International Journal of Advanced Biotechnology and Research (IJBR)
ISSN 0976-2612, Online ISSN 2278–599X,
Vol-7, Special Issue3-April, 2016, pp98-103
http://www.bipublication.com

Research Article

Noise Removing of Audio Speech Signals by Means of Kalman Filter

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ABSTRACT:
Nowadays, multimedia (audio and video) processing is among the most important subjects discussed in engineering sciences. To apply digital filters, especially adapting filters, in the above process, are of crucial importance. Theory of adapting filters such as that of Wiener or Kalman, have been fully discussed within the continuous field, the same as in discrete-time one; in spite of this, due to the presence of computers and digital processors, the adaptable filters defiantly have more efficiency in continuous field rather than discrete-time filed. One digital filter along with an adaptable algorithm is usually applied in adaptable filters so that the filter factor can be determined by means of adaptable algorithm. In the present article the Kalman filter-which counts as one of the best filters- has been surveyed whose appropriate factors is being calculated to design a efficient filter. First of all a sample signal is randomly selected which can be the same as an Autoregressive signal. Then a merely random Gaussian noise is applied on Autoregressive signal; and consequently the noisy signal is analyzed. As soon as we analyze the noise removed. The aforesaid operation has been assimilated through the Matlab software. The results have been demonstrated as well.

Keywords: Adaptive filters, Kalman filter, Gaussian noise, Removing the noise.

1. INTRODUCTION

Due to recent significant developments in the field of engineering sciences, communication lies among the most important subjects discussed here. Paralleling to science enhancement, their accuracy and quality have grown as well. The fundamental function of the digital system involves receiving sounds waves- for example- in an analogue status and turning them into digital signals, on which then the major process is carried on. At this stage, waves conveying both useful and useless information are put under intended filtration process, which in turn leads to favorable results.

Digital filters constitute the most prominent factors of processing at this stage. Among digital filters there exist some by the name of adaptive filters, which have been provided the name due to their adaptability rate to external conditions and exertion of their signals on transfer function. Afterwards, digital filters as well as their performance will be elaborated. Next introducing of adaptive filters will be put forward. Kalman filters and its Algorithm performance will be presented in detail. Finally one distorted voice signal is being recovered, regaining its initial healthy status, by means of Kalman filter plus appropriate determination of factors.

2. DIGITAL FILTERS

During signal processing, the performance of a filter is not controlled to eliminate unwanted portion of the signal but rather the filter excludes some of its important parts as well (Doucet et al. 2000). Figure 1 illustrates conception of a filter in general.

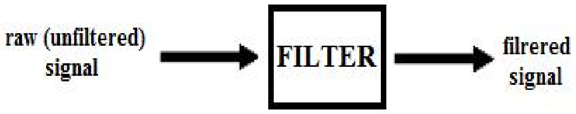


Figure 1: A block diagram of a filter

A digital filter makes use of a digital processor by which it carries out digital calculations upon a sample amount of the signal. Its processor can be an ordinary computer such as a PC or a pocket processor like DSP

In this filter the input analog signal has to be sampled and converted into a digital one with the help of a converter. The result causes some binary numbers which in succession are the same as some amounts of sampled input signals transferred into the processor. This calculation, for instance, consists of multiplying a number by the input amount or adding two other separate amounts. If necessary, the calculation results are converted into analog signals by a digital to analog convertor (Fong et al, 2002. Gehrig et al, 2005).

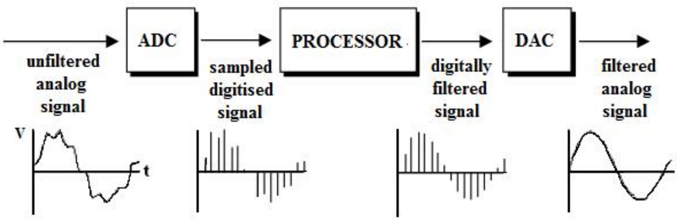


Figure 2: A block diagram of a digital filte

A digital filter enjoys some merits proving it to be conspicuous among other filters (Niedzwiecki et al, 2015), as:

1- A digital filter is a programmable system.
2- Digital filters are easily designable, testable and able to be installed on ordinary computers.
3- Contrary to the analog ones, digital filters are able to accurately transfer signals holding low frequency.
4- Digital filters possess higher capability to process signals through different techniques; additionally it can change itself of its own characteristics so as to be adapted to the signals.
5- The swift DSP processor is capable of being composed of complex filters in a parallel or serial way.

3. **ADAPTIVE FILTERS:** An adaptive filter is self-organized; conversion performance of which is based on an optimized algorithm. It is generally optimized since its algorithm is rather complicated. Most of the adaptive filters are digital ones, carrying out the processing of digital signals, coordinating their own performance to the input signals, while non-adaptive filters hold constant stable factors (Kutty et al, 2011. Diniz, 2013). Figure 3 shows a block diagram of an adaptive filter.

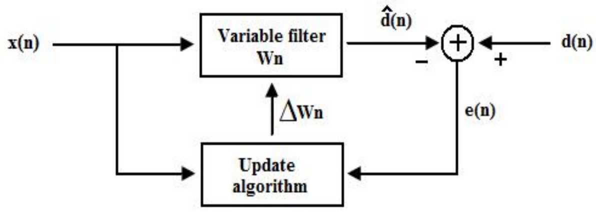


Figure 3: A general block diagram of adaptive filter

Nowadays adaptive filters are used in communication systems and signal processing, which includes channel modification, removing of reflective signals, noise reduction and etc. These filters are regulated to serve as a processor and to deal with the minimum mean square error. By error here we mean the discrepancy between filter outputs and the otherwise desired signals (Isen, 2008. Lee et al, 2009).

These filters can additionally serve to realize and assess the signals, channels and unstable systems (zarchan, 2005). They can be used on three following grounds as regards signal processing:

1- To remove noises and to coordinate channels: this is when the filter is set to remove the noises of an unstable signal such as a noisy talk or graph, and clears the channel up from the distorting effects.
2- To assess pathways: This is when the filter is engaged in assessing and predicting the pathway of unstable and distorted signals. In this regard we can remind Kalman filter which was applied to assess the pathway of Apollo spacecraft.
3- To identify systems: This is when filters are set to evaluate the system time variant parameters.

4. KALMAN FILTER

Kalman filter works on the principle that it should perform the technique of the Bayesian recursive least square error. The use of this technique makes it possible to assess a signal transmitted by a distorted channel, while gaining some noises at the same time (Dutoit and Marques, 2009. Vaseghi, 2007).

Formulation of this filter, in order that it cans remove the noise and distortion, is based on state space. In this regard, x(m) vector is taken to show the desired vector and y(m) vector shows the output noisy vector. Equations 1 and 2 show the vectors of the state space and output filter.

$$x(m) = A\,x(m\text{-}1) + B\,u(m) + e(m) \qquad (1)$$

$$y(m) = H\,x(m) + n(m) \qquad (2)$$

Where

X(m) is the P-dimensional signal, or the state parameter vector at time m;

A is a P ×P dimensional state transition matrix that relates the states of the process at times m−1and m;

B is a P ×P dimensional control matrix, used in process control modeling;

U(m) is the P-dimensional control input;

E(m) is the P-dimensional uncorrelated input excitation vector of the state equation, e(m) is a normal (Gaussian) process p(e(m)) ~N(0,Q);

N(m) is an M-dimensional noise vector, also known as measurement noise, n(m) is a normal (Gaussian) process p(n(m) ~N(0,R);

Q is the P ×P dimensional covariance matrix of n(m);

Y(m) is the M-dimensional noisy and distorted observation vector;

H is the M ×P dimensional channel distortion matrix;

R is the M ×M dimensional covariance matrix of n(m).

Figure 4 is the block diagram of Kalman filter. The place of vectors are showed in this figure Y(m) and X(m).

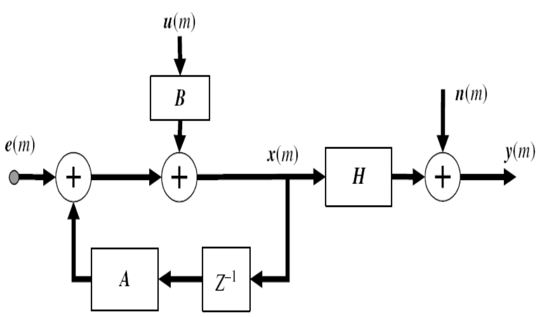


Figure 4: A block diagram of Kalman filter

It is should be pointed out that the U(m) output is mostly used in tracing and pinpointing and it can be excluded for performances such as communication signal or voice processing. Consequently, equations concerning Kalman filters can be abridged into 3 and 4 ones.

$$x(m) = A\,x(m\text{-}1) + e(m) \qquad (3)$$

$$y(m) = H\,x(m) + n(m) \qquad (4)$$

Now the equations are coming into use. In order to apply these equations we have to perform according to the following algorithm. The observed output, noisy and distorted, is adopted as the input of Kalman filter. Having implemented the following algorithm, we will be able to achieve an appropriate assessment of the desired original signal devoid of any noise or distortion.

5. KALMAN FILTER ALGORITHM

- ✓ Input: the observed vectors, the same as y(m)
- ✓ Output: signal vectors or status, the same as x(m)
- ✓ original conditions

The matrix for error prediction covariance is obtained by equation 5.

$$P(0|\text{-}1) = \delta I \qquad (5)$$

Output prediction is demonstrated by equation 6.

$$\hat{x}(0|-1) = 0 \qquad (6)$$

Algorithm for m parameters are continued as m=0,1,…by the following equations.

- ✓ Updated equations for predicting the procedure

The equation for status predicting generally is in the form of equation 7.

$$\hat{x}(m|m\text{-}1) = A\hat{x}(m\text{-}1) \qquad (7)$$

The matrix for the error predicting covariance is in accordance with the equation 8.

$$P(m|m\text{-}1) = AP(m\text{-}1)A^{T} + Q \qquad (8)$$

- ✓ Equations for assessing the signal

Kalman Gain vector is obtained by equation 9.

$$K(m) = P(m|m\text{-}1)H^{T}(HP(m|m-1)H^{T} + R)^{-1} \qquad (9)$$

The updated general status is obtained by equation 10

$$n) = \hat{x}(m|m\text{-}1) + K(m)(y(m) - H\hat{x}(m|m-1)) \qquad (10)$$

The matrix for error assessment covariance is demonstrated by equation 11

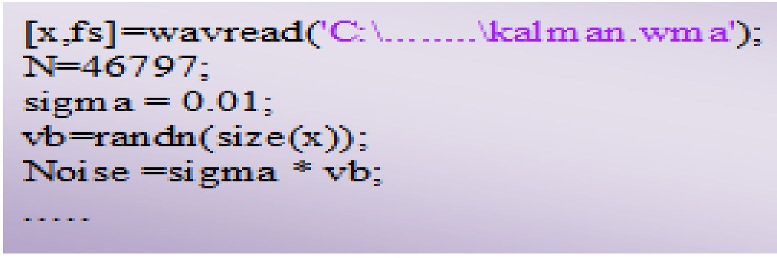
$$P(m) = [I - KH]P(m|m-1) \quad (11)$$

6. KALMAN FILTER SIMULATION FOR VOICE SIGNALS

By Choosing appropriate factors and order for kalman filter in aforesaid algorithm in pervious section, we can reconstruct the distorted noisy signal by means of Matlab software (Poularikas and Ramadan, 2006. Grewal and Andrews, 2015). In this section, with the help of the software we recall a sample signal called X which equals an autoregressive signal. Next, a random Gaussian noise is added to it; and finally the noise added to signal is removed by means of a well-designed Kalman filter so as to extract the desired signal

In figure 5, the signal 'x' is a one of which a sample has been taken with the help of a suitable frequency of 46797. Afterwards, a generated Gaussian noise will be added to it.

Figure 6 demonstrates an input signals devoid of noise.



```
[x,fs]=wavread('C:\........\kalman.wma');
N=46797;
sigma = 0.01;
vb=randn(size(x));
Noise =sigma * vb;
.....
```

Figure 5: part of voice recalling program and a random generation of Gaussian noise

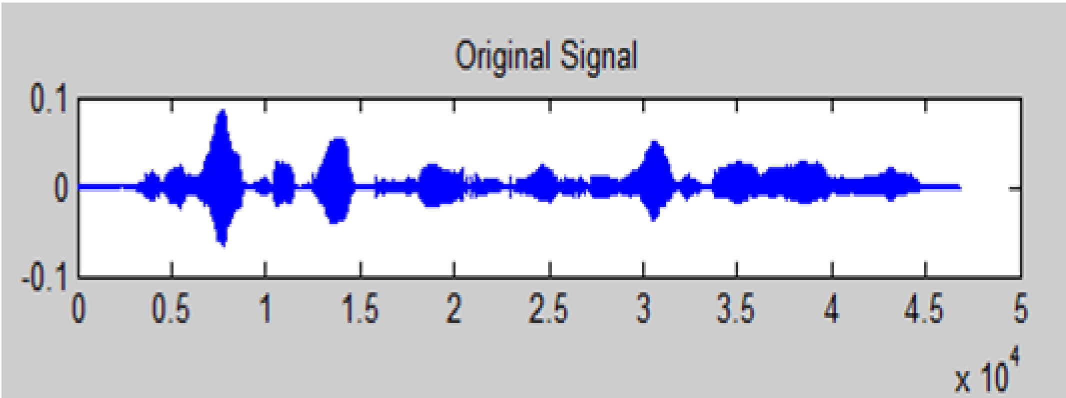


Figure 6: The input voice signal devoid of noise

After adding Gaussian noise, signal goes under distortion which is shown in figure 7.

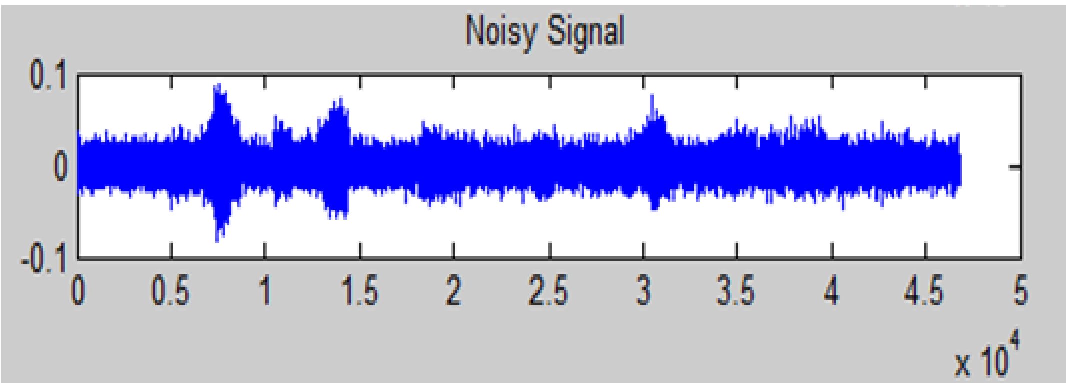


Figure 7: The input voice signal together with Gaussian noise

Having used the appropriate designed filter, part of which is shown in figure 8, we accomplished to eliminate the noise from signal so as to gain the desired one. The signal hereafter is comprehensible for the audience.

In figure 9 the output signal is demonstrated.

```
--- ----
function [a g]=ar(f,bw,gi,NP)

for k=1:NP
   r(k)=exp(-bw(k)*pi)
end

for k=1:NP
   if (f(k)==0)
      sos(k,:)=[1 0 0 1 r(k) 0]
   else
      k
      sos(k,:)=[1 0 0 1 -2*r(k)*cos(2*pi*f(k)) r(k).^2]
   end
end

[b a]=sos2tf(sos);
fr=20*log10(abs(freqz(1,a,1000)));
frmax=max(fr);
g=10^((gi-frmax)/20);
--- ----
function [x]= Kalman(A,Q,R,y,N,p)
P=100*eye(p);
H=eye(p);
I=eye(p);
x=y;
for i=p+1:N
   i;
   x0=A*x(i-1:-1:i-p)';
   P0=A*P*A'+Q;
   K=P0*H'*(H*P0*H'+R)^-1;
   x(i:-1:i-p+1)=x0+K*(y(i:-1:i-p+1)'-H*x0);
   P=(I-K*H)*P0;
end
```

Figure 8: Some parts of the program for noise removing from voice signal using Kalman filter

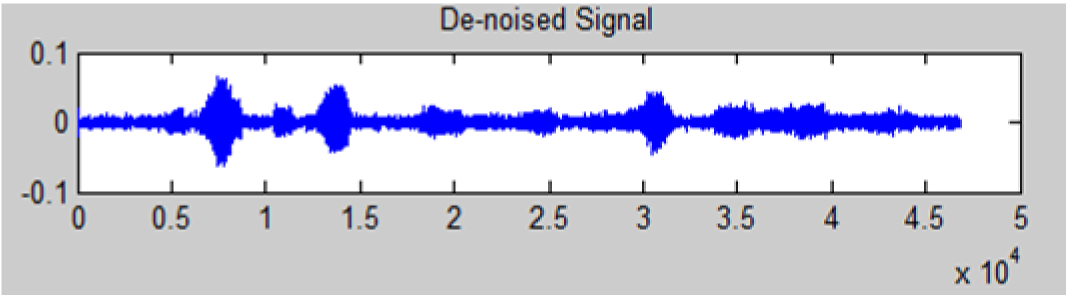


Figure 9: The output voice signal form Kalman filter

7. CONCLUSION

Concerning the fact that our selected signal is of Autoregressive kind, we are able to employ IIR filter to eliminate the Gaussian noise through eliminating the added noise, using the minimum average of quadrated error technique, based on which Kalman filter does the error finding and predicting procedure. In order for the filter to perform properly, we are required to calculate the factors of Kalman filter. In so doing, we have implemented a P order filter, the same as a Matrix P, holding n*m dimensions. Its obtained factors then have been arranged in a matrix approach so that we can separate the desired signal from the noisy one. It is possible to evaluate the performance quality of the designed filter by comparing input signals with output ones. The comparison will results in designed Kalman filters proving to be successful in removing the noises added to voice signals.

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