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Comparative Study of Wiener-Hopf Solution and LMS Algorithm for Adaptive Noise Cancellation of Noisy Speech

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ABSTRACT

The performance of Wiener-Hopf and Least Mean Square (Online and Batch) methods are considered for recovering the desired signal buried under noise using adaptive noise cancellation techniques. A reference signal and a desired signal are available. To combat the noisy environment an adaptive noise cancellation filter is developed. This filter tries to converge in least mean square sense to the optimal Wiener-Hopf solution to filter the noise from the signal. In the analysis part the weight and learning tracks are shown. Effects of leakage and effects of interchanging the primary and reference inputs to the adaptive filter are also discussed. In the end a comparison is drawn on intelligibility of the recovered signal from both the methods.

1. INTRODUCTION

Adaptive noise cancellation (ANC) is a variation of optimal filtering that is highly useful in applications like recovering speech buried under noise [1-3]. In practical applications the filtering of the reference signal is achieved using a finite impulse response (FIR) filter. The filter coefficients also known as the tap weights of the tap delay line are adjusted using a gradient descent search algorithm such as the Least Mean Square (LMS)[4] algorithm that minimizes the mean squared error cost function. This technique of adaptive noise cancellation works very good in certain conditions and not so well in others and it is also less accurate than the Wiener Hopf optimal filtering scheme. Factors that decide the effectiveness of the ANC are as follows- 1) Its performance degrades as the non-stationarity of the signal increases. 2) The search algorithm converges very slowly at times. 3) The error may diverge depending on the step size of the iterations. 4) High order filters are often required giving rise to higher computational burden.

The objective of this paper was to compare the performance of the Wiener-Hopf solution with two solutions found using the LMS (On-line and Batch methods). Two microphones were used to record the speech of a guest speaker. The input to the reference speaker was corrupted by an ambient noise making the speech inaudible. Our goal was to recover the speech using ANC techniques. Other assumptions made are as follows- 1) Noise in the primary and reference signals are correlated to each other. 2) Neither is correlated with the desired signal. 3) There is no leakage of the desired signal into the reference signal.

In addition to this, effects of leakage of the desired signal into the reference were studied, a case was considered when the desired signal and the reference signal are interchanged, and lastly a comparative analysis of the intelligibility of recovered speech using each of three methods was done.

2. ADAPTIVE NOISE CANCELLER

Figure 1 shows the schematic diagram of the ANC. Signal $d(n)$ is the speech signal corrupted by noise and is made up of two components, $s(n)$, the information bearing signal and $u1(n)$ the noise component. The reference signal $u(n)$ is the pure noise signal which is correlated to $u1(n)$ but is uncorrelated to $s(n)$. $u(t)$ is passed through the adaptive filter, the filter operates on this to generate an estimate of the interference, which is then subtracted from the primary to yield an estimate of the signal $\hat{s}(t)$. Since the characteristics of the filter, $h(t)$, is usually unknown, an adaptive filtering approach proved to be superior to any fixed-tap filter method. The filter parameters can be adjusted using LMS algorithm by minimizing a cost function, $E\{[d(n)-y(n)]^2\}$, with the output being the estimate of the signal $\hat{s}(t)$.

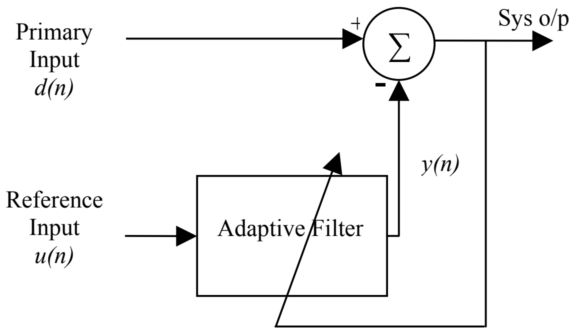

Fig. 1: Adaptive noise canceller.

3. WIENER HOPF SOLUTION

Linear optimum discrete-time filters are collectively known as Wiener filter [4]. The filter input consists of a time series $u(0), u(1), u(2) \ldots$, and the filter is characterized by the impulse response $w^0, w^1 \ldots w^z, w^q$. The length of this depends on the number of tap weights chosen for implementation of the filter. The output is used to provide an estimate of a desired response, $d(n)$, the estimation is accompanied by an error with statistical characteristics of its own. The goal is to reduce this error in some statistical sense. In our case a tap delay line of 30 weights was used and the desired signal, $d(n)$, was corrupted by noise and the reference signal was a correlated version of this noise. Figure 2 shows the Wiener Hopf solution schematic diagram.

The equations of the Wiener-Hopf in the matrix form (shown in bold) are given below.

The M×M correlation matrix is

$$\mathbf{R} = E[\mathbf{u}(n)\, \mathbf{u}^H(n)]. \quad (1)$$

The input is

$$\mathbf{u}(n)=[\, u(n), u(n-1), \ldots, u(n-M+1)]^{T+}. \quad (2)$$

The M×1 cross-correlation matrix between desired and the reference signal is denoted by P as

$$\mathbf{P} = E[\, \mathbf{u}(n)\, \mathbf{d}^*(n)]. \quad (3)$$

Combining Eqs.1, 2 and 3 we can write the Wiener- Hopf equations as

$$\mathbf{R}\mathbf{w_0} = \mathbf{P}. \quad (4)$$

Hence the optimal weight vector is given by

$$\mathbf{w_0} = \mathbf{R}^{-1}\mathbf{P}. \quad (5)$$

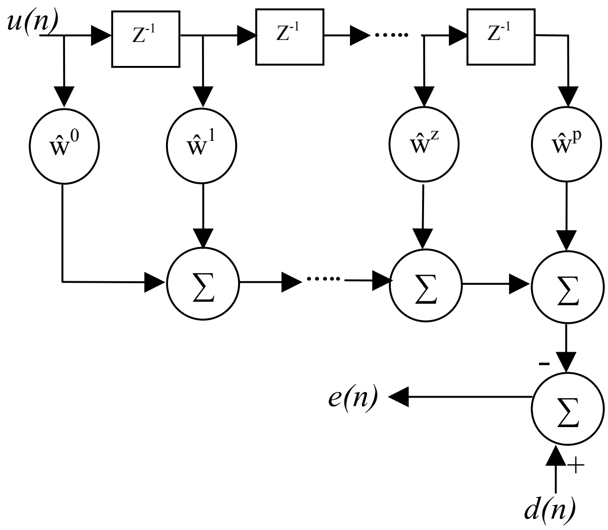

Fig. 2: Schematic diagram of a tap delay line.

This method gives us the best results if the desired signal is stationary throughout the speech. In this case from the LMS method (Fig. 5) we can see that the signal changes in its stationarity at the midpoint so if we split the signal at this point then the Wiener-Hopf gives a perfect recovery of the signal as in Fig. 3.

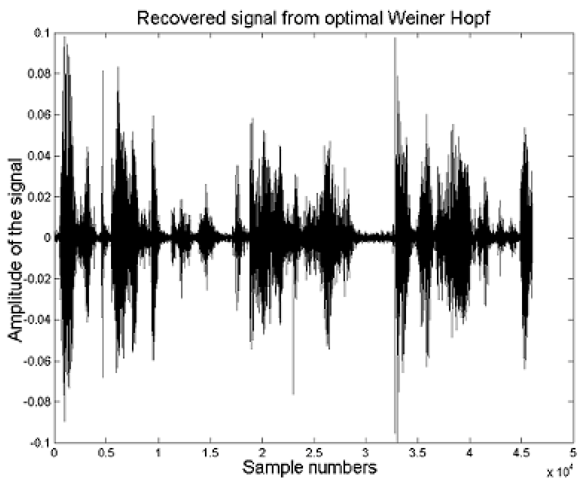

Fig. 3: Recovered signal from Wiener Hopf method.

4. LMS SOLUTION

The Least Mean Square (LMS) algorithm is an important member of the family of stochastic gradient algorithms[2-4]. A significant feature of LMS is its simplicity also it does not require measurements of the pertinent correlation function, nor does it require a matrix inverse. The process can be broken into two parts, *viz*- the signal is filtered by passing it through a tap delay line (Fig. 2) and generating the error signal, which is the best estimate of the speech signal. The filter weights are adapted in accordance with the mean square error. It is assumed that the tap-input vector, *u(n),* and the desired response, *d(n)*, are drawn from a wide-sense stationary environment. Also this method does not directly terminate to the optimal Wiener-Hopf solution but it executes a random motion around the minimum point of the error-performance surface.

The equations to calculate the weights using the steepest-descent algorithm are-

The filter output

$$y(n) = \hat{\mathbf{w}}^H(n)\, \mathbf{u}(n). \quad (6)$$

The error estimation

$$e(n) = d(n) - y(n). \quad (7)$$

The tap weight adaptation for the next cycle

$$\hat{\mathbf{w}}(n+1) = \hat{\mathbf{w}}(n) + \mu \mathbf{u}(n) e^*(n). \quad (8)$$

Where μ is the step size. The LMS method can be divided into two parts, On-line method and Batch method. In the following sections both these methods are discussed from the project point of view.

5. LMS ONLINE METHOD

In this method the weights are updated at every point and these weights are used to calculate the new error. To begin with the filtering, we need to find the tap order and then the optimal step size. To find out the number of taps in the tap delay line, a step size was chosen and the whole sentence was iterated for different tap weights for minimum mean square error. It was found that after 15 weights the curve flattens out and so a step size of 15 was taken. Once the tap weights were decided upon, the sentence was now iterated for different values of step sizes with mean square error as the criterion. At 0.19 we get a minimum (Fig. 4), so the step size was chosen to be 0.19. With this step size and tap order the LMS routine is initialized with zero initial weights. The propagation of the weights with the input can be seen from the weight track plot (Fig. 5). Also we calculate the values of mean square error at all the points as we move across the signal. This can be seen from the learning curve plot (Fig. 6). The final extracted speech using the LMS method is shown in Fig. 7.

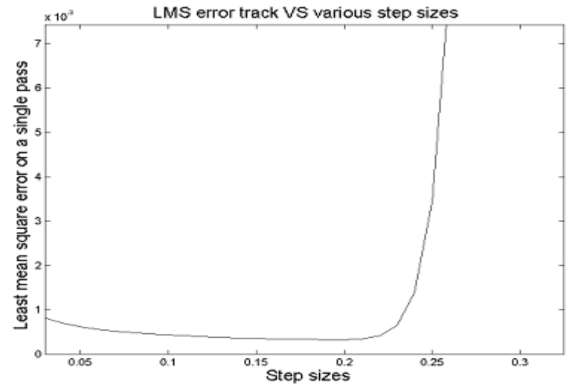

Fig. 4: Plot of error.

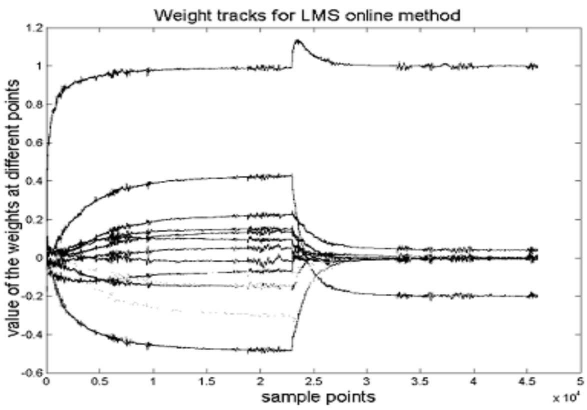

Fig. 5: Weight track for LMS online method.

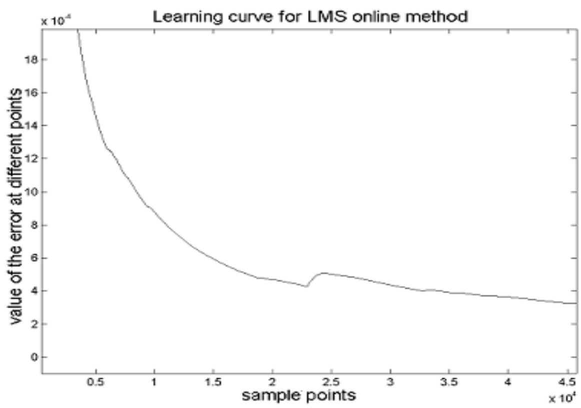

Fig. 6: Learning curve of LMS online.

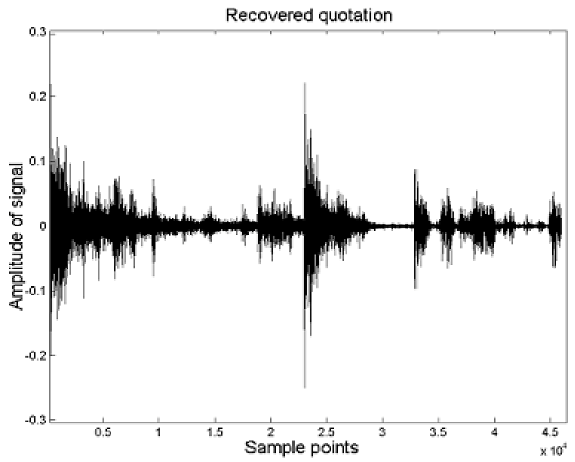

Fig. 7: Recovered quotation from LMS online method.

6. LMS BATCH METHOD

In this method the weights are updated only after points which are equal to the batch size. Everything else is exactly as the online method discussed earlier. The reason behind this system is that online gives a continuous adaptation of the weights which may lead to oscillation of the weights before reaching a stable value at that point. Whereas in batch we take the average of all the weights in one batch window and use this as the next update weight thus reducing on the oscillations. The propagation of the weights across the signal in steps can be seen from Fig. 8. Also the learning curve for the batch method is shown in Fig. 9. Figure 10 shows the recovered quotation using the batch method. As we can see, this does not recover the signal efficiently.

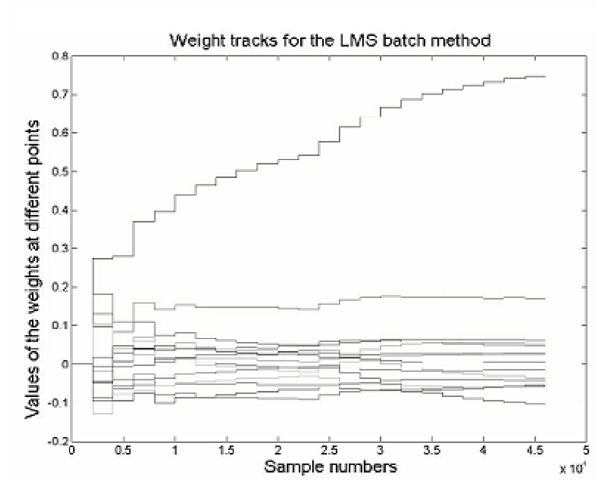

Fig. 8: Weight tracks for LMS batch.

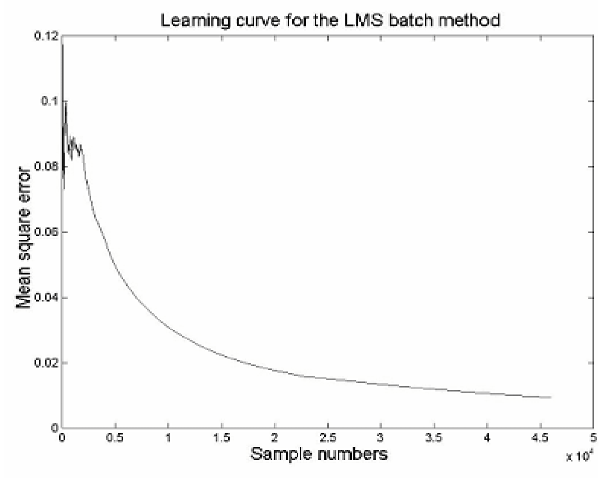

Fig. 9: Learning curve for LMS batch method.

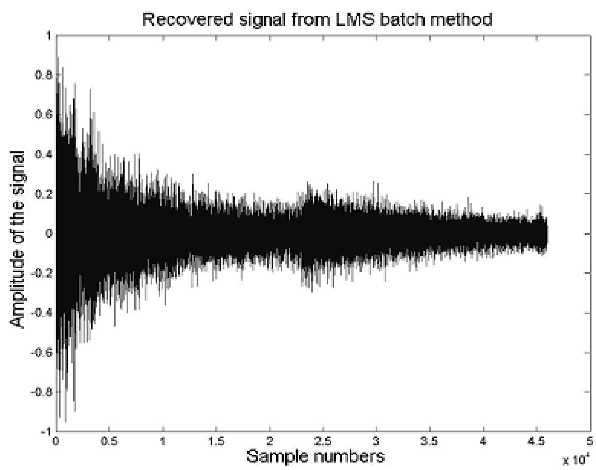

Fig. 10: Recovered quotation using LMS batch method.

7. RESULTS

The quotation, which was embedded in noise, was "Logic clearly dictates that the needs of the many are with the needs of the few". The LMS weights tracks change at 23000 samples, which indicates a microphone settings change i.e. after 2.0862 sec from the start. The Eigenvalue spread of the autocorrelation matrix is 1193.2. J_{min} for the Wiener Hopf is 0.0029. From Fig. 4 we see that after 0.25 seconds the error diverges so the maximum step size to ensure stability is 0.21. Minimum overall time constant for LMS was 1.2940 using $\tau_{min} = \lambda_{max}/(4\lambda_{avg})$. The error for online method was 0.000327 and for batch was 0.0094 hence online was better than the batch. Because of the non-stationarity in between the sample, Wiener-Hopf didn't give optimal results.

8. CONCLUSIONS

If the two inputs are interchanged, the following can happen: There exists a transfer function $H'(z)$ relating the two noise signals in the reference and primary signals. Also the tap delay line is a FIR all zero filter so if this $H'(z)$ is an all pole filter then after interchanging the inputs this becomes an all zero filter just as the tap delay line; giving us perfect recovery of the speech signal. On the other hand if the $H'(z)$ is an all zero filter which after interchanging the input becomes an all pole we will not be able to recover the signal. The intelligibility across the whole utterance is the best with the LMS online method, next is the Wiener Hopf and then LMS batch. Actually because of the non-stationarity Wiener Hopf gives a poorer result than LMS online. If leakage of the desired signal takes place in the reference signal, the adaptive filter will try to remove this value from the estimate of the desired value. Also d(n) and u(n) will become correlated which is not according to the requirements of ANC. Thus an extremely poor recovery will take place.

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