

Speech Enhancement Using Adaptive Kalman Filter Combined With Perceptual Weighting Filter

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Abstract: The speech enhancement is one of the important techniques used to improve the quality of a speech signal i.e. degraded by noise. Speech enhancement using conventional Kalman filter requires calculating the parameters of AR (auto-regressive) model, and performing a lot of matrix operations, which is non-adaptive. In this paper the proposed method i.e. adaptive Kalman filter combined with perceptual weighting filter is used to eliminate the matrix operations, reduce the calculating time and reduce the complexity. However the perceptual characteristics of the speech signal depend upon the perceptual characteristics of the human ear. To further improve the performance of the speech enhancement system, an adaptive Kalman filter combined with a perceptual weighting filter, which is based on the masking characteristics of the human auditory system, is used. Comparison with the previous method shows it is very effective for speech enhancement.

Keywords: conventional Kalman filter, Speech enhancement, adaptive Kalman filter, Perceptual weighting filter, SNR.

I. Introduction

Kalman filtering is a mathematical method named after Rudolf E. Kalman (1960), through Peter Swerling, who actually developed a similar algorithm earlier (Kalman (1960) and Kalman and Bucy (1961)). It was developed as a recursive solution to the discrete-data linear filtering problem.

A Kalman filter is simply an optimal recursive data processing algorithm. There are many ways of defining optimality, dependent upon the criteria chosen to evaluate performance.

The Kalman filter is optimal with respect to virtually any criterion that makes sense. One aspect of this optimality is that the Kalman filter incorporates all information that can be provided to it. The different methods were proposed by [2]-[6]. Many of the methods need to estimate the parameters of the AR model at first, and then perform the noise reduction using the Kalman filter algorithm. In this process, the calculation of the LPC (linear prediction coding) coefficient and the inverse matrix increase the complexity of the filtering algorithm. [3] and [4] have given a simple Kalman filtering algorithm without calculating the LPC coefficient in the AR model, but the algorithm still contains a large number of redundant data and matrix inverse operations. This algorithm is non-adaptive.

To overcome the drawback of the conventional Kalman filter for speech enhancement, a new method i.e. adaptive Kalman filter combined with perceptual weighting filter is proposed. This algorithm constantly updates the first values of the state vector $Z(n)$, which eliminates the matrix operations and reduces the complexity of the algorithm. Identification of the exact type of environmental noise is difficult and it affects the application of the Kalman filtering algorithm. So we need a real-time adaptive algorithm to estimate the ambient noise. The perceptual weighting filter is used to provide human auditory characteristics. Simulation results show that, compared with the conventional Kalman filtering algorithm, the adaptive algorithm of Kalman filtering is more effective. At the same time, it reduces its running time without sacrificing the quality of the speech signal. And also simulation results show that, compared with the conventional Kalman filter and adaptive Kalman filtering algorithm, perceptual weighting filtering is more efficient in the case of human auditory systems.

II. Kalman Filtering Algorithm

A. Conventional Kalman Filtering Method

A clean speech signal $s(n)$ can be defined as a p -th (AR) autoregressive process and n -th of the noisy speech signal $y(n)$ is expressed as

$$s(n) = \sum_{i=1}^p a_i(n)s(n-i) + w(n) \quad (1)$$

In (1), a_i is the i -th AR coefficient, $w(n)$ is the white Gaussian noise which has a mean of zero and a known variance.

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

In (2) $v(n)$ is the additive observation noise, its mean is zero and its variance is known.

In this paper, it is assumed that the variance is known, but in practice we need to estimate it by the initial segment included in the $y(n)$.

(1) and (2) can be expressed as the state equation and the observation equation which are given by

State equation is

$$x(n) = F(n)x(n-1) + Gw(n) \quad (3)$$

Observation equation is

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

$F(n)$ is the p by p transition matrix expressed as

$$F(n) = \begin{bmatrix} 0 & 1 & 0 & \dots & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 & \\ & \vdots & & \ddots & & \vdots \\ 0 & 0 & 0 & \dots & 1 & \end{bmatrix} \quad (5)$$

Where G is the input vector and H is the observation vector.

By using the LPC coefficient in the conventional Kalman filter is to estimate the observations of the speech signal, this process is easy. This part spends half the time of the total algorithm.

The transition matrix F and the observation matrix H are modified. They have defined as

$$F = H = \begin{bmatrix} 0 & 0 & 0 & \dots & \dots & 0 \\ 1 & 0 & 0 & \dots & 0 & \\ & \vdots & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & \dots & 0 \end{bmatrix} \quad (6)$$

It is also defined as the $p \times 1$ state vector $Z(n) = [s(n), \dots, s(n-p+1), s(n-p+2)]$, the $p \times 1$ input vector $Q(n) = [s(n), 0, \dots, 0]$, and the $1 \times p$ observation vector $R(n) = [1, v(n), \dots, v(n-p+2)]$.

Finally, (3) and (4) can be written into the matrix operations by

State equation is

$$Z(n) = F \times Z(n-1) + Q(n) \quad (7)$$

Observation equation is

$$Y(n) = H \times Z(n) + R(n) \quad (8)$$

State equation consisted of the speech signal, and an observation equation consisted of the speech signal and additive noise [3].

The purpose of each iteration of a Kalman filter is to update the estimation of the state vector of a system (and the covariance of that vector) based upon the information in a new observation.

The recursive estimation of Kalman filtering algorithm is shown below

$$Z(0|0) = 0, M(0|0) = I \quad (9)$$

$$T_V(n) = \delta_v^2 \quad (10)$$

$$T_S(n)[i, j] = \begin{cases} E(Y(n) * Y(n)) - \delta_v^2 & (i, j = 1) \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

[iteration]

$$M(n|n-1) = F * M(n-1|n-1) * F^T + G * T_S(n) * G^T \quad (12)$$

$$K(n) = M(n|n-1) * G^T / (G * M(n|n-1) * G^T + T_V(n)) \quad (13)$$

$$Z(n|n-1) = F * Z(n-1|n-1) \quad (14)$$

$$Z(n|n) = Z(n|n-1) + K * (y(n) - G * Z(n|n-1)) \quad (15)$$

$$M(n|n) = (I - K * G) * M(n|n-1) \quad (16)$$

$$S(n) = K * y(n) \quad (17)$$

In the above case the noise variance δ_v^2 is known. This algorithm abrogates the computation of the LPC coefficient.

B. Adaptive Kalman Filtering Algorithm

Due to the noise changes with the surrounding environment, it is necessary to constantly update the estimation of noise. So we can get a more accurate expression of noise. An adaptive Kalman filtering algorithm for speech enhancement can adapt to any changes in environmental noise, and also it can constantly update the estimation of background noise.

Everyone known Kalman filtering algorithm is very well. Adaptive kalman filtering algorithm can estimate system process noise and measurement noise on-line according to the measured value and filtered value, tracking changes of noise in real time to amend the filter parameters, and improve the filtering effect. In this adaptive kalman filter, we can set a reasonable threshold, it is used to determine whether the current speech frame is noise or not. It consists of mainly two steps: one is updating the variance of the environmental noise $T_v(n)$, and the second one is updating the threshold U .

1) Updating the variance of the environmental noise by

$$T_v(n)=(1-d)\times T_v(n)+d\times T_u(n) \quad -(18)$$

In above equation d is the loss factor that can limit the length of the filtering memory, and enhance the role of new observations under the current estimates. Making new data play a major role in the estimation, and leaving the old data forgotten gradually. According to the [7].....? its formula is

$$d=1-b/1-b^{t+1} \quad -(19)$$

b is the forgetting factor ($0 < b < 1$), usually ranged from 0.95 to 0.99. In this paper the value of b is considered 0.99.

before implementation of (18), we will compare between the variance of the current speech frame $T_u(n)$ and threshold U which has been updated in the previous iteration. If $T_u(n)$ is less than or equal to U the current speech frame can be considered as noise, and then the algorithm will re-estimate the noise variance.

In this paper, $T_u(n)$ can't replace $T_v(n)$ directly. In order to reduce the error, we used.

2) Updating and threshold by

$$U=(1-d)*U+ d* T_u(n) \quad -(20)$$

In (17), d is used again to reduce the error. However, there will be a large error when the noise is large, because the updating threshold U is not restricted by the limitation $T_u(n) < U$. It is only affected by $T_u(n)$. So we must add another limitation before implementation of (20). In order to rule out of speech frames which their SNR (Signal-to-noise rate) is high enough, it is defined that δ_r^2 is the variance of pure speech signals, δ_x^2 is the variance of the input noise speech signals, and δ_v^2 is the variance of background noise. we calculate two SNRs and compare between them. According to [6], one for the current speech frame is

$$SNR_1(n)=10 \times \log_{10} \left(\frac{\delta_r^2(n)-\delta_v^2(n)}{\delta_v^2(n)} \right) \quad -(21)$$

Another for the whole speech signal is

$$SNR_0(n)=10 \times \log_{10} \left(\frac{\delta_r^2-\delta_v^2(n)}{\delta_v^2(n)} \right) \quad -(22)$$

In (21) and (22), n is the number of speech frames, and δ_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 $SNR_0(n)$, or $SNR_0(n)$ is less than zero and then these frames will be followed by the second limitation ($T_u(n) \leq U$). However, if $SNR_1(n)$ is larger than $SNR_0(n)$, the noise estimation will be attenuated to avoid damaging the speech signals.

C. Perceptual Weighting Filter Algorithm

Weighting filters are widely used in the measurement of electrical noise on telephone circuits, and in the assessment of noise as perceived through the acoustic response of different types of instruments.

Usually, the perceptual weighting procedure often results in speech coder performance. A commonly used weighting filter is based on the linear prediction coefficients that represent the short-term correlation in the speech signal [8]. A representative perceptual weighting filter $W(z) = \frac{A(z)}{A(\gamma)}$ is given by

Where $A(z)$ represents the p th-order LP analysis filters and a_i is the LP coefficient. To compute the filter coefficients for this filter, linear predictive analysis is used in [8]. Also, γ is a perceptually weighting factor which does not alter the center formant frequency, but just broadens the bandwidth of the formants. Specifically, frequency broadening δ_f given by $\delta_f = (fs/\pi) \ln \gamma$. Where fs is the sampling frequency in hertz.

For that reason, the weighting filter deemphasizes the formant structure while emphasizing the formant valleys of the speech signal. This results in a larger matching error in the region of the formants, where spectral masking makes the auditory systems less sensitive to quantization error. The most suitable value of γ is subjectively selected by listening tests, and for 8KHZ sampling, γ is adopted as 0.9 here.

III. Matlab Simulation

The comparison between the Conventional, the Fast Filtering Method and perceptual weighting filter
The Performance Evaluation of Adaptive Method:

The conventional and improved filtering method is called non-adaptive method for short and the adaptive algorithm of kalman filtering is called adaptive method for short. We will compare the simulation result in 2 different phases: (a) signal wave, (b) performance for the non adaptive method, adaptive and perceptual weighting filter method.

In these simulations, two pure speech signals, which have been added with the colored noise, are selected the male and female speech signals in above section.

(a) Compare the filtering efficiency in the view of signal wave. we can see that the adaptive method can achieve higher performance noise suppression capability than the non-adaptive method while the back ground noise changes all the time.

(b) Below table shows the results of the filtering efficiency SNR_{out} under the condition $SNR_{in}=6.71$ [dB] for the female signal and $SNR_{in}=3.40$ [dB] for the male signal. Below table shows that the SNR_{out} of the adaptive method is higher than the non-adaptive method when the speech signals is degraded by the colored noise.

TABLE
SNROUT RESULT FOR THE NOISY SPEECH SIGNAL WITH COLORED NOISE

| SNR _{in} [dB] | | SNR _{out} [dB] | | |
|------------------------|------|-------------------------|----------|----------------------|
| | | Non-adaptive | Adaptive | Perceptual weighting |
| Female | 6.71 | 9.35 | 10.57 | 14.197 |
| Male | 3.40 | 4.90 | 5.05 | 9.014 |

From (a) and (b), it is clear that the adaptive method can achieve higher performance noise suppression capability than the non-adaptive method when the speech signal is degraded by the colored noise.

Different filtering methods comparison of MSE for male and female speech signal

| Speech Signal | Kalman Filter | Adaptive Kalman Filter | Perceptual Weighting Filter |
|---------------|---------------|------------------------|-----------------------------|
| Male | 0.432 | 0.0451 | 0.002 |
| Female | 0.324 | 0.0321 | 0.001 |

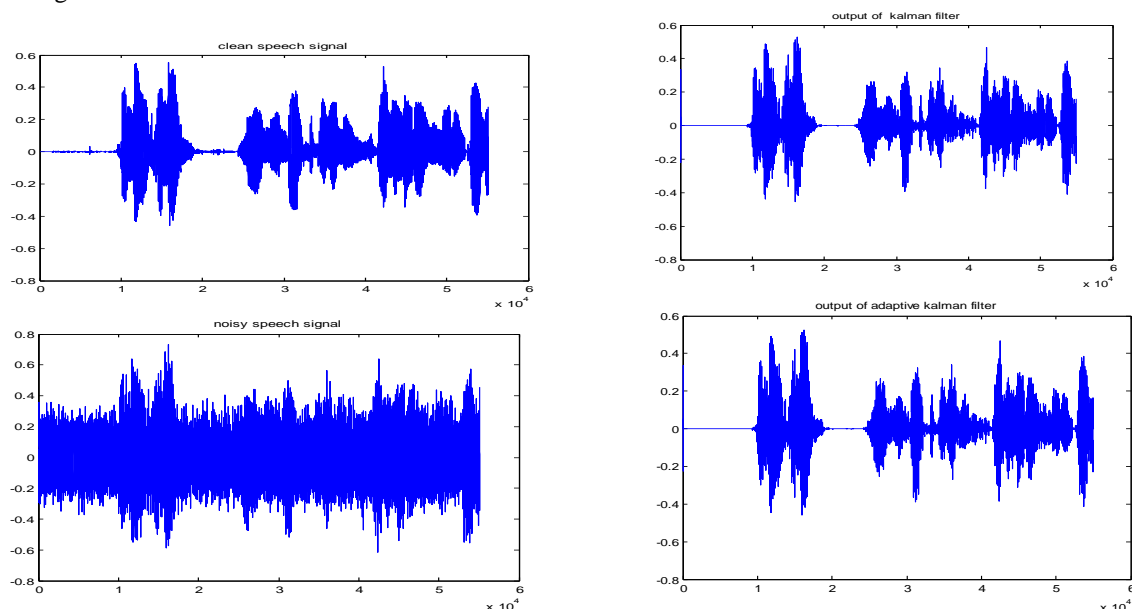
Different filtering methods comparison of CPU time for male and female speech signal

| Speech Signal | Kalman Filter | Adaptive Kalman Filter | Perceptual Weighting Filter |
|---------------|---------------|------------------------|-----------------------------|
| Male | 9.603 sec | 5.773 sec | 3.801 sec |
| Female | 8.560 sec | 3.456 sec | 2.956 sec |

From (a) and (b), it is clear that the adaptive method can achieve higher performance noise suppression capability than the non-adaptive method when the speech signal is degraded by the colored noise.

Comparisons of above three tables SNR, MSE, and CPU time. The proposed method is very better.

For all the testing results, the figures and tables shows that the proposed method is simpler and can achieve a better filtering efficiency despite greatly reducing running time without sacrificing quality of the speech signal.



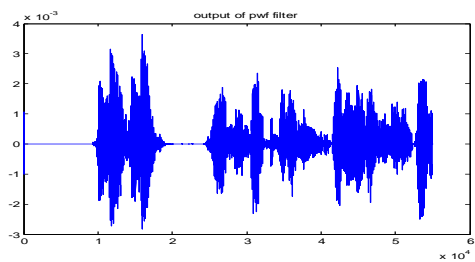


Fig.1. the filtering results for the male speech with noise.

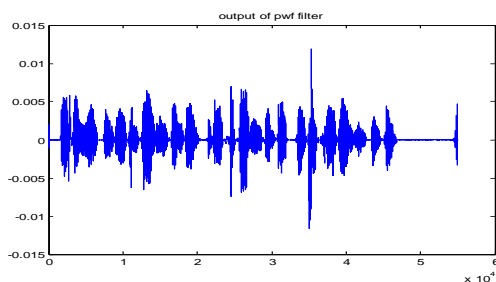
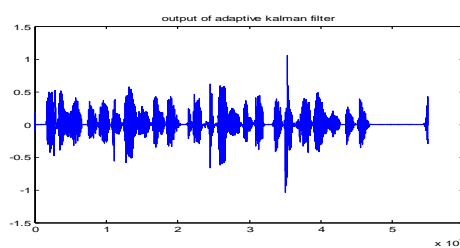
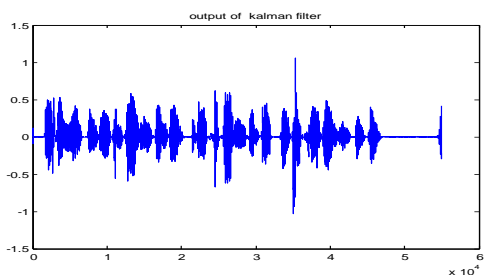
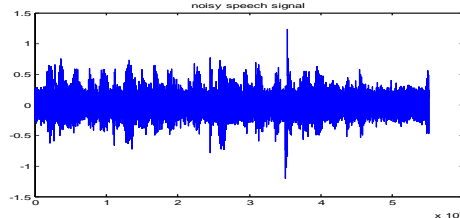
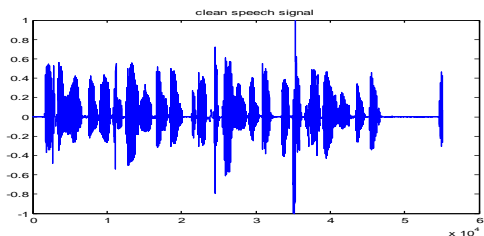


Fig.2. the filtering results for the female speech with noise.



IV. Conclusion

This paper has presented speech enhancement using adaptive kalman filter combined with perceptual weighting filter by eliminating the matrix operation and designing a coefficient factor, and also provide human auditory characteristics. It has been shown by numerical results and subjective evaluation results that the proposed algorithm is fairly effective.

Especially the proposed method of two state multiplications in each procedure so that it requires Less running time and the SNR_{out} of this proposed method is higher when the speech signals are degraded by the colored noise. It is concluded that is proposed algorithm is simpler and can realize the good noise suppression despite the reduction of the computational complexity without sacrificing the quality of the speech signal. In the further study, we will improve the adaptive algorithm based on this paper to make it a more accurate assessment of environmental noise.

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