EMG feature extraction for tolerance of white Gaussian noise

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Abstract: White Gaussian Noise (WGN) is a major problem in analysis of surface electromyography (sEMG) signals. Therefore, noise reduction is an important step before performing feature extraction, which is used in EMG-based gestures classification. However, the solutions to remove white Gaussian noise are limited. This research is aimed to select a feature that tolerate with white Gaussian noise. As a result, noise removal algorithms are not needed. Eight features in time domain and frequency domain were tested with additive white Gaussian noise at various signal-to-noise ratios (SNRs). Results showed that Willison amplitude was the best feature comparing with others. Subsequently, evaluations of threshold of Willison amplitude were tested between 5-50 mV. Willison amplitude with 5 mV threshold showed better than others. From the above experiment results, it is shown that Willison amplitude with 5 mV thresholds can use for feature extraction and can exclude removal noise algorithm.

Key words: *white Gaussian noise, Feature Extraction, EMG, Electromyography*

1. INTRODUCTION

Varieties of noises originated from measure instruments are major problems in analysis of surface electromyography (sEMG) signals. Therefore, methods to eliminate or reduce the effect of noises have been one of the most important problems. Power line interference or instability of electrode-skin contact can be removed using typical filtering procedures but the interference of white Gaussian noise (WGN) is difficult to remove using previous procedures. Adaptive filter or wavelet denoising filter, advance signal processing method has been received considerable attention in the removal of white Gaussian noise [1-2]. However, the limitation of the solutions to remove white Gaussian noise cannot remove one hundred percent of noises and sometimes remove some important signals from sEMG.

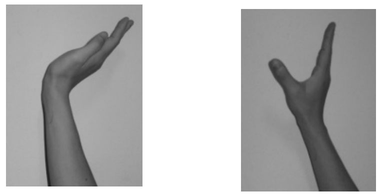
Furthermore, the general acquisition and analysis of sEMG signal for the control of multifunction myoelectric control involves several steps [3]. The first and the second important steps are signal conditioning and preprocessing, and feature extraction. The first step preprocesses the sEMG in order to reduce noises and improve spectral component for sEMG signal analysis. The second important step is used for highlighting the relevant structures in the data and rejecting noise and irrelevant sEMG signal.

This study is motivated by the fact that the limitation of the solutions to remove white Gaussian noise in the first step and EMG-based gestures classification need to do the second step. This research is aimed to select a feature that tolerate with WGN. As a result, WGN removal algorithms in the first step are not needed.

2. EXPERIMENTS AND DATA ACQUISITION

In this section, we describe our experimental procedure for recording surface myoelectric control system (sMES). The sMES was recorded from extensor carpi radialis longus of a healthy male by two pairs of surface electrodes (3M red dot 2.5 cm. foam solid gel). Each electrode was separated from the other by 20 mm. The frequency range of EMG is within 0-1000 Hz, but the dominant energy is concentrated in the range of 10–500 Hz. A band-pass filter of 10-450 Hz bandwidth and an amplifier with 60 dB gain were used. Sampling rate was set at 1000 samples per second using a 16 bit A/D converter board (IN BNC-2110, National Instruments Corporation).

A subject performed two limb motions including hand open and wrist extension as shown in Fig. 1. Ten datasets were collected for each motion. The sample size of the EMG signals is 256 ms for the real-time constraint that the response time of the MES should be less than 300 ms.



Wrist Extension Hand Open

Figure 1. Estimated six hand motion.

3. METHODOLOGY

The success of EMG pattern recognition depends on the selection of features that represent raw sEMG for classification. In this research, we selected eight features in time domain and frequency domain [4-5] representing most features in EMG classification.

Generally, most of the attempts to extract features from EMG signal can be classified into three categories including time domain, frequency domain, and time-frequency domain methods. We considered only former two categories because they have computational simplicity and they have been widely used in research and in clinical practice.

3.1. Time domain feature extraction

3.1.1. Root Mean Square

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whose RMS is related to the constant force and non-fatiguing contraction. It relates to standard deviation, which can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \quad , \qquad (1)$$

where N denotes the length of the signal and x_n represents the EMG signal in a segment n.

RMS represents features in time domain based on signal amplitude such as mean absolute value, mean absolute value slop, and variance. In comparison, RMS results in powerful performance in robust noise tolerance than the others.

3.1.2. Waveform Length

Waveform length (WL) is the cumulative length of the waveform over the time segment. WL is related to the waveform amplitude, frequency and time. It is given by

$$WL = \sum_{n=1}^{N-1} \left| x_{n+1} - x_n \right| \qquad (2)$$

3.1.3. Zero Crossing

Zero crossing (ZC) is the number of times that EMG signals crosses zero. The threshold value is 20 mV. It can be formulated as

$$ZC = \sum_{n=1}^{N-1} \left[\operatorname{sgn}\left(x_n \times x_{n+1} \right) \cap \left| x_n - x_{n+1} \right| \geq threshold \right];$$
$$\operatorname{sgn}(x) = \begin{cases} 1, & if \ x \geq threshold \\ 0, & otherwise \end{cases} \qquad (3)$$

ZC is related to slope sign change (SSC). These features provide a rough estimate of the properties in frequency domain.

3.1.4. Willison Amplitude

Willison amplitude (WAMP) is the number of counts for each change in the EMG signal amplitude that exceeds a predefined threshold where threshold value is 10 mV. It is defined as

$$WAMP = \sum_{n=1}^{N-1} f\left(\left| x_n - x_{n+1} \right| \right);$$
$$(4) \qquad f(x) = \begin{cases} 1, & if \ x \geq threshold \\ 0, & otherwise \end{cases}$$

WAMP is related to the firing of motor unit action potentials (MUAP) and the muscle contraction level.

3.1.5. Histogram

Histogram (HIST) divides the elements in EMG signal into b equally spaced segments and returns the number of elements in each segment. HIST is an extension of the ZC and WAMP. Three segments are chosen in this work.

3.2. Frequency domain feature extraction

3.2.1. Median Frequency

Median Frequency (FMD) is the frequency at which the spectrum is divided into two regions with equal power. It can be expressed as

$$\sum_{j=1}^{FMD} P_j = \sum_{j=FMD}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j \ , \qquad (5)$$

where P_j is the EMG power spectrum at frequency bin j.

3.2.2. Mean Frequency

Mean Frequency (FMN) is the average frequency. FMN is calculated as the sum of the product of the power spectrum and the frequency, divided by the total sum of spectrogram intensity, as in

$$FMN = \sum_{j=1}^{M} f_j P_j \bigg/ \sum_{j=1}^{M} P_j \ , \qquad (6)$$

where f_j is the frequency of spectrum at frequency bin j.

3.2.3. Auto Regressive

Auto Regressive (AR) model is described each sample of sEMG signals as a linear combination of previous samples plus a white noise error term.

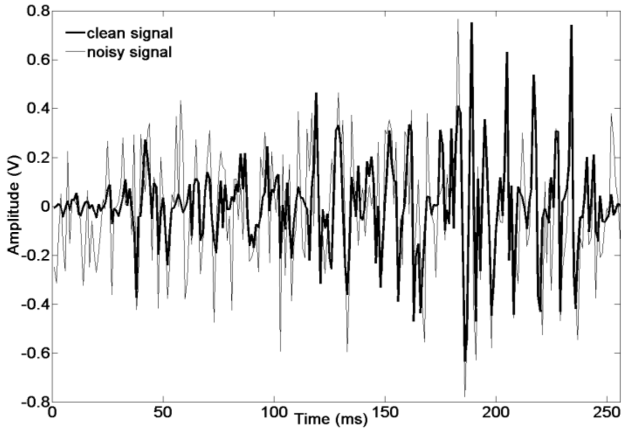


Figure 2. Clean EMG signal and noisy EMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.

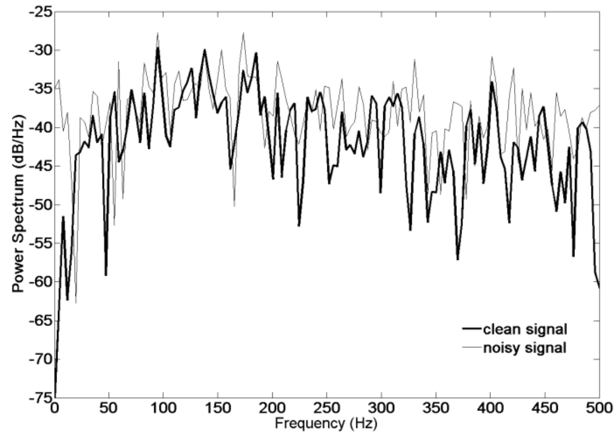


Figure 3. Power spectrum of clean EMG signal and noisy EMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.

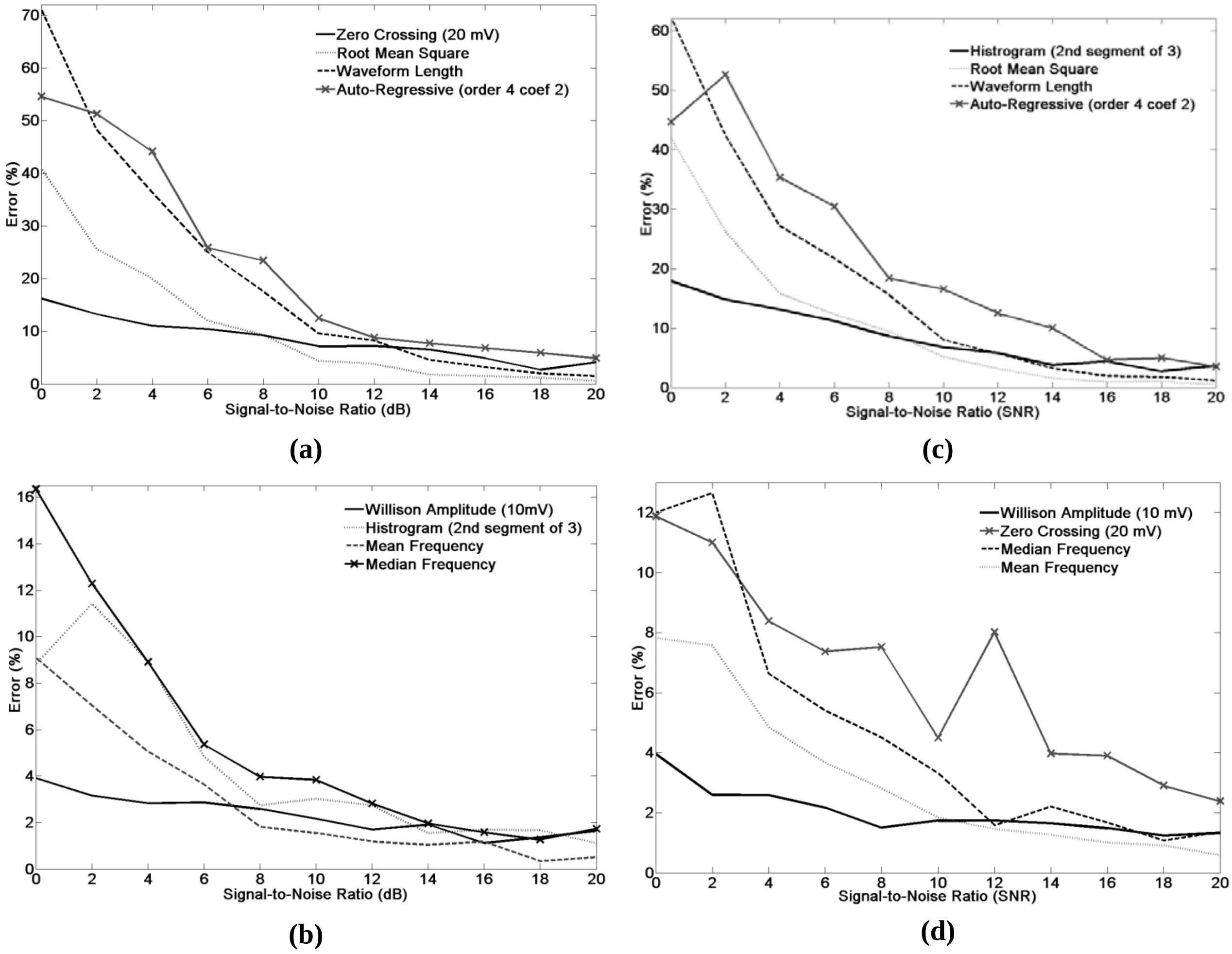


Figure 4. (a-b) Percentage error of eight features at various signal-to-noise ratios (20-0 dB SNRs) in wrist extension motion (c-d) Percentage error of eight features at various signal-to-noise ratios (20-0 dB SNR) in hand open motion.

AR coefficient is used for feature extraction. The model is basically of the following form:

$$x_n = -\sum_{i=1}^{p} \alpha_i x_{n-i} + w_n \,, \qquad (7)$$

where x_n is a sample of the modeled signal, α_i is AR coefficients, w_n is white noise or error sequence, and p is order of AR model.

The forth order AR was applied in this study because lots of experiments and suggestions from the previous research [6].

3.3. Evaluation

The percentage error (PE) is used to evaluate the quality of the robust of white Gaussian noise, as in

$$PE = \frac{feature_{clean} - feature_{noise}}{feature_{clean}} \times 100\% \,, \qquad (8)$$

where $feature_{clean}$ denotes the feature vector of the original EMG signal and $feature_{noise}$ represents the feature vector of the noisy EMG signal.

The performance of the algorithms is the best when PE is the smallest value. We calculated PE averages for each motion with ten repeated datasets. Therefore, there are 20 datasets for each feature and SNR of each datasets was varied from 20 to 0 dB. SNR is calculated by

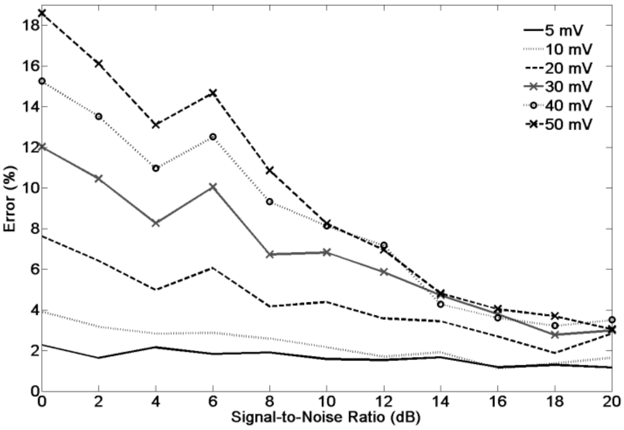
$$SNR = 20 \log \frac{x_{clean}}{x_{noise}} \,, \qquad (9)$$

where x_{clean} is the original EMG signals and x_{noise} is the white Gaussian noises.

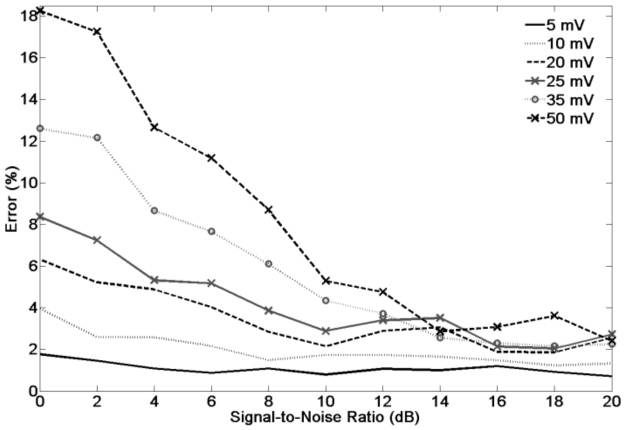
In time domain, EMG signal and noisy EMG signal at 0 dB is shown in Fig. 2. Power spectrum of original EMG signal and noisy EMG signal at 0 dB is shown in Fig. 3.

4. RESULTS AND DISCUSSION

To test the robustness of eight features, we measured the percentage error with EMG signal with additive WGN. The results of percentage error are plotted for SNR from 20 dB to 0 dB as shown in Fig. 4. Fig. 4(a) and Fig. 4(b) show the percentage error in wrist extension motion and the percentage error in hand open motion are shown in Fig. 4(c) and Fig. 4(d). By comparing Fig. 4(a-b) and Fig. 4(c-d), the results of percentage error in each motion is the same trend. As the SNR decreases, the percentage error of each feature increases. For SNR over 7 dB in wrist extension and over 10 dB in hand open,



(a)



(b)

Figure 5. Percentage error of willison amplitude at various thresholds (5-50 mV) (a) wrist extension motion (b) hand open motion.

FMN has the smallest percentage error, followed closely by the WAMP and FMD. For SNR less than 7 dB in wrist extension and less than 10 dB in hand open, WAMP has the smallest percentage error. On the other hand, the percentage error of FMN and FMD rapidly increased.

ZC and HIST have slightly larger error compared to WAMP, FMN, and FMD. The percentage error of RMS, WL, and AR are large that they were expected to perform poorly. In the figure, AR is the second coefficient of a fourth-order AR. It was adopted because percentage errors of the other AR coefficients are much bigger than the second one. Furthermore, the second bin of the third segment HIST was adopted.

The results above show that Willison amplitude was the best feature comparing with others in two motions. In addition, WAMP can adapt threshold parameter, while FMN cannot do it. This point may provide a better result.

Consequently, evaluations of threshold of willison amplitude were tested. The threshold values of WAMP have been varied within ranging from 5 to 50 mV as shown in Fig. 5. When threshold value gets smaller, the robust performance of WAMP improves. Willison amplitude with 5 mV threshold showed better than the others. Willison amplitude has error only 2.28% in wrist extension motion and 1.79% in hand open motion at SNR value of 0 dB. At a very high noise EMG signals, WGN at 0 dB, the percentage error is very small. As a result, willison amplitude with 5 mV thresholds can use for feature extraction and can exclude removal noise algorithm. In practice, we can adjust threshold parameter for suitable with each application.

5. CONCLUSION

The objectives of this study were to select a feature that tolerate with white Gaussian noise (WGN). Eight features in time domain and frequency domain were tested with additive WGN at various signal-to-noise ratios (SNRs). Results showed that Willison amplitude was the best feature comparing with others. Subsequently, evaluations of threshold of Willison amplitude were tested between 5-50 mV. Willison amplitude with 5 mV threshold showed better than others. Willison amplitude has error only 2.28% in wrist extension motion and 1.79% in open hand motion at SNR value of 0 dB. From the above experiment results, it is shown that willison amplitude with 5 mV thresholds can use for feature extraction and can exclude removal noise algorithm. Future work is recommended to find the new feature parameters to be tested and used the robust features as inputs to the EMG pattern classifier.

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REFERENCES

[1] C.F. Jiang and S.L. Kuo, "A Comparative Study of Wavelet Denoising of Surface Electromyographic Signals," Proc. IEEE 29th Annu. Int. Conf. IEEE EMBS, Lyon, 2007, pp.1868-1871.
[2] M.B.I. Reaz, M.S. Hussain, and F. Mohd-Yasin, "Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications," Biol. Proced. Online, Vol. 8, No. 1, pp.11-35, March. 2006.
[3] M.A.Oskoei and H. Hu, "Myoelectric control systems-a survey," Biomed. Signal Process. Control (Elsevier), vol. 2, no. 4, pp. 275–294, Oct. 2007.
[4] M. Zecca, S. Micera, M.C. Carrozza, and P. Dario, Control of multifunctional prosthetic hands by processing the electromyographic signal, in: Critical Reviews™ in Biomedical Engineering, Begell House, 2002, pp. 459–485.
[5] R. Boostani and M.H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," Physiological Measurement, vol. 24, pp. 309-319, 2003.
[6] O. Paiss and G.F. Inbar, "Autoregressive modeling of surface EMG and its spectrum with application to fatigue," IEEE Trans. Biomed. Eng., vol. 34, pp. 761-770, Oct. 1987.

Chaotic Coding Generated by A Dark Soliton Pulse within a Nano Ring resonator

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Abstract: This paper proposes a new concept of chaotic signal application for dark soliton chaotic code (DSCC) by the nano ring resonator. The behavior of nonlinear light known as four-wave mixing is introduced by the Kerr nonlinear effects type within the nano ring resonator device. The possible chaotic signals can be encoded to the logical pulse "0" or "1" and performed. The ring parameter used with the ring 5-10 μm and the coupling coefficients (κ) are 0.15-0.95. This is shown the potential of the controlled the chaotic signal encoding and the randomly quantized control chaotic signal encoding could be application in the security communication.