Efficiency Analysis of Noise Reduction Algorithms

Analysis of the best algorithm of noise reduction from a set of algorithms

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Abstract—**For greater advancement in future communication, efficient noise reduction algorithms with lesser complexity are a necessity. Noise in audio signal poses a great challenge in speech recognition, speech communication, speech enhancement and transmission. Hence the most efficient algorithm for noise reduction must be chosen in such a way that the cost for noise removal is a less as possible, but a large portion of noise is removed. The common method for the removal of noise is optimal linear filtering method, and some algorithms in this method are Wiener filtering, Kalman filtering and spectral subtraction technique. Here, the noise signal is passed through a filter or transformation. However, due to the complexity of these algorithms, there are better algorithms like Signal Dependent Rank Order Mean algorithm (SD-ROM), which removes noise from audio signals and retains the characteristics of the signal. The algorithm can be adjusted depending on the characteristics of noise signal too. To remove white Gaussian noise, discrete wavelet transform technique is used. After each of the techniques are applied to the samples, SNR and elapsed time are calculated. All of the above techniques show an increased Signal to Noise Ratio (SNR) after processing, as seen in the simulation results.**

Keywords—Signal to Noise Ratio, Kalman Filter, Spectral Subtraction, Elapsed time, filter, Additive Noise, Gaussian Noise

I. INTRODUCTION

Natural audio signals are never available in pure, noiseless form. Every signal experiences some distortion due to background noise. Hence, every speech signal must be treated with noise reduction tools before storage or transmission. There are several noise reduction algorithms available. However, many of the algorithms have two major drawbacks. Firstly, some algorithms are really complex and hard to implement for real world scenarios. Secondly, some algorithms remove noise but alter the characteristics of the original audio signal in the process. Hence the audio signal after the treatment of noise is distorted and has different characteristics. Hence, the noise removal algorithms chosen must be less complex and must cause minimum or no distortion to the audio signal.

There are several algorithms for the aforesaid purpose. Examples include adaptive filter algorithms, temporal filtering, spatial filtering etc. One of the most widely used algorithms is optimal linear filtering algorithm. Several methods such as the Kalman filtering and Wiener filtering have been developed.

The Wiener filtering process [1] uses a linear time invariant filter. It estimates the desired random process by removing the additive noise. It reduces the mean square error in the signal. If a signal of interest is corrupted by noise to produce a known signal, the Wiener Filter filters out the noise from the corrupted signal and returns the signal of interest. In addition to noise removal, wiener filter is used in Wiener deconvolution. It reduces the effect of deconvolved noise at certain regions in the frequency spectrum where signal to noise ratio is poor. Due to the properties of Wiener filter wherein it returns the desired signal, it can be used for signal detection applications too, most commonly speech detection.

Kalman filters [2] have very less response time, making them very efficient. They are suited for dynamic systems. Hence this filter is appropriately used for real world problems. It is used in the guidance, navigation and control of aircraft and spacecraft vehicles. They are used in robotic motion control and for modelling the human central nervous system. Kalman filter works in two steps. It first produces estimates of the current state values, along with their uncertainties. The signal is generally corrupted with random noise. Once the outcome of the next measurement is observed, these estimates (error values) are changed using a weighted average, with more weight being given to estimates with higher uncertainty. It is a recursive algorithm.

Boll spectral subtraction [3] partitions the given noisy signals into frames. Each frame is multiplied by a window function. Spectral Subtraction Algorithm is very simple to implement, hence it is used widely. Assuming the noise is additive and using linearity of Fourier transform

$$X(e^{j\omega})=P(e^{j\omega})+N(e^{j\omega}) \quad (1)$$

Where $X(e^{j\omega})$ is the Fourier Transform of the noisy signal, $P(e^{j\omega})$ is the Fourier transform of the noiseless signal and $N(e^{j\omega})$ is the Fourier Transform of the noise. A rough estimate of the noiseless signal spectrum is

$$|P(e^{j\omega})| =|X(e^{j\omega})|-|N(e^{j\omega})| \quad (2)$$

The spectral subtraction eliminator is calculated using the amplitude and phase of the noiseless signal. Hence a subtraction of the amplitude spectrum of the noisy signal and the amplitude spectrum of noise can return the noiseless signal.

Signal dependent rank order mean (SDROM)[4] is an efficient nonlinear algorithm to remove noise from highly corrupted audio signals while preserving the characteristics of the signal. The method is applicable to all noise models. If a signal sample is detected as a corrupted sample, it is replaced with an estimation of the true value, based on the neighboring information. Otherwise it is kept unchanged. This technique improves SNR to a great extent at the same time also preserves the characteristics of the signal. It is one of the best noise reduction algorithms available.

Discrete Wavelet Transform filter for White Gaussian Noise: White Gaussian noise[5] is very hard to remove, mainly because it is spread over all frequencies. Discrete Wavelet transform is used to convert the noisy audio signal to the wavelet domain. In the wavelet domain, it is very easy to separate the signal and noise as high amplitude coefficients represent signals and low amplitude coefficients represents the noise. After removal of noise in wavelet domain, conversion to time domain is done and the result is a de-noised signal

Least Mean Square filter (LMS) filter[6] is used to filter the noise by calculating the least mean square of the error signal which is the difference between the actual signal and required signal. LMS filters are simple to implement. It can also be described in the frequency domain. Normalized Least Mean Square algorithm is used for Gaussian noise[7].

II. NOISE REDUCTION PARAMETERS

A. Signal to Noise Ratio(SNR)

Ratio of the signal strength to Noise strength is called SNR, the signal to noise ratio. After noise reduction, the signal to noise ratio of the signal improves. It is the ratio of the power of the signal to the power of the noise. It is also the ratio of the square of amplitude of the signal to the square of the ratio of the square of amplitude of noise[8].

$$SNR = \frac{Psig}{Pnoise} \quad (3)$$

Hence, the signal to noise ratio is an exact measure of degree of de- noisiness in a signal.

B. Elapsed Time

Elapsed time is the time interval between the peak of a signal and the peak of the immediately neighboring noise signal. More the elapsed time, more noise reduction and better SNR value can be observed. This is because a larger time is taken to reach from the peak of the signal to the peak of the noise signal[9].

III. DESCRIPTION OF ALGORITHMS

A. Kalman Filter

The Kalman filter takes the input signal consisting of the noise and required signal and gives the unknown quantities that are close to the true value which is necessary. It uses positioning and velocity[10]. It picks out the signal of interest from inaccurate observations. State Space Representation of a Kalman Filter is as follows

$$X(k+1)=F(k)x(k)+G(k)u(k)+v(k) \quad (4)$$

Where x(k) is the state vector u(k) is the known vector which is given as input and v(k) is the unknown noise with covariance. The Kalman filter checks the estimates of the state:

A(k|k)- estimates of A(k), given measurements are b(k), b(k-1)….. and so on.

A(k+1|k)- estimates of A(k+1), given measurements are b(k), b(k-1)….. and so on.

An error covariance matrix checks the estimates of the state:

P(k|k)- covariance of A(k), given measurements are b(k), b(k-1)…..

P(k+1|k)- covariance of A(k+1), given measurements are b(k), b(k-1)..

The quantities known to us are A(k|k), u(k), P(k) and the new measurement z(k+1)

$$A(k+1|k)=F(k)A(k|k)+G(k)u(k) \quad (6)$$

$$v(k+1)=z(k+1)-\hat{z}(k+1|k) \quad (7)$$

$$A(k+1|k+1)=A(k+1|k)+W(k+1)v(k+1),$$

Where W(k+1)is the Kalman gain. (8)

Since the above equations can be implemented very easily, the Kalman filter is used for real time applications.

B. Boll Spectral Subtraction

The Boll Spectral Subtraction Algorithm[11] enhances the audio signal by using spectral averaging and the leftover noise is removed. The spectrum of a noise signal is found by Fast Fourier Transform and subtracted from the spectrum of the spectrum of the mixed noisy signal. Hence the new signal is denoised and inverse Fourier transform is applied to get the clean signal. This method involves subtraction of spectra of the given signal and noise signal.

C. White Gaussian Noise Filter

White Gaussian Noises are disturbances that naturally occur and this filter removes them considering an average case. This kind of noise has uniform power distribution and is distributed normally throughout the time domain. The filter characteristics are changed in the algorithm due to which the band pass filter and band stop filter are used to allow or stop different set of frequencies depending upon the noise. Hence, using tunable filters, the Gaussian noise can be removed.

D. LMS Adaptive Filter

The Least Mean Square algorithm uses a linear filter and an adaptive algorithm. The input signal is fed into the linear filter and sent to the feedback system consisting of the adaptive algorithm.

The LMS algorithm can be defined as follows

Parameters: x filter order

a step size

Initial conditions : $\hat{h}(0)$=zeros(x)

Calculations: X(n)=[x(n),x(n-1),x(n-2),….x(n-p+1)]’

LMS adaptive filter also uses the concept of error signal. The error signal e(n) is defined as

$$e(n)= d(n)-y(n)x(n) \quad (9)$$

where y(n) is $\hat{h}^H(n)$ and h(n) are the weighted means for the nth signal.

E. SDROM

The Rank Order Function runs a rank-order filtering with an order of N[12]. It computes the percentile of the data on a window of size N.

Say a window of size 5 is taken with w={x(n-2),x(n-1),x(n+1),x(n+2)} The samples are sorted in ascending order. The difference $r_i(n)$-x(n) is called rank ordered differences. When the rank ordered differences are considered to be greater than the threshold value, it indicates the presence of noise. Every noise impulse detected is replaced by the rank ordered mean $(r_2+r_3)/2$. It is a recursive algorithm.

IV. METHODOLOGY

Over fifty audio signals were collected from different sources and were plotted graphically using MATLAB. Then, different types of noises were added to the signals and were tested on the aforesaid algorithms. The values of SNR and elapsed time were calculated for all samples. Various types of noises were added to the signals and tested. The main quantity tested was SNR. The plots of the noisy signal and de-noised signal were made using MATLAB. These plots were compared. . Four samples were picked whose SNR values and elapsed time are shown in the table below. It was also noted that some filters were efficient only for a certain kind of noise, like additive Gaussian noise for white Gaussian filters.

V. RESULTS OF FILTERS

SIGNAL TO NOISE RATIO (SNR) FOR VARIOUS SAMPLES

SlNo	Kalman Filter	Boll Spectral Subtraction	White Gaussian Filter	LMS Adaptive Filter	SDROM
1	28.0	43.5	49.1	53.4	59.27
2	24.9	45.7	45.6	52.1	59.56
3	28.8	48.2	49.9	56.6	59.08
4	27.5	44.8	47.1	58.8	59.33

ELAPSED TIME (in ms) FOR ALL THE SAMPLES

Sl No	Kalman Filter	Boll Spectral Subtraction	White Gaussian Filter	LMS Adaptive Filter	SDROM
1	55.20	57.10	56.01	57.12	57.14
2	146.41	146.08	146.59	146.01	146.15
3	15.92	17.57	16.02	17.02	17.92
4	16.13	18.64	17.09	18.00	19.12

VI. CONCLUSION

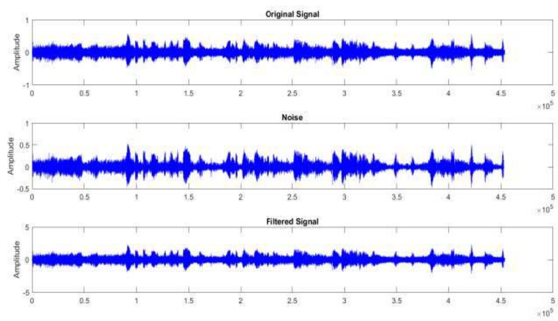
From the values of SNR and elapsed time, it is evident that the SDROM algorithm is the best algorithm for noise reduction as it has the highest SNR value and the largest elapsed time too. It is also very simple to implement and the algorithm has a lot complexity. It also does not distort the input signal. Hence SD ROM algorithm can be used frequently for noise reduction. Boll Spectral Subtraction is also very easy to implement and also gives reasonably high values of SNR and elapsed time. Kalman filter, though easy to implement, does not improve the SNR much. White Gaussian Filter and LMS Adaptive filter are easy to implement but are efficient only for certain types of noises.

Hence, before reducing noise in a given signal, the algorithm must be analyzed for its efficiency. The algorithm giving the maximum SNR, causing minimum distortion and having least complexity must be chosen.

VII. PLOTS OF THE SIGNALS

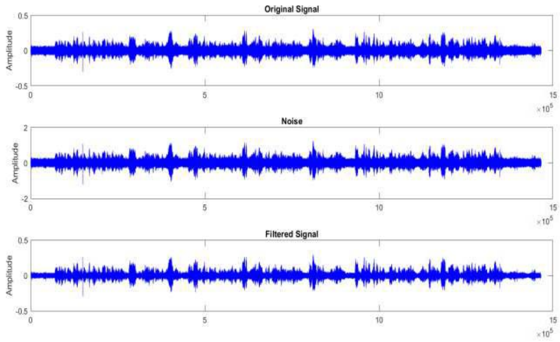
In every filter, the first plot shows the original signal, the second plot is the signal with added noise and the third plot is the signal without noise

Kalman Filter



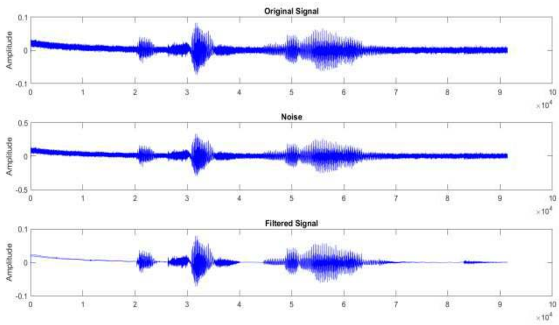
As seen in the graph, the third plot has much lesser noise than the second plot.

Boll Spectral Subtraction



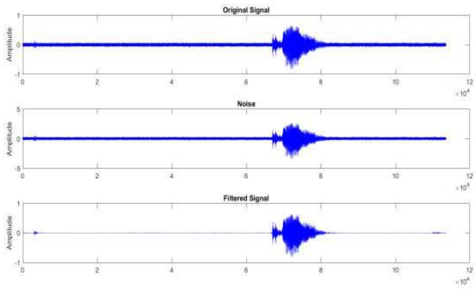
In Boll Spectral Subtraction, the quality of the signal is preserved and noise is removed appreciably.

White Gaussian Noise Filter



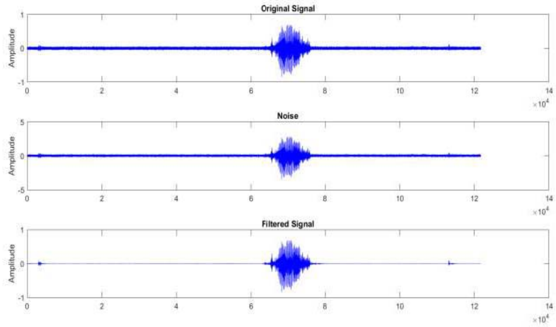
Gaussian noise is removed and the signal is shown in the third plot.

LMS Adaptive Filter



The third plot shows the denoised signal which has a smooth curve. Hence, LMS filters too remove noise efficiently.

SD ROM Filter



SD ROM preserves the quality of the signal and it is evident from comparing the first and the third plots

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