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Detecting Noise Reduction in EMG Signals by Different Filtering Techniques

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A common problem in processing of EMG signals for assessment of their applications in different biomedical fields such as diagnosing fatigue level, rehabilitation and control of wrist and finger movements in individuals suffering from c5 and c6 spinal traumas is the high susceptibility of the signals to noise. The EMG signal is highly variable in terms of intensity and frequency and has a high frequency range, so its noise also has a high frequency. This paper is focused on filtering the signal in order to reduce a considerable part of the noise. It includes the use of three filters named butterworth, Wiener, and least mean square (LMS). The LMS is a member of the adaptive filters group, while Wiener is a linear filter. Different techniques are used to compare the said filters. A non-linear parameter like correlation dimension and covariance are used to estimate the amount of filtered noise. The other technique includes using a random unbiased parameter like cross-correlation. The non-linear parameter showed better accuracy in showing the amount of non-linear noise reduction. The Wiener filter eliminated larger percents of noise. Data was collected from 10 individuals all being of perfect health and free of any specific disease.

Keywords: Least Mean Square Adaptive Filters, Wiener Filter, Butterworth Filter, Surface Electromyogram.

1. INTRODUCTION

By means of biological signals the physiological activities of different organs including protein, gens, nerves, heart rhythms and tissues are studied in a visual manner. The goal is to process the signals to extract the information they carry.[20] One of the most important goals of this process is to clean the signals from the noise they contain by means of filters.[1,6,16] One of the most important sources of noise is the power line.[20,24] Other noises are created through interactions of body organs.[20] One way to reduce and eliminate noise is to use random noise in such a way that the unique characteristics of each signal are obtained by Wiener filtering[6,16] and Kalmen filtering.[21] The process of noise reduction by spectrum position is a very complicated one.[24] Another way of eliminating noise is through the least square means (LSM) method.[2,25] In this method the noise is reduced by reducing the LMS error between input of the main signal and the source signal.[24] The technique of noise elimination and interference is divided into categories depending on the method used to find the source signal:[24] (1) a technique in which the source signal is registered and the noise it carries is correlated with the input signal; (2) using an artificial source signal as the main input signal by means of a predictor filter with one delay.[24] The problem with the first technique is that it requires lots of hardware and a good source signal is hard to achieve in most cases.[24] The second problem with the LMS filter is that its adaptation speed depends on the SNR output that tends to reduce the filter adaptation ratio as it increases.[24] It is used in the non-linear analysis for comparison of different muscular contraction conditions.[17] Scholars have come to the conclusion that non-liner analysis is better than estimating the power spectrum of the mean frequency (MF).[18,19] In this paper the SEMG signal is compared in terms of non-linear and random parameters. The goal is to calculated covariance, cross-correlation, and correlation dimension for extraction of SEMG signal elements. The SEMG single noise has high frequency elements and the power line has to be taken as an additional source of noise. This paper demonstrates that the correlation dimensions provide more reliable results in comparison to other processing parameters. It also focuses on introduction and explanation of filters used for such purposes, including the butterworth filter which is made up of several high-pass and low-pass filters as well as a notch filter followed by a Wiener filter (a linear model). They were all used to reduce and eliminate noises before an adaptive filter LMS was applied.

2. METHODOLOGY

2.1. Correlation Dimension

In the distortion theory correlation dimension measures dimensions of the space occupied by random points which are normally

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taken as a type of fractal dimension.[1–3] Two characteristics defined by the correlation dimension are the fractal dimension of a subject. Methods for measuring dimensions include the following: Hausdroff dimension, information dimension, box-counting dimension, the other being the non-linear nature.[16] Correlation dimension is chosen due to its simple and easily calculated structure and low noise susceptibility.[16, 36]

M: indicates the spatial dimensions of the subject (EMG signal), N: indicator of the number of points, and (i): indicator of the time delay.

$$[x1(i), x2(i), x3(i), \ldots, xm(i)] \tag{1}$$

$$C(\varepsilon) = \lim_{N\to\infty} \frac{g}{N^2} \tag{2}$$

g is the total number of point pairs with distances smaller than ε.[36] For points inclined to be limited rather than their distances reduced to zero, this technique is used to detect distortion and random behavior. But it is not a good way to express the system behavior in face of complicated mechanisms.[1, 16] The c operand is made of two arbitrary points on the trajectory closer than r. Normally each pair is calculated separately and its n factor stored in a bins. A normal way to calculate a correlation dimension is to produce a time series by an appropriate number of repeating x factors, and then to separate the factor pairs in an xy space by a c operand. The correlation integral is calculated for small ε values according to the following equation:

$$C(\varepsilon) \to \varepsilon^V \tag{3}$$

In this technique first the data is divided into intervals of 1000 and then each factor is separately multiplied in it from 0 to 1000. Then two points are chosen and their slope is calculated. If the two points are equal the slope will be taken as 1. The farthest and closest points from the source point are taken and their maximum and minimum are clarified. To calculate the next point the minimum point and the ratio of the distance of the maximum and minimum are added to all 100 samples and multiplied in 10. Finally the logarithm of the obtained results is calculated.

2.2. Cross-Correlation

It is used to measure two samples of the same wave as the function of a time-lag applied to one of them, and is normally used to extract signal properties in a long time period in a short time. Among its applications are pattern detection such as signal analysis, electron mean tomography, and neurophysiology, calculated from the following equation:

$$f^* g[n] = \int_{-\infty}^{\infty} f^*(\tau) g(t+\tau)\, d\tau \tag{4}$$

Cross-correlation is in fact the convolution of two functions. In probability and static theory correlation is used as a standard factor whose value ranges from -1 to $+1$. Cross-correlation is between two variable values of x and y. When the correlation of a random x vector is compared, correlation is taken as a matrix of x value scales. If x, y are parameters of the independent variable of a density function with probability of f, g the probable density may be expressed by cross-correlation. The convolution of $f \times g$ may be obtained by adding the density probability function of $x+y$. In this method there are two simple inputs one being the main data carrying the noise and the other being the filtered data coming through the filters which will be explained later in this paper. But the output is the result of a point-to-point correlation of the input point.[6]

2.2.1. Covariance

In probability and static theory covariance is the assessing criteria for two random variables which are exchanged with one another. If the large value of one parameter goes with the large value of another parameter, the least similar value is normally taken as the system behavior which is the positive covariance value. However, if the large value of a variable equals the small value of another, the covariance will be negative and the variance domain will not be interpreted easily. For this the covariance of the correlation coefficient is normalized and the domain is shown with a single linear relation. In fact covariance is the variance of two variables.[7]

2.3. Filter Techniques

2.3.1. Least Mean Square Filter

In 1950 a lot of researchers worked on adaptive filters and their efforts finally resulted in the etraction of the LMS algorithm which was designed for the following filter: an algorithm for the design of adaptive transversal (taped-delay-line) filter. The LMS algorithm was proposed by Windrow and Hoff in 1950. In order to study the machine (system) model with an adaptive linear factor, it is normally referred to Adalin[8, 9] the LMS algorithm is a stochastic gradient algorithm that iterates tap weight of the transversal filter in the direction of the instantaneous squared error signal with respect to the tap weight in question. The LMS algorithm equation is as follows:[34]

$$w[n+1] = w[n] + \mu u[n][d(n) - w^h(n)u(n)]^* \tag{5}$$

$w[n]$ = tap-weight, n = iterations, μ = step-size parameter, $d(n)$ = desired signal, $u(n)$ = tap-input vector. $*$ = indicator of the complex H structure in the above equation signifying a Hermition transfer. Equation (5) shows the simplicity of the filter whose characteristics and practical uses[10, 11] make it a good subject for processing of adaptive signal study. The nature of stochastic LMS is unique. In fact in a static environment and with the minimum step-size parameter it is done ina Brownian motion form. The theory of the least step-size in the LMS filter of discontinued time is calculated from the following equation[10]

$$\Delta v_k(n+1) - v_k(n) - \mu\lambda_k v_k(n) + \varphi_k(n) = \Delta v_k \qquad k = 0, 1, 2, \ldots, m \tag{6}$$

It consists of two parts:
(1) Damping force = $\mu\lambda_k v_k$.
(2) Stochastic force = φ_k.
(3) Filter order = m.
(4) $\lambda = K$th eigen value of the correlation matrix of the input vector $u(n)$ is expressed by the correlation matrix R.
(5) $e0(n)$ = Optimized signal error, like the Wiener filter that produces the desired response $d(n)$ by the input vector $u(n)$.
(6) Q = factor of $(-\mu QHu(n)e \times (n))$ vector.

2.3.2. Wiener Filter

The Wiener filter was studied in 1940 by Norber Wiener and gain popularity in 1949.[12] It was meant to help in the comparison of the noise existing in the signal with the desired signal in one estimation effort. Wiener filter is not a member of the adaptive filters group because its supporting theory assumes that its input is a stable mode.[13] If the desired signal is at hand a type of filter which is the Wiener is used. The basic concept of the Wiener theory is that the difference between the outputs of desired signal and the filtered signal is very small. To calculate the Wiener filter there is need for static modes of both signals (noise and desired signal). Wiener filter discusses in the field of frequency and it is estimated by Fourier transform.[14,15]

$$G \times X = \hat{S} \tag{7}$$

$$\frac{H^* \cdot P_S}{P_{n+} \cdot P_S \cdot |H|^2} \tag{8}$$

P_s = power spectrum of the signal process obtained by taking the Fourier transform of the signal auto-correction; P_n = power spectrum of the noise signal process obtained by taking the Fourier transform of the noise signal auto-correction; P_s/P_n = ration of signal to noise.[14]

Wiener filter cannot reconstruct the factors that have been destroyed by noise, it can only stop it. Also, it has no power to keep factors whose Fourier transform is zero. If Wiener filter is to be used in the frequency field its relational mode is hardly used. To speed up the Wiener filter, one can inverse its Fourier transform and finds its impulse response. This impulse response can be truncated spatially to produce a convolution mask. The spatially truncated Wiener filter is inferior to the frequency domain version, but may be much faster.

To design a filter in noise-free conditions, it is assumed that the noise is of simple and low-energy type. The first step is to derive it:[14]

$$|HdG - f|^2 = |n|^2 \tag{9}$$

$$G = f \cdot H - 1 \tag{10}$$

This is very much like inverse filters. It is good for small noise (nearly zero), but when the frequency noise is high another model will be offered that reduces noise energy: $J(G) = |QG|^2$. The Q matrix is chosen in the LTI system. If the Q value is above normal values the undesired factors will be more normal than the un-constrained mode. Lagrange's formula is used to solve the above problem. One constant is added to the Lagrange equation and its value is increased. With a derivation on G and taking the value as zero the G value is obtained and taken as a constant.[14]

$$H(u) = \frac{H_d^*(u)}{|H|_d^2 + |Q_{(u)}|^2} \qquad G = \partial \tag{11}$$

Since $Q = 1$ only estimates the energy, if calculation of the signal and noise is difficult, simple filters are better in use than Wiener filters. The ∂ constant is defined for several reasons:

(1) It has a small frequency response in high frequencies.
(2) This constant is multiplied in the convolution of Wiener filter and taken as $P_s/P_n =$. In the standard signal model the signal spectrum is reduced with the frequency square and increased by the denominator frequency square of $H(u)$. It causes the energy to be estimated in a more normal manner.
(3) As a different secondary operant with impulse response whose impulse response matches Q (FIR is constrained).[15]

2.3.3. Butterworth Filter

The domain of EMG signal is a rather wide one and its filtering requires a filter capable of eliminating its noise in high ranges, which are mostly due to the motional artifact. This is why a high-pass filter is used.[30] On the other hand, according to studies already complete the EMG signal in its low ranges contains useful information which is destroyed when it passes through a high-pass filter. The signal must then pass through a low-pass filter.[16,28] However, the power line noise during the registration phase plays a major role in the creation of noise in the EMG signal that must be eliminated in the process. For the same reason the present study made use of Butterworth filters, using a second level high-pass filter with a frequency of 10 Hz and a low-pass filter of level 8 with a frequency of 400 Hz and a notch filter of second six level with frequencies of 50,[28] 100, 150, 200, 250, and 300 Hz in order to eliminate the EMG single noise.[16]

3. EXPERIMENT SETUP

To register an EMG from the hand a surface Ag/AgCl electrode is used. The hand must first be cleaned and made free of any dirt and grease on the elbow, which may prevent a good connection between the skin and the electrode. Such a problem will cause more noise.

3.1. Devices

The system includes a power lab machine registering the signal from the subject. It works with Matlab software for analysis of obtained data, and of course Ag/AgCl electrodes.

3.2. Experiment Protocol

Each individual is exposed to the registration process for 2 minutes. He then rests for 5 minutes and then registration is repeated. This same process must be repeated on another day with similar clinical conditions.

4. RESULTS AND DISCUSSION

4.1. Result

This part is focused on the results obtained from filtration of EMG signals by various filtering techniques including adaptive filtering, Wiener filtering, and Butterworth filtering. The results will then be compared.

Table I show the correlation dimensions of each person in different techniques filtering, CD(R) being the expected value, CD(D) being the noise value, CD(B) being the Butterworth filter value, CD(w) being the wiener filter value and CD(LMS) being the LMS filter value. When compaire these value underastood that in correlation dimension give a best result for showing the removal noise specially non linearity noise in SEMG signal.

Table I. Correlation dimension of different filters.

Number subject	CD(R)	CD(D)	CD(B)	CD(W)	CD(LMS)
1	2.27	4.80	3.70	2.25	2.23
2	1.98	3.91	3.32	1.95	1.95
3	1.33	4.20	3.53	1.32	1.31
4	2.15	5.15	4.66	2.18	2.21
5	1.46	4.76	2.45	1.46	1.47
6	1.17	3.32	2.88	1.20	1.20
7	1.29	2.96	2.41	1.24	1.21
8	1.40	4.10	3.69	1.42	1.44
9	2.50	2.70	2.12	2.56	2.53
10	2.11	5.26	4.27	2.01	2.00

Table II. Cross-correlation of different filters.

Number subject	CC(B | D)	CC(W | D)	CC(LMS | D)
1	6.71	4.31	4.82
2	7.33	7.13	7.42
3	4.22	3.80	3.92
4	6.01	3.61	3.88
5	3.75	3.25	3.69
6	3.60	2.68	3.14
7	1.90	1.43	1.65
8	1.53	1.41	1.44
9	5.13	3.76	3.85
10	5.31	3.81	4.12

Table III. Covariance of different filters.

Number subject	COV(B | D)	COV(W | D)	COV(LMS | D)
1	3.77	2.31	2.34
2	3.38	2.00	2.04
3	3.54	1.44	1.46
4	4.74	2.28	2.31
5	2.51	1.78	1.83
6	2.98	1.41	1.52
7	2.41	1.25	1.29
8	3.73	1.61	1.74
9	2.18	2.73	2.85
10	4.33	2.01	2.11

Table II show the cross-correlation of each person in different techniques filtering, CC(B | D) being the Butterworth filter value to noise value, CC(w | D) being the wiener filter value to noise value and CC(LMS | D) being the LMS filter value to noise value. In this part compare these cross-correlation with different filters but the result not suitable for extracting featuring of ratio of SEMG's noise.

Table III show covariance of each person in different techniques filtering, CO(B | D) being the Butterworth filter value to noise value, CO(w | D) being the wiener filter value to noise value and CO(LMS | D) being the LMS filter value to noise value. In this part compare covariance to estimate and extracting some featuring from SEMG. Result show the covariance good estimator for comparing noise signals.

Figure 1 show the real data noise signal that an other parts describe the behavior of signal after filtering.

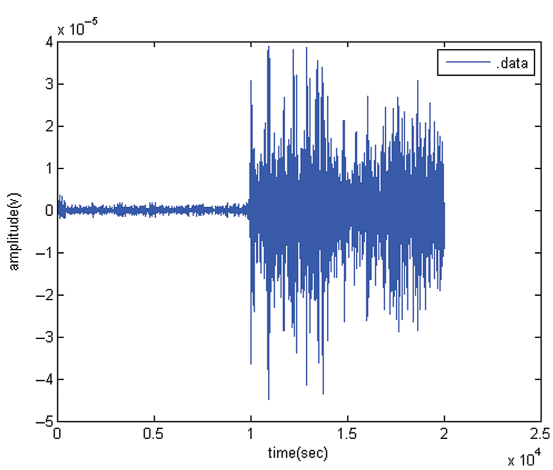

Fig. 1. Data (SEMG signal).

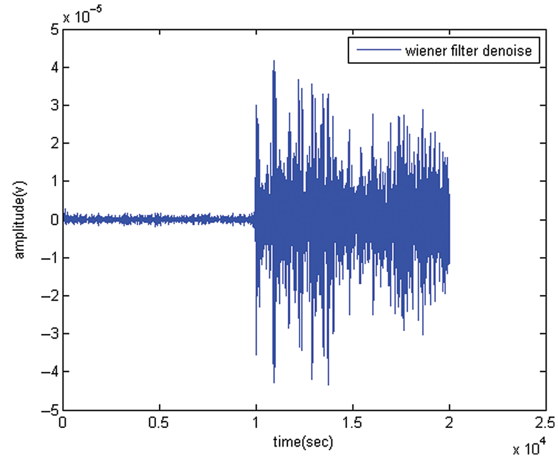

Fig. 2. Wiener filter denoised.

In Figure 2 shows the de noising signal with wiener filter with high quality. But important thing that is noticeable in this paper was about the noise signal that assumed knowing. If the researcher do not know the noise they should have been use another filter for removing their noise or record data infinite noise place that is far from power line or electromagnetisms.

In Figure 3 shows the signal that has been smoothed with LMS filter. One thing was very noticeable in Adaptive filter and wiener is for designing them, there needed to be a lot of experience for designing. In this figure the noise could control but not az wiener filter control.

In Figure 4 shows the de noising signal with butterworth filter az the figure that has been seen the noise could not remove from the signal like seen in previous figures [Figs. 2, 3].

Figure 5 shows mean covariance, dimension correlation, and cross-correlation during muscular contraction. This mean was taken for 15 Trailes. The data were normalized and it was demonstrated with time that the subjects rested for 5 minutes between the experiments. The elbow angle for contraction was up to 90 degrees. Each subject was given 2, 5, and 7 Kg weights and experiments were repeated several times to increase reliability of the results. Figure 5 was obtained from clean data using Wiener filter, Since SEMG has infinite noise in clinical conditions, if it

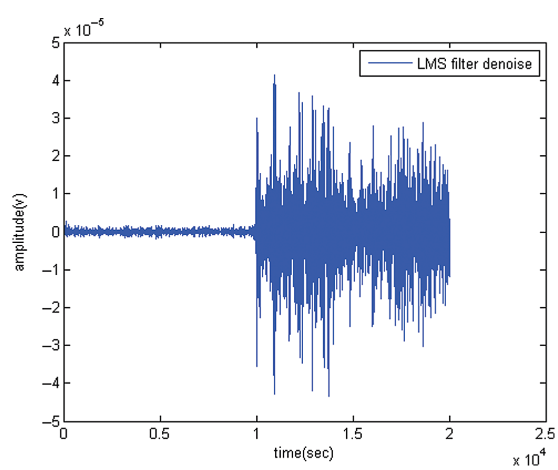

Fig. 3. LMS filter denoised.

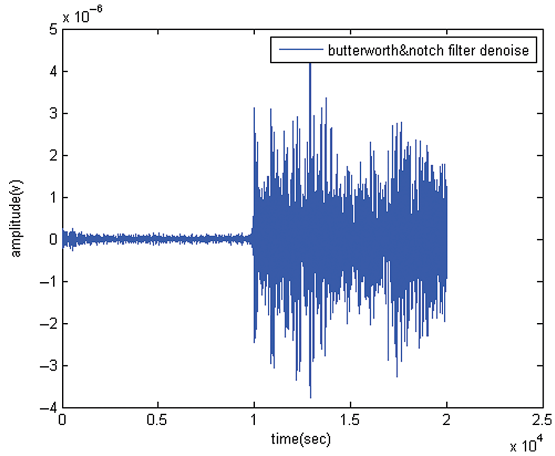

Fig. 4. Butterworth filter denoised.

is normalized by a Butterworth filter and compared its behavior will not be visible enough due to distortions, and its mean will therefore be useless for studying.

4.2. Discussion

A number of linear[6,7] and non-linear[16] parameters may be extracted from the SEMG signal. Among them correlation dimension, covariance, and cross-correlation were chosen for the analysis of SEMG signal. The correlation dimension was chosen because it may be used to extract noise containing non-linear parameters.[16] Also by choosing a source point and finding the closest and farthest points, one will be capable of estimating the position of other points. Hence a general view of the signal may be created. Despite the countless studies focused on the non-linearity of the SEMG signal[31] and its relations with correlation dimension, the subject has not yet been addressed seriously because of the noise and distortion found in clinical conditions in which signals are registered when clearly the calculation of correlation dimension needs very clean data. Cross-correlation was chosen because it provided a chance for finding the correlation and ration of the main signal containing noise and the filtered signal, and extracting the parameter that could be chosen as a s/n ration[33] for the SEMG signal factor. The reason behind the selection of covariance was that each signal had a different variance and that difference might be used to help in the reduction

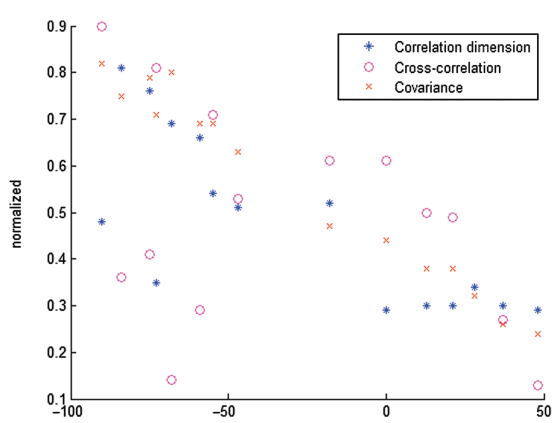

Fig. 5. The mean of the trailes during contraction.

of noises.[33] When the electrodes were fixed at the upper and lower parts of the elbow, the values of cross-correlation, correlation dimension and covariance were calculated for both parts. It was evident that the value for the upper and lower elbow were different. Results showed [Table I] that when a Wiener filter and an adaptive filter were used the results of correlation dimension were better than covariance and cross-correlation, while the use of Butterworth filter did not bring the same good results because there was infinite distortion and dispersion. The dispersion of the correlation-dimension was less for Wiener than adaptive filters. Normally adaptive filters have some sort of convergence on Wiener filters [Matlab tool box]. The signal passing through them carries common information but they are both difficult to use, particularly because the SEMG signal has a high rate of noise.[32] In Table I correlation dimension is used depending on the good filter for extraction of SEMG signal characteristics. A look at the correlation dimension in Figure 5 makes one notice that in each moment of the time correlation dimension experienced a time lag after moment $t = 0^{16}$ after which the value remains in a fixed range. On the other hand, covariance (which is the bidirectional variance in fact) behaves similarly to the correlation dimension. This shows that first correlation dimension and then covariance contain the information loans, while the cross-correlation carries no information load. Also, in covariance the loading of information is done with a delay compared to correlation dimension and of course the volume of information is less than correlation dimension as well. To verify the results quoted in Figure 5 more experimental and static data must be tested so that a full model of physiological behaviors of SEMG signal for processing analyses. One problem in the calculation of correlation dimension is that if the noise is not taken care of by the filters it suffers dispersion and the results will not be good enough for an accurate analysis. This paper focused on special noises with unstable natures. One of them was the noise inserted into the signal in a stochastic (random) manner and creates distortion.[32] The other noise was due to power lines which plague all electronic devices working at 50 Hz or other multiples of 50.[16] This type of noise destroys the signal order but the use of adaptive filters for short time series will prove essential, particularly for SEMG signals.[35] The time lag creates another type of distortion preventing the parameters from providing good results. When a notch filter is used it creates 50 Hz and other multiple frequencies. For example, when this filter is used to eliminate the 50 Hz factor of the signal it passes all frequencies from 1 to 49 and from 51 to the last, except for 50 (if no other notch filter is used for 50 multiple frequencies). Due to the gap between frequencies 49 and 51 the filter will be unable to converge the signal on frequency 51 with that at 49 Hz, resulting in the elimination of part of the signal information plus those on frequency 51. Another type of noise in SEMG signals is the ECG signal.[29] Pulmonary motions also cause displacement of the muscles connected to EMG signal registration devices[29] which causes an unreal domain above the actual domain of the original signal.

5. CONCLUSION

Lots of methods have been proposed for elimination of noise from EMG signals, each depending on the use of a different technique for noise reduction and elimination. This paper focused on Wiener, Butterworth and adaptive filters. According to the good statistical results obtained from experiments, the first rank was given to Wiener filters. Adaptive filters ranked second, and Butterworth filters ranked third because of the large difference in their noise reduction performance. To analyze and compare the filters in terms of their noise reduction parameters such as correlation dimension, cross-correlation and covariance were studied. There covariance was chosen as a good choice for elimination of noise in linear parameters, while correlation dimension was better in elimination of noise from non-linear parameters.

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