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HYBRID FEATURE EXTRACTION MODEL FOR EMG CLASSIFICATION USED IN EXOSKELETON ROBOTIC DESIGN

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Abstract: *Exoskeleton is an artificial external supporting structure that covers, supports, and protects the body. Exoskeleton robots help the physically disabled to perform their daily -life activities with convenience. Surface myoelectric signal is one of the control signals for controlling this Exoskeleton robot. In the commercial market the number of products has been developed that utilize these myoelectric signals. However, the functionality of these products is inadequate to satisfy the requirements of disability. This paper mainly focuses on the classification accuracy and classification algorithms of different surface myoelectric signals that come from upper limb i.e. the deltoid region to the hand, including the arm, axilla and shoulder. For the purpose of comparison, two groups and ten different activities of electromyogram classification methods have been developed. Four different feature sets are involved that resolves the problem of classification and gives better performance. This can be given to the classifier, which helps in giving information for the further processing. In summary, feature vector and support vector machines algorithms showed a remarkable performance in terms of high classification accuracy for two different groups of surface myoelectric data.*

***Keywords*—Powered prosthesis, upper limb, support *vector machines* algorithms.**

I. INTRODUCTION

Bio signals are the electrical signals generated from various tissues and organs. In the last few years, the bio signals like electroencephalogram (EEG), electro oculo gram (EOG), electrocardiogram (ECG) and electromyogram (EMG) played a key role on various clinical conditions and also for controlling various assistive devices [2]. Among these bio-signals for recognizing the human intention, Electromyogram (EMG) has been widely employed both in the commercial market and the research area because of its simplicity and practicality [1]. Surface EMG (SEMG) is one of methods for acquiring EMG signals. SEMG was mostly used method because of its non-invasive characteristic [1,2]. These SEMG has been a help to improve the independence of the physically-impaired people using electric powered wheelchairs and artificial limbs [2]. In this study, a three channel EMG sensor was developed and EMG signals for ten types of upper limb movements were acquired from four healthy volunteers. Different features and classification techniques used to discriminate a number of motion classes, such as Aggressive and Normal activities with a few channels of SEMG is a practical approach. The main purpose of feature extraction is to find representative characteristics from EMG raw data because of its non-stationary characteristic. Therefore the raw data needs the appropriate feature extractions. In general three types of features are presented in the myoelectric control literature [1]; time domain, frequency domain, and time-frequency domain features. The time domain features are calculated directly from EMG raw data because the data signal is voltage and frequency domain features need a transformation to calculate its power spectral density. Time-frequency domain features include both time and frequency information which are generated by time and frequency analysis, such a Wavelet Transform (WT), Wavelet Packet Transform (WPT). Also, support vector machines algorithms show a remarkable performance in terms of high classification accuracy for two different groups, such as Aggressive activities shown in Fig.1 and Normal activities shown in Fig.2. There are internally ten different activities under Aggressive and Normal activities.

Fig.1. Aggressive Activities

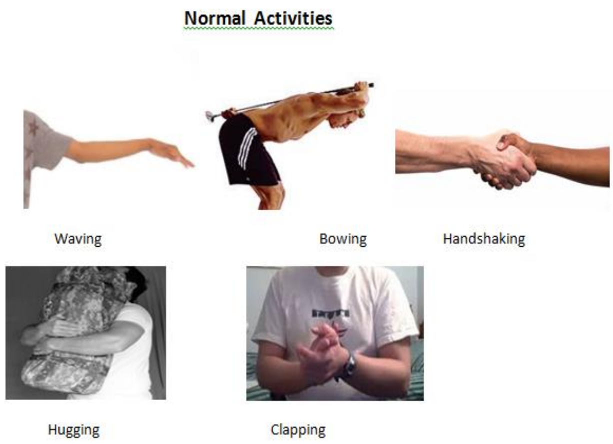

Fig.2. Normal Activities

II. MATERIALS AND METHODS

A. Data Acquisition:

In total, two classes and ten motion activities are formed as a target classes. In aggressive group: Elbowing, Hammering, heading, pulling, pushing, punching and slapping shown in Fig.1. In normal group as bowing, clapping, handshaking, hugging and waving shown in Fig.2. During process of data collection, each motion activities was held for three seconds and a three-second rest was placed between motions activities [1].To gather training samples for a classifier, a three-channel surface EMG signal acquisition system was used. The first channel was located on the flexor carpi radials muscle while the second channel was located on the extensor carpi radials longus muscle and final channel was located on extensor carpi ulnaris muscle. General electrodes (EL100) and a muscle sensor (SEN-13723) measurement system (NI ELVIS II**)** with 1 kHz sampling rate, made by NI Educational Laboratory, were used to collect raw EMG signals**.** All experiments and computational tasks were conducted on a personal desktop computer, Intel core i3,8 GB RAM, 64 bit Windows 7 OS, and Matlab® 8.1 64 bits.

B. Feature Extractions:

Selecting feature extractions is critical because features calculated from the raw EMG data should be representative of muscle motion. In this paper, four feature sets were selected with different combinations of time domain features ,frequency domain features and time-frequency domain features:(1) TD feature set, first four moments of the time series; (2)Wavelet energy features; (3)wavelet entropy features; (4) Fourier transform Energy feature in frequency domain .In this paper classifiers were tested with these four different feature sets individually and combined.

C. Classification Methods:

Generally, Seven classifiers are widely used in the literature those are Naïve Bayes (NB), k-Nearest Neighbour (KNN), Linear Discriminate Analysis (LDA), Decision Tree (DT), Multi-Layer Perception (MLP), Quadratic Discriminate Analysis (QDA), and Support Vector Machine (SVM).The classification accuracy of SVM was the highest, followed by QDA and NN in WTS[1]. In this paper, a binary Support Vector Machine with Kernel Function was suggested. In binary Support Vector Machine has number Kernel Function are presented those are Linear, Polynomial of different orders, Gaussian Radial Basis function (RBF) and Sigmoid. SVM with a Polynomial of different orders kernel was applied for SEMG upper limb motion classification. In order to break down the multiclass-extremity motion problem to a set of binary classification problems, which is needed binary SVM classifier, one-versus-the-rest approach was implemented in this paper.

D. Classifier Training Schemes:

To train a classifier, there are two Training Schemes are presented. The first training scheme is Whole Training Scheme (WTS) and the second training scheme is Partial Training Scheme (PTS). In Whole Training Scheme, all feature values were calculated from all data samples, and then test sets were randomly selected from all feature values, the rest feature values were used for training sets. The fold cross validation (CV) technique was used to select the Training and testing data set. In Partial Training Scheme, motion samples of each group class were divided into six pieces. And then, a piece was chosen as a test set in the leave-one-out CV manner. In this paper, Whole Training Scheme (WTS) was implemented because in the WTS method classifiers were trained for all motion samples is shown in Fig.3.SVM with TD feature performed best in both WTS and PTS[1].

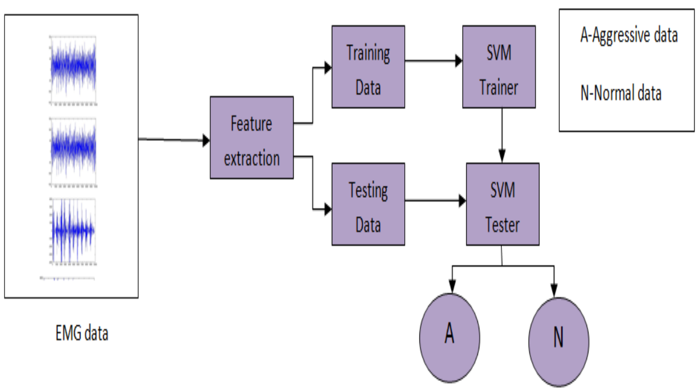

Fig.3 Block diagram of EMG data classification

III. RESULTS AND DISCUSSION

A. EMG signal acquisition:

Commercially available EL100 disposable electrodes were used as the muscle sensor(SEN-13723).These electrodes reduces motion artefacts in the recording of the EMG signals .The electrodes were placed at three positions on the forearm, namely, the flexor carpi radials muscle, carpi ulnaris muscle and the extensor carpi radials longus muscle are shown in Fig. 4. Shielded wires were used to connect the electrodes to NI ELVIS. The EMG data was recorded from four volunteers for ten types of upper limb movements, namely Elbowing, Hammering, pulling, pushing and punching in the group of Aggressive and bowing, clapping, handshaking, hugging and waving in group of normal activities. Collette EMG data from different group activities i.e. aggressive EMG data and normal EMG data is shown in Fig.5 and Fig.6.

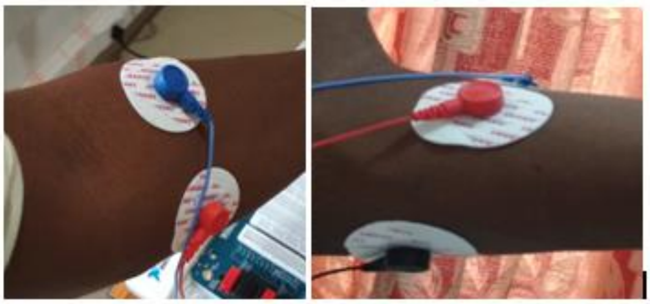

Fig. 4 Electrodes Placement

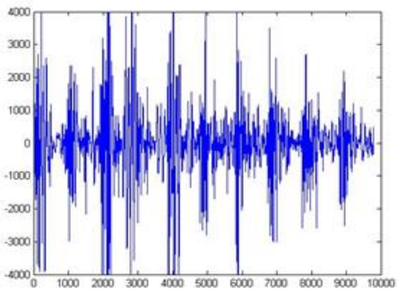

Fig.5. Aggressive EMG signal

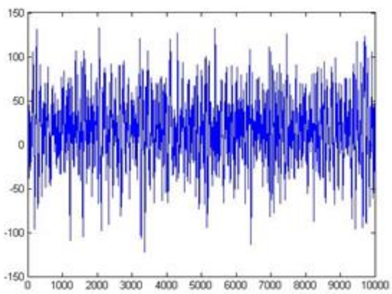

Fig.6. Normal EMG signal

B. EMG signal processing and classification:

All the acquired EMG data from four volunteers were processed using an in-lab developed Lab VIEW program to obtain their envelopes of 3 sec duration. These data were loaded into a MATLAB program to extract four features, namely, first four moments of the time series, Wavelet energy features, wavelet entropy features and Fourier transform - Energy feature. The results obtained from these analyses are tabulated in Table.1. However, we consider only the first 10 principal components of future vector. In terms of the SVM classification parameter, we used a Polynomial of order 1 for kernel and sequential minimal optimization (SMO) algorithm is used for finding the support vector .We used 10-fold cross validation (CV) technique i.e. , training with 9 folds and testing on 1 fold . Finally, evaluate the performance measures as an average of 100 runs. The classification performance with all features is 97.77% with kappa coefficient 0.953 and both accuracy levels are shown in Table-1. The individual performance and the combined performance of the extracted featured accuracies are shown in Fig. 7and Fig.8.

Table.1: Kappa Accuracy levels of features involved

Models used	Kappa accuracy	Classification Accuracy
Time series	94%	97%
Wavelet Energy Features	74%	87%
Wavelet Entropy	91%	95%
FFT	82%	91%
Template Entropy	88%	94%
Combined featured response	95%	97%

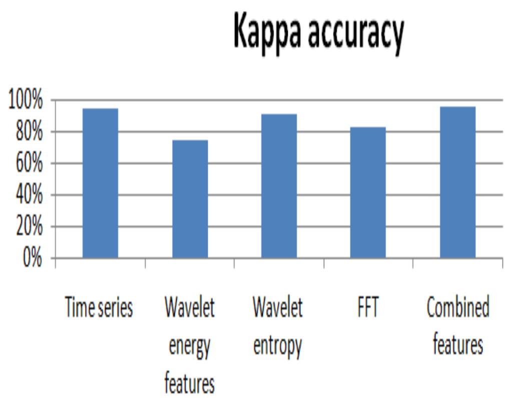

Fig 7: Kappa accuracies of extracted features

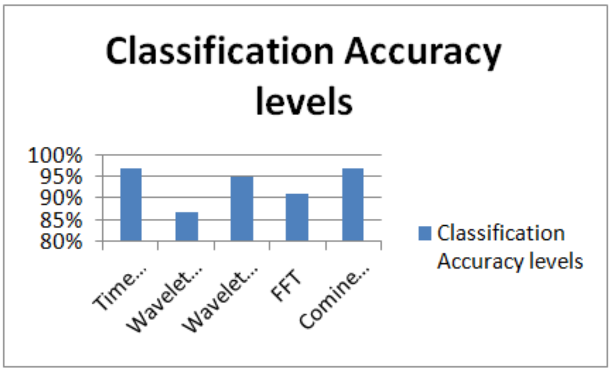

Fig 8 : Accuracy levels of features extracted
Confusion matrix of EMG data as shown in Table.2.

Table 2: Confusion matrix

	A	N
A	27	0
N	1	20

CONCLUSION:

Among the individual and the combined features, combined features gives better results with high accuracy for the features which are mentioned in the above sections. For this the Aggressive and normal responses are 95.36% and 92.00% respectively. By using the polynomial ordered kernel SVM the data was classified into aggressive and normal data with accuracy 97.77% and kappa coefficient 0.9536. By using this classification, hierarchical approach can be further used for dividing this data into other sub-groups.

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