

# Selective Classification for Surface EMG Based Control of Upper Limb Prosthetic Hand

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**ABSTRACT:** Nowadays, the rate of disabled and the people who find difficulties in using their limbs due to age are increasing. Recent literature in pattern recognition-based myoelectric control has highlighted a disparity between classification accuracy and the usability of upper limb prostheses. This paper suggests that the conventionally defined classification accuracy may be idealistic and may not reflect true clinical performance. An accurate and computationally efficient means of classifying electromyographic (EMG) signal patterns has been the subject of considerable research effort in recent years. Herein, a novel myoelectric control system based on SVM and ANN classification scheme, capable of rejecting unknown data patterns, is introduced. This scheme is shown to outperform other popular classifiers when compared using conventional classification accuracy analysis that may be more representative of real prosthetic use. Additionally, the classification scheme allows for real-time, independent adjustment of individual class-pair boundaries making it flexible and intuitive for clinical use.

**KEYWORDS:** EMG, SVM, MUP, MES, TMR, MAV, ANN

## I. INTRODUCTION

The surface electromyogram (EMG) provides a noninvasive method of measuring muscle activity, and has been extensively investigated as a means of controlling prosthetic devices. Amputees and partially paralyzed individuals typically have intact muscles that they can exercise varying degrees of control over. Further, there is evidence that amputees who have lost their hand are able to generate signals in the forearm muscles that are very similar to those generated by healthy subjects. Thus, the ability to decode EMG signals can prove extremely useful in restoring some or all of the lost motor functionality in these individuals. Since most disabled people have problems manipulating current assistive robots and rehabilitation devices that employ traditional user interfaces, such as a joystick and/or keyboard, they need more advanced hands-free human-machine interfaces. Surface myoelectric signals (MESs), which are collected from the skin covering muscles, contain rich information that can be used to recognize neuromuscular activity in a noninvasive manner. A myoelectric control system (MCS), which uses MES as a reference input signal to manipulate assistive robots or rehabilitation devices, has the potential to become a competent alternative to traditional body-powered user interfaces. A pattern-recognition-based MCS, functions by recognizing different pretrained signal patterns, and applies corresponding predefined motion commands to electric motors and/or actuators. It provides hands-free and proximal function control based on neuromuscular activity. The success of myoelectric control depends greatly on classification accuracy. Effective feature extraction and classification methods are crucial to achieving high classification performance in pattern recognition. As we know robots find useful in many fields. The human-robot interface has been proposed in several studies earlier. Most of the previous work proposes complex mechanisms where the user should be trained to map his/her action to the motion desired for the robot.

The application of pattern recognition to myoelectric control schemes was first introduced in the 1960s–1970s [1], [2]; however, due to limited acquisition instruments and computing capacity at that time, real-time control was not feasible. Hudgins *et al.* [3] were pioneers in developing a real-time pattern-recognition-based MCS. Using time-domain (TD) features and a multilayer perceptron (MLP) neural network, they succeeded in classifying four types of upper limb motion, with an accuracy of approximately 90%. This work was continued over the last 15 years, by employing various classifiers, such as linear discriminant analysis (LDA) [4], [5], MLP/radial basis function (RBF) neural networks [6], time-delayed artificial neural network (ANN) [7], fuzzy [8], [9], NEUROfuzzy [10], fuzzy ARTMAP

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networks [11], fuzzy-MINMAX networks [12], Gaussian mixture models (GMMs) [13]–[15], and hidden Markov models (HMMs) [16].

Small electrical currents are generated in the muscle fibers before the muscle contraction is produced. These currents are due to the ionic exchange across the membranes of the neural-muscular junctions, which propagate through the resistive surrounding tissues and generate small potential differences. These signals, called electromyographical (EMG), represent fibers contraction, and can be used as a muscular activity indicator and, therefore, be interpreted to control an external electromechanical device. Muscles consist of muscle fibers, activated by motoneurons. Impulses from the spinal cord arrive to the motoneuron and trigger a group of several muscle fibers, called motor unit. To produce a movement, each muscle fiber composing the muscle contracts, carries the contraction to the whole muscle and achieves the desired action. In most of the cases, even for a fine movement, several muscles are simultaneously involved to accomplish that action.

## II. BACKGROUND

Myoelectric control uses the EMG generated by muscular contractions as an input for controlling a desired terminal device, such as a prosthetic limb. In pattern recognition-based control, patterns in the EMG generated during distinct contractions are learned by training a classifier using salient features extracted from the EMG. Subsequently, when the patterns are detected by the classifier during use, the corresponding control outputs are generated by the system. Hudgins *et al.* were one of the first to develop a real-time pattern recognition-based control system using a set of time-domain (TD) features and a multilayer perceptron [17]. Since then, others have extended this work using various feature sets (such as wavelet packets [18]) and classifiers (such as linear discriminant analysis (LDA) [19], Principle component analysis (PCA) and Gaussian mixture models (GMM) [20]).

More recently, several groups have used support vector machines (SVM), SVM is a kernel-based approach with a strong theoretical background, which has become an increasingly popular tool for machine learning tasks involving classification and regression. It has recently been successfully applied to several applications, ranging from face identification [21] and text categorization [22] to bioinformatics and database mining. An SVM constructs an optimal separating hyperplane in a high-dimension feature space of training data that are mapped using a nonlinear kernel function. Therefore, although it uses a linear learning machine method with respect to the nonlinear kernel function, it is in effect a nonlinear classifier. The use of a nonlinear kernel function greatly increases the power of learning and generalization. However, it can also increase the risk of overfitting, which may lead to bad generalization. Therefore, the flexibility of the kernel-induced feature space is controlled by setting an upper band for generalization risk. Having control on the generalization performance improves the robustness against noisy data such as MES. Training an SVM involves the optimization of a convex cost function; there are relatively few free parameters to adjust, and the architecture does not have to be found via experimentation.

Artificial neural networks (ANNs) are formed of cells simulating the low-level functions of biological neurons. In ANN, knowledge about the problem is distributed in neurons and connections weights of links between neurons [23]. The neural network must be trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs.

ANNs are particularly useful for complex pattern recognition and classification tasks. The capability of learning from examples, the ability to reproduce arbitrary non-linear functions of input, and the highly parallel and regular structure of ANN make them especially suitable for pattern classification tasks [24].

ANNs are widely used in the biomedical field for modelling, data analysis and diagnostic classification. The most frequently used training algorithm in classification problems is the backpropagation (BP) algorithm, which is used in this work also. There are many different types and architectures of neural networks varying fundamentally in the way they learn. In this paper, neural network relevant to the application being considered, i.e., classification of EMG data will be employed for designing classifiers.

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## III. METHODOLOGY

### A.Data Collection

Four channels of EMG signals are used as main input signals to estimate the user's upper-limb motion intention. Elbow Flexion and Extension EMG Signal is acquired. Four subject were used to get the EMG signal and is stored in excel data base w.r.t time sequence. The acquired EMG signal is then uploaded in MATLAB to analyse the data[25]. DCT is used to compress and reduce the combined EMG signal of Elbow Extension and Flexion. Feature projection(PCA) based dimensionality reduction is used to deduce the principle components which deals with characteristic values of the uploaded signal. Since raw EMG signals are not suitable as input signals to the controller, the feature of the raw signal must be somehow extracted. In order to extract the feature of the raw EMG signal, Mean, Entropy, PSD, Standard Deviation, Variance of the EMG signal is calculated. A single Raw EMG signal is shown in fig. 1.2. These feature values are used as an input for the SVM and ANN classifier for resulting out the desired output parameter for evaluating the measured EMG Signals.

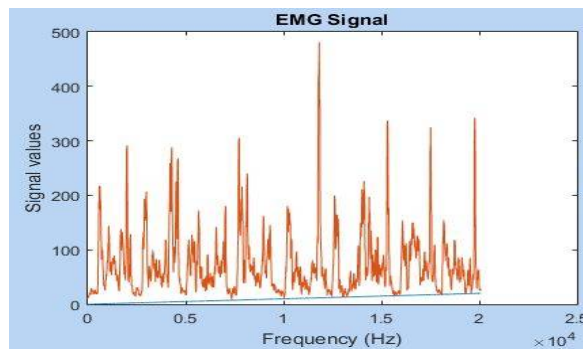


Fig. 1.2 Single EMG Signal

The proposed methodology is shown in fig.1 below:

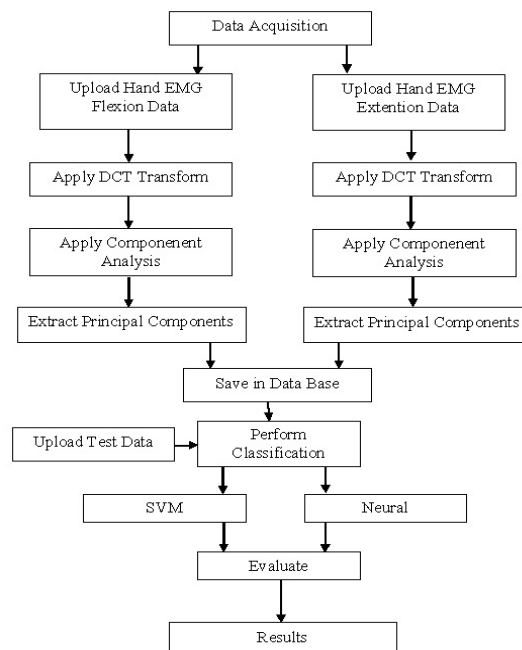


Fig.1.1 Proposed Methodology

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The data used in this experiment were 4 different subject elbow muscle. EMG data representative of four classes of motion were collected from four subjects. The motion classes consisted of elbow flexion and extension. The acquired EMG signal is stored in the excel data base which is used for the offline analysis is uploaded into the MATLAB. The matrix form representation of the uploaded EMG Extension and Flexion data is shown in fig. 1.3 and the corresponding signal value representation of the combined waveform is shown in fig. 1.4.

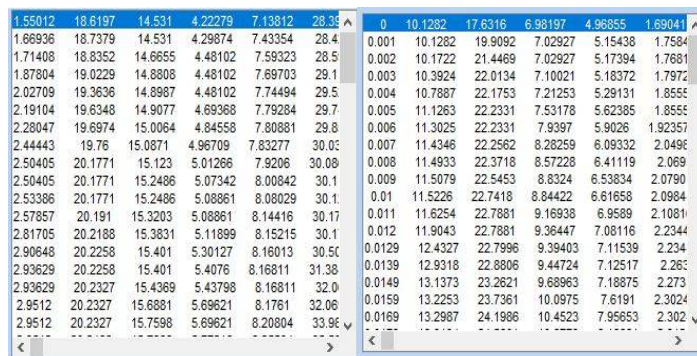


Fig. 1.3(a)(b)

Matrix Representation of Combined EMG Extension (a) and Flexion Signal (b)

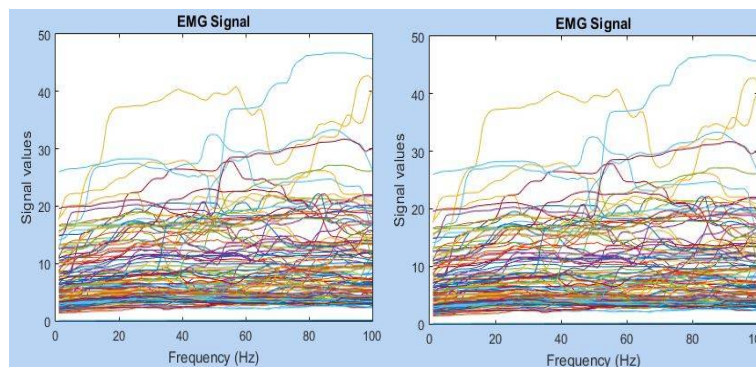


Fig. 1.4(a)

(b)

Signal Value Representation of Combined EMG Extension (a) and Flexion Signal (b)

The subjects were asked to rest their elbow on an armrest, and to elicit repeatable, constant force contractions. Electrode gains were adjusted to maximally span the dynamic range of the amplifiers. Data were acquired using a custom data acquisition software g-tech analyzer, sampled at 1 kHz per channel. Data were collected over Eight trials, each consisting of two 4-s repetitions of each motion class. The inter-repetition delay was varied between trials from 3 to 0 s. Subjects were given periods of rest between trials in order to avoid fatigue.

## B. Data Analysis

After the data recording, the acquired samples are converted into features which are used for classification. The features are extracted using using DCT. There are several compression methods. One distinguishes the lossless and the lossy methods. The lossless methods are applied on texts, archives, executable files... The most usual are: Differential Pulse Code Modulation (DPCM), Run Length Encoding (RLE), arithmetical coding, entropic encoding... The most usual lossy methods are included in transformations methods (Karhunen-Loeve Transform(KLT), Fourier Transform and its variants like DCT, Wavelet Transform and its variants like WPT...), prediction methods (DPCM), fractal methods and under sampling methods. Lossy methods are applied on images, sounds, video... and include usually a lossless coding step[26]. The compression methods using the oriented transforms have been applied successfully on electrophysiological signals. Most of these methods gave rise to algorithms of compression bound to the specific characteristics of the processed signal thus, not applicable in a general way in the compression. This justifies the



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existence of many compression algorithms. Due to the nature of the signal, these transformations must be able to better localization in both time and frequency[27].

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. The DCTs are generally related to Fourier Series coefficients of a periodically and symmetrically extended sequence whereas DFTs are related to Fourier Series coefficients of a periodically extended sequence[28]. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), whereas in some variants the input and/or output data are shifted by half a sample.

The compressed EMG signal using discrete cosine transform (DCT) is shown in fig. 1.5.

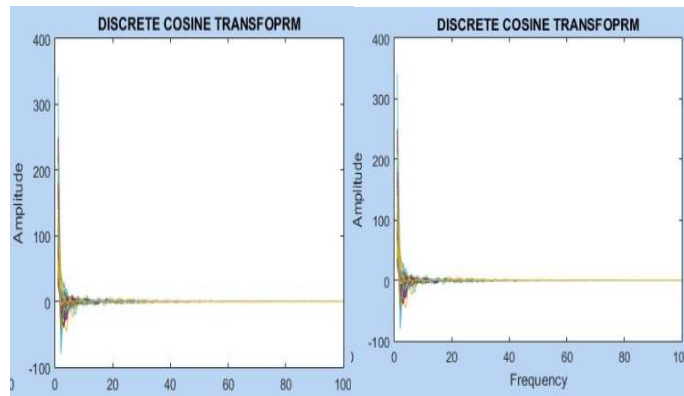


Fig. 1.5 (a) (b)  
Discrete Cosine Transform Signal Representation of Combined EMG Extension (a) and Flexion Signal (b)

Feature extraction is a significant method to extract the useful information which is hidden in surface electromyography (EMG) signal and to remove the unwanted part and interferences. To be successful in classification of the EMG signal, selection of a feature vector ought to be carefully considered[29]. The results shown in fig. 1.6, which were verified by scatter plot of features, statistical analysis and classifier, indicated that most time domain features are superfluity and redundancy.

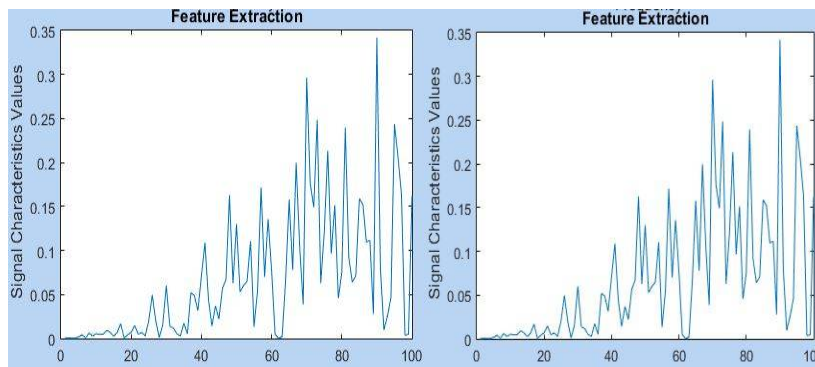


Fig. 1.6 (a) (b)  
Feature Extracted Signal Representation of EMG Extension (a) and Flexion Signal (b)

Features	Elbow Extention	Elbow Flexion
Mean	0.066578	0.066578
Entropy	4.8417	4.8417
PSD	0.59995	0.5995
Standard Deviation	0.074991	0.074991
Variance	0.0056237	0.0056237

Table 1.1 Feature Values of EMG Extension (a) and Flexion Signal (b)

## IV. RESULTS

The EMG signals were obtained using surface electrodes at distant positions on the limb. In the normal functioning healthy hand EMG feature extraction was performed for several actions and databases were created. Conventional classification accuracies were calculated for each of the aforementioned classification schemes using the same classes during training and testing. The resulting MSE, PSNR and Accuracy are shown in Table 4.1 for the elbow extension and flexion movement of subjects. The actions done were directional movement i.e. Elbow Extension and Elbow Flexion. The ANN and SVM Classification output are analysed in terms of the performance parameters and then compared. ANN Classification techniques results out the best classification accuracy of 99.6% with MSE as 0.004 and PSNR value of 23.962. Fig. 1.8 shows the performance analysis of ANN.

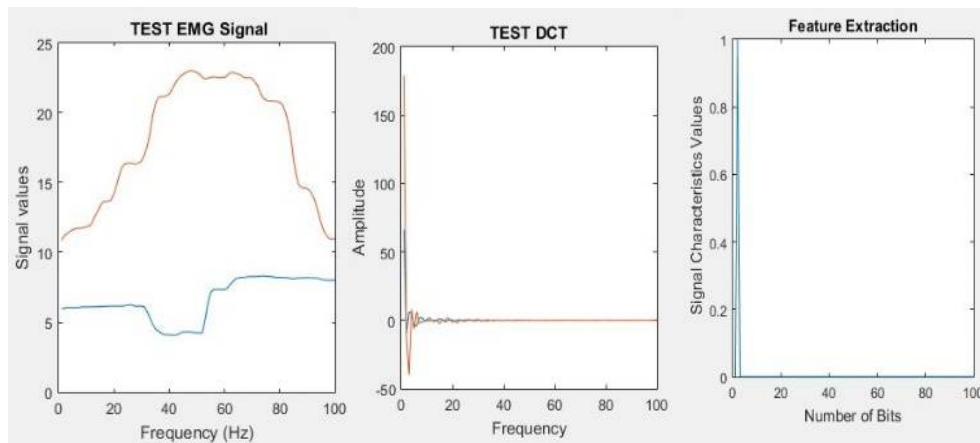


Fig. 1.7 (a) (b) (c)

Test EMG Signal (a), Test Descrete Cosine Transform output (b) and Feature Extracted Signal (c)

Classification Technique	MSE	PSNR	ACCURACY
SVM	0.023785	16.2369	97.62
ANN	0.004	23.962	99.6

Table. 1.2 Classification Output Performance of SVM and Artificial Neural Network

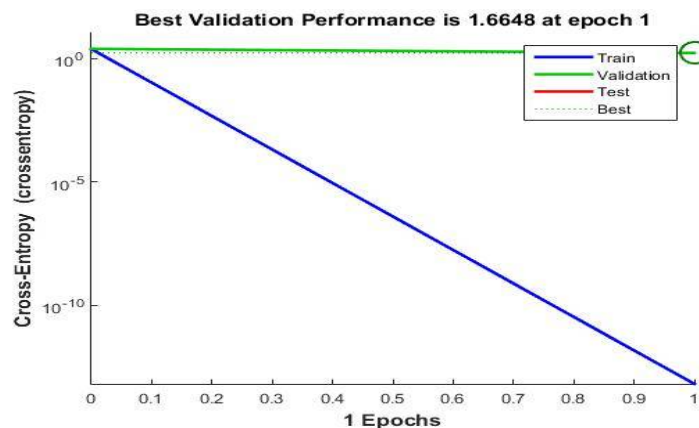


Fig. 1.8 ANN Performance Analysis

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## V. CONCLUSION

This paper describes a novel classification scheme for pattern recognition-based myoelectric control. The proposed control scheme was shown to outperform other commonly used classification techniques when reporting standard classification error (MSE). EMG signals can be classified with an extremely high degree of accuracy. A careful offline analysis of classification problem based on EMG signals for four subjects as a function of the number of recording sites (electrodes) used for classification. The ANN and SVM Classifier output performance parameters in terms of MSE, PSNR and Accuracy are compared and analyzed as shown in Fig. 1.9. From the comparative plot it can be seen that ANN result out as an more efficient and accurate classification technique for the classification of the EMG signal for elbow extension and flexion movement having higher PSNR, lower MSE and larger accuracy result.

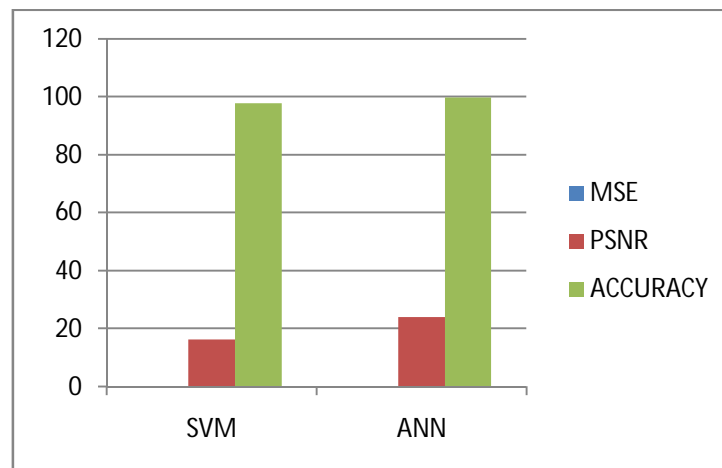


Fig. 1.9 Comparative Analysis of SVM and ANN Classifier

Artificial neural network classifier(ANN) and Support Vector Machine(SVM) classifier have been considered in this research for human arm EMG signal analysis for Elbow extension and flexion movements. The accuracy of the EMG signal has been tested against the Performance parameters. The ANN classifier has shown better accuracy when compared against SVM classifier and the average classification accuracy is 99.6%.

The objective of the proposed work is to get the higher Power Signal to noise ratio(PSNR) and reduce the mean square error(MSE) for carrying out better accuracy result. Our result shows that a greater PSNR value of 23.962 and MSE as low as 0.004 can be achieved using ANN classification as compared to that of SVM classification technique which results out PSNR of 16.236 and MSE as 0.023. A PCA method of training and testing was used to compare the classifiers response to data with class origins other than those seen during training. Using this approach, which may more meaningfully reflect usability, ANN classifier was shown to significantly outperform all other classifiers[30].

The ANN classified the signals successfully from the different elbow movement and the efficiency of the classification can be increased if more number of signals are taken. However the EMG signal itself varies from time to time[31]. The designed ANN has successfully classified the gestures with minimum computational time. The classified EMG signals can be used to develop the human computer interface which help the disabled people to interact with computer devices.

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