ISSN : 0974 - 7435 Volume 11 Issue 9

BioTechnology

An Indian Journal

FULL PAPER

BTAIJ, 11(9), 2015 [340-346]

Comparative study of myoelectric pattern recognition using SVM and PNN classifiers based on wavelet analysis

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ABSTRACT

The choice of a proper wavelet family with a fast and robust classifier is an important step in the construction of a myoelectric control pattern recognition system for a prosthetic hand. In this study, five hand motions were classified by using six wavelet functions extracted features from sEMG signals. The selected wavelet families that were used to decompose the recorded sEMG signals are Biorthogonal (bior). Coiflet (coif), Daubechies (db), and Symmlet (sym). Two different recognition methods were employed for classification procedure: support vector machine (SVM), probabilistic regression neural network (PNN). The results of our experiment demonstrate that the use of wavelet families at a high decomposition level increases the recognition rate of hand motions. The highest achieved classification rate was 96%, by using the PNN classifier based on coif4 at the sixth decomposition level.

KEYWORDS

EMG;
Bio-signal processing;
Pattern recognition;
Wavelet analysis;
Probabilistic regression neural network and artificial intelligence;
Human-machine interface.

INTRODUCTION

The usage of a forearm sEMG signal to classify different types of hand motions has become a challenging topic for many researchers[1-5]. The sEMG signal is a bioelectrical signal detected from the skin surface that is generated by the electrical activity of the muscle fibers during contraction or relaxation.

An electromyogram (EMG) is a method of recording the electrical activity of the muscle. The recorded potential is proportional to the level of the muscle activity. The recorded potential is proportional to the level of the muscle activity. In general, EMG has been used for diagnosis of neurological and neuromuscular problems and in assistive technology and rehabilitation engineering. The shapes and firing rates of Motor Unit Action Potentials (MUAPs) in EMG signal contain considerable information for the diagnosis of neuromuscular and neurological disorders[6-8].

In general, there are two kinds of EMG electrodes. The first type is invasive electrode: A needle electrode is inserted through the skin into the muscle (painful). The other type is a non-invasive electrode: The surface electrode mounted directly on the skin, a shift in the electrode placement will provide a completely different sEMG signal, which will affect the classification rate[9]. In this research, disposable moisture Ag/AgCl surface electrode type was used to obtain the sEMG signals from the surface of the skin.

A surface electromyographic (sEMG) signal has a non-stationary, stochastic, and complicated nature that makes it more difficult to analyze[10]. The introduction of a myoelectric signal directly into a classifier is impractical and time-consuming due to the large amount of raw data. Thus, it is practical to map the input data into a feature vector[11]. In the following section of the manuscript, we present some of the previous works related to pattern recognition of sEMG signal.

To classify four hand motions, the performance of different classification algorithms were investigated LDA, QDA and k-NN[9]. They extracted three time domain features from sEMG signals: integrated absolute value (IAV), difference absolute mean (DAMV) and difference absolute standard deviation (DASDV). Classification rates obtained using K-NN, QDA, LDA classifiers were 84.9%, 82.4%, and 81.1% respectively.

Three wavelet families (Haar, db, and sym) at different decomposition levels were tested by other researchers[12], who found that the use of sym4 and sym5 at the decomposition rates 8 and 9 can obviously distinguish between sEMG signals related to fatigued and non-fatigued muscles.

Another research group[13] collected sEMG signals from a muscle under sustained contractions for a period of four seconds using different loads and then analyzed the signal using fast Fourier transform (FFT), discrete wavelet transform (DWT), and wavelet packet transform (WPT). Based on their study, these researchers recommend the use of Daubechies, Symmlet, and Coiflet families for sEMG analysis.

The recorded sEMG signals were decomposed at the third, fourth, fifth, and sixth levels using sym4, sym5, db8, db10, bior3.3, and coif4. The result of this research can be used in constructing prosthetic hands that can help amputees restore some of the capabilities of their lost hand.

The remainder of this manuscript is divided into four sections. The first gives the reader information on the experimental protocol. The second section introduces the classification algorithms that were used in this research study. The last two sections present and discuss the results obtained from the experiment and present the conclusions drawn from the results and suggestions for future work, respectively.

DESIGN EXPERIMENT

Ten right hand-dominant healthy subjects (males aged from 20 to 38 years) without any neuromuscular disorders participated in this experiment. To collect two sEMG signals from the forearm muscles, one pieces sEMG signal recording equipment (AD Instrument's Power Lab 4/25 T) was used. The data acquisition system (DAS) has two channels, and each channel is responsible for collecting one sEMG signal. In total, two sEMG signals were acquired from two different forearm muscles, extensor carpi radialis and flexor carpi ulnaris.

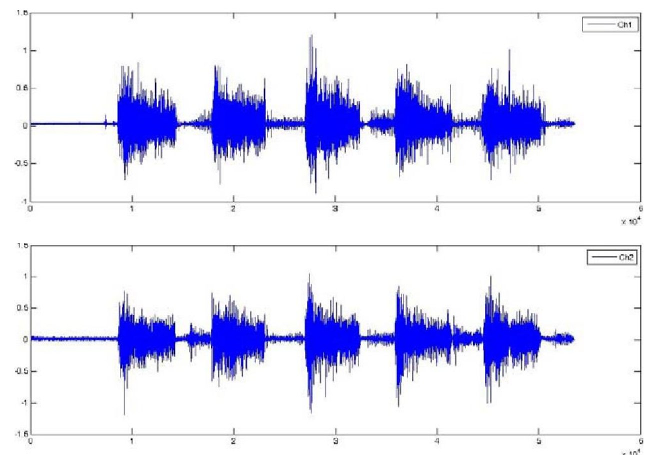

Figure 1 : Two channels sEMG signals were recorded using EMG data acquisition system. The subject performs close hand movement and repeats it five times. The acquired sEMG signal was sampled at 1 kHz. The amplitude of the sEMG signal is represented on the Y axis.

The distance between the electrodes corresponding to the same channel was maintained constant for all of the experiments. All of the subjects were asked to perform five movements. Each movement/action was repeated five times, and each action was held for five seconds. Figure 1 shows two channels sEMG signal was recorded using EMG data acquisition systems.

A bandpass filter with a 10- to 500-Hz bandwidth, a 50-notch filter, and a mains filter were used. The data were sampled at 1 kHz. All of the data were segmented into consecutive 500-ms epochs. In this paper, we attempted to recognize the five hand movements clarified in Figure 2.

The block diagram of the proposed system is presented in Figure 3. The structure consists of four steps. The first step is responsible to collect and store the

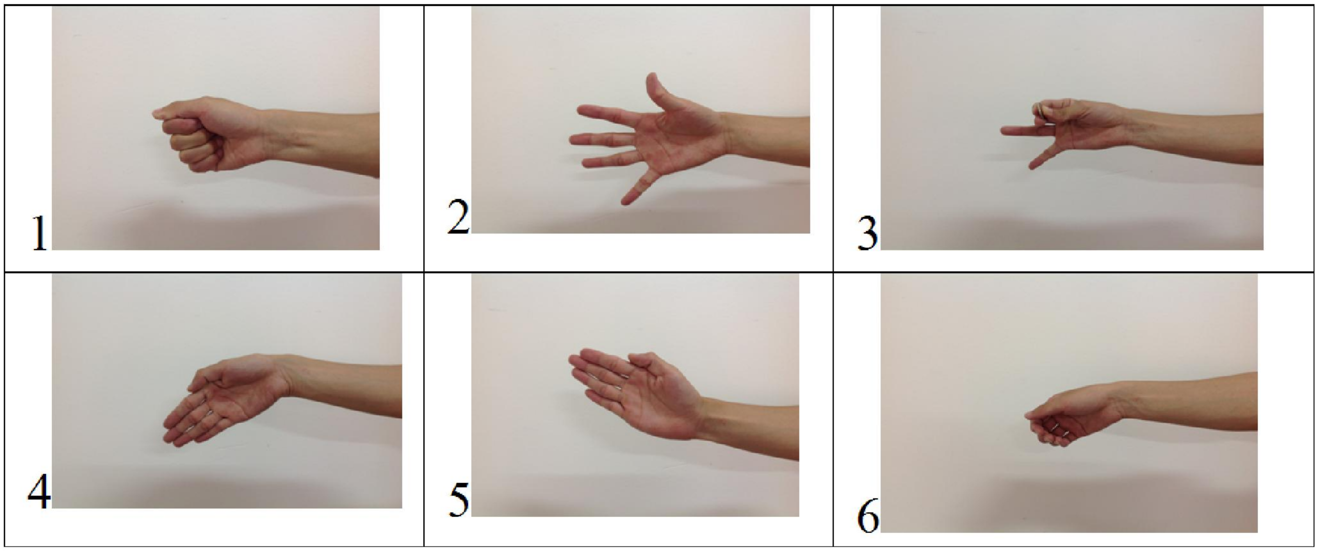

Figure 2 : Five classified hand motions: 1- grip (GP), 2- open hand (OP), 3- catch a coin (CCO), 4- wrist flexion (WF), 5- wrist extension (WE), and 6- rest position (REST).

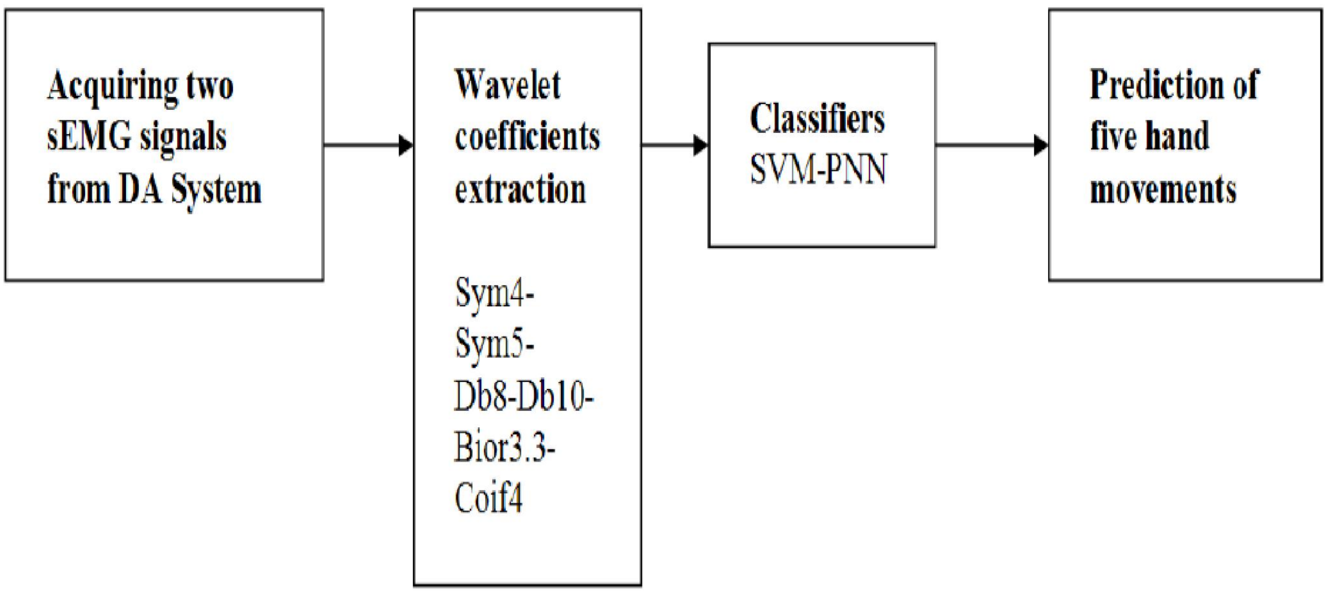

Figure 3 : Flow diagram showing the key elements of the proposed sEMG pattern recognition system. This system mainly consists of three steps: 1- data acquisition, 2-features extraction which represented by wavelet coefficients and 3- classification of the extracted feature vector by using SVM and PNN classifiers.

sEMG raw data and prepare them to the next stage. The second step wavelet coefficients were extracted from sEMG signal. In the third stage, two different classifiers were employed to classify five different wrist motions.

In our research study wavelet coefficients were used to represent the recorded EMG signals using discrete wavelet transform (DWT). Wavelet analysis is a powerful mathematical tool that has been employed as a fast and effective method for the analysis of bio-signals[14-17]. In this paper, the selected wavelet families / sym4, sym5, db8, db10, bior3.3, and coif4 /were used to decompose the recorded sEMG signals. Our experience from previous experiments and the results obtained by other researchers were taken into account in our decision of this selection[13,18,19]. The MATLAB computational software was used to extract the wavelet coefficients from the sEMG signal and for the classification procedure.

In total, we analyzed ten subjects, five classified movements, two channels, and five repetitions of each movement, which results in total of 500 subsets (10x 5x 2x 5= 500 subsets). The data divided into three sets, 30% for training, 30% validation and 40% for test.

CLASSIFICATION METHODS

In this study two classifiers were selected, support vector machine (SVM), probabilistic regression neural network (PNN). In general, classification methods require initial values of parameters that leads to complicated calculations[20].

Support vector machine (SVM)

Support vector machine theory was introduced by Vapnik. SVM is a supervised learning method used to solve classification and regression problems. SVM had been applied in many engineering fields such as speech analysis, image processing. SVM exhibits good performance in classification and regression problems. SVM locates a hyperplane in the predictor space based on the input vectors and dot products in the feature space. The dot product can be used to find the distances between the vectors. SVM locates the hyperplane that divides the support vectors without representing the space explicitly. More details on SVM can be found in Wang literature[21]. However, the limitation of SVM is its complexity, which is on the order of the number of samples and not on the order of the dimension of the samples[22]. Another difficulty associated with the SVM classifier is that selection of parameter values for the kernel function[23]. In this research RBF(radial basis function) kernel support vector machine was implemented[24]. The selected parameter range of the RBF kernel function was set to minimum=0.2, maxi-

TABLE 1 : Average classification rates using the PNN classifier at different decomposition levels (DL). The bold numbers represent the highest classification accuracies among the wavelet families.

Classifier	Wavelet Family	DL	Movements					
			GR	OP	WF	WE	CCO	Average %
SVM	sym4	3rd	81	83	71	70	75	76
		4th	80	79	70	74	73	75
		5th	86	87	78	76	67	79
		6th	91	85	77	76	71	80
	sym5	3rd	75	76	65	76	65	71
		4th	85	86	71	75	72	78
		5th	91	86	78	76	70	80
		6th	88	91	87	89	85	88
	db8	3rd	92	94	98	89	70	89
		4th	93	97	92	90	70	89
		5th	96	96	94	95	73	91
		6th	94	96	95	97	86	94
	db10	3rd	76	85	73	73	69	75
		4th	88	85	77	76	67	79
		5th	93	96	93	91	83	91
		6th	95	98	92	94	90	94
	bior3.3	3rd	82	82	86	82	76	82
		4th	87	82	83	80	85	83
		5th	87	89	87	87	90	88
		6th	82	89	89	85	86	86
	coif4	3rd	92	90	87	95	89	91
		4th	93	96	92	89	88	92
		5th	96	95	95	98	76	92
		6th	97	95	95	96	89	94

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Probabilistic regression neural network (PNN)

The PNN was first introduced by Specht (1990). This kind of neural network consists of four layer, input layer, pattern layer, summation layer and output layer. PNN based on the Bayesian classification and classical estimators for probability density function (PDF). PNN estimates the PDF of features of each class from the available training samples using Gaussian kernel[25-28]. Parzen estimate (F) defined by equation (1):

$$F_1(x)\frac{1}{2(\pi)^{\frac{m}{2}}\sigma^m n}\sum \exp\left[\frac{\left(x-x_j\right)^T\left(x-x_j\right)}{2\sigma^2}\right] \quad (1)$$

F : Parzen estimate of PDF for pattern P1; x_j : If the jth training pattern for pattern P1; n : number of training patterns; m : the input space dimension; j : pattern number.

σ : adjustable smoothing parameter.

The performance of the PNN classifier depends on the smoothing parameter σ value. This value controls the non-linearity of the decision boundaries for the PNN network. In this study, the σ value was in the range minimum= 0.05, maximum= 0.5 in steps of 0.01.

RESULTS

This result is deduced from TABLE 1:

The result of this investigation shows that the highest classification rate was 96% and this rate was achieved using the PNN classifier based on coif4 at sixth decomposition level. Also the results of our experiment demonstrated that the use of wavelet families at a high decomposition level increases the recognition rate of hand motions.

Based on the data shown in the TABLE 2, the utilization of the SVM classifier gives the following results: SVM classification algorithm was employed to differentiate hand motions. To extract the wavelet coefficients from the recorded sEMG signal, the same wavelet functions were implemented, then the coefficients was introduced into SVM classifier. In this research, we used SVM polynomial kernel function (PLN). We found that the best classification rate was 94%, and this rate was

TABLE 2 : Average classification rates using the SVM classifier at four different decomposition levels (DL).

Classifier	Wavelet Family	DL	Movements					
			GR	OP	WF	WE	CCO	Average
PNN	sym4	3rd	86	93	77	89	76	84
		4th	89	98	93	76	76	86
		5th	76	95	93	88	85	87
		6th	95	82	76	95	97	89
	sym5	3rd	86	84	79	85	87	84
		4th	76	93	84	93	88	87
		5th	76	93	84	93	88	87
		6th	89	96	89	95	76	89
	db8	3rd	95	79	80	76	76	81
		4th	96	89	92	86	76	84
		5th	95	84	88	88	76	86
		6th	90	93	77	76	82	88
	db10	3rd	93	79	80	76	76	81
		4th	87	76	85	76	95	84
		5th	84	79	88	76	93	84
		6th	83	93	91	93	88	90
	bior3.3	3rd	76	84	88	88	76	82
		4th	88	93	77	76	82	83
		5th	91	89	88	84	89	88
		6th	90	89	85	89	87	88
	coif4	3rd	92	91	95	88	90	91
		4th	91	93	92	89	90	91
		5th	95	96	89	93	86	92
		6th	96	96	95	96	95	96

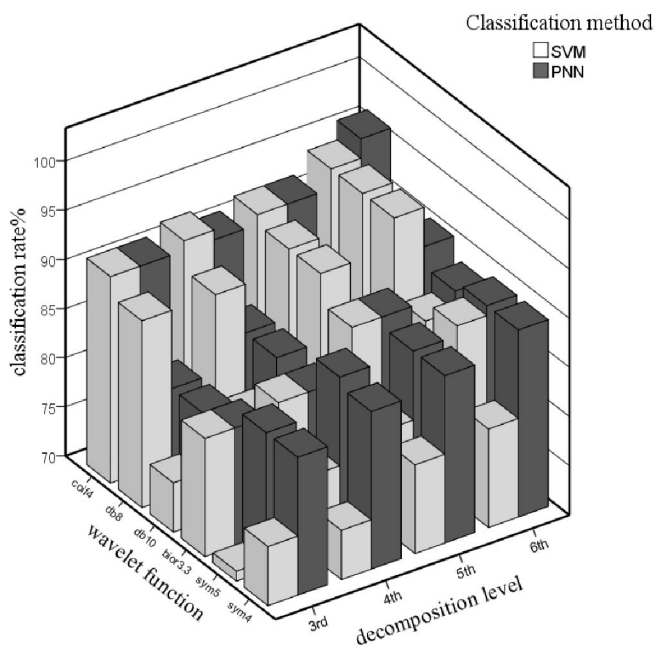

Figure 4 : Comparison of the performance of two classifiers PNN and SVM. Six wavelet functions were utilized (sym4, sym5, db8, db10, bior3.3 and coif4) at the third, fourth, fifth, and sixth decomposition levels.

obtained using coif4, db8-10 at six decomposition rate. Also it is obvious that increases in the decomposition level of the wavelet family increases the classification rate value. In contrast, the highest misclassification of 29% was obtained using the SVM classifier based on sym5 at the third decomposition level. These results are graphically shown in Figure 4.

In general, it is obvious that the performance of PNN is better than that of SVM for the selected wavelet families (sym4-5). Our experimental results also demonstrated that the coif4 wavelet function exhibits a stable and robust performance for PNN and SVM with a high classification rate (higher than 90%) for all of the studied decomposition levels.

CONCLUSION

In this study, we succeeded to achieve 96% high classification rate by using the PNN classifier based on coif4 at the sixth decomposition level. This result is considered to be a high classification rate in case five hand motions are recognized based on two sEMG signals.

This manuscript also shows that the performance of two recognition algorithms (SVM, PNN) using six wavelet functions (sym4-5, db8-10, bior3.3, and coif4) leads to different average classification accuracies ranging from 71% to 96%. These results show that the choice of a proper wavelet family and the decomposition level is an important step before the classification.

We found out that the placement of sEMG electrodes, wavelet families and classification method play a major role in determination of hand motion-classification accuracy. But shifting in the electrode position will provide a completely different sEMG signal that leads to totally wrong result. While choosing a proper wavelet family at a specific decomposition rate and implementing a robust PR algorithm significantly improve the accuracy rate 25%.

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