]. We have also simulated the case when multiple sub-filters is adapted using known delays and sub-filters order denoted as MSF (Ideal). The results for each structure at SNRs 40 dB are presented in Fig.2. It can be observed

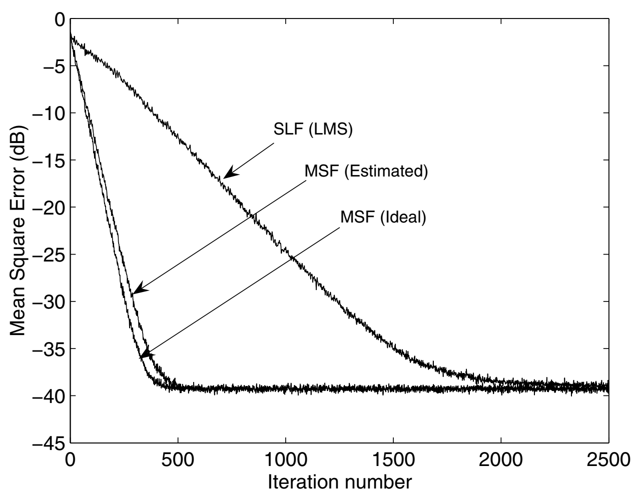

Figure 2: Convergence of the MSE for Different Filter Structures at SNR= 40 dB

from the results that for all the cases considered MSF has faster convergence as compared to SLF (LMS).

4. TRACKING PERFORMANCE

In this section the tracking performance of MSF (Estimated) and SLF (LMS) are studied for the case when the impulse response of the acoustic channel is time varying. Thus the delays and attenuation coefficients of the paths are allowed to change at random time instants and the resulting mean square error (MSE) is investigated for MSF (Estimated) and SLF (LMS). The system model for $M = 2$ is shown in Fig.3 wherein we show that the delays and attenuation coefficients are subject to change. The interval between two consecutive instants of change in delay is denoted by t_d and is assumed to have a Gaussian distribution. The change in delay between two consecutive instants at which parameters change is denoted by D. We assume that D is

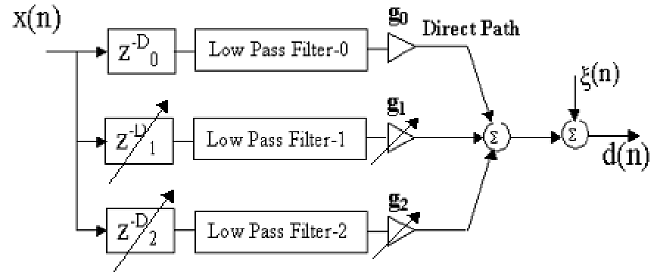

Figure 3: Time Varying Multipath Acoustic Channel Model for $M = 2$

a random variable that is uniformly distributed in the interval $[-U_D, \; U_D]$.

4.1 Simulation Results

Simulation of tracking behaviour has been carried out with the initial parameter values: $D_0 = 0$, $g_0 = 1.0$, $D_1 = 115$, $g_1 = 0.9$, $D_2 = 165$, $g_2 = 0.85$ respectively. Each path in the multipath acoustic channel has been modelled as a low pass filter of order $L_i = 12$, $i = 0,1,2$. The input to the channel is assumed to be white Gaussian with zero mean and unit variance. The mean and variance of t_d has been chosen as 500 and 10^4 respectively. To simplify the simulation it has been assumed that the changes in the parameter values D_2 take place only in the third path. It is assumed that the maximum value that D_2 can take is 200. Therefore, the order of the SLF has been taken to be $L = 212$. The results have been obtained by averaging over 100 independent runs.

We consider two different situations, one in which the delay changes are small and the other in which delay changes are allowed to be large. Small change case corresponds to the situation when there is slow movement of objects within the enclosure. To simulate the small change case we have taken D to be uniformly distributed in the interval $[-6,6]$ while to simulate the large change case D is assumed to be uniformly distributed in the interval $[-24,24]$. Large change case corresponds to situations when there is a movement of speaker, receiver or any other sudden change in the enclosure. While it is quite straightforward to simulate the SLF (LMS) in this case, in the case of MSF (Estimated) it is not so. Thus for MSF (Estimated) we need to decide as to when and how often the delays D_i need to be estimated if the channel is time varying, as in the situation under consideration in this section.

In order to track the changes in delay D_2, we obtained an estimate of D_2 after every 1000 samples. While we used only 800 samples of the received signal to obtain an estimate of D_2, we have assumed that the computation time required to obtain a new estimate of the delay is equal to 200 samples. Hence, a new estimate of D_2 is available after every $800+200 = 1000$ samples. If we decide to obtain the new delay estimates at a faster rate say after every 600 samples, it will lead to inferior estimates since the observation length will be reduced, but we will be able to respond more quickly to any changes that may take place in the channel. On the other hand, if we decide to obtain the new delay estimates at a slower rate, say after every 1200 samples, the estimates will be better, but we will be able to track the changes in the channel at a slower rate. To estimate the initial parameter values of the MSF, 2500 samples of the received signal $d(n)$ were used.

Small Change: In this case we have taken $U_D = 6$. Since the changes are small, we have assumed that these changes do not cause any change in the attenuation coefficients. The actual delays and their estimates are presented in Fig.4. Fig.5 show the MSE for the MSF (Estimated) and SLF (LMS) when SNR=40 dB.

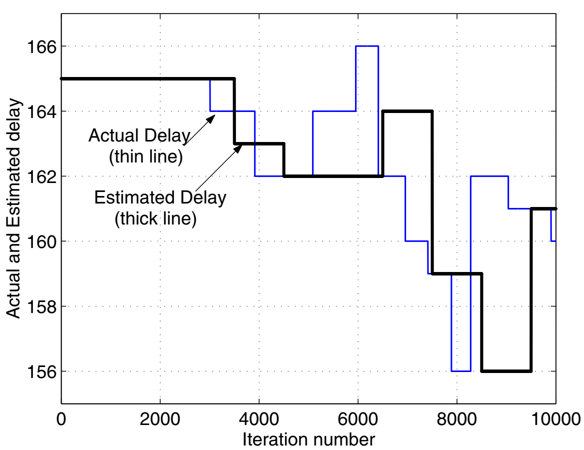

Figure 4: Actual and Estimated D_2, $U_D = 6$

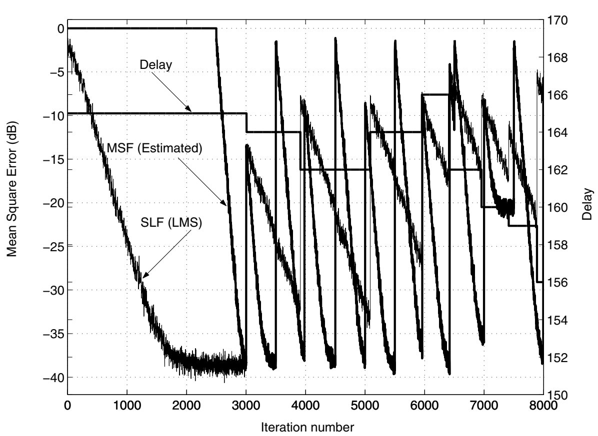

Figure 5: MSE of MSF and SLF, and D_2, $U_D = 6$

From the results it can be seen that while SLF (LMS) achieves a MSE of -32 dB, MSF (Estimated) achieves up to -40 dB. The reason is that each branch in the MSF structure is of smaller length and requires less time for adaptation. On the other hand, the single long adaptive filter has large number of coefficients resulting in slower convergence. Furthermore when there are fast changes in delay for eg. during the interval 7000-8000, the performance of both the filters is poor although MSF (Estimated) is the better of the two. The reason is that the rate at which delay changes is high compared to the mean convergence time of MSF as well as that of the single long adaptive filter.

Large Change: In this case we have taken $U_D = 24$. The actual delays and their estimates for $U_D = 24$ are presented Fig.6. The attenuation coefficient has been changed in proportion to the change in delay. MSE of MSF (Estimated) and SLF (LMS) at SNR= 40 dB are shown in Fig.7.

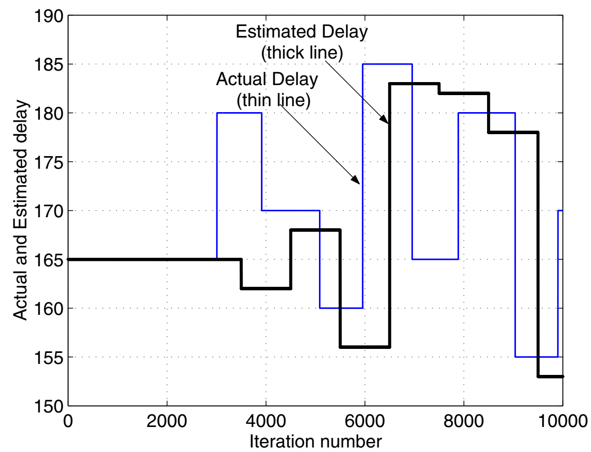

Figure 6: Actual and Estimated D_2, $U_D = 24$

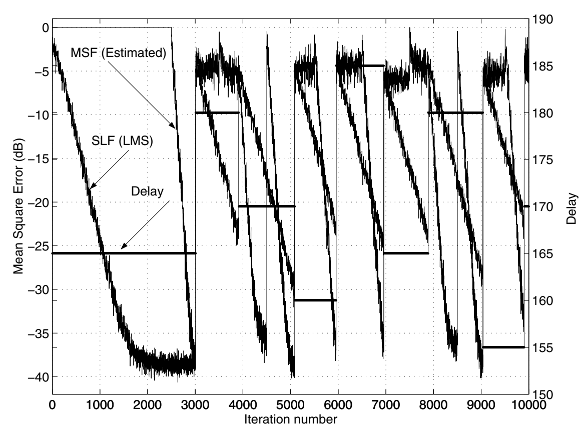

Figure 7: MSE of MSF and SLF, and D_2, $U_D = 24$

Thus the MSE of MSF (Estimated) and SLF (LMS) are shown in the same figure. Like in the small change case, here too it can be observed that the performance of MSF is better than that of the SLF because of the faster convergence of MSF. However, not surprisingly, it is poorer as compared to the performance of MSF in the small change case.

To study the effect of small change in delay on the performance of the MSF when its parameters are not updated, we did the following simulation. The order and initial delays were chosen to be same as that of the channel. The delay D_2 of the channel was perturbed by δD inducing error in the delay parameter of the MSF. The delay change δD is made about the nominal value $D_2 = 165$. The tracking performance was studied without updating the parameters. The results are shown in Fig.8 for different value of changes $\delta D = 3,4,5,6,7,8$. MSEs for both MSF (without updating the delay estimate) and SLF (LMS) for small delay changes $\delta D < 5$ at SNR= 40 dB is shown in Fig.9.

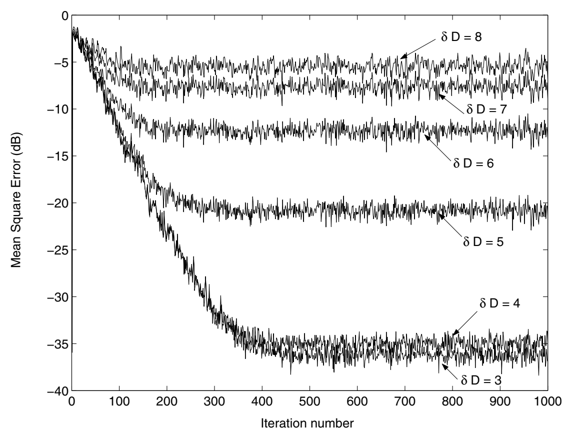

Figure 8: MSF Performance for Small δD without Delay Estimation

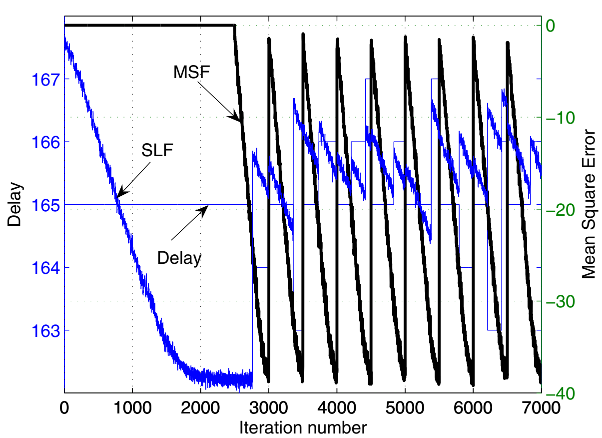

Figure 9: MSE of MSF and SLF, and D_2 for Small δD Changes without Delay Estimation

From these figures it can be observed that the MSF is able to track the changes when $\delta D < 5$, even without the correct delay estimates. This observation is in tune with the earlier observation that the performance of MSF for large change is poorer as compared to the small change case. Hence it can be concluded that in both the cases (small or large changes) MSF performs better than the SLF. This is true despite the fact that additional time is needed by MSF (Estimated) for computing new delay estimates which is not needed in SLF (LMS).

5. CONCLUSIONS

In this paper the convergence and tracking behaviour of multiple sub-filter has been studied and compared with the single long adaptive filter . It has been found that multiple sub-filter has faster convergence and good tracking capability as compared to that of single long adaptive filter. We also observed that multiple sub-filter has better tracking when the magnitude of delay change is small as compared to large delay change. Further, when there are frequent changes in delay multiple sub-filter is able to track those changes, but single long adaptive filter performs poorly. Interestingly, in a tracking environment, although there is an additional computation involved in estimating the delay changes in multiple sub-filter, still it is able to perform better.

REFERENCES

[1] J. Benesty, Y. Huang, Adaptive Signal Processing-Application to Real-World Problems, Springer-Verlag, 2003.

[2] C. Breining, P. Dreiseitel, E. Hänsler, A. Mader, B. Nitsch, H. Puder, T. Schertler, G. Schmidt, J. Tilp and J.S. Lee, "Acoustic Echo Control-An Application of Very-High-Order Adaptive Filters," IEEE Signal Processing Magazine, vol.16, no.4, pp.42-69, Jul. 1999.

[3] M. Niedzwiecki, Identification of Time -Varying Processes, John Wiley and Sons, Ltd. 2000.

[4] J.J. Shynk, "Frequency Domain and Multirate Adaptive Filtering," IEEE Signal Processing Magazine, vol.9, no.1, pp.14-37, Jan. 1992.

[5] J. Benesty and T. Gänsler, "A Multidelay Double-Talk Detector Combined with the MDF Adaptive Filter," EURASIP JASP, vol.2003, no.11, pp.1050-1063, Oct. 2003.

[6] K. Mayyas, "New Transform-domain Adaptive Algorithms for Acoustic Echo Cancellation," Elsevier Digital Signal Processing, vol.13, no.3, pp.415-432, Jul. 2003.

[7] K. Mayyas and T. Aboulnasr, "Reduced-Complexity Transform-Domain Adaptive Algorithm with Selective Coefficient Update," IEEE Trans. Circuits and Systems-II: Express Briefs, vol.51, no.3, pp.136-142, Mar. 2004.

[8] R.N. Sharma, A.K. Chaturvedi, and G. Sharma, "Acoustic Echo Cancellation using Multiple sub-filter," Proc. IEEE TENCON 2003, vol.1, pp.393-396, Oct. 2003.

[9] R.N. Sharma, A.K. Chaturvedi, and G. Sharma,, "Multipath Delay Estimation for Acoustic Echo Channel," Proc. IEEE TENCON 2004, vol.1, pp.21-24, Nov. 2004.