

## Online Speech Enhancement Using Fast Adaptive Kalman Filter with Signal Subspace Algorithm

**G.Srilakshmi**

Assistant Professor,  
Dept of ECE,  
Pragati Engineering College,  
Surampalem, India.

**A.Vineela**

PG Student (Embedded Systems),  
Pragati Engineering College,  
Surampalem, India.

### ABSTRACT :

Speech signals recorded in a room are commonly degraded by reverberation. In most cases, both the speech signal and the acoustic system of the room are unknown and time-varying. Eliminating this effect without affecting the original quality of the speech is a challenge of research in present days. The process of DE noising input speech signals is more helpful in the process of providing efficient sound system. Fast adaptive Kalman filter is designed for the removal of the noises in the signals.

Fast adaptive Kalman filtering is employed for the removal of the noises from the signal which is based on the prediction and estimation of the noise level in the signal. The input speech signal is denoised with the help of the Fast adaptive Kalman filter. State transition and observation models need not be linear functions of the state but may instead be non-linear functions. The function can be used to compute the predicted state from the previous estimate and similarly the function can be used to compute the predicted measurement from the predicted state.

The nonlinear functions employed for the prediction and estimation process improves the performance of the adaptive kalman filter process. The non-linear functions defined for the kalman filtering process is designed so that the process is reduced in iterations and more adaptive. And using signal subspace algorithm.

The filtered signal and the original signal is then compared in order to measure the performance of the process. The performance is measured with the help of performance metrics like SNR.

### Index Terms:

Speech enhancement, Speech DE noising, Speech Communication.

### INTRODUCTION:

In speech communication, quality and intelligibility of speech is of utmost importance for ease and accuracy of information exchange. The speech processing systems used to communicate or store speech are usually designed for a noise free environment but in a real-world environment, the presence of background interference in the form of additive background noise and channel noise drastically degrades the performance of these systems, causing inaccurate information exchange and listener fatigue. Speech enhancement algorithms attempt to improve the performance of communication systems when their input or output signals are corrupted by noise.

Techniques for recording and preprocessing audio have many applications in communication, surveillance and entertainment. When recording audio, it is important to eliminate all unwanted noise before further application specific processing is performed. Noise present due to the uncontrollable nature of a recording environment can be problematic to reduce as it consists of interfering sources and is statistically non-stationary.

Because the characteristics of the noise change over time, classical single channel filtering techniques cannot be used to remove this noise as they will also distort the speech signal of interest. Recently, the use of multichannel processing techniques has been investigated to see if spatial information provided by microphone arrays can be exploited to improve noise reduction. One specific application where the noise environment is particularly hard to control is in the area of speaker identification.

Speaker identification algorithms today are fairly accurate when speech samples are taken in a quiet environment with the speaker talking directly into the microphone. However, in applications such as surveillance, the noise environment cannot always be controlled and the speaker will not always speak directly into a microphone. This reduction in signal to noise ratio ultimately limits the performance and confidence of speaker identification algorithms.

It is therefore important to investigate the feasibility of deploying microphone arrays in conjunction with multichannel noise reduction techniques to aid in speaker identification. In particular, this thesis looks to see if these techniques can be effectively applied in different common environmental scenarios with surveillance applications in mind

#### **KALMAN FILTER:**

The Kalman filter was created by Rudolf E. Kalman in 1960, though Peter Swerling actually developed a similar algorithm earlier. The first papers describing it were papers by Swerling (1958), Kalman (1960) and Kalman and Bucy (1961). It was developed as a recursive solution to the discrete-data linear filtering problem. Stanley Schmidt is generally credited with the first implementation of a Kalman filter..

In this process, the calculation of LPC (linear prediction coding) coefficient and inverse matrix increase the complexity of the filtering algorithm and have been given a simple Kalman filtering algorithm without calculating LPC coefficient in the AR model.

#### **EM Algorithm:**

The iterative KEMD algorithm proposed that is based on the EM algorithm proposed by Dumpster, Laird, and Rubin. In the derivation of the KEMD, both the acoustic systems and the noise were assumed to be time-invariant. The EM consists of two steps, repeated iteratively until convergence. In the E-step of the  $n$ -th iteration is calculated using the entire data set and the latest parameter estimate. In the M-step, the parameters are re-estimated. By iteratively repeating the E- and M-steps, the convergence of to a local maximum of the likelihood function is guaranteed.

#### **PROPOSED METHOD:**

The process of DE noising input speech signals is more helpful in the process of providing efficient sound system. The process of removing noise in the signals is done based on the filters designed for removing noises in the images. Fast adaptive Kalman filter is designed for the removal of the noises in the signals. Kalman filter includes two steps the prediction step and the estimation step. In the prediction step the noises in the signal were estimated. In the estimation step the estimated noises in the images were removed based on the calculation of the amount of noise estimated. The performance of the process is measured by the calculation of the performance metrics.

The input speech signal is denoised with the help of the Fast adaptive Kalman filter. Fast adaptive kalman filter filters the signal based on the transition functions. State transition and observation models need not be linear functions of the state but may instead be non-linear functions. The function can be used to compute the predicted state from the previous estimate and similarly the function can be used to compute the predicted measurement from the predicted state.

The prediction and the estimation process are the steps in the kalman filter. The nonlinear functions employed for the prediction and estimation process improves the performance of the adaptive kalman filter process. The non-linear functions defined for the kalman filtering process is designed so that the process is reduced in

iterations and more adaptive. Kalman filtering consists of two steps Prediction and Estimation steps. In the prediction step the noises in the signals were predicted. The prediction step is estimated based on the identification of noise location in the signal. In the estimation step the predicted noise were updated by updating the predicted noise levels. The Kalman gain is estimated using the predicted and the estimated step. The prediction and the estimation steps were both repeated till the number of the speech samples in the input signal.

The threshold range for the identification of noise is estimated correlation between the features. The signal subspace algorithm which Signal subspace based speech enhancement techniques decompose dimensional spaces into two subspaces: a signal subspace and a noise subspace. It is assumed that the speech signal can lie only within the signal subspace while the noise spans the entire space. Only the contents of the signal subspace are used to estimate the original speech signal The filtered signal and the original signal is then compared in order to measure the performance of the process. The performance is measured with the help of performance metrics like SNR

**FAST ADAPTIVE KALMAN FILTER:**

There are always noise changes with the surrounding environment. To design the fast adaptive Kalman filtering algorithm, we need to know information about environmental noise for that it is necessary to constantly update the estimation of noise. Here in the fast adaptive Kalman filtering algorithm, it can constantly update the estimation of background noise and update the threshold U. So it consists of two steps.

1) Updating of variance of noise is obtained by

$$Rv(n) = (1-d) \times Rv(n) + d \times Ru(n)$$

Where d is the loss factor which limits the memory of the filtering. ‘d’ is defined as:  $d(21)$

Where b is a constant whose value ranges in between 0.95 and 0.99. The loss factor d is used to reduce the error.

2) Updating of the threshold is known from

$$U = (1-d) \times U + d \times Ru(n)$$

Here the loss factor d is used which can reduce the error. We always compare the  $Ru(n)$  [variance of the current speech frame] with the threshold U which is updated above. We calculate the SNR of current speech frame and the whole speech signal and compare them.

$$SNR_1(n) = 10 \log_{10} \left( \frac{\delta_x^2(n) - \delta_v^2(n)}{\delta_v^2(n)} \right)$$

$$SNR_0(n) = 10 \log_{10} \left( \frac{\delta_x^2(n) - \delta_v^2(n)}{\delta_v^2(n)} \right)$$

When the current speech frame  $SNR_1(n)$  is less than or equal to whole speech frame  $SNR_0(n)$  or  $SNR_0(n)$  is less than zero then the speech frame is noisy and it can follow  $Ru(n) \leq U$ . However, when  $SNR_1(n)$  is larger than  $SNR_0(n)$  then the noise estimation will be attenuated to avoid damaging the speech signals. According to this attenuation can be expressed as,

$$Rv(n) = Rv(n)/1.2$$

The whole algorithm for A Fast Adaptive Kalman Filter is as follows:

[Initialization]  $s(0) = 0, Rv(1) (1)$

[Iterations]

If  $SNR_1(n) \leq SNR_0(n) \parallel SNR_0(n) < 0$  then

If  $Ru(n) \leq U$  then

1)  $Rv(n) = (1-d) \times Rv(n) + d \times Ru(n)$

End

2)  $d = (1-b)/(1-b^2)$

3)  $U = (1-d) \times U + d \times Ru(n)$

Else

$$4) Rv(n) = Rv(n)/1.2$$

End

$$5) Rs(n) = E(y(n) \times y(n)) - Rv(n)$$

$$6) K(n) = Rs(n) / (Rs(n) + Rv(n))$$

$$7) s(n) = K(n) \times y(n)$$

**SIGNAL SUBSPACE ALGORITHM:**

The basic method for speech enhancement is Spectral Subtraction approach. It is very simple method and easy to implement. The conventional power spectral subtraction method substantially reduces the noise levels in the noisy speech. But it introduces an annoying distortion in the speech signal called musical noise. With the passage of time Spectral Subtraction has undergone many modifications. Evaluation of spectral subtractive algorithms revealed that these algorithms improve speech quality and not affect much more on intelligibility of speech signal. So the other method called Signal Subspace method is proposed that allows better and more suppression of the noise. The aim of this method is to improve the quality, while minimizing any loss in intelligibility.

The approach includes the utilization of a signal dependent transform to disintegrate an uproarious signal into two separate subspaces, the signal in addition to noise subspace, and the noise-just subspace. Only the contents of the signal subspace are used to estimate the original speech signal. The point here is to enhance the quality. The speech enhancement procedure can now be summarized as follows: (1) Separate the (signal+noise) subspaces from the (noise only) subspace, (2) Remove the (noise-only) subspace, (3) Remove the noise components in the (signal + noise) subspace.

**Signal to noise ratio (SNR):**

The Signal-to- Noise Ratio is used to measure the amount of desired signal level with the noise level or SNR is defined as the ratio of power between the

signal and the unwanted noise. SNR is calculated using the formula One of the most important goals of any speech enhancement technique is to achieve highest possible SNR. Higher the SNR ratios, better the performance of speech signal enhancement.

$$\frac{S}{N} = \frac{n_{signal}}{n_{noise}}$$

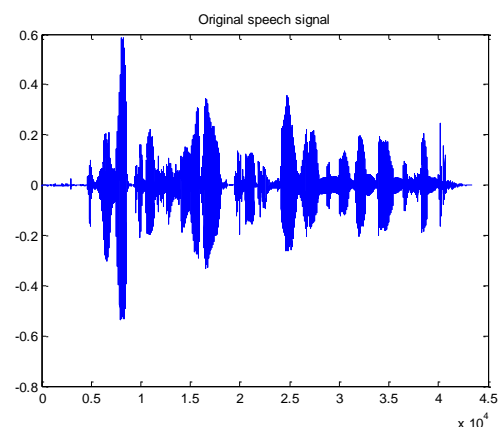
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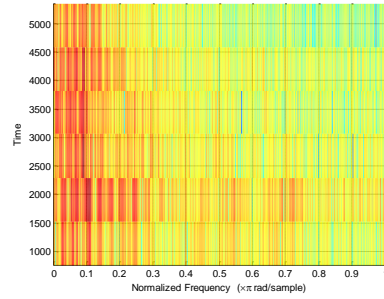
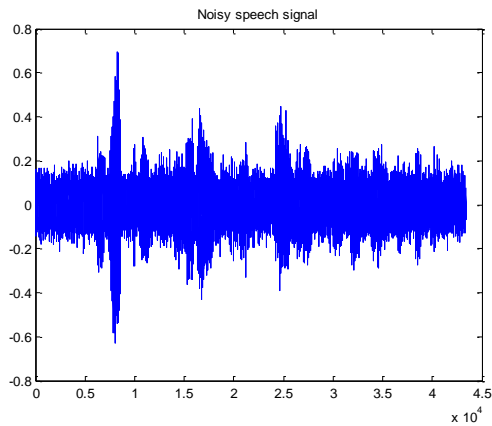
Implemented on Raspberry pi kit



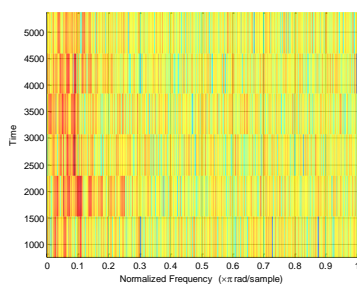
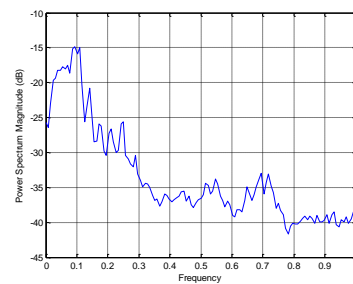
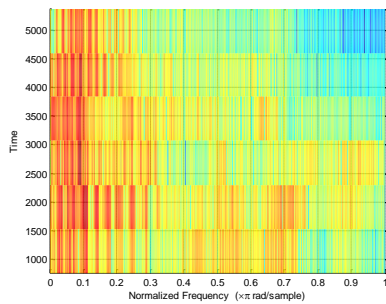
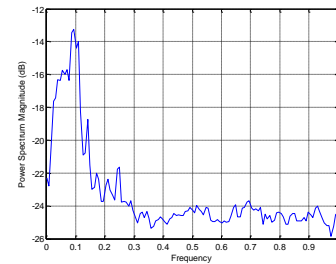
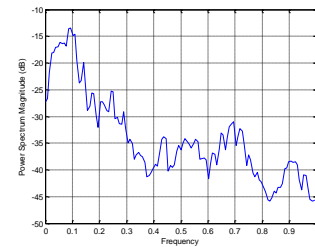
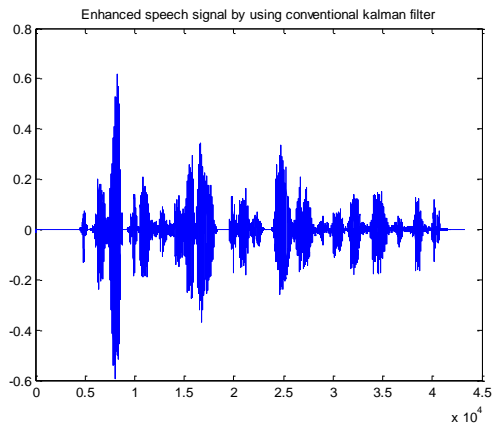
**RESULT:**

SNR improvement from the kalman filter to Fast adaptive Kalman filter also obtained in similar fashion. The proposed system is capable of removing the noise from the noisy signal we take the results For comparison with the speech signal performance we have taken results for noise signal as input. Calucateof snr for kalman filter and Fast adaptive Kalman filter .

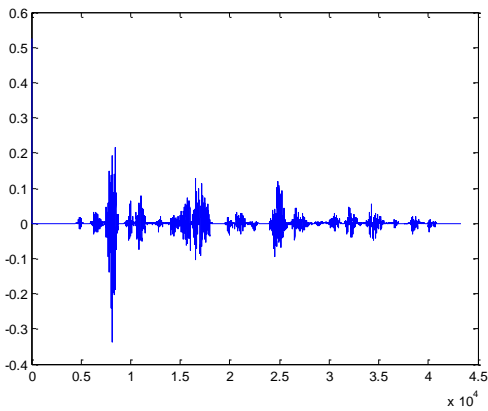
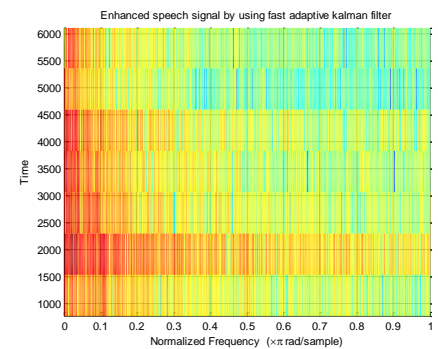
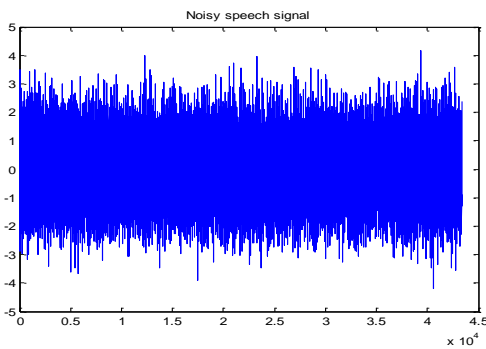
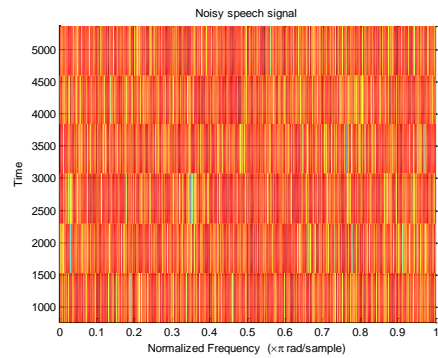
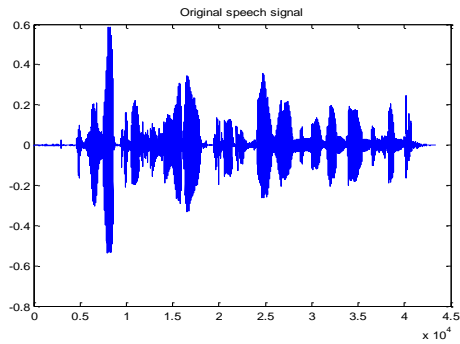




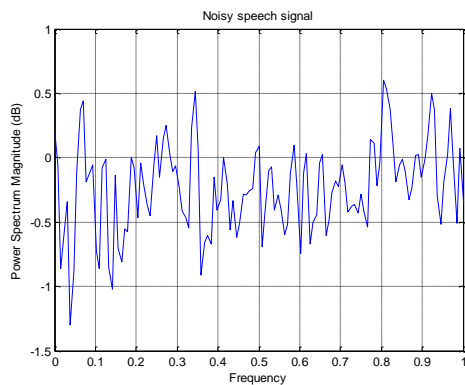
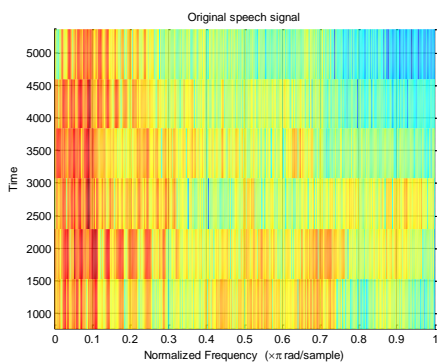
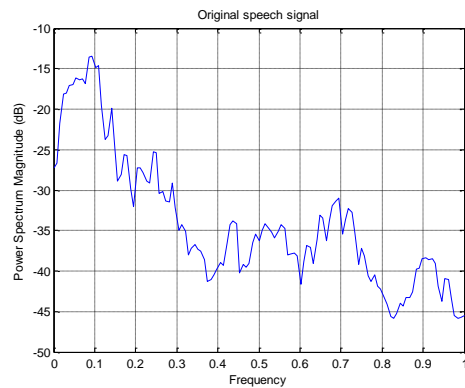
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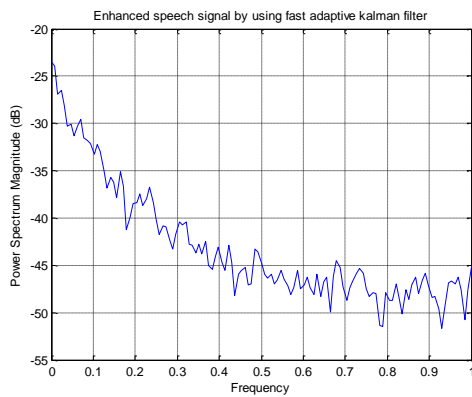


Simulation results for echo cancellation using FastAdaptive Kalman filter algorithm for speech as input



**PSD:**





### Conclusion and future work:

The process of denoising of the speech signals is employed in the proposed approach. The process of denoising of the signals were more helpful in the speech applications. The process can be more applicable in hearing aids. The input speech signals were denoised based on the fast adaptive Kalman filtering process with signal subspace algorithm.

The fast adaptive Kalman filtering process employs the prediction and the estimation steps for the identification and removal of the noises. The signal subspace algorithm is used to remove noise and to increase SNR value. The performance of the process is measured with the help of the performance metrics. The application of the fast adaptive kalman filtering process is more enhanced compared to the previously applied kalman filtering process which is based on the non-linear functions for the estimation and prediction function calculation.

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