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A Effective Speech Enhancement By Using Robust Adaptive Kalman Filtering Algorithm

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Abstract

In This paper Introduces a new technique for speech enhancement to enhance speech degraded by noise corrupted signal. When speech signal with an additive Gaussian white noise is the only information available processing. So many techniques are to improve the efficiency for enhancement. Kalman filter is one of the technique for speech enhancement. But in kalman filter needs to calculate the parameters of Auto-Regressive model, For this a lot of matrix operations required. In which speech signal is usually modeled as autoregressive (AR) process and represented in the state-space domain. In this paper presents a alternative solution for estimate the speech signal. In proposed technique to eliminates the matrix operations and calculating time by only constantly updating the first value of state vector X(n). The experiments results show that the Improved algorithm for adaptive Kalman filtering is effective for speech enhancement.

Keywords- Kalman Filter, Speech Enhancement, AR model, Noise

I. INTRODUCTION

Speech enhancement aims to improve speech quality by using various algorithms. Intelligibility and pleasantness are difficult to measure by any mathematical algorithm. Usually listening tests are employed. However, since arranging listening tests may be expensive, it has been widely studied how to predict the results of listening tests. No single philosopher's stone or minimization criterion has been discovered so far and hardly ever will.

The central methods for enhancing speech are the removal of background noise, echo suppression and the process of artificially bringing certain frequencies into the speech signal. We shall focus on the removal of background noise after briefly discussing what the other methods are all about. First of all, every speech measurement performed in a natural environment contains some Amount of echo. Echoless speech, measured in a special anechoic room, sounds dry and dull to human ear. Echo suppression is needed in big halls to enhance the quality of the speech signal. it is crucial not to harm or garble the speech signal. Or at least not very badly. Another thing to remember is that quiet natural background noise sounds more comfortable than more quiet unnatural twisted noise. If the speech signal is not intended to be listened by humans, but driven for instance to a speech recognizer, then the comfortless is not the issue. It is crucial then to keep the background noise low.

Background noise suppression has many applications. Using telephone in a noisy environment like in streets of in a car is an obvious application. All the speech enhancement methods aimed at suppressing the background noise are (naturally) based in one way or the other on the estimation of the background noise. If the background noise is evolving more slowly than the speech, i.e., if the noise is more stationary than the speech, it is easy to estimate the noise during the pauses in speech. Finding the pauses in speech is based on checking how close the estimate of the background noise is to the signal in the current window. Voiced sections can be located by estimating the fundamental frequency. Both methods easily fail on unstressed unvoiced or short phonemes, taking them as background noise.

In this approach the signal is modeled as an AR process. The estimation of time-varying AR signal model is based on robust recursive least square algorithm with variable forgetting factor. The variable forgetting factor is adapted to a non stationary signal by a generalized likelihood ratio algorithm through so-called discrimination function, developed for automatic detection of abrupt changes in stationarity of signal. In this paper the signal is modeled as an AR process and a Kalman filter based-method is proposed by reformulating and adapting the approach proposed for control applications by Carew and Belanger [7]. This method avoids the explicit estimation of noise and driving process variances by estimating the optimal Kalman gain.

After a preliminary Kalman filtering with an initial sub-optimal gain, an iterative procedure is derived to estimate the optimal Kalman gain using the property of the innovation sequence.

II. IMPROVED KALMAN FILTERING ALGORITHM

A. Conventional Kalman Filtering Method:

Speech driven by white noise is All-pole linear output from the recursive process. Under the short-time stable supposition, a pure speech can establish L step AR model by

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

(1)

In (1) $a_i(n)$ is the LPC coefficient, ω(n) is the white Gaussian noise which the mean is zero and the variance is. In the real environment, the speech signal s(n) is degraded by an additive observation noise v(n). Its mean is zero, and its variance is δ_v^2.This noise isn't related to s(n) . A noisy speech signal y(n) is given by

$$\mathbf{y(n) = s(n) + v(n)}$$

(2)

In this paper, it is assumed that the variance δ_v^2 is known, but in practice we need to estimate it by the "silent 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]

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

(3)

[Observation equation]

$$y(n)=Hx(n)+v(n)$$

(4)

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

(5)

F(n) is the L X L transition matrix expressed as G is the input vector and H is the observation vector. It is easy to see that the conventional Kalman filtering is using the LPC coefficient to estimate the observations of the speech signal. This part spends half the time of the whole algorithm.

In [2] the transition matrix F and the observation matrix H are modified. They has defined as

$$F=H=\begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}$$

(6)

It also has defined the L×1 state vector X(n) =[s(n) ....s(n-L+1) s(n-L+2)] , the L×1input vector Q(n = [s(n) 0 …… 0] , and the 1× L observation vector R(n) = [1,v(n),...v(n-L+ 2)] .Finally, (3) and (4) can be rewritten into the matrix equations by

[State equation]

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

(7)

[Observation equation]

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

(8)

Then the recursion equation of Kalman filtering algorithm is given in Table I. In this case the noise variance δ_v^2 is known.

TABLE I
THE CONVENTIONAL METHOD PROCEDURE

[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]

$$P(n/n-1)=F\times P(n-1/n-1)\times F^T+G\times R_s(n)\times G^T \quad (9)$$

$$K(n)=P(n/n-1)\times G^T/(G\times P(n/n-1)\times G^T+R_v(n)) \quad (10)$$

$$X(n/n-1)=F\times X(n-1/n-1) \quad (11)$$

$$X(n/n)=X(n/n-1)+K\times(y(n)-G\times X(n/n-1)) \quad (12)$$

$$P(n/n)=(I-K(n)\times G)\times P(n/n-1) \quad (13)$$

This algorithm abrogates the computation of the LPC coefficient. The number of calls for the filtering equations is equal to the number of sampling point's n of the speech signals, so the algorithm's time complexity is O (Ln).

B. Improved Filtering Method:

By the recursive equations of the conventional Kalman filtering algorithm, we can find that (5) - (13) contain a large number of matrix operations. Especially, the inverse matrix operations lead to an increase in the algorithm's complexity. If we can reduce the dimension of matrix or eliminate matrix operations, we can greatly reduce the complexity of the algorithm. In Table I, we can find that (11) constantly pans down the value of state vector X(n), and then (12) constantly updates the first value s(n) of X(n). However, during the whole filtering process, only the value of s(n) is useful. So we can use the calculation of s(n) instead of the calculation of the vector in order to avoid the matrix inversion[4]. Furthermore, computational complexity of the algorithm can be reduced to O(n). The recursive equations of the improved filtering method are shown in Table II.

TABLE II
AN IMPROVED FILTERING METHOD PROCEDURE

[Initialization]	
$s(0)=0$, $R_v=\delta_v^2$,	
$R_s(n)=E(y(n)\times y(n))-\delta_v^2$	
[iteration]	
$K(n)=R_s(n)/(R_s(n)+R_v)$	(14)
$s(n)=K(n)\times y(n)$	(15)

C. **The Adaptive 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. Here we further improve the Kalman filter algorithm, so that it can adapt to any changes in environmental noise and become a fast adaptive Kalman filtering algorithm for speech enhancement. The key of the fast adaptive algorithm is that it can constantly update the estimation of background noise. We can set a reasonable threshold to determine whether the current speech frame is noise or not. It consists of two steps: one is updating the variance of environmental noise, $R_v(n)$ the other is updating the threshold U[5].

*1)*Updating the variance of environmental noise by

$$R_v(n)=(1-d)\times R_v(n)+d\times R_u(n) \quad (16)$$

In (16), 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. According to [4] its formula is

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

(17)

(B is a constant between 0.95 and 0.99. In this paper, it is 0.99) Before the implementation of (16), we will use the variance of the current speech frame $R_u(n)$ to compare with the threshold U which has been updated in the previous iteration. If $R_u(n)$ 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, $R_u(n)$ can't replace directly $R_u(n)$, because we do not know the exact variance of background noise. In order to reduce the error, we use d.

2) Updating the threshold by

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

(18)

In (15), 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 $R_u(n)$ <U. It is only affected by $R_u(n)$ So, we must add another limitation before implementation (18). In order to rule out the speech frames which their SNR (Signal-to-noise rate) is high enough, it is defined that δ_r^2 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 frames is

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

(19)

Another for whole speech signal is

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

(20)

In (19) and (20), 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 follow the second limitation ($R_u(n) \le$ U) [6]. 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 implementation process for the whole algorithm can be seen in Table III.

III. MATLAB/ SIMULATION RESULTS

A. The Comparison between the Conventional and the Fast Filtering Method The simulations are done under the following conditions:

1) The pure speech signals were recorded in an anechoic chamber with 16 kHz sampling frequency and digitized.

2) The background noises are an additive white Gaussian noise which is produced by MATLAB.

TABLE III
THE ADAPTIVE METHOD PROCEDURE

[Initialization]
$s(0) = 0$
$R_v(1) = \delta_v^2(1)$
(variance of the first speech frame)
[iteration]
If $SNR_1(n) <= SNR_0(n)$ ||
$SNR_0(n) < 0$ then
If $R_u(n) \leq U$ 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、 $K(n) = R_s(n)/(R_s(n) + R_v(n))$
6、 $s(n) = K(n) \times y(n)$

Function awgn. The noise variance δ_v^2 is assumed to be known, and the SNR of the noise signal SNR in, is defined by

$$SNR_{in} = 10\log_{10}[\{\frac{1}{n+1}\sum_{i=0}^{n} d^2(i)\} / \delta_v^2][dB]$$
(21)

where i is the total number of samples for the speech signal. We adopt two patterns of the noisy speech as the signal samples for the simulations. One is the speech signal corrupted with a background noise, In this section, we will compare the simulation result in the 3 different phases: (a) signal wave, (b) performance, (c) running time for the fast filtering method and the conventional Kalman filtering method.

(a) To compare the filtering efficiency in the view of signal wave, the results are shown in Fig.1 and Fig.2. Each figure contains the wave of pure speech signal, and noise speech signal, filtering the result by the conventional method and filtering the result by the improved method under the condition of SNR 10[dB] in . We can see that the improved method gives quite the same results as the conventional method [7]-[8].

(b) Compare the SNR of them in the view of performance:

$$SNR_{out} = 10\log_{10}[\sum_{i=0}^{n} d^2(i) / \sum_{i=0}^{n} \{d(i) - d(i)\}^2][dB]$$
(21)

means the dimension of the transition matrix;

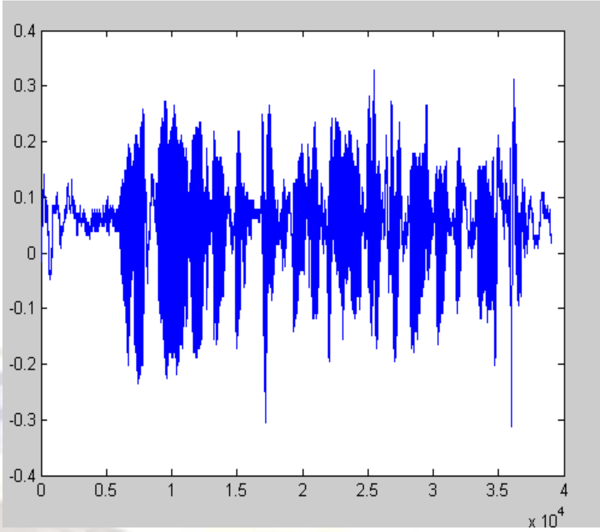

Fig.1 Pure Speech signal

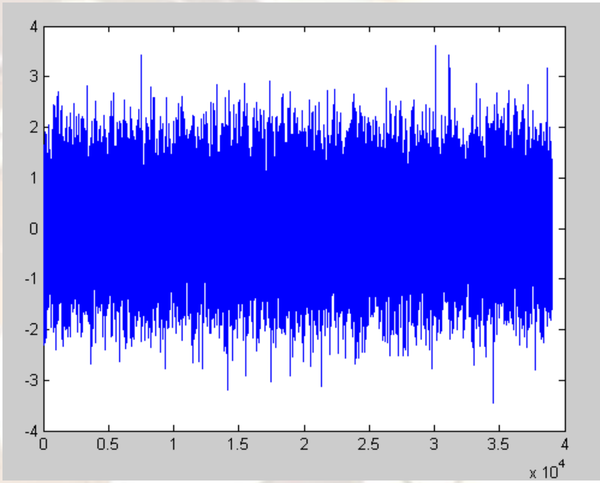

Fig.2 The noise speech

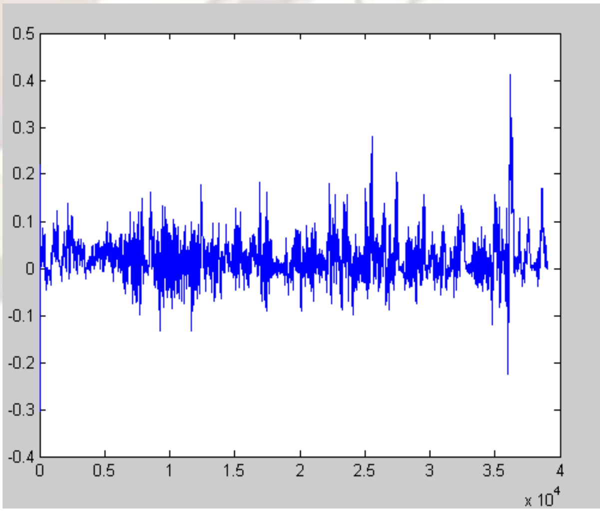

Fig.3 The conventional Kalman filter method

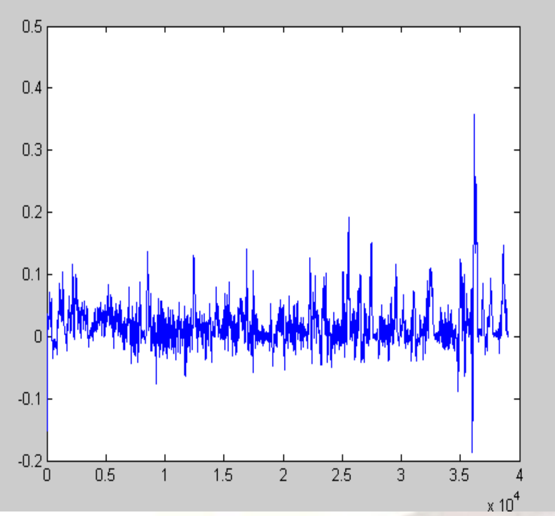

Fig.4 Improved version of speech signal by using proposed method

(c) Compare the running time of the conventional with the improved method. Table I and the improved filtering method in Table II. Both of them are running under this condition:

V CONCLUSION

This paper has presented a Robust Kalman filtering algorithm for speech enhancement by eliminating the matrix operation and designing a coefficient factor. It has been shown by numerical results and subjective evaluation results that the proposed algorithm is fairly effective. Especially, the proposed method contains two-step 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 this 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. On the other hand, the algorithm will be applied to the embedded-speech-recognition system at the hardware level, so that it can improve the robustness of the system.

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