Robust Features Of Surface Electromyography Signal

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Abstract. Nowadays, application of robotics in human life has been explored widely. Robotics exoskeleton system are one of drastically areas in recent robotic research that shows mimic impact in human life. These system have been developed significantly to be used for human power augmentation, robotics rehabilitation, human power assist, and haptic interaction in virtual reality. This paper focus on solving challenges in problem using neural signals and extracting human intent. Commonly, surface electromyography signal (sEMG) are used in order to control human intent for application exoskeleton robot. But the problem lies on difficulty of pattern recognition of the sEMG features due to high noises which are electrode and cable motion artifact, electrode noise, dermic noise, alternating current power line interface, and other noise came from electronic instrument. The main objective in this paper is to study the best features of electromyography in term of time domain (statistical analysis) and frequency domain (Fast Fourier Transform). The secondary objectives is to map the relationship between torque and best features of muscle unit activation potential (MaxPS and RMS) of biceps brachii. This project scope use primary data of 2 male sample subject which using same dominant hand (right handed), age between 20-27 years old, muscle diameter 32cm to 35cm and using single channel muscle (biceps brachii muscle). The experiment conduct 2 times repeated task of contraction and relaxation of biceps brachii when lifting different load from no load to 3kg with ascending 1kg. The result shows that Fast Fourier Transform maximum power spectrum (MaxPS) has less error than mean value of reading compare to root mean square (RMS) value. Thus, Fast Fourier Transform maximum power spectrum (MaxPS) show the linear relationship against torque experience by elbow joint to lift different load. As the conclusion, the best features is MaxPS because it has the lowest error than other features and show the linear relationship with torque experience by elbow joint to lift different load.

1. Introduction

Nowadays, application of robotics in human life has been explored widely. Robotics exoskeleton system are one areas in recent robotic research that has high impact in human life. These system have been developed significantly to be used for human power augmentation, robotics rehabilitation, human power assist, and haptic interaction in virtual reality. This paper focus on solving challenges in problem using neural signals and extracting human intent. Commonly, surface electromyography signal (sEMG) are used in order to control human intent for application exoskeleton robot[1-5]. But the problem lies on the difficulty of pattern recognition of the sEMG features due to high noises which

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are electrode and cable motion artifact, electrode noise, dermic noise, alternating current power line interface, and other noise came from electronic instrument [1,2]. For sure unlike the robots used in industry, the robotic exoskeleton systems should be designed with special consideration since they directly interact with human user which is well known as anthropomorphic design. This paper presents a study to find the best features for electromyography signal. Then connected with relationship between best features muscle unit activation potential against torque produced by elbow joint for lifting different load. In this paper propose the novel technique to get the best features by using error to mean percentage.

2. Research Methodology
The purpose of this experiment is to acquire data for recording sEMG signals. The sEMG signal was recorded from biceps brachii muscles (refer in SENIAM group muscle position) of two healthy male (normal BMI and age range from 20-27 years old) by a Z03-002 EMG Preamplifier gain 300 with consist of medical grade stainless steel surface electrode (Motion Lab System, Inc) on the dominant hand. Sampling frequency was set at 1kHz using NI USB-6009 14 bit,48ks/s multifunction input/output (National Instruments). The NI USB-6009 attach with Z03-002 EMG Preamplifier connected to the PC by type-B cable as shown in figure 1.

2.1 Skin Preparation Procedure
When deal with acquisition of EMG signal need to bear in mind that noise are the main disturbance that can effected the informative raw EMG signal. Thus, for minimizing the error, skin preparation need to be done in order to acquire the informative raw EMG signal. Firstly, skin must be cleaned by shaved the hair to reduce impedance on the skin and clean again with alcohol prep to remove the death skin. After that, measured the skin impedance by using multi meter to ensure that the skin impedance is less than 10kΩ [3]. If the impedance reading high than 10kΩ then the skin need to be done skin preparation procedure until reach less than 10kΩ in order acquire an informative EMG signal.

2.2 Experimental Protocol and EMG Data Gathering
In this experiments, 2 healthy subjects were asked to perform the lifting exercises during the flexion-extension tasks (muscles isometric contraction) . A range of dynamic contraction was from a full extension (0°, forearm in the vertical position) to a full flexion (approximately 150°) with 10s in duration (2s start lifting, 4s holding full flexion position, 2s falling down). Four different loads, consisting of 0, 1, 2, and 3 kg, were experience by all subject while done this experiment. For this task, there are 2 trials in each load experience by all subject. The experiment setup is shown in figure 2.
2.3 Extraction features

From the raw EMG data acquire by undergoes experimental procedure the signal can be extracted in term of three main domain: (1) time domain, (2) frequency domain and (3) time-frequency domain[7,9]. But commonly the raw EMG signal extracted in term of two different type domain which is time domain and frequency domain. In time domain features, raw EMG signal extracted into five features which are sum absolute value (IEMG), Mean absolute value (MAV), Root Mean Square (RMS) value, standard deviation (STD), and Variance (VAR). In addition, in frequency domain by using Fast Fourier Transform (FFT) had been extracted into five features which are Mean value, Absolute median value, Absolute Root Mean Square, Maximum Power Spectrum (MaxPS) value and Minimum Power Spectrum (MinPS) value[7,9].

2.3.1 Time domain Features Extraction

Generally, time domain features is the most simple analysis of sEMG signal. In this analysis basically can be extracted the sEMG signal in term of sum absolute value (IEMG), Mean absolute value (MAV), Root Mean Square (RMS) value, standard deviation (STD), and Variance (VAR). All this features commonly used to learn a pattern of sEMG signal in the machine learning system[6].

2.3.1.1 Integrated EMG

Integrated EMG (IEMG) is calculated as the sum of absolute values in the sEMG signal amplitude. Generally, IEMG is act as an onset index to detect the muscles activity that used for control command of assistive control device. It is related to the sEMG signal sequence firing point, which can be expressed as

\[ IEMG = \sum_{n=1}^{N} |x_n| \]  

Where \( N \) denotes the length of the signal and \( x_n \) represents the sEMG signal in segment.
2.3.1.2 Mean Absolute Value
Mean Absolute Value (MAV) is equivalent to average rectified value (ARV). It can be calculated using the moving average of full-wave rectified EMG. On the others word, it is calculated by taking the average of the absolute value of sEMG signal. It is an easy way for detection of muscle contraction levels and it is a popular features used in myoelectric control application. It is represent as

$$MAV = \frac{1}{N} \sum_{n=1}^{N} |x_n|$$  \hspace{1cm} (2)

2.3.1.3 Root Mean Square
Root mean square (RMS) is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction[6]. It is relates to standard deviation, which can be defined as

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2}$$  \hspace{1cm} (3)

2.3.1.4 Standard deviation of EMG
Standard deviation is commonly used to measure confidence in statistical conclusion of sEMG signal. A low standard deviation indicate that the data points tend to be very close to mean and vice versa if a high standard deviation value. Generally, the standard deviation of experimental data, and only effects that fall far outside the range of standard deviation which is consider statistically significant.

$$STD = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} x_n^2}$$  \hspace{1cm} (4)

2.3.1.5 Variance of EMG
Variance of EMG (VAR) uses the power of the sEMG signal as feature. Generally, the variance is the mean value of square of deviation of that variable. However, mean of EMG signal is close to zero. It can be shown as

$$VAR = \frac{1}{N-1} \sum_{n=1}^{N} x_n^2$$  \hspace{1cm} (5)

2.3.2 Frequency Domain
In frequency domain, commonly by generate power spectrum of Fast Fourier Transform (FFT) as the tool to extract sEMG signal in term of five features component which is Mean value, Absolute median value, Absolute Root Mean Square, Maximum Power Spectrum (MaxPS) value and Minimum Power Spectrum (MinPS) value[7,9].

2.3.2.1 Absolute Mean value
Mean value is the most common extraction features technique that used had been used for pattern recognition of sEMG purpose. Generally can be expressed as

$$AMV = abs(\frac{1}{N} \sum_{n=1}^{N} x_n)$$  \hspace{1cm} (6)

2.3.2.2 Absolute median value
Absolute median value is a robust estimator dispersion that used to estimate the dominant frequency for sEMG signal. In other word can be define as
2.3.2.3 Absolute root mean square
Absolute root mean square is basically the absolute value of root mean square of the sEMG signal that had been FFT. It can be represent as

$$ARMS = abs\left(\sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2}\right)$$

(8)

2.3.2.4 Maximum Power Spectrum (MaxPS)
Maximum Power Spectrum (MaxPS) is maximum amplitude frequency spectrum via a Fourier Transform of the sEMG signal. For this project performed spectrum analysis of the entire signal. It can be simplified as

$$z = abs(Y)$$

$$MaxPS = max(z)$$

(9)

Where $Y$ is power spectrum of sEMG signal and $z$ is absolute value of $Y$.

2.3.2.5 Minimum Power Spectrum (MinPS)
Minimum Power Spectrum (MinPS) is minimum amplitude frequency spectrum via a Fourier Transform of sEMG signal.

$$z = abs(Y)$$

$$MinPS = min(z)$$

(10)

Where $Y$ is power spectrum of sEMG signal and $z$ is absolute value of $Y$.

2.4 Testing the robustness of features
After extracted all the features, the next to test the robustness of the features. In this paper present the technique without using machine learning to indicate the best features [9] as shown in equation 11 and If the error to mean percentage less than 6% thus the features choose as the best features for sMEG signal [9].

$$EMP(\%) = \left|\frac{x_i(actual) - \mu(mean)}{\mu(mean)}\right| \times 100\%$$

(11)

3. Result and Discussion
The result show the examples of signal acquire from experiment. This graph show that from first of samples data until 18866 sample data, subject was doing isometric contraction of elbow flexor. Then, from 18867 sample data until 25000 sample data subject was relaxing of elbow flexor. During the isometric contraction of elbow flexor show that the amplitude of voltage increase dramatically until reach the full contraction of biceps muscle then will decrease drop when muscle start to relax until full relax from any others muscles activity.
Figure 3. Show example of sEMG signal acquire from same experiment setup. Noted that the reading of sEMG voltage give different amplitude voltage value for each repeated task. Thus need to be get the mean value in order to calculate the error to mean percentage.

Table 1: Error to mean percentage for time domain statistical analysis of raw sEMG signal show that IEMG is the lowest value which is less than 10% of overall error to mean percentage compare with RMS, STD, MAV, and VAR.

| Error to mean percentage(%) | Sample subject A | Sample subject B |
|-----------------------------|------------------|------------------|
|                             | 0kg task         | 1kg task         | 2kg task | 3kg task | 0kg task | 1kg task | 2kg task | 3kg task |
| IEMG                        | 5.52             | 4.50             | 8.16     | 8.62     | 9.45     | 8.85     | 5.82     | 7.29     |
| MAV                         | 2.23             | 1.28             | 4.74     | 5.47     | 12.37    | 44.06    | 4.98     | 13.74    |
| RMS                         | 1.27             | 2.93             | 3.60     | 6.66     | 9.83     | 30.44    | 2.75     | 11.33    |
| STD                         | 1.85             | 2.93             | 3.60     | 6.66     | 9.98     | 30.44    | 2.76     | 11.33    |
| VAR                         | 4.37             | 5.82             | 7.25     | 13.25    | 19.47    | 55.72    | 5.52     | 22.37    |

Table 2: Error to mean percentage for frequency domain analysis of power spectrum sEMG signal show that the lowest error to mean percentage is MaxPS (less than 10%) followed by ARMS, AMDV, MinPS and lastly AMV.

| Error to mean percentage(%) | Sample subject A | Sample subject B |
|-----------------------------|------------------|------------------|
|                             | 0kg task         | 1kg task         | 2kg task | 3kg task | 0kg task | 1kg task | 2kg task | 3kg task |
| AMV                         | 36.26            | 57.93            | 15.13    | 42.59    | 40.22    | 30.92    | 35.22    | 37.10    |
| AMDV                        | 9.67             | 11.57            | 23.77    | 21.88    | 31.37    | 43.57    | 32.96    | 31.83    |
| ARMS                        | 4.56             | 5.83             | 9.54     | 4.91     | 19.57    | 31.33    | 4.95     | 34.66    |
| MaxPS                       | 3.68             | 4.52             | 0.43     | 8.83     | 11.35    | 6.80     | 3.28     | 3.27     |
| MinPS                       | 15.36            | 16.27            | 40.88    | 44.31    | 50.10    | 29.36    | 19.83    | 4.92     |

By refer to the table 1 and table 2 can be conclude that the best features is MaxPS because overall error to mean percentage record 5.27% error compare to others features.
The graph directly map from 2 sample subject data acquired in this experiment shown that the relationship between MaxPS features and torque experience by elbow joint to lift hand. Figure below shows linear relationship between MaxPS and torque experienced by elbow joint while was doing isometric contraction task using different load.

Figure 4 (a). The graph plot from data acquire by subject sample A. The graph show the relationship between MaxPS and torque experience by elbow joint for isometric contraction task using different load.

Figure 4 (b). The graph plot from data acquire by subject sample B. The graph show the relationship between MaxPS and torque experience by elbow joint for isometric contraction task using different load.

Figure 4 (a) shows that maximum amplitude of MaxPS value is 0.4181 compare to 0.162. This is because the difference in muscle strength (due to diameter of biceps brachii). It can be predicted that if the person have the larger diameter of biceps brachii, it will show bigger value activation voltage of muscle during isometric contraction[8].
CONCLUSION

As the conclusion, the best features is Maximum Power Spectrum (MaxPS) of Fast Fourier Transform because it has the lowest error than other features which is 5.17% and show the linear relationship with torque experience by elbow joint during isometric contraction.

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