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Wrist movement detection for prosthesis control using surface EMG and triaxial accelerometer

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Abstract— **The most important issue of prosthesis control is to get the correct control signal. In most studies, there is only one kind of signal applied to control the prosthesis, which is prone to error. In this study, a platform including measurement circuit and monitor software was developed to acquire mechanomyography (MMG) and electromyography (EMG) signals synchronously from flexor carpi radialis muscle of left arm as the signals to control prosthesis. The MMG signals were detected by a triaxial accelerometer, and they were analog pre-processed. The EMG signal was detected by three surface electrodes and an instrumentation amplifier was used to preprocess the differential EMG signal. For the first test, a pattern recognition experiment of four kinds of wrist movement was implemented. The experiment was carried out on six subjects. Using the Support Vector Machine (SVM) algorithm, the accuracy of pattern recognition classification was 96.06% by using MMG features combined with EMG features, which is higher than the accuracy of using just MMG (91.81%). The average accuracy of EMG features was 61.86%. It verified that acquisition of both the signals to control prosthesis would produce better results.**

Keywords- triaxial accelerometer; mechanomyography (MMG); surface EMG; Support Vector Machine (SVM); prosthesis control

I. BACKGROUND

Bio-signals, such as electromyography (EMG) and mechanomyography (MMG), are widely researched and used in various applications of interest, especially for prosthesis control [1]. But only one of them is acquired as control signal in most studies [2], [3], [4]. The EMG signal is an electrical signal of neuromuscular activation associated with a contracting muscle. It is especially used in research on muscle contraction of hand, wrist, elbow and leg [5], [6]. Surface electrode detection is the most popular method for detecting EMG signals without invasion, which usually uses two or more electrodes placed on the specific muscle for detection [7]. MMG signals are also widely investigated in such application. It is the mechanical signal obtained from muscle contractions. One of the major benefits of MMG signals is that it is not related to the impedance to the skin because it is a mechanical signal. Additionally, it does not generate electromagnetic interferences on the skin that affects other measurements. Those advantages facilitate the usage combined with other biological signals. MMG signals can be acquired using accelerometers [8], [9], piezoelectric contact sensors [10], microphones [11], or laser distance sensors [12].

In order to control the prostheses, researchers have studied many features and classification methods for discrimination of movement. The characteristic parameters of EMG and MMG signals can be delineated in time domain and time-frequency domain including root means square (RMS), mean power frequency (MPF), autoregressive modeling coefficient (ARC), and wavelet package transform coefficients. Reza Boostani et al. [13] studied 19 kinds of characteristic parameters of EMG signals to discuss the optimal parameters and parameter groups. Alcimar Soares et al. [2] measured the EMG signals of four kinds of movements from the biceps long head, biceps short head, triceps short head, triceps median head and triceps lateral head. In two separated experiments, Multi-Layer Perceptron architecture was used as classifier when classifying EMG signals using fourth-order ARC parameters and tenth-order ARC parameters. Mean rates of success from 95% to 96% were achieved. Mohamed R. Al-Mulla et al. [14] recorded MMG signals on the belly of the biceps brachii by an accelerometer. The acquired signals were grouped into fatigue and non-fatigue epochs. To identify muscle fatigue, a wavelet decomposition was utilized, and the accuracy of 81% showed in the classification results of genetic algorithm (GA). In addition, algorithms such as k-Nearest Neighbor (k-NN) classifiers, Nearest Mean, Decision Trees, and Support Vector Machine (SVM) were also frequently used for classification studies on bio-signals [13], [15], [16], [17].

In this research, a platform has been designed to acquire EMG and MMG signals synchronously from flexor carpi radialis muscle of left arm. The EMG signal was detected using surface electrodes and the MMG signal was derived from an accelerometer. In our experiment, signals for four kinds of activities were detected and SVM was used to discriminate with different combinations of signals.

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II. SYSTEM DEVELOPMENT

A. Sensors and Hareware Development

Two surface electrodes (H92SG, Kendall) were placed on flexor carpi radialis muscle of the left arm for detecting the surface EMG signal with a third electrode placed on biceps brachii muscle as the reference electrode. An acceleration sensor (ADXL337, Analog Devices) was placed in the middle between the positive and negative surface electrodes to detect the MMG signal. It is a low-power triaxial accelerometer with the measurement range of ± 3 g and a sensitivity of 300 mV/G. It can be used not only for the measurement of tilt angle, but also for the measurement of dynamic acceleration generated by movement and vibration. The bandwidth of the sensor is 1600 Hz for X and Y axes and 550 Hz for Z axis. The placement of the sensor is demonstrated in *Figure 1*.

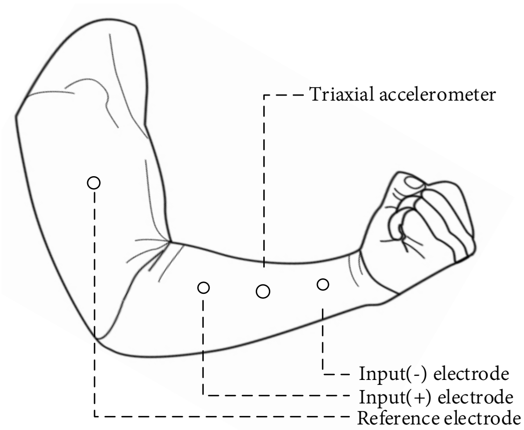

Figure 1: Placement of sensors.

The block diagram (see

Figure *2*) shows that the platform for data acquisition consists of several parts. For MMG signal acquisition, a triaxial accelerometer is used as the sensor. Actually, the signal from each axis of the accelerometer is regarded as one channel of MMG signal. Thus, there are three accelerometer outputs. The acceleration signals consist of a superposition of a low frequency component (f < 5 Hz) and a high frequency component (f ⩾ 5 Hz) in this application. The low frequency component is caused by the gravitation and contents the information of the tilt. The high frequency component is generated by the muscle contractions. Both the information is useful, but the amplitudes of the high-frequency component are much smaller than the low-frequency signal component. Therefore, just this component shall be amplified before digitizing the signal. In the block diagram it can be seen, that for this purpose, the MMG-signals are frequency separated by analog highpass filters (fc=5 Hz) and lowpass filters (fc=2.5 Hz) of 2nd order. Afterwards the high-frequency component is amplified with a gain of G=10, using a non-inverting amplifier circuit (OPA734, Texas Instruments). Instead of using 2 separate ADC channels for both the components, the signal components are analog added (OPA734, Texas Instruments) before digitized by the internal ADC of an Arduino Uno board with a resolution of 10 bits and a sampling rate of 1000 SPS. To acquire the EMG signal, three surface electrodes are used. The measured differential signal is amplified by an instrumentation amplifier (INA128, Texas Instruments) with a gain of G=250. An active high pass filter was utilized for baseline drift removal. Since the ADC is just able to digitize positive voltages, a direct current component of half range of power supply is appended to EMG signal before digitizing. Afterwards, the acquired data is sent to a computer through a medical USB isolator (USB-GT interface-Isolator, Meilhaus Electronic) for digital signal analysis.

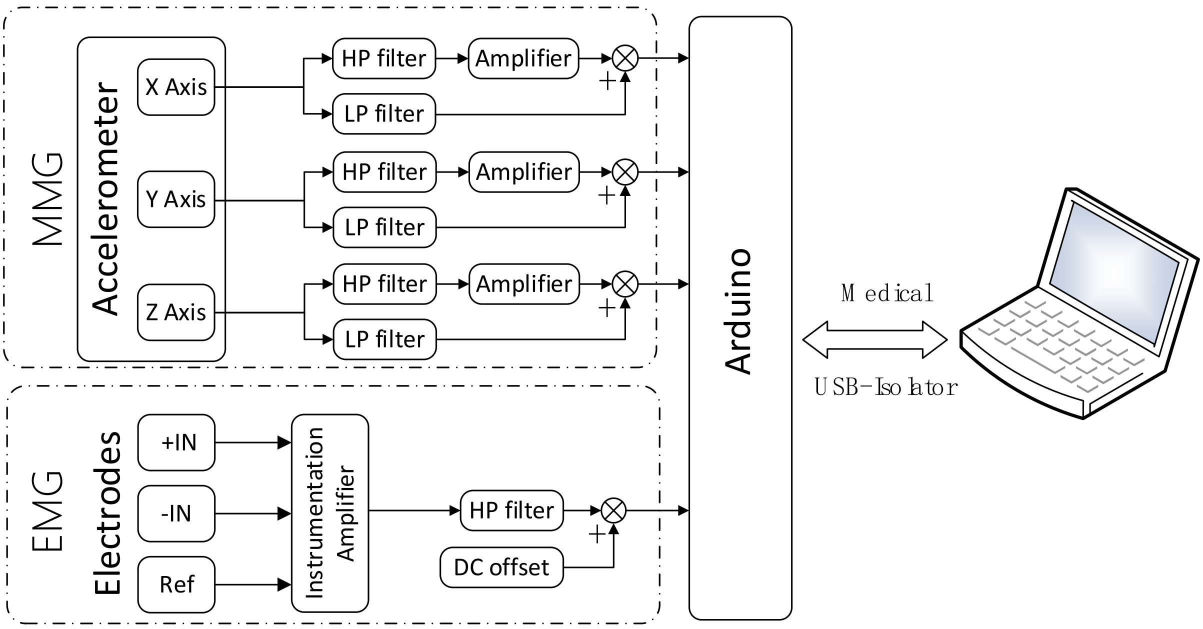

Figure 2: Block diagram of electrical system. (HP = high pass, LP = low pass, Ref = reference, DC = direct current)

B. Deveplopment of a Graghical User Interface

In order to monitor the collected data and facilitate the acquisition process, a graphical user interface (GUI) for acquisition was developed in this research. It is programmed in C# language and enables to check the signals during the measurement procedure. After the acquisition, the operator can review the signals, further to judge the reliability of the signal in time domain and frequency domain and whether it conforms to the characteristics of the MMG and EMG. The Fast Fourier Transform spectrum is calculated using the DSPLib for .NET 4.0 [18]. The signals can be saved as text files for further analysis, which is convenient for other programs to import the signals, and greatly improves the flexibility of processing signals by using different software. A screenshot of the GUI is shown in *Figure 3*.

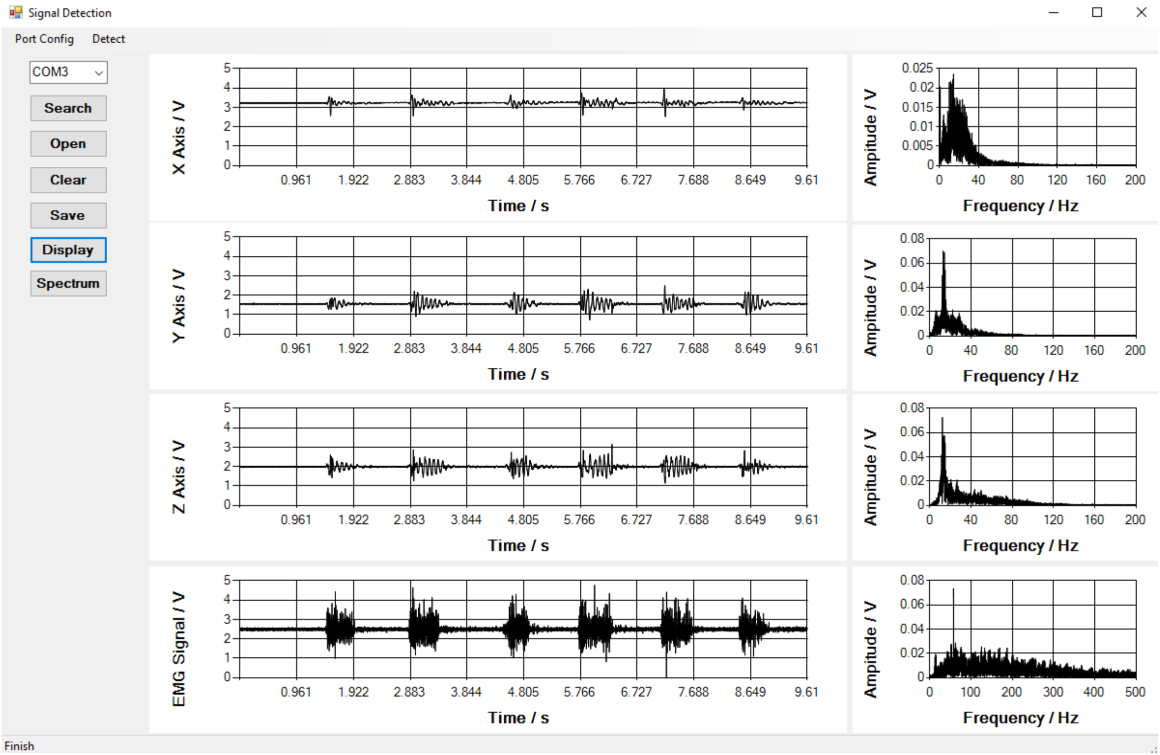

Figure 3: Graphical user interface for data acquisition. The left buttons are function selection, and the middle chart shows the signals collected for a period of time, while the spectrum can be displayed in the four charts on the right after collection.

III. Experiment

A. Subjects and activities

In order to verify the ability of acquired signals for prosthesis control, a collecting experiment was carried out for 6 volunteers (four males and two females). The acquisition of four groups of movement, which are Wrist Flexion (WF), Wrist Extension (WE), Ulnar Wrist Flexion (UWF) and Hand Grasp (HG), is carried out for each subject. Figure 4 shows the illustration for these movements. Each group of movement was collected continuously and repeated 30 times to obtain 30 movement segments. The interval between two actions is two seconds to ensure that each action is independent of each other. After a group of movement is completed, a rest is taken before measuring the next group. Figure 5 shows the typical signals of each movement from triaxial accelerometer and surface EMG electrodes.

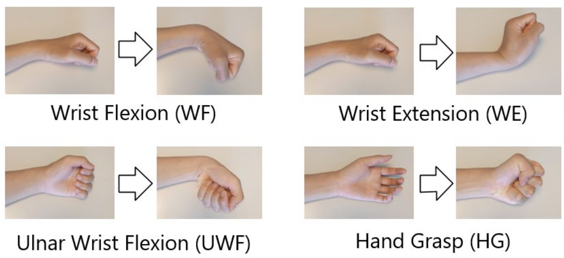

Figure 4: Illustration of movements.

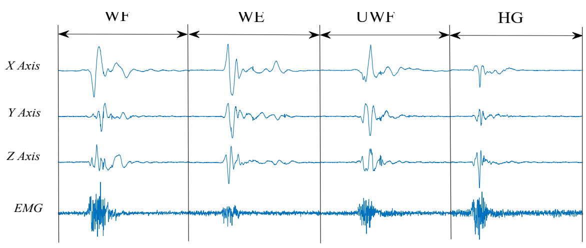

Figure 5: Illustration of signal segments of four movements.

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B. Data Analysis

Before classification, the signal features should be selected primarily. According to previous publications [2], [14], [19], the fourth-order ARC and integral of absolute value (IAV) are common features for biological signal classification, so they are selected as the features for classification in this experiment. In this way, five features can be obtained for each segment to represent itself. And there are four such segments in one movement, so twenty features can be obtained to represent the movements. The equation for ARC is expressed as

$$y_k = \sum_{i=1}^{p} a_i y_{k-i} + \omega_k \tag{1}$$

where y_k is the value at the K-th sampling point, y_{k-i} is the value of i-th sampling point before K, a_i is ARC, p represents the order of the auto-regressive model, and ω_k is the residual white noise. A critical problem is suitable choice of order to reduce the residual white noise. Previous studies showed that the fourth-order autoregressive model for processing EMG and MMG signals performed well [20], [21], so the fourth-order autoregressive model is also chosen to represent patterns of signals in this research.

IAV is expressed as:

$$IAV = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2}$$

where y_i represents the signal value at the *i-th* sampling point, and *N* represents the length of the signal segment, which reflects the overall characteristics of the signal segment. In this research, the SVM is used as the classification algorithm. SVM is a machine learning method developed on the basis of statistical learning theory, which is proposed by the optimal classification hype-plane under the linearly separable condition of model classes. Many scholars have made many outstanding contributions in the period from proposing to developing of this algorithm [20]. The LIBSVM library for Mathworks MATLAB [22] was developed by Chih-Chung Chang's research group of National Taiwan University, which is very convenient for users. A graphical user interface for classification was also developed based on the LIBSVM library, which is shown in Figure 6. The operator can choose the subject to classify by a popup menu. Three buttons are used for reviewing data, calculating parameters for classification and classifying in SVM. Each parameter of channels can be selected or not selected for classification. This chart shows the result of the last classification and the average accuracy (rate of success by SVM when classifying signals modelled by ARC and IAV) is also shown under the chart.

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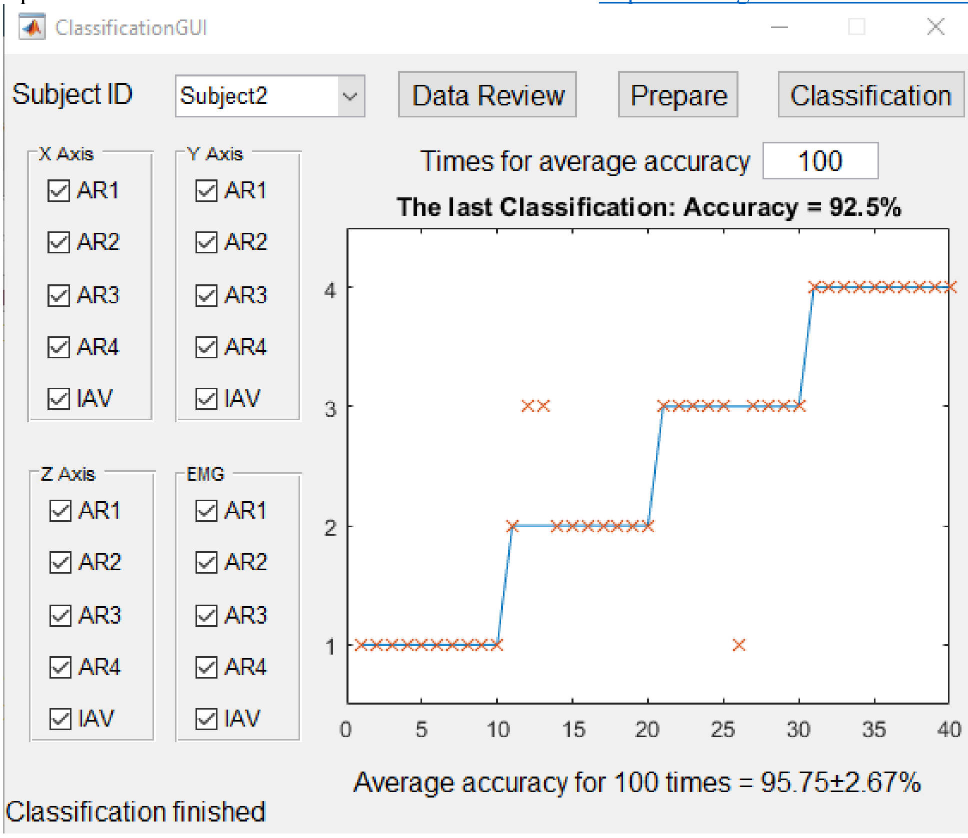

Figure 6: Graphical user interface for classification.

C. Results

In the classification process, the signals were divided into training group and prediction group. In order to avoid artificial intervention, 20 segments from the same channel were randomly selected as the training samples, with the remaining 10 samples as the prediction samples. Hence, each object will use 80 signal segments for training, and 40 segments for prediction. The average accuracies of the 100 times of prediction experiments are shown in Table 1. The average accuracy of only using MMG signals was (91.81±2.76)%.The average accuracy of EMG was (61.86±6.05)%, while the classification accuracy of using both MMG signal and EMG signal was (96.06±2.42)%. The results of using accelerometer and surface electrodes were clearly superior to that of using a single signal source.

TABLE 1: THE AVERAGE ACCURACY OF 100 TIMES OF CLASSIFICATION PERFORMED BY EACH SUBJECT.

Accuracy (%)	MMG		EMG		MMG + EMG	
	mean	std	mean	std	mean	std
Subject 1	88.00	1.97	69.75	2.75	98.75	1.32
Subject 2	87.50	2.89	53.85	6.19	95.75	2.67
Subject 3	90.50	2.84	50.23	7.23	92.78	3.59
Subject 4	91.93	3.87	71.50	4.90	95.03	2.98
Subject 5	99.75	0.75	62.25	8.81	99.95	0.35
Subject 6	93.15	4.24	63.55	6.39	95.08	4.10
AVERAGE	91.81	2.76	61.86	6.05	96.06	2.42

IV. Summary and outlook

In this paper, a triaxial accelerometer and surface EMG electrodes were used, and the corresponding circuit was designed to acquire the MMG and EMG signals synchronously. The signal of the accelerometer was filtered and amplified. Experiments were carried out using both kinds of signals in SVM algorithm to classify actions (wrist flexion, wrist extension, ulnar wrist flexion and hand grasp). It was found that the accuracy of classifying in the experiment by using the triaxial accelerometer was (91.81±2.76)%, while the average accuracy of MMG signals combined with EMG signals was (96.06±2.42)%. Therefore, the combination of using MMG signals and EMG signal would be more accurate and efficient in the field of prosthesis control. In this experiment, the ARC and IAV features were used for classification to verify the ability of acquired signals for prosthesis control. In future study, other relevant parameters can be used to optimize the classification results. Moreover, if the two kinds of signals can obtain higher classifying accuracy, the combination of the two signals will be able to crosscheck detected movements, making it more secure and reliable in such application field.

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