Speech Background Noise Removal Using Different Linear Filtering Techniques

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1 Introduction

Among the human beings, speech is the simplest and reliable way of communication. A speech signal transmits different information to the listener like type of language being spoken and emotion, gender and identity of the speaker [1]. The individual characteristic like pitch, fundamental frequency, formant frequency can be distinguishing components of human speech. The three main processes by which sound generates—are twisting of nerves, wire beating of membranes or blowing of air through holes but the mechanism of human voice is different as it comes out in different languages and feelings by the control of brain [2]. The range of frequency under which the speech signal falls is the 300–3400 Hz. However, the audible frequency range for human beings are from 20 Hz to 20 KHz [3]. Audio signal processing often suffers from noise trouble [4]. Speech background noise is an undesired signal which mixed with speech signal at the time of generation of speech signal or at the time of transmission [5]. The quality and the intelligibility of the speech signal gets degraded because of the present background noise. Therefore, it becomes important to reduce this background noise from the speech. For removing or reducing the noise, different filtering techniques are there like adaptive filter, Kalman filter, sub-band coding, wavelet transform, etc. The various filters that have been designed and tested are presented in this paper. First, the different kinds of adaptive filtering techniques have been implemented on both the additive white Gaussian noise (AWGN) and the practical noise then the results of both have been compared. After the adaptive filters the optimum filter, i.e., Kalman filter is implemented for both types of the noise. Finally, the results of adaptive filters and the Kalman filter have been analyzed.

2 Adaptive Filtering

In any filter, if the weights of the filter get self-adjusted according to an optimizing algorithm or some predefined rule then the filter is called

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an adaptive filter [6]. According to Premanada B.S et al. the parameters which are used for the processing of the signals change according to some predefined criterion, usually this criterion is chosen as estimated mean squared error (MSE) or correlation. This phenomenon can be considered as an adaptive filtering [7]. A general block diagram of an adaptive filter is shown in Fig. 1. An adaptive filter is a self-regulating system that takes help of recursive algorithm for processing. First input and training are compared and accordingly error signal is generated and that is used to adjust some previously assumed filter parameters under the effect of incoming signal. Filter parameter adjustment continues until steady-state condition. As far as application of noise reduction from speech is concerned, adaptive filters can give best performance. Reason for that noise is somewhat similar to the randomly generates signal and every time its very difficult to measure its statistic. Design of fixed filter is a completely failed phenomena for continuously changing noisy signal with the speech. Some of the signal changes with very fast rate in the context of information in the process of noise cancelation which requires the help of self regularized algorithms with the characteristics to converge rapidly. Some applications of adaptive filtering are system identification, channel equalization, and signal enhancement by noise reduction [8].

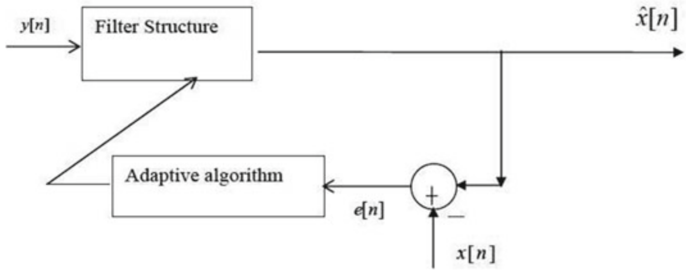


Fig. 1. General block diagram of adaptive filter

2.1 Least Mean Square Algorithm (LMS)

If an adaptive filter is driven by a Least Mean Square algorithm (LMS) then the filter is said to be a LMS filter. LMS filter is class of adaptive filter which is used to mimic a desired signal by finding the coefficient of the filter in terms of least mean square error of the signal. It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time [9]. The LMS filtering algorithm can be expressed by three expressions as follows:

1. Output of the filter: $Y(n) = \hat{w}(n)u(n)$
2. Estimated error: $e(n) = d(n) - y(n)$
3. Updated weight: $\hat{w}(n+1) = \hat{w}(n) + \mu u(n)e^*(n)$

where $\hat{w}(n)$ is the weight vector, μ is the step size, and $e^*(n)$ is the conjugate of error vector.

Adem Ukte et al. proposed a performance evaluation application of LMS adaptive algorithm for removing the noise and training an adaptive filter is given in [10].

2.2 Normalized Least Mean Square Algorithm (NLMS)

In the standard form of a least mean square filter, weight vector of the filter at iteration $(n + 1)$ gets the necessary adjustment and gives the product of three terms as follows:

1. The step size parameter μ, which subject to design concept
2. The input vector $u(n)$, which is actual input information to be processed
3. The estimated error $e(n)$ for real-valued data, or its complex conjugate $e^*(n)$ for complex-valued data, which is calculated at iteration n.

There is a direct relationship between the adjustment and the input vector $u(n)$. AS a result LMS filter fails because of its gradient noise amplification problem in the case when $u(n)$ is very large. As a solution to that problem of LMS normalized LMS filter can be used [9]. The term normalized can be considered because the adjustment given to the weight vector at iteration $(n+1)$ is "normalized" with respect to the squared Euclidean norm of the input vector $u(n)$. Sivaranjan Goswami et al. proposed an example of NLMS filter for noise filtering from speech, where they have considered the first 0.5 s to be the noise reference and based on that they have trained the adaptive filter to remove the noise from the input noisy speech signal [11].

3 Kalman Filter

The Kalman filter operates through a prediction and correction mechanism, because of this it is also called as a mathematical procedure. Kalman filter combines all the available data, i.e., measured, system knowledge, and the measurement devices to get an estimation of the desired variables in such a manner that the error between the measured and original data gets statistically minimized [12]. Usually, Kalman filter is used for white noise reduction. However, different methods were developed to fit the Kalman approach to reduce the colored noises also. A discrete Kalman filter can be used to estimate a process $d(n)$ from a set of observation $x(n) = d(n) + v(n)$. If this $d(n)$ and $x(n)$ are jointly wide sense stationary process then it can be predicted by using the Wiener filter but as in practical most of the process are nonstationary, therefore Wiener filter cannot be used. A causal Wiener filter for estimating a process $x(n)$ from a noisy measurement can be written as

$$y(n) = x(n) + v(n) \tag{1}$$

Considering a specific problem of estimation an autoregressive $AR(1)$ process of the form

$$\hat{x}(n) = a(1)x(n-1) + w(n) \tag{2}$$

where $w(n)$ and $v(n)$ are uncorrelated white noise process. The optimum estimation of $x(n)$ using all of the measurements, $y(k)$, for $k \leq n$ for k could be computed with a recursion of the form

$$\hat{x}(n) = a(1)\hat{x}(n-1) + K[y(n) - a(1)\hat{x}(n-1)] \tag{3}$$

where K is a constant, referred to as the Kalman gain, that minimizes the mean square error $E\{|x(n) - \hat{x}(n)|^2\}$

An application of Kalman filter to reduce the noise from the old audio recordings in which quality is degraded by aging or limitation of the recording reproduction mechanism is described by Rayan Kutty P et al. [13] such application of Kalman filter is based on the noise variance estimation from the silent region of the signal. It takes the same consideration like spectral subtraction where the initial first one or two seconds of recording are considered to be noise [14]. Orchisama Das et al. in their paper [15], they have used a Kalman filter to filter the noise by tuning its measurement noise covariance factor and distinct Kalman gain for silent and voiced frames.

4 Experimental Details

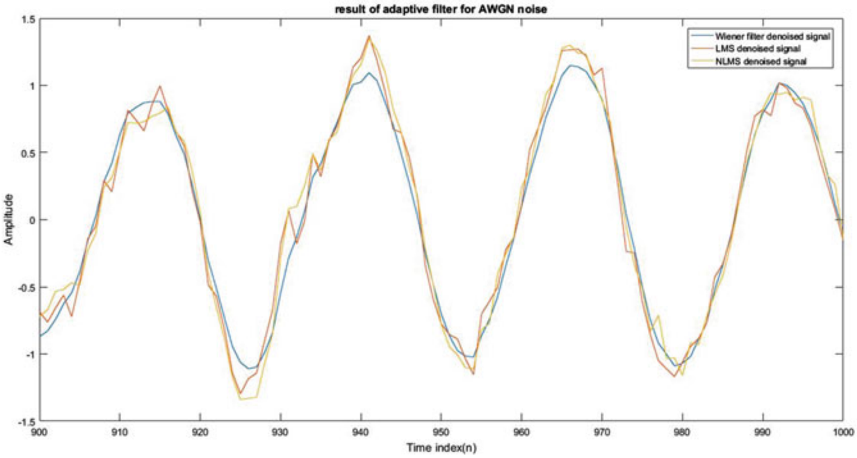
For testing of the various speech background noise removal filtering techniques, three different practical speech signals are recorded, i.e., a clean speech signal without any noise, a noisy version of the same speech signal and a noise signal which is present in the noisy speech signal. As the number of samples in all the signals are very high so only a segment of all the signals is tested on the designed filters. For theoretical noise analysis, the AWGN noise is considered.

As referred in Sect. 2 the various adaptive filters for both AWGN noise and practical noise mixed signals results are given below. The filter length of the filter is 7 and which is kept constant for all the filters.

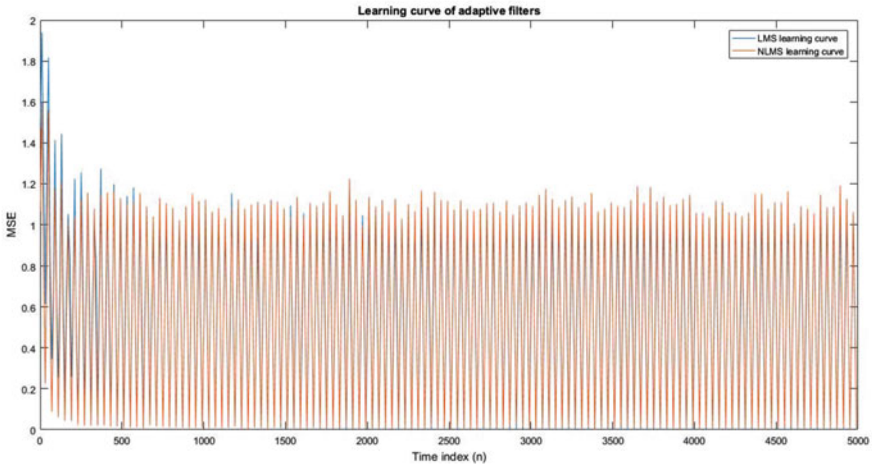
Figure 2a shows the output of the different adaptive filters, as the Wiener filter result was assumed to be the optimum so from here it can be concluded that both LMS and NLMS tried to match the Wiener filter result. From the Fig. 2b it can clearly concluded that the convergence of NLMS is faster than LMS. Now, the same adaptive filters are applied to practical signals and their results are shown below.

Figure 3a, b shows the time domain plot of the desired signal and the input signal respectively. These signals were recorded using stereo mode and then converted into the mono mode.

Figure 4a, b shows the output of both LMS- and NLMS-adaptive filter with desired signal. Here, the Wiener filter output is considered as the optimum solution and based on that it can concluded that the NLMS filter gives the best approximation of the Wiener filter result.



(a) Filtered signal of the LMS and NLMS filter with Wiener filter as optimum



(b) Theoretical learning curve of both LMS and NLMS filters

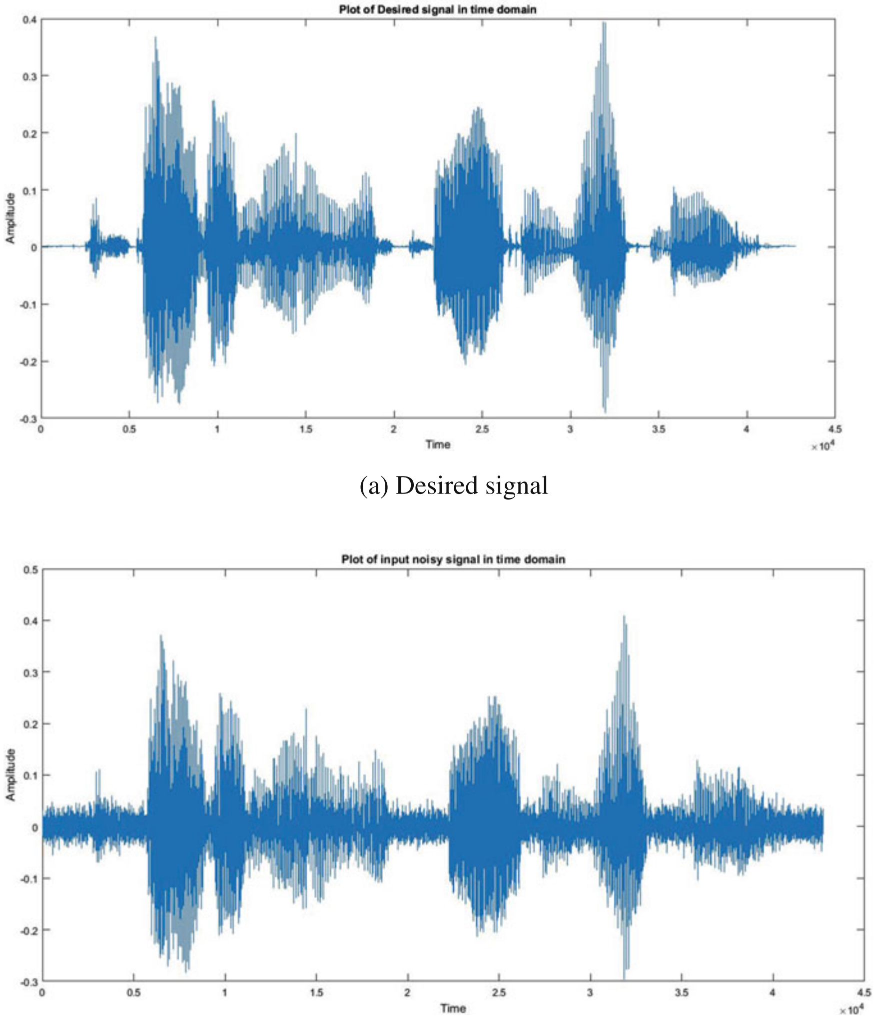
Fig. 2. Adaptive filter results

To verify whether the noise is suppressed or not in the filtered signal, the power spectral density of the input signal is calculated before and after filtering. From the Fig. 4c it is confirmed that the level of SNR is high in the output signal of both LMS and NLMS filter as compared to the input signal.

Now, as referred in Sect. 3 a Kalman filter is implemented on the same signals and the results were compared.

Figure 5a shows the time domain plot of both the desired and output of the Kalman filter and it is found that both the signals are quite similar.

Now to analyze the output of the Kalman filter the Mean Squared Eerror (MSE) was calculated and also the power spectral density of the input signal



(a) Desired signal

(b) Noisy signal

Fig. 3. Input signals

and the output signal of Kalman filter is computed to see the effect of noise reduction.

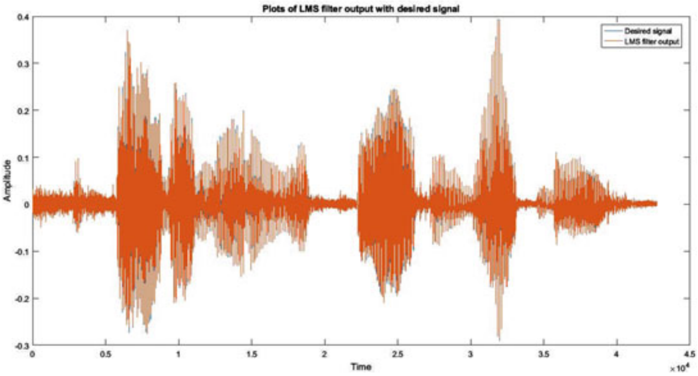
In Fig. 5b, c gives the PSD of the input signal of the Kalman filter and the output signal of the Kalman filter and mean square error of the estimated signal of the Kalman filter.

5 Comparison

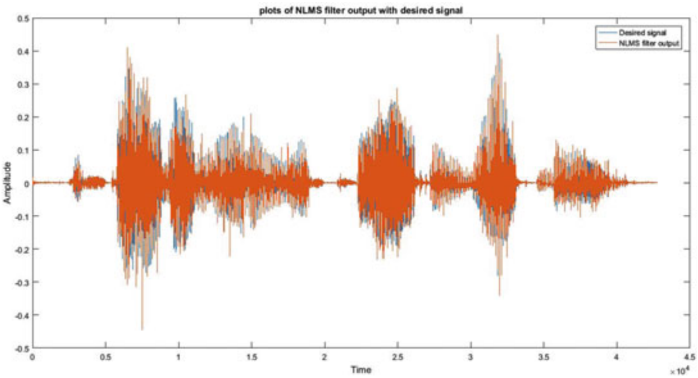
A table of comparison of all the implemented filters with Additive White Gaussian Noise (AWGN) and with practical noise based on the Peak

Table 1. Comparisons of the filter with practical noise

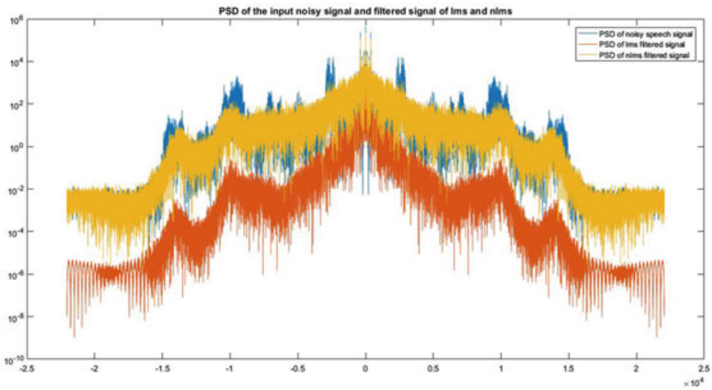
Sl No.	Parameter	LMS	NLMS	Kalman
(a) Comparisons of the filter with awgn noise				
1	PSNR	56.2380	57.8854	69.6564
2	MSE	0.1546	0.1058	0.0017
3	Max error	2.1650	1.4057	1.3563
4	L2Rat	62.87	43.2673	40.4175
(b) Comparisons of the filter with practical noise				
1	PSNR	93.2435	78.7775	75.7824
2	MSE	$3.0813e^{-05}$	$8.6166e^{-04}$	0.0017
3	Max error	0.0366	0.3719	0.4084
4	L2Rat	1.0084	0.9614	0.2973



(a) Filtered Signal with desired signal for LMS

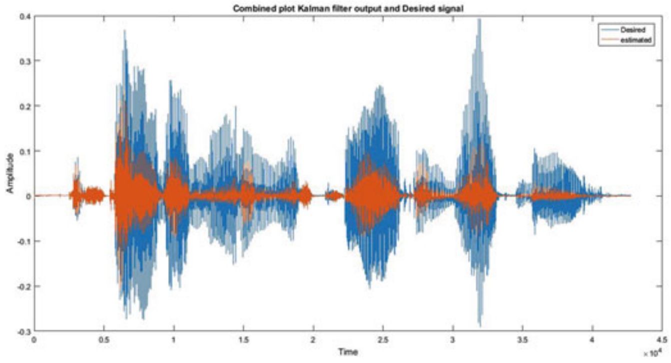


(b) Filtered Signal with desired signal for NLMS

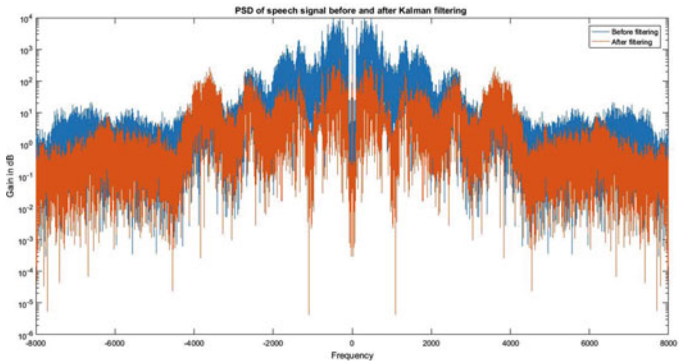


(c) PSD of input signal and output signal of LMS and NLMS filter

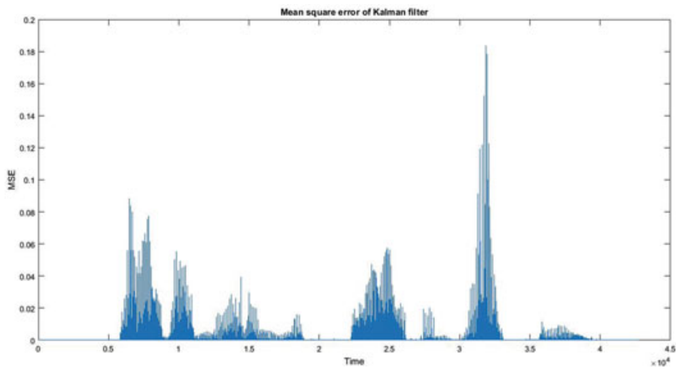
Fig. 4. Filtered signal with desired signal and PSD plot of all the signals



(a) Combine plot of Desired signal and estimated signal of Kalman filter



(b) PSD plot of the signal before and after Kalman filtering



(c) Mean square error of the output signal of Kalman filter

Fig. 5. Kalman filter outputs

Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Maximum Error (Max error), and Ratio of Squared Norms (L2Rat) is summarized below.

From the above Table 1a, b it is seen that for AWGN noise the performance of Kalman filter is better than the other adaptive filters, but when the noise becomes practical the performance varies.

6 Conclusion

For removing the background noise in speech signal different techniques have been implemented such as adaptive filters (LMS, NLMS, and Wiener) and Kalman filter. The Wiener filter result was assumed to be optimum. In the literature, it is found that the Kalman filter gives better result then other adaptive filter like LMS and NLMS, also from the result we have found that for AWGN noise the performance of Kalman filter is better than LMS, NLMS, and wiener filter but in practical noise the performance varies. Therefore, from the analysis it can be concluded that for AWGN noise the Kalman filter performance is the best among all the filters but for practical noise this is not true.

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