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Noise free Speech Enhancement using Fast Adaptive Kalman Filtering

Narendrapurapu V D Mahesh[1], Dr. I. Santhi Prabha[2]
Department of ECE, University college of engineering, JNTU Kakinada 533003, Kakinada, Andhra pradesh

***Abstract*—A fast adaptive speech enhancement algorithm in presence of environment noise is proposed in this paper. In order to eliminate the matrix operations and reduce its running time without sacrificing quality of speech signal by constantly upgrading the first value of the state vector, the fast adaptive kalman filtering is developed. It also has good adaptability to improve the algorithm robustness. To evaluate the system performance we employed the calculation of SNR and least mean square error. Finally we compare these characteristics parameters with those of conventional methods and shows fast adaptive kalman filtering is effective for speech enhancement.**

***Keywords*— Speech enhancement, conventional Kalman filtering, matrix operations, running time.**

I. INTRODUCTION

Many applications of speech communication systems always suffer from the reduction of speech quality under adverse noise conditions. Noise can occur from anywhere for example noise from external environment when a person is using mobile while travelling. Thus urgent attention is required in order to overcome deterioration of speech. Enhancing of speech degraded by noise, is the most important field of speech enhancement such as mobile phones, teleconferencing system, speech recognition etc., Hence speech enhancement techniques are must in the communication systems. Many filtering techniques have been proposed by [1]-[5] to study the noise problem in the speech signal. Most of those methods need the estimation of the parameters of the auto-regressive (AR) model which requires to perform lot of matrix operations. In the noise suppression using the Kalman filtering the calculation of linear predictive coding coefficient and matrix inversion increase the computational complexity of the algorithm.

Simple Kalman filtering techniques are proposed by [3] and [4] without calculating LPC in AR model, but they still has a large number of matrix inverse operations and redundant data. To overcome the drawback of the conventional Kalman filtering a fast adaptive Kalman filtering is proposed. This algorithm constantly updates the initial value of the state vector, thereby eliminates the matrix operations. It also has good adaptability in improvement of robustness.

II. CONVENTIONAL KALMAN FILTERING ALGORITHM

The speech signal represented in auto-regressive model of order L is given by

$$s(n) = \sum_{i=1}^{L} \alpha_i(n) \times s(n-i) + \omega(n) \qquad (1)$$

The reason for the name regressive is because it is a linear model relating a dependent variable *s* as a set of independent variables $\alpha_1, \alpha_2, \alpha_3, \ldots\ldots\alpha_L$ are the LPC coefficients plus an error term $\omega(n)$ is the white Gaussian noise whose mean is zero and the variance is δ_u^2. The speech signal S(n) mean is zero and its variance is δ_v^2.

The noisy speech signal *y(n)* is given by

$$y(n) = s(n) + v(n) \qquad (2)$$

(1) And (2) in terms of state equation and observation equation are given by

State equation

$$x(n) = F(n)x(n-1) + G\omega(n) \qquad (3)$$

Observation equation

$$y(n) = Hx(n) + v(n) \qquad (4)$$

Where F(n) is the $L \times L$ transition matrix expressed as

$$F(n) = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ a_L(n) & a_{L-1}(n) & a_{L-2}(n) & \cdots & a_1(n) \end{bmatrix}$$

And H is the Observation vector and G is the input vector. This part spends nearly half of the time taken for the whole algorithm.

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The modified F and H matrices are as follows

$$F = H = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \vdots & \ddots & 1 \\ a_L(n) & a_{L-1}(n) & \cdots & \cdots & a_{1(n)} \end{bmatrix}$$

The $L \times 1$ state vector is defined as

$$X(n) = [s(n), \ldots\ldots s(n-L+1), s(n-L+2)] \tag{5}$$

The $L \times 1$ input vector is defined as

$$Q(n)^T = [s(n) \quad 0 \quad \cdots \quad 0] \tag{6}$$

And the $L \times 1$ observation vector is

$$R(n) = [1, v(n), \ldots\ldots v(n-L+2)] \tag{7}$$

Now (3) and (4) can be rewritten as

$$X(n) = F \times X(n-1) + Q(n) \tag{8}$$

$$Y(n) = H \times Y(n-1) + R(n) \tag{9}$$

The state equation is the speech equation and an observation matrix is of the speech and the noise signal. The noise is assumed to be Gaussian white noise.

The Kalman filtering algorithm recursion equation whose noise variance is δ_v is proposed as

[Initialization]

$$X(0|0) = 0, \; P(0|0) = I$$

$$R_v(n) = \delta_v^{\,2}, \; G = [1 \quad 0 \quad \cdots \quad 0]$$

$$R_s(n)[i,j] = \begin{cases} E(Y(n) \times Y(n)) - \delta_v^2 & (i, j = 1) \\ 0 & (others) \end{cases}$$

[Iteration]

$$P(n/n-1) = F \times P(n-1/n-1) \times F^T + G \times R_s(n) G^T$$

$$K(n) = P(n/n-1) \times G^T / (G \times P(n/n-1) \times G^T + R_v(n))$$

$$X(n/n-1) = F \times X(n-1/n-1)$$

$$X(n/n) = X(n/n-1) + K \times (Y(n) - G \times X(n/n-1))$$

$$P(n/n) = (I - K(n) \times G) \times P(n/n-1)$$

Where X(n/n-1): the prediction vector of x(n) based on the previous observed vectors
P(n/n-1): the autocorrelation matrix of the predicted state error vector.

K(n): the Kalman gain vector.

Here the number of iterations is equal to the number of speech signal sampling points. Hence there exists time complexity.

III. Perceptual Kalman Filtering Algorithm

From the recursive equations of the conventional Kalman filtering, one can find large number number of matrix operations which leads to an increase in the computational complexity. Hence by reducing the dimension of matrix the complexity of the algorithm is reduced to a maximum extent. During total filtering process only the **s(n)** is useful, so calculation of **s(n)** is alone done instead of calculating the vector to avoid the matrix inverse operation in the improved filtering method. Further the complexity of the algorithm is gradually reduced when compared to the conventional filtering. The recursive equations of the perceptual Kalman filtering are defined as

$$[Initialization]$$

$$s(0) = 0, \; R_v = \delta_v^{\,2},$$

$$R_s(n) = E(Y(n) \times Y(n)) - \delta_v^2$$

$$[iteration]$$

$$K[n] = R_s(n) / (R_s(n) + R_v)$$

$$s(n) = K(n) \times Y(n)$$

IV. Fast Adaptive Kalman Filtering Algorithm

The proposed method can adapt the changes in he surrounding environment by constantly updating the estimation of the noise so as to obtain the accurate expression of noise signal. The fast adaptive kalman filtering constantly updates the variance of the noise and also updates the threshold U.

1) Updating of variance of noise is obtained by

$$R_v(n) = (1-d) \times R_v(n) + d \times R_u(n)$$

Here d is the loss factor which limits the memory of the filtering. As proposed by [3]'d' is defined as

$$d = \frac{1-b}{1-b^{t+1}},$$

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Where b is a constant whose value ranges from 0.95 to 0.99. Here b is taken as 0.99. The loss factor d is used to reduce the error.

2) Updating of the threshold is known from

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

Whenever the noise is high the error is also large so again the loss factor d is used. The SNR (signal to noise ratio) of the current speech frame and the whole speech signal is defined by

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

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

Where n is the number of frames of the speech signal, $\delta_r^2(n)$ is the pure speech signal variance, $\delta_x^2(n)$ is the variance of the noisy speech input and $\delta_v^2(n)$ is the variance of environment noise.

When the speech frame noise $SNR_1(n)$ is less than or equal to the $SNR_0(n)$ else if $SNR_0(n)$ is less than zero then these frames follows $R_u(n)\le U$, however when $SNR_1(n)$ is greater than $SNR_0(n)$, the noise estimation is attenuated and is expressed as $R_v(n) = R_v(n)/1.2$.

The procedure for the fast adaptive filtering is defined as

$[Initialization]\ s(0)=0,\quad R_v(1)=\delta_v^2(1)$

$[Iteration]$

$if\ \ SNR_1(n) \Leftarrow SNR_0(n) \,\|\, SNR_0(n) < 0\ then$

$if\ \ R_u(n)\le U\ then$

1. $R_v(n) = (1-d)\times R_v(n) + d\times R_u(n)$

end

2. $U = (1-d)\times U + d\times R_u(n)$

$else$

3. $R_v(n) = R_v(n)/1.2$

end

4 $R_s(n) = E(Y(n)\times Y(n)) - R_v(n)$

5. $K[n] = R_s(n)/(R_s(n)+R_v)$

6. $s(n) = K(n)\times Y(n)$

V. Experimental Results

In this section the speech signals of male and female were recorded and the additive white Gaussian noise produced by using awgn function. The variance of the noise $\delta_v{}^2$ is assumed to be known and the SNR of the noise signal is defined by

$$SNR_{in} = 10\log[\{\frac{1}{n+1}\sum_{i=0}^{n} d^2(i)\}/\delta_v^2]dB$$

The efficiency of the filter is known by comparing the signal to noise ratio. The SNR of the filter output is calculated by

$$SNR_{out} = 10\log[\sum_{i=0}^{n} d^2(i)\}/\sum_{i=0}^{n}\{d(i)-d(i)\}^2]dB$$

Where $d(i)$ is the filtered speech signal. Fig. 1 shows the simulation result of the pure speech signal of the female speech of the duration 4 seconds and the additive white Gaussian noise signal. Next the different filtering patterns using conventional kalman filtering, perceptual kalman filtering and fast adaptive kalman filtering is observed.

And fig.2 shows the simulation samples of the male speech of duration 4 seconds and the different filtering techniques results.

The simulation result is compared in two different phases: (a) accuracy and (b) running time.

(a) To compare the accuracy of the filtering methods the SNR is calculated. Table I shows fast adaptive kalman filter achieves high performance filtering accuracy when compared to remaining filtering methods.

TABLE I

	Signal to noise ratio		
	Conventional	Perceptual	Fast adaptive
Female	4.8956	14.1681	14.8592
Male	0.8696	2.0736	2.9833

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(b)Table II shows the comparison of the running time of the fast adaptive kalman filter with the conventional and the perceptual filter. It is clear that the fast adaptive kalman filter running time is comparatively very less than the other techniques. The running time depends on the speech signal duration. Here the speech signal taken is of 4secs of both male and female speech. The running time is improved without degrading the quality of speech.

TABLE II

	RUNNING TIME(SEC)		
	CONVENTIONAL	PERCEPTUAL	FAST ADAPTIVE
FEMALE	12.1601	19.5327	8.3055
MALE	14.2790	19.8904	8.4766

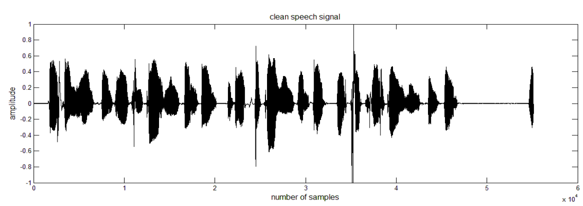

Fig.1. Clean female speech signal

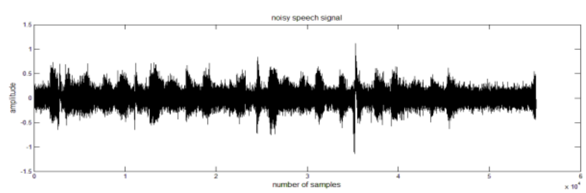

Fig.2. Noisy female speech signal

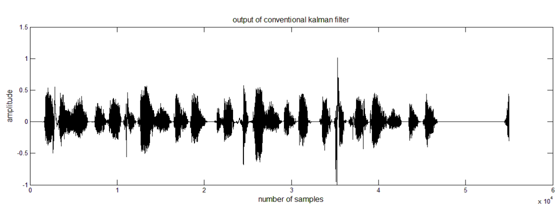

Fig.3. Output of conventional kalman filtering

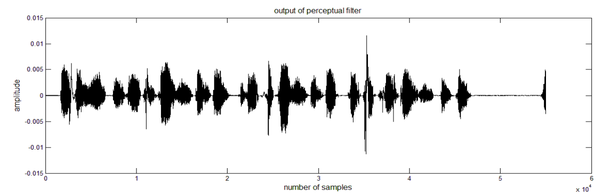

Fig.4. Output of perceptual filter

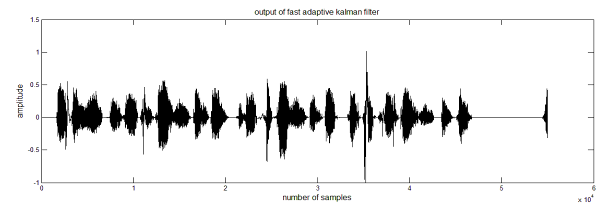

Fig.5. Output of fast adaptive kalman filter

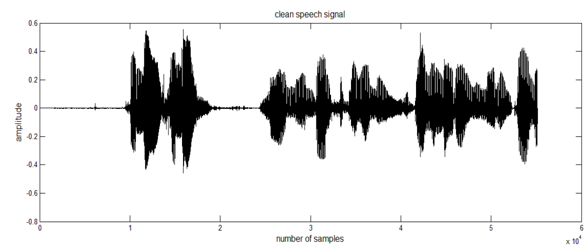

Fig.6. Clean Male Speech Signal

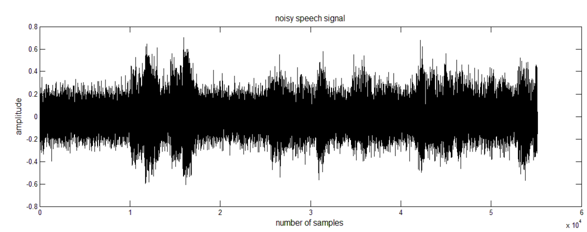

Fig.7.Noisy male speech signal

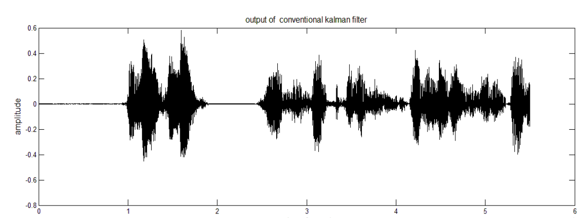

Fig.8. Output of conventional kalman filtering

EXPLORING RESEARCH AND INNOVATIONS

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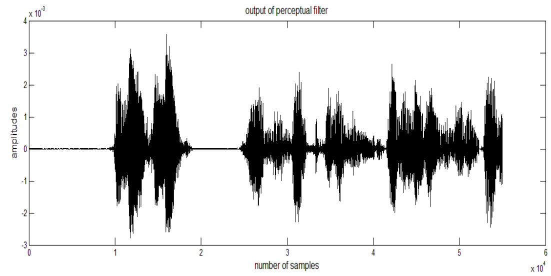

Fig.9. Output of perceptual filter

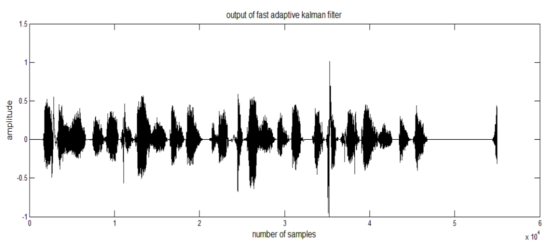

Fig. 10. Output of fast adaptive kalman filter

VI. CONCLUSION

In this paper the process of noise removal from the speech signal using fast adaptive kalman filtering is presented. The experimental results shows that the proposed algorithm can effectively suppress the presence of noise in the speech signal with the reduction in the computational complexity and at the same time it reduces the running time without sacrificing quality of the speech signal.

At the hardware level this algorithm can be applied to the embedded-speech-recognition system for the improvement of system robustness.

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