An Affine Combination of TVLMS Adaptive Filters for Echo Cancellation

[1,]B. Srinivas, M.Tech, [2,]Dr. K. Manjunathachari,
[1,]Miste (Life Member)
[2,]M.Tech, Ph.D
[1,]Assistant Professor, ECE Department, Sagar Institute of Technology
[2,] Professor & HOD, ECE Department, GITAM University, Hyderabad

Abstract

This paper deals with the statistical behaviour of an affine combination of the outputs of two TVLMS adaptive filters that simultaneously adapting the same white Gaussian inputs and it's cancelling the echoes by system identification. The purpose of the combination is to obtain TVLMS adaptive filters with faster convergence and small steady-state mean-square deviation (MSD). The linear combination is used in this paper, is a generalization of the convex combination, in which the combination factor $\lambda(n)$ is restricted to interval (0, 1). The viewpoint is taken that each of the two Filters produces dependent estimates of the unknown channel. Thus, there exists a sequence of optimal affine combining coefficients which minimizes the MSE and it find's the unknown system response. These results will be verified on the MAT LAB 7.8.0 version software by using signal processing tool box. The applications of this paper are System Identification with low MSE and Echo Cancellation. Now a day in real time applications can be implemented using an affine combination of TVLMS adaptive filters because, it is easy way to design, implementation, robustness, with low MSE, and high level noise cancellation and it requires less number of computational operations.

Keywords—Adaptive filters, affine combination, analysis, time varying least mean square (TVLMS), stochastic algorithms.

1. INTRODUCTION

The design of many adaptive filters requires a trade-off between convergence speed and steady-state mean-square error (MSE). A faster (slower) convergence speed yields a larger (smaller) steady-state mean-square deviation (MSD) and MSE. This property is usually independent of the type of adaptive algorithm, i.e., least mean-square (LMS), normalized least mean-square (NLMS), recursive least squares (RLS), or affine projection (AP). This design trade-off is usually controlled by some design parameter of the weight update, such as the step size in LMS or AP, the step size or the regularization parameter in NLMS or the forgetting factor in RLS. Variable step-size modifications of the basic adaptive algorithms offer a possible solution to this design problem. Fig. 1 shows where $W_1(n)$ adaptive filter uses a larger step size than adaptive filter $W_2(n)$.

The key to this scheme is the selection of the scalar mixing parameter $\lambda(n)$ combining the two filter outputs. The mixing parameters adaptively optimized using a stochastic

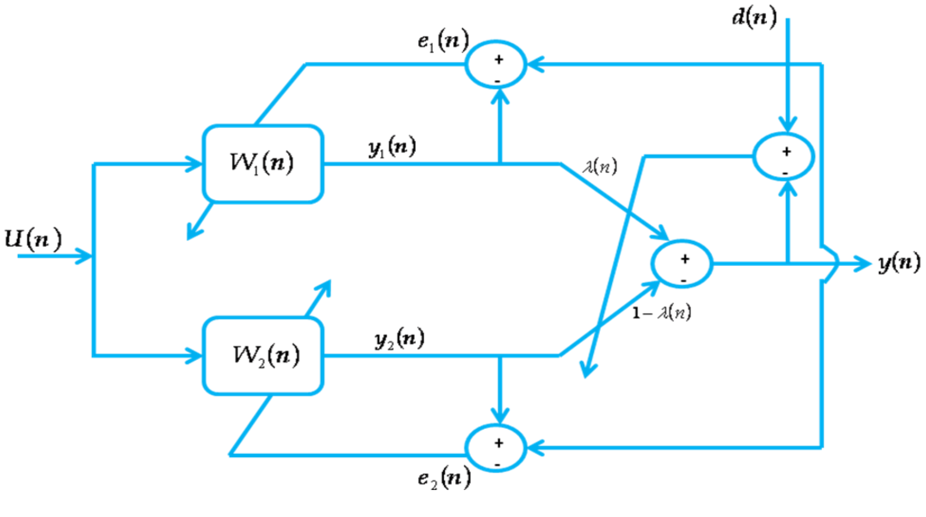

Fig.1 Adaptive combining of two transversal adaptive fitters

gradient search which minimizes the quadratic error of the overall filter. The convex combination performed as well as the best of its components in the MSE sense. These results indicate that a combination of adaptive filters can lead to fast convergence rates and good steady-state performance, an attribute that is usually obtained only in variable step-size algorithms. Thus, there is great interest in learning more about the properties of such adaptive structures. This paper provides new results for the performance of the combined structure. The achievable performance is studied for an affine combination of two TVLMS adaptive filters using the structure shown in Fig. 1 with stationary signals. Here, the combination parameter $\lambda(n)$ is not restricted to the range (0, 1). Thus, Fig. 1 is interpreted from the viewpoint of a linear combiner. Each adaptive filter is estimating the unknown channel impulse response using the same input data. Thus, $W_1(n)$ and $W_2(n)$ are statistically dependent estimates of the unknown channel. There exists a single combining parameter sequence $\lambda(n)$ which minimizes the MSD. The parameter $\lambda(n)$ does not necessarily lie within (0, 1) for all. Thus, the output in Fig. 1 is an affine combination of the individual outputs $y_1(n)$ and $y_2(n)$ the convex combination is a particular case [1] - [2].

2. THE OPTIMAL AFFINE COMBINER

A. THE AFFINE COMBINER

The system under investigation is show in Fig. 1. Each filter uses the LMS adaption rule but with different step size $\mu_i, i = 1,2$;

$$W_i(n+1) = W_i(n) + \mu_i e_i(n) U_i(n), i = 1,2 \qquad (2.1)$$

$$\text{Where} \quad e_i(n) = d(n) - W_i^T(n) U(n), i = 1,2 \qquad (2.2)$$

$$d(n) = e_o(n) + W_o^T(n) U(n), i = 1,2 \qquad (2.3)$$

Where $W_i(n), i = 1,2$ are the N-dimensional adaptive coefficient vectors, $e_o(n)$ is assumed zero-mean, and statistically independent of any other signal in the system, and the input process u (n) is assumed wide-sense stationary, $U(n) = [u(n),....,u(n - N + 1)]^T$ is the input vector. It will be assumed, without loss, that $\mu_1 \supseteq \mu_2$, so that $W_1(n)$ will, in general, converge faster than $W_2(n)$. Also $W_2(n)$ will converge to the lowest individual steady-state weight maladjustments. The weight vectors $W_1(n)$ and $W_2(n)$ are coupled both deterministically and statistically through $U(n)$ and $e_o(n)$ [2] – [4].

The outputs of the two filters are combined as in Fig. 1:

$$y(n) = \lambda(n) y_1(n) + [1 - \lambda(n)] y_2(n) \qquad (2.4)$$

Where $y_i(n) = W_i^T(n) U(n), i = 1,2$ can be any real number and the overall system error is given by

$$e(n) = d(n) - y(n) \qquad (2.5)$$

The adaptive filter output combination is an affine combination, as y (n) can assume any value on the real line. This setup generalizes the combination of adaptive filter outputs, and can be used to study the properties of the optimal combination.

B. The Optimal mixing parameter

Equation (2.4) can be written as

$$y(n) = \lambda(n) W_1^T(n) U(n) + [1 - \lambda(n)] W_2^T(n) U(n) = \{\lambda(n)[W_1(n) - W_2(n)] + W_2(n)\}^T U(n)$$

$$= \{\lambda(n) W_{12}(n) + W_2(n)\}^T U(n) \qquad (2.6)$$

$$\text{Where } W_{12}(n) = W_1(n) - W_2(n)$$

Equation (2.6) shows that y (n) can be interpreted as a combination of $W_2(n)$ and weighted version of the difference filter $W_{12}(n)$. It also shows that the combined adaptive filter has an equivalent weight vector given by

$$W_{eq}(n) = \lambda(n) W_{12}(n) + W_2(n) \qquad (2.7)$$

Subtracting Equation (2.1) for i=2 from Equation (2.1) for i=1 yields a recursion for $W_{12}(n)$:

$$W_{12}(n+1) = [I - \mu_1 U(n) U^T(n)] W_{12}(n) + (\mu_1 - \mu_2) e_2(n) U(n) \qquad (2.8)$$

Next, let us consider a rule for choosing $\lambda(n)$ that minimizes the conditional MSE at time n $E[e^2(n) \mid W_1(n), W_{12}(n)]$.

Writing e(n) in equation (2.5) as

$$e(n) = e_o(n) + [W_{o2}(n) - \lambda(n) W_{12}(n)]^T U(n) \qquad (2.9)$$

Where $W_{o2}(n) = W_0(n) - W_2(n)$ yields

$$\frac{\partial E\left[e^2(n) \mid W_1(n), W_{12}(n)\right]}{\partial \lambda(n)} = -2E\left[e(n)W_{12}^T(n)U(n) \mid W_2(n), W_{12}(n)\right]$$
$$= 0 \qquad (2.10)$$

Using equation (2.9), taking the expectation over U (n) and defining the input conditional autocorrelation matrix

$$R_u = E\left[U(n)U^T(n) \mid W_{12}(n), W_{12}(n)\right] \qquad (2.11)$$

Solving Equation (2.11) for $\lambda(n) = \lambda_o(n)$

$$\lambda_o(n) = \frac{W_{o2}^T(n)R_u W_{12}(n)}{W_{12}^T(n)R_u W_{12}(n)} \qquad (2.12)$$

3. SYSTEM IDENTIFICATION

In the class of applications dealing with identification, an adaptive filter is used to provide a linear model that represents the best fit to an unknown plant. Here, same input is given to both the adaptive filter and the plant. The output of the plant will serve as the desired signal for the adaptation process. In this application the unknown system is modelled by an FIR filter with adjustable coefficients. Both the unknown time –variant system and FIR filter model are excited by an input sequence u(n). The adaptive FIR filter output y(n) is Compared with the unknown system output d(n) to produce an estimation error e(n). The estimation error represents the difference between the unknown system output and the model (estimated) output. The estimation error e(n) is then used as the input to an adaptive control algorithm which corrects the individual tap weights of the filter. This process is repeated through several iterations until the estimation error e(n) becomes sufficiently small in some statistical sense. The resultant FIR filter response now represents that of the previously unknown system. It can show in Fig. 2 and Fig 3.

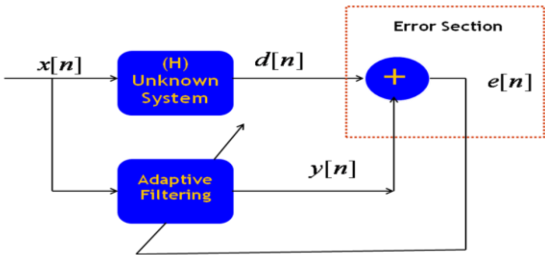

Fig.2 Block diagram of the System Identification

In Fig 3, instead of Adaptive algorithm, we can take the affine combination of two TVLMS algorithm, because it provides new better results for the performance of the combined structure for system identification [5].
The following toolboxes are used during programming of above algorithms

1. Signal processing Toolbox.
2. Filter design toolbox.
3. General purpose commands.

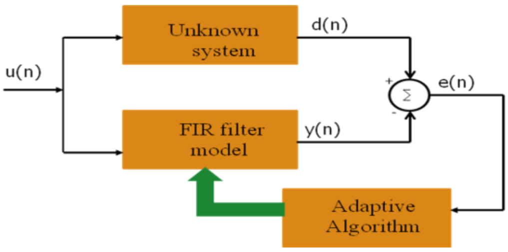

Fig.3 Block diagram of the System Identification model

4. Applications

A. Advantages and Disadvantages of TVLMS algorithm

(i). The TVLMS algorithm changes (adapts) the filter tap weights so that e (n) is minimized in the mean-square sense. When the processes are x (n) and d (n) are jointly stationary or Non- stationary, this algorithm converges to a set of tap-weights which, on average, are equal to the wiener-Hopf solution [3] – [4].
(ii). Simplicity in implementation,
(iii) .inherently stable and robustness performance against different signal conditions, and
(iv). slow convergence (due to eigenvalue spread).

B. Applications

Because of their ability to perform well in unknown environments and track statistical time-variations, adaptive filters have been employed in a wide range of fields. However, there are essentially four basic classes of applications for adaptive filters. These are: Identification, inverse modeling, prediction, and interference cancellation, with the main difference between them being the manner in which the desired response is extracted.The adjustable parameters that are dependent upon the applications at hand are the number of filter taps, choice of FIR or IIR, choice of training algorithm, and the learning rate. Beyond these, the underlying architecture required for realization is independent of the application. Therefore, this thesis will focus on one particular application, namely noise cancellation, as it is the most likely to require an embedded VLSI implementation. This is because it is sometimes necessary to use adaptive noise cancellation in communication systems such as handheld radios and satellite systems that are contained on a 16 single silicon chip, where real-time processing is required. Doing this efficiently is important, because adaptive equalizers are a major component of receivers in modern communications systems and can account for up to 90% of the total gate count [2].

1. System Identification
2. Inverse modelling
3. Prediction
4. Interference Cancellation: Adaptive Noise cancellation, Echo cancellation

5. Result Analysis

Fig.4.shows the adaptive noise cancellation by using affine combination of TVLMS adaptive filters.

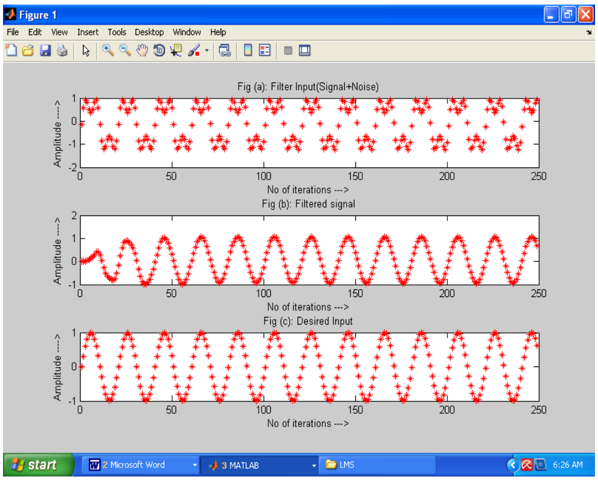

Fig.4: The adaptive noise cancellation

For simulations a sinusoidal signal of frequency 1500HZ is used as desired input. The input to the filter is a noisy signal consisting of multiple sine frequencies and Gaussian random noise. The simulation results are also obtained for the adaptive filter with standard LMS, TV-LMS, RLS, Affine combination of LMS and TVLMS algorithms using the same configuration. The results are generated for different number of iterations ranging from 50 to 1000. Finally, the performance of the TV LMS algorithms is compared with standard LMS, Affine LMS and RLS algorithms are good and easiest one in the implementation part.

No. of iterations	Affine combination of two TVLMS Adaptive filters MSE
50	0.0262
100	0.0147
500	0.0066
850	0.0057
900	0.0057
950	0.0056
1000	0.0055

Table 5.1: Iterations Vs MSE of TVLMS algorithm for de-noising noisy-sine wave

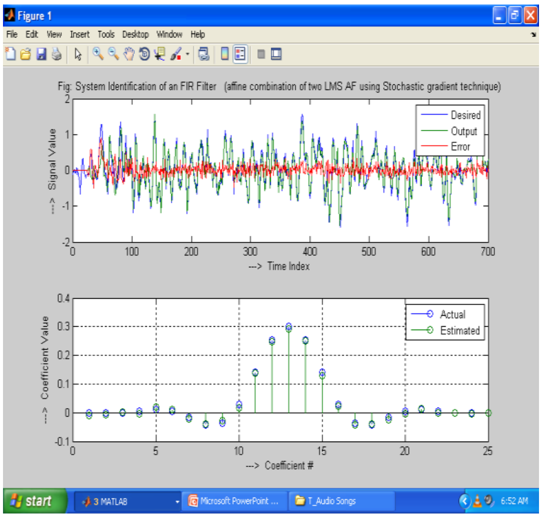

Fig.5: System identification of an FIR filter with 700 iterations (An affine combination of LMS adaptive filters using stochastic gradient technique)

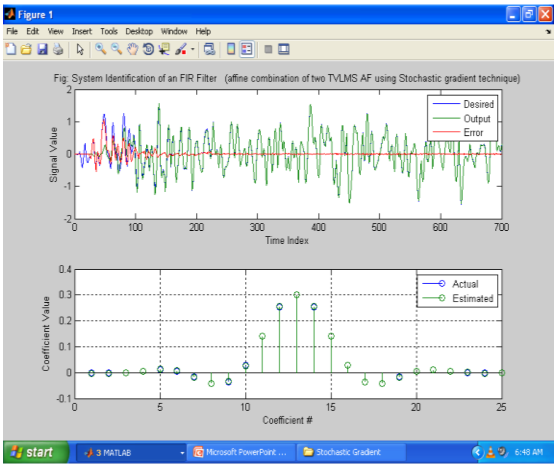

Fig.6: System identification of an FIR filter with 700 iterations (An affine combination of TVLMS adaptive filters using stochastic gradient technique)

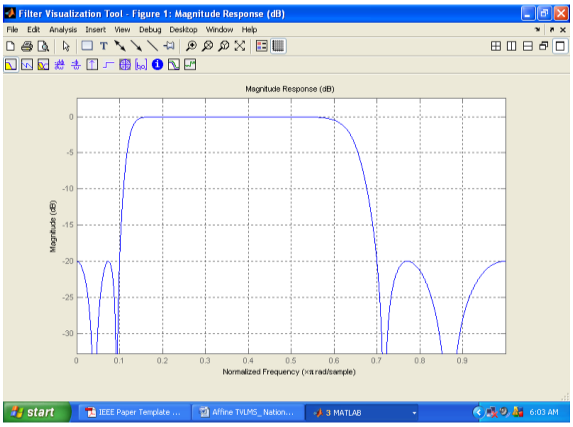

Fig.7: The magnitude response of FIR model

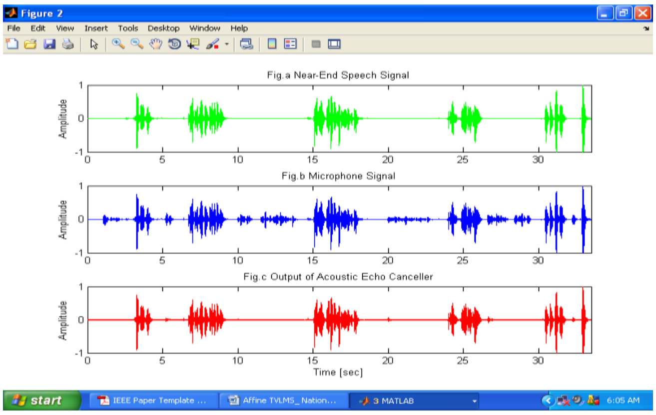

Fig.7: The adaptive Echoes cancellation

6. Conclusions

This paper has studied the statistical behaviour of an affine combination of the outputs of two time varying LMS adaptive filters that simultaneously adapt using the same Gaussian inputs. The purpose of the affine combination is to obtain a TVLMS adaptive filter with faster convergence and small steady state Mean Square Deviation. First, the optimal unrealizable affine combiner was studied and provided the best possible performance. Then, two new schemes were proposed for practical applications. The first scheme performed nearly as well as the optimal unrealizable combiner, providing the same convergence time and steady-state behaviour. A second new scheme was investigated that depended upon the time-averaged instantaneous squared error of each adaptive filter. The viewpoint is taken that each of the two Filters produces dependent estimates of the unknown channel. Thus, there exists a sequence of optimal affine combining coefficients which minimizes the mean-square error (MSE) and it find's the unknown system response.Now a day in real time applications, video conferences can be implemented using an affine combination of LMS adaptive filters because, it is easy way to design, implementation, robustness, with low MSE, and high level noise cancellation and it requires less number of computational operations.

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AUTHORS

Mr B.Srinivas, an M.Tech from JNT University, Hyderabad, has an experience of more than 6.5 years of Teaching. At present Mr. B. Srinivas serving the Sagar Institute of Technology (Sagar Group of Institutions), Chevella, Ranga Reddy, and A.P, as an Assistant Professor of the department of Electronics and Communication Engineering. He is the Life member of ISTE.

Dr. K. Manjunathachari, an M.Tech from JNT University, Hyderabad, and Ph.D from JNT University, Hyderabad, A.P, has an experience of more than 16 years of Teaching and 3 years of Industry. At present Dr. K. Manjunathachari serving the GITAM University, Hyderabad and A.P, as a Professor and Head of the department of Electronics and Communication Engineering.