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Speech Quality Enhancement Using Fast Adaptive Kalman Filter

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Abstract- **Due to the existence of the background noise speech quality and intelligibility might significantly decline, mainly when the speech signal is subjected to subsequent processing. Especially, automatic speech recognition (ASR) systems and voice coders were designed to perform on pure speech signals might be in effective due to the existence of background noise. The traditional Kalman filter algorithm executes a plenty of matrix operations and it needs to compute the AR (auto-regressive) model parameters, for speech enhancement. Usually, the standard Kalman filter algorithm is non-adaptive. The improved Kalman filter algorithm proposed in this paper removes the matrix calculations and decreases the computation time by constantly upgrading the first value of the state vector X (n). A coefficient factor is designed for adaptive filtering in order to rectify the evaluation of background noise. Speech enhancement techniques and its algorithms are attracted many researchers. The speech extension technique is one of the effective techniques to resolve the speech degenerated by noise. We presented Kalman filter-based algorithms with some enlargements, adjustments, and developments of foregoing work. In this paper a fast speech enhancement method for noisy speech signals is presented, which is based on improved Kalman filtering. Fast adaptive Kalman filter is designed for the removal of the noises in the signals. The process of denoising input speech signals is more helpful in the process of providing efficient sound system. 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. Simulation results show that the fast adaptive Kalman filtering algorithm is quite effective for speech enhancement.**

Index Terms- **Fast adaptive kalman Filter, speech enhancement ,Linear Prediction coding**

INTRODUCTION

Speech or voice signals can be corrupted by background noise-like traffic noise, mall noise, babbles noise, etc., in voice communication. As the result of the background noise the communication quality will be affected with less intelligibility. The speech-enhancement techniques can improve the speech signals quality. The Kalman filtering technique is one of those techniques to improve the speech quality. There are so many applications depending on the Kalman filtering algorithm. The noisy speech signals are modelled by it and represented in form of observation equation and state space equation. A standard Kalman filtering algorithm results in a very high computational complexity as it needs to perform the calculations of linear prediction coding (LPC) coefficient and inverse matrix calculations. Years and years ago, depending on Kalman filtering algorithm there were a plenty of applications in the speech enhancement.

Most of the methods need to evaluate the parameters of the auto regressive model, and perform the noise elimination by using the conventional one. In this method, the computations of inverse matrix and linear prediction coding coefficient would greatly increase the computational complexity. Even though these methods can attain a better filtering efficiency, the noise suppressed signal may destroy the quality of the speech signal depending on estimation of the AR model parameters. A simple conventional Kalman filtering algorithm has given by the previous methods without computing any LPC coefficient of the AR model. However this algorithm still holds a much number of matrix inverse operations and unnecessary data. Moreover, this algorithm is non-adaptive. We introduce a fast adaptive Kalman filtering algorithm for speech enhancement in order to eliminate the drawback of the conventional Kalman filtering. This fast adaptive filtering method will constantly upgrades the initial value of a state vector X (n), so that it reduces the time complexity and eliminates the matrix operations. Literally, it is arduous to find which kind of background noise is exactly and it will affect the applications of the Kalman filtering algorithm. That is why we require a real-time algorithm in order to estimate the surrounding noise. In order to catch the real noise we add the forgetting factor to amend the evaluation of background noise by using the observation data accordingly. The fast adaptive algorithm of Kalman filtering is more efficient than the conventional Kalman filtering algorithm. In the meanwhile, it improves speech signal quality by reducing its running time. It has the good adaptability in order to have the robustness.

The main aim of the speech enhancement technique is to reduce or eliminate environmental noise without distorting the speech signal. In the Kalman filtering algorithm usually the speech signal is modeled as an autoregressive (AR) process with the LPC (linear prediction coding) coefficient and is known as an effective speech enhancement technique. So many filtering techniques have been developed to study the issue caused by the noise in the speech signal.

The advantage of the Kalman filtering for speech enhancement was formerly introduced by Basu and Paliwal. The simulation results show its distinct advantage on the Wiener filter, for the case where the estimated speech parameters are obtained from the clean speech signal. Here the clean speech is nothing but before being corrupted by the noise. Gibson et al. was proposed to improve the advantage of the Kalman filter by consolidating a colored noise in order to achieve the better enhancement performances for some particular class of noises. The drawback of the Kalman filtering algorithms is that they have not given any address to model parameters estimation problem. Gibson and Koo proposed an algorithm that repeats between the corrupted speech measurements of the Kalman filtering, and the enhanced speech waveform given by estimated speech parameters. The originating algorithm is known as an approximated EM algorithm.

Kalman filtering algorithm for speech enhancement

Conventional Kalman Filtering Algorithm

An auto regressive (AR) process can be represented in the form of speech. An all-pole linear system output is essentially an auto regressive (AR) process, which is driven by white noise sequence. Therefore the speech signal at n-th time instant, s (n) is given by:

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

Where,

$a_i(n)$ is the LPC coefficient and,

W (n) is the white Gaussian noise with mean zero and variance $\delta_u{}^2$.

In the real environment, due to an additive observation noise v(n) the speech signal s(n) is degraded. V(n) is the additive observation noise with mean is zero, and its variance is $\delta_v{}^2$. An additive observation noise is not related to s(n).

The above equation can be expressed as the state equation which is given by

[State equation]

$$X(n) = F\,X(n-1) + Gu(n)$$

Where

1. The sequences u(n) is the Gaussian white noise whose mean is zero and the variances is $\delta_u{}^2$.

2. X(n) is the L× 1 state vector

$$X^T(n) = [s(n-L+1)\ldots s(n-1), s(n)]$$

3. $F(n)$ is the L × L transition matrix

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

4. G is the L×1 input vector which is defined as follows:

G = [0 0 . . . . . 1]

When only the noise corrupted signal y (n) is available, the observation process can be written in the following form: y(n) =s(n) +v(n)

This equation can be written in the matrix form as follows:

y(n) =H x(n) +v(n)

Where

1. The sequences v (n) is Gaussian white noise whose mean is zero and the variances is $\delta_v{}^2$.

2. x(n) is the state vector already defined by equation (4)

3. H is the observation matrix given by:

H $= G^T$ = [0 0 . . . . 0 1]

The conventional Kalman filtering is using the LPC coefficient to estimate the observations of the speech signal [6]. This part require half the time of the whole algorithm. In [2] the transition matrix F and the observation matrix H are modified. They has defined as

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

It also has defined the L×1 state vector, $X(n) = [S(n) \ldots S(n-L+1)\ S(n-l+2)$, the L□1 input$Q(n)^T = [S(n)\ \ 0 \ldots 0]$, and L×1 the observation vector

$R(n) = [1, v(n), \ldots v(n-l+2)$, finally the state equation and observation equation can be rewritten into the matrix equations by

[State equation]

$$X(n) = F \times X(n-1) + Q(n)$$

[Observation equation]

$$Y(n) = H \times X(n) + R(n)$$

Then the recursion equation of Kalman filtering algorithm is given below. In this case the noise variance $\delta_v{}^2$ is known.

The Kalman filtering algorithm provides the updating state vector estimator equations

[Initialization]

$X(0 \mid 0) = 0$, $P(0 \mid 0) = I$

$R_v(n) = \delta_v^2$, $G = [0\ 0 \ldots 1]$

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

[Iteration]

$e(n) = y(n) - H \times X(n/n-1)$

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

$K(n) = P(n-1/n-1) \times H^T \times [G \times P(n/n-1)G^T + R_s(n)]^{-1}$

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

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

$P(n/n) = [I - K(n)H] \times P(n/n-1)$

Where

1.X(n/n − 1) is the minimum mean-square estimate of the state vector X(n) given the past n − 1 observations y(1) . . . , y(n − 1)

2. X(n/n − 1) = X(n) – X(n/n − 1) is the predicted state-error vector

3. P(n/n − 1) = E[x(n/n − 1)XT (n/n − 1)] is the predicted state- error correlation matrix

4. X(n/n) is the filtered estimate of the state vector x(n)

5. X(n/n) = X(n) − X(n/n) is the filtered state-error vector

6. P(n/n) = E[X(n/n)×XT (n/n)] is the filtered state error correlation matrix

7. e(n) is the innovation sequence

8. K(n) is the Kalman gain

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

Perceptual Kalman Filtering Algorithm

From the equations of the conventional Kalman filtering, one can find large number of matrix operations which leads to an increase in the computational complexity. Hence the complexity of the algorithm is reduced to maximum extent. To avoid the matrix inverse operation in the improved filtering method, calculation of s(n) is alone done. The estimated speech signal can be retrieved from the state vector estimator

s(n) =H×X(n/n)

The recursive equations of the perceptual Kalman filtering are defined as:

[Initialization]

$s(0)=0$, $R_v(n) = \delta_v^2$, $R_s(n) = E(y(n) \times y(n)) - \delta_v{}^2$

[Iterations]

$K(n) = R_s(n) / (R_s(n) \times R_v)$

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

Fast adaptive Kalman filtering algorithm

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

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

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

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

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

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

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.

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

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

Where n is the number of speech frames, and $\delta_v{}^2$ has been updated in order to achieve a higher accuracy. The speech frame is noise when $SNR_1(n)$ is less than or equal to $SNR_0(n)$, $SNR_0(n)$ or is less than zero, and then these frames will be follow the second limitation $R_u(n) \leq U$. However, if $SNR_1(n)$ is larger than$SNR_0(n)$, the noise estimation will be attenuated to avoid damaging the speech signals. According to [7], this attenuation can be expressed as

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

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

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

[Iterations]

If $SNR_1(n)$ <=$SNR_0(n)$ || $SNR_0(n)$ <0 then

If $R_u(n) \leq U$ then

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

End

2) $d=(1\text{-}b)/(1\text{-}b^2)$
3) $U=(1\text{-}d) \times U + d \times R_u(n)$

Else

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

End

5) $R_s(n)= E(y(n) \times y(n))\text{-} R_v(n)$

6) $K(n)= R_s(n)/ (R_s(n)+R_v(n))$
7) $s(n) = K(n) \times y(n)$.

CONCLUSION

A fast adaptive Kalman filtering algorithm has presented in this paper for speech enhancement, which designs a coefficient factor and eliminates the matrix operations. The subjective evaluation results and numerical results showed that our proposed algorithm is adequately effective. Conspicuously, as the proposed method involves two-step multiplications in each procedure, it needs less running time. When the speech signals are degenerated by the colored noise, the SNRout of our method is higher. Depending on the fast adaptive Kalman filtering process, the input speech signals were denoised by using a signal subspace algorithm. A denoised speech signals is employed in our proposed approach, were more useful in speech applications. It is concluded that this proposed algorithm is quite simpler and reduces the computational complexity without relinquish the standard speech signal.

Furthermore, based on this paper we will improve the adaptive algorithm to make it a more meticulous evaluation of background noise. However, the proposed algorithm will be applied to the embedded-speech-recognition system in order to improve the robustness of the system, at the hardware level.

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