Comparison of Different Time and Frequency Domain Feature Extraction Methods on Elbow Gesture's EMG

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Abstract

Objective: In this study we will get EMG signals from arm for different elbow gestures, than filtering the signal and later classification the signal. The reason for doing is that, EMG signals are used for many rehabilitation and assistive prostheses of paralyzed or injured people. **Methods:**Filtering a biological signal is the key point for these type studies. Filtering the EMG signals needed and starts with the elimination of the 50 Hz mains supply noise. After filtering the signal, feature extraction will be applied for both wrist flexion and wrist extension cases. There are many feature extraction methods for time and frequency domain. After feature extraction, classification of hand movements will be studied using extracted features. Classification is made using K Nearest Neighbor algorithm. The dataset used in this study is acquired by the EMG signal acquisition tool and belong to us. **Results:**90 % accuracy performance is obtained by K Nearest Neighbor algorithm purposed signal classification. **Conclusion:**This system is capable of conducting the classification process with a good performance to biomedical studies. So,this structure can be helpful as machine-learning based decision support system for medical purpose.

Keywords: Elbow Gesture's EMG,Feature Extraction, Time and Frequency Domain.

1. Introduction

EMG signal is one of the main signals produced by the human body especially by the muscles. Although the results of electromyography are nonspecific electromyography is very sensitive [1]. EMG signal is widely used in many applications recently. The most active area of this application is prosthesis hand control. EMG signal also used for human-machine interface. EMG has advantages compare to other biological signals. Because EMG signals are powerful and have high signal to noise ratio.

2. Theory

2.1. EMG Data Acquisition

EMG signals are generated by the exchange of ions across the muscle membranes and detected with the help of electrodes as shown fig. 1.
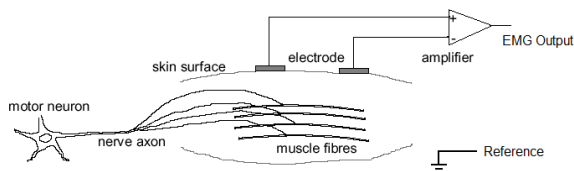

Figure 1. EMG acquisition from muscles [2]

Olimex Shield EKG/EMG device is used inorder to acquire EMG signals from arm. This device has one channel and 10 bit resolution. The sampling frequency of the device is 256Hz. This device amplifies the amplitude of the EMG which is acquired by the electrodes from skin surface of arm. The electrodes are disposable gelled silver-silverchloride(Ag-AgCl) type.

2.2. Filtering the EMG Data

Amplitude of the EMG signals vary between 0 to 10mV(peak to peak) or 0 to 1.5mV(rms). The meaningful signal is between 0 to 500Hz range[3]. Meaningful signals are those with energy above the electrical noise level. In order to get meaningful signal, filtering the EMG signal is very important. The most available noise signals in the EMG are AC mains power line noise and movement artifacts. So high pass filtering is necessary in order to eliminate low frequency movement artifacts(typically <10Hz)[4]. Notch filter is necessary for AC mains power line artifact removal. Also low pass filter can be used in order to remove high-frequency components to avoid signal aliasing.
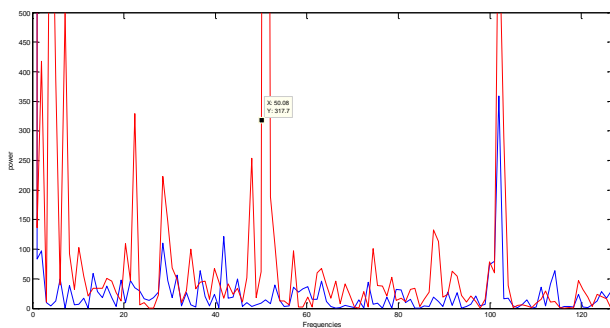

Figure 2. Raw and Filtered EMG Data

In figure 2 there is a plot of raw(red) and filtered(blue) EMG signal. According to plot there are dominant signals available at below 10Hz, at 50 Hz(also marked by data cursor) in red plot. These signals represent 50Hz power line interferenceand motion artifact interference(<10Hz). In blue plot these dominant signals are eliminated using 50 Hz notch filter and high pass filter.

2.3. Feature Extraction

Feature extraction is necessary for identifying the surface EMG signals. In this work two hand gestures will be identified. These gestures are as declared before wrist flexion and wrist extension as shown in fig 3.

Figure 3. Hand gestures [5].

Both flexion and extension gestures will be realized by muscles. Muscles will work different for two cases. We will get two different EMG signals. Sometimes when EMG signals are visualized the difference for two different gesture may be

observed by human eye. But the difference of two signal should be revealed by statistically or mathematically. In order to realize this signal must be handled in time domain and frequency domain. Table 1 shows the common feature extraction

methods for time and frequency domains.

Table 1. Time and Frequency Domain Features

Time Domain Features		Frequency Domain Features
Average Amplitude Change	Max. Fractal length	Amplitude of the first burst
Approximate Entropy	Multiple hamming windows	Critical exponent analysis
Autoregressive Coefficients	Multiple trapezoidal windows	Max to min drop in power density ratio
Box-Counting Dimension	Myopulse percentage rate	Frequency ratio
Cepstral Coefficients	Root mean square	Max. amplitude
Difference absolute stdev value	Sample Entropy	Median frequency
Detrended fluctation analysis	Skewness	Mean frequency
Higuchi's fractal dimension	Slope Sign Change	Mean power
Histogram	Simple square integral	Power spectrum deformation
Integral abs. value	Absolute temporal moment	Peak Frequency
Standard deviation	Variance	Power spectral density fractal dimension
Kurtosis	Variance Fractal Dimension	Power spectrum ratio
Log detector	v-order	Spectral moment
Modified mean abs val 1	Willison amplitude	Signal to motion artifact ratio
Modified mean abs val 2	Waveform length	Signal to noise ratio
Meanabs deviation	Zero Crossing	Total power
Mean abs val. slope	Mean	Variance of central frequency

In this work features used are written bold in the table1. As seen in table1. 17 features are used for feature extraction. 11 features are time domain features 6 features are frequency domain features.This statistical methods will identify the EMG signal for two class which are wrist flexion and wrist extension.

2.3.1.Time Domain Features

Time domain features are extracted from raw EMG signal so they are easy to implement. The easy implementation is an advantage of EMG signals but major disadvantage of time domain features comes from a non-stationary property of the EMG signal, changing in statistical properties over time, but time domain features assume the data as a stationary signal[6]. Time domain features are calculated from signal amplitude values, so much interference that is acquired through the recording come to be another disadvantage of these features.

a. Mean

Mean is the most common and easy implemented feature of the time domain. It only finds the mean of EMG amplitude values over sample length of the signal.

$$\text{mean}(\mu) = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad (1)$$

b. Variance

Variance is also most common statistical method for time domain feature extraction.

$$var = \frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2 \qquad (2)$$

c. Standard Deviation

$$std(\sigma) = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2} \qquad (3)$$

d. Skewness

Skewness is measure of asymmetry of a signal or measure of third order cumulative[7].

$$skew = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^3}{\sigma^3} \qquad (4)$$

e. Kurtosis

Kurtosis is measure of peakness of probability distribution or measure of fourth order cumulative.

$$kurt = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^4}{\sigma^4} \qquad (5)$$

f. Mean Absolute Deviation

The average of the absolute deviations of data points from their mean[8].

$$MAD = \frac{1}{N} \sum_{n=1}^{N} |x_n - ORT| \qquad (6)$$

g. AR Coefficients

AR coefficients are popular feature extraction method for biological signals. AR modeling is getting an equation which fits the signal. AR modeling tries to model the signal by previous data points of the signal.

$$x[n] = -\sum_{k=1}^{p} a_k \, x[n-k] + e[n] \qquad (7)$$

Here p is degree of the AR model, $x[n]$ is data signal which composed of n data points, a_k is real valued AR coefficients and $e[n]$ is white noise term which is independent from previous samples[9]. Choosing AR model order is an important issue. Because lower order of AR model cannot represent signal exactly, higher order of AR model overfit the signal and represent too much noise. In this work Akaike Information Criterion(AIC) is used in order to estimate optimal AR model order.

$$AIC(\rho) = \ln(\sigma_\rho^2) + \frac{2\rho}{N} \qquad (8)$$

Here ρ is model order, N is signal length and σ_ρ^2 is variance of error array at order ρ.
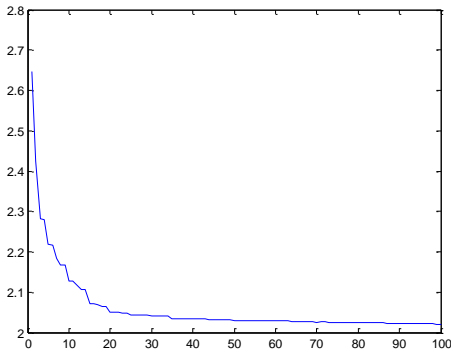

Figure 4. AR model selection criteria plot

According to plot of the AR order of EMG signal until 100th order, there is no change after 20th order of AR model as shown in fig. 4. So there is no need to use AR order more than 20th order. Much of the change is realized at orders until 10. Also some change after 10 to 20. So we can choose an order of between 10 and 20. In this work AR model order is chosen 13.

h. Waveform Length

Waveform length is a measure of complexity of the EMG signal. It is defined as cumulative length of the EMG waveform over the time segment.

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \qquad (9)$$

i. Zero Crossing

Zero crossing is a representation of frequency information of the signal at time domain. Zero crossing is count of thetimes that amplitude values of the EMG signal cross zero amplitude level. In order to eliminate voltage fluctuations or background noises, threshold can be used in the calculation.

$$ZC = \sum_{n=1}^{N-1} [sgn(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq threshold]; \qquad (10)$$

$$sgn(x) = \begin{cases} 1, & if \ x \geq threshold \\ 0, & otherwise \end{cases}$$

j. Willison Amplitude

Willison amplitude also related with the signal frequency information in time domain.

$$WAMP = \sum_{n=1}^{N-1} [f(|x_n - x_{n+1}|)]; \qquad (11)$$

$$f(x) = \begin{cases} 1, & if \ x \geq threshold \\ 0, & otherwise \end{cases}$$

g. Slope Sign Change

It is a count of number of times that slope of the EMG signal sign change. This feature is a method for representing frequency information of the EMG signal. Threshold is used in order to eliminate background noise of the EMG signal. The mathematically expression of slope sign change is like below.

$$SSC = \sum_{n=2}^{N-1} [f[(x_n - x_{n-1}) \times (x_n - x_{n+1})]]; \qquad (12)$$

$$f(x) = \begin{cases} 1, & if \ x \geq threshold \\ 0, & otherwise \end{cases}$$

2.3.2. Frequency Domain Features

Frequency domain features are extracted widely using Power Spectral Density(PSD). In this work Periodogram is used in order to estimate Power Spectral Density. 6 frequency domain features are extracted from PSD and their mathematical definitions are given below.

a. Mean Frequency

Mean frequency is an average frequency which is calculated as sum of product of the EMG power spectrum and the frequency divided by total sum of the spectrum intensity[5].

$$MNF = \left. \sum_{j=1}^{M} f_j P_j \middle/ \sum_{j=1}^{M} P_j \right. \qquad (13)$$

Here, f_j is frequency of spectrum, P_j is EMG power spectrum and M is the length of the frequencies.

b. Median Frequency

Median frequency is a frequency at which the spectrum is divided into two regions with equal amplitude.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \qquad (14)$$

c. Maximum to Minimum Drop in Power Density Ratio

Maximum to Minimum Drop in Power Density Ratio is the ratio of the highest mean power density value and lowest mean power density value, with a frequency band user defined.

d.Signal to Noise Ratio

Signal to Noise Ratio is a ratio of the signal power and noise power[10]. The signal power and noise power are estimated separately.

e. Power Spectrum Deformation

The Power Spectrum Deformation ratio is sensitive to changes in spectral symmetry and provides a indication of spectral deformation [10].

$$\Omega = \frac{\sqrt{M_2/M_0}}{M_1/M_0} \qquad (15)$$

M_n is the nth spectral moment defined as:

$$M_n = \sum_{i=0}^{i_{max}} P_i f_i^n \qquad (16)$$

Here P_i is the power spectral density value at frequency f_i.

f. Signal to Motion Artifact Ratio

As stated before motion artifact is low frequency artifact ofEMG signals. They are below 20Hz. The signal to noise artifact ratio was computed as a ratio of the sum of all power densities for frequencies below 600Hz and the sum of all power densities that exceed a straight line between the axis origin and the highest mean power density value, with a frequency above 35Hz[10].

2.4. EMG Signal Classification

After features are extracted from both time and frequency domains the EMG signals belong to elbow gestures are ready for classification. There are many classification algorithms are available. The most common classification algorithms are K-Nearest Neighbor Algorithm(KNN), Linear Discriminant Analysis(LDA), Artificial Neural Networks(ANN) and Support Vector Machines(SVM). In this work KNN algorithm is used because of its robustness and easy application.

2.4.1.K-Nearest Neighbor Classification Algorithm

KNN algorithm is one of the most common used algorithm in classification problems. Distances of one of the test class sample to all samples in the training class are calculated. Shortest distance of the training sample gives the class of the test sample. Assume two featured, two class of samples belong to A class and B class and assume one test sample like below. Nearest neighbor to X is belong to A training sample, so we can say X belong to A class.
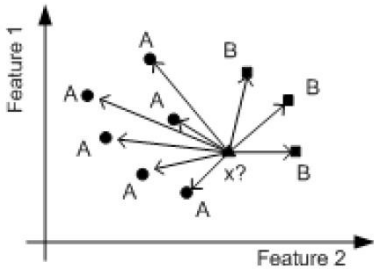

Figure 5. K-nearest neighbor algorithm[9].

Euclidian theorem is commonly used theorem for distance calculation in the KNN algorithm as shown in fig. 5. Distance between two pointsis calculated by Euclidian theorem like below.

$$d_E(p, q) = \sqrt{\sum_{i=1}^{R} (p_i - q_i)^2} \qquad (17)$$

Here R is feature quantity. KNN classifier takes consideration of k number of nearest neighbor and uses majority rule. K is commonly small and odd number. Bigger k helps to reduce the impact of noisy samples but increases de calculation difficulty. The impact of the k is explained below.
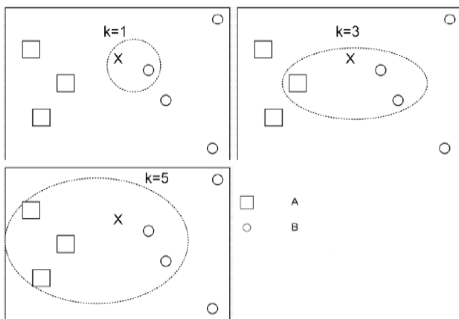

Figure 6. K- selection criteria[9]

In the example in fig. 6 when k=1 x is classified as it belong to class B, when k=3 and k=5 x is classified B and A respectively. This should be noted that k should be chosen like k=3. Because optimal k should be chosen $\sqrt{N}$ here N=7, and $\sqrt{7} \cong 3$.

3. Results and Conclusion

Using 17 features of the two classes of hand gestures (one for elbow flexion and elbow extension) EMG signals are classified separately from eachother by K-NN classification algorithm. The classification accuracies of the each feature are given in the table below. Here classification accuracies are the count of true classified pattern number in 100 pattern.

Table 2: Feature performances

Time Domain Features		Frequency Domain Features	
Feature	**Performance**	**Feature**	**Performance**
AR	93%	mtom drop	45%
std	81%	median fre.	83%
kurtosis	74%	mean freq.	65%
meabdev	83%	PSD	50%
skewness	72%	SMR	61%
slp.sgn.ch	49%	SNR	35%
var	79%		
wamplitude	71%		
wflength	80%		
zerocrossing	58%		
mean	91%		

According to table 2 the most successful features in time domain is Auto Regressive Coefficients(AR) and mean, median frequency is the most successful feature in time domain.

4. Acknowledgement

5. References

[1] GöçmezC, Kamaşak K,An important cause of tetraparesis:Cervical spondylotic myelopathy, Dicle Medical Journal 40:513-520, 2013.

[2] Jamal MZ, Signal acquisition using surface EMG and circuit design considerations for robotic prosthesis. INTECH Open Access Publisher, 2012.

[3] De Luca CJ, Surface electromyography: Detection and recording. DelSys Incorporated, 10, 2011.

[4] Day S, Important factors in surface EMG measurement. Bortec Biomedical Ltd publishers, Calgary, pp 1–17, 2002.

[5] Website: http://www.badmintoncentral.com (Accepted:07.02.2016).

[6] Phinyomark A., Phukpattaranont P., Limsakul C., Feature reduction and selection for EMG signal classification, Expert Systems with Applications,39:7420-7431, 2012.

[7]   Chowdhury R. H., et al, Surface Electromyography   Signal Processing and Classification Techniques. Sensors, 13:12431-12466, 2013.

[8]   Rasheed S., A Multiclassifier Approach to Motor Unit Potential Classification for EMG Signal Decomposition, Thesis, University of Waterloo, 2006.

[9]   R. Palaniappan, Biological Signal Analysis, 2010.

[10] Kendell C., et al, A novel approach to surface electromyography: anexploratory study of electrode-pair selection basedon signal characteristics, Journal of NeuroEngineering and Rehabilitation,9:24, 2012.