Classification of hand gestures from forearm electromyogram signatures from support vector machine

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Article Info

ABSTRACT

Robotic prosthetics is increasingly adopted as an enabling technology for amputees. These are vital not only for activities of daily living but to display expression and affection. A vital element to this system is an intelligent model that can identify signatures from the remaining limb that can be mapped to specific effector movements. Therefore, the study proposes the use of forearm electromyogram to classify between different types of hand gestures; fingers spread, wave out, wave in, fist, double tap, and relaxed state. Data are acquired from 32 subjects using Myo armband. Initially, a total of 248 time-and frequency-domain features are extracted from the eight-channel device. Neighborhood component analysis has reduced them to a total of fourteen features. A hand gesture classification model based on electromyogram signal has been successfully developed using support vector machine with overall accuracy of 97.4% for training, and 88.0% for testing.

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1. INTRODUCTION

The hand is an important musculo-skeletal effector that allows us to perform most activities of daily living. These include acts of displaying expression and affection [1]. It is often observed that amputees exhibit emotional outcomes such as depression, anxiety, denial, grief, and shock [2]. To help them overcome this traumatic experience, various solutions involving advanced prosthetics and enabling technologies [3], [4] have been proposed. With the recent advances in wearable technologies, there are many technology to drive the wearable devices based on electromyography (EMG) signals.

The EMG signals can be acquired from the surface of the skin using surface electrodes. Milosevic *et al.* [5] used Ottobock 13E200 EMG system which captured five motions from nine subjects. Data from their EMG system is then used to develop the classification model using support vector machines (SVM) with Gaussian kernel with accuracy of 76.3%. A realtime hand tracking system using Microsoft Kinect sensor with finger-earth mover's distance techniques was used by [6]. In this paper, they have succesfully classified ten hand gestures with up to 93.9% accuracy based on data from ten subjects. In another paper [7], Wrist-band contour feature system has been used to recognise complicated static hand motions. Two wristbands are fitted precisely at two different hand segments to get the accurate contour features from the hand movements. This technique has succesfully identified 29 Turkish fingerspelling hand sign movements

with 99.31% accuracy. In paper [8], the wearable Myo armband and smart glove with configurable pressure sensor arrays are used to collect data from fingers movements and palm pressure. The classification model was able to discriminate ten hand motions from ten subjects with a total of 192 input features, yielding the overall accuracy of 77.78%. Two channel surface EMG system has been used by [9] to collect seven temporal domain features for three different hand gestures from five subjects. Principle component analysis and regression tree were used to split the data into partitions and later smaller groups. This techniques produced a classification model with accuracies up to 80.85%. There are many others studies in this area using EMG signals for similar purposes. EMG signals are recognised to be capable to be used for control wearable devices such as prothesis and exoskeletons that are specifically developed for the amputees and paralysed individuals.

Data obtained from the EMG needs to be pre-processed so that the unwanted noises are removed before being used in the next stage. The proprocessing techniques commonly use low-pass filters as the EMG signals contains high frequency noises. This can easily be achieved since most of the established EMG systems are integrated with built-in filter systems. There are many features extraction techniques can be applied to extract most significant parameters from the EMG signals. In EMG signals, most suitable features extraction techniques used by the researchers are time and frequency-domain features [10], as well as discrete wavelet transform [11], [12]. Neighborhood component analysis (NCA) has been implemented for reduction redundant EMG features [13]. This feature selection algorithm is widely established and is suitable for use in EMG classification model development.

Classification model using artificial intelligence and machine learning techniques are usually used to classify the different types of body movements especially for the upper and lower limbs. The ability of these techniques to recognise the movements are very useful to drive the controller for the devices. These allow robust integration between sensors, processors, controllers and effector components. It acts as a brain for the system, allowing adaptation with the functional complexity of human system [14]. Kim *et. al* [15] used three different algorithm such as k-nearest neighbor (k-NN), quadratic discriminant analysis, and linear discriminant analysis (LDA) to develop classification models for classifying five different wrist motion direction from 30 EMG features. The accuracy of three proposed models are between 81% to 85%. Convolution neural network (CNN) is used by [16] to recognised six different hand motions from EMG signals obtained using Myo armband from 20 subjects. The developed model accuracy is more than 98% for traning, testing and validation dataset. CNN is also proven to be a good algorithm to be used as a prediction model integrated with the controller to move bionic manipulator in real-time with accuracy of 89% [17]. Pancholi and Joshi [18] used EMG signals from 29 subjects to developed classification models to classify seven hand gestures for their upper limb prosthesis applications. In this paper, LDA algorithm is found to be the best model for prdicting hand movement with more than 99% accuracy. Hassan *et.al* [19] has used the LDA algorithm with support vector machines (SVM) and k-NN to feed their actuators for controlling five-degree robotic arm. In this paper, model using SVM algorithm gives the highest accuracy of 95.26% compared to LDA with accuracy of 92.58%. k-NN yielded the lowest classification model accuracy at 86%. Other suitable algorithms to be used in this area is conventional artificial neural network (ANN). In paper [20], classification model developed from EMG signals of 20 subjects for similar application using ANN with radial basis function (RBF) algorithm has produced a prediction model with accuracy of 98%.

From an extensive review, the algorithms and classification models based on the EMG signals are still predicting movement with acceptable accuracy despite using a small sample size. The outcomes from these related studies lead to more sophisticated innovation and intervention techniques to assist the amputees. Vast amount of literature on prosthetic hands are focused on grasping motions. Therefore, this work proposes the development of an intelligence model to classify six different gestures based on EMG signals and SVM algorithm.

2. RESEARCH METHOD

The framework is comprised of data acquisition, EMG processing, feature selection using NCA, development of SVM model, and performance analysis on hand gesture classification. Figure 1 illustrates the general overview of research methods. It is separated into three stages; data collection and features extraction from the EMG signals, feature selection using NCA to identify only significant parameters are used for the last stage where the classification model is developed and validated.

EMG is acquired using Myo armband from Thalmic Labs. The armband is composed of dry sensors that measures muscle activities from eight cross-sectional points around the forearm. Signal acquisition is performed at sampling frequency of 200 Hz with 8-bit resolution. The real-time data is transmitted to MATLAB [21] via Bluetooth smart connection. Furthermore, the device is also capable of recording angular orientation, velocity, and acceleration of input axes through built-in inertial measurement unit [22]. Figure 2 shows the Myo armband used for EMG acquisition.
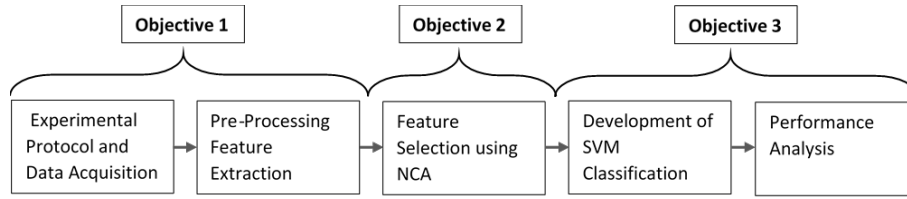
Figure 1. Overview of research methods

Relatively, the Myo armband provides a low-cost solution that is small-sized and lightweight. Its software development kit allows the device to relay information to the classification model. Using the inertial measurement unit, the armband can determine the movement, direction, and rotation of the forearm. In this work, the EMG from forearm is analyzed for five types of hand gesture; fist, wave in, wave out fingers spread, double tap. The gestures are illustrated in Figure 3. These specific movements are subsequently compared with the hand in relaxed state.

A total of 32 heathy subjects (age range = 22–35 years) have participated in this study. These subjects have no history of neuromuscular or joint diseases. All information related to experimental protocol and purpose of the study is first explained to the subjects. They have given written consent prior to data collection. The subjects are required to sit in comfortable chair with relaxed arm. EMG is recorded from arm using the following sequence: 1) relaxed state, 2) specific hand gesture, 3) relaxed state. Each gesture is maintained for approximately 5 seconds. These are repeated three times for each type of gesture. The EMG for each channel will give different signatures as it records the signal from muscles directly underneath the sensor. Figure 4 shows the different effector muscles will give unique EMG patterns for different gestures
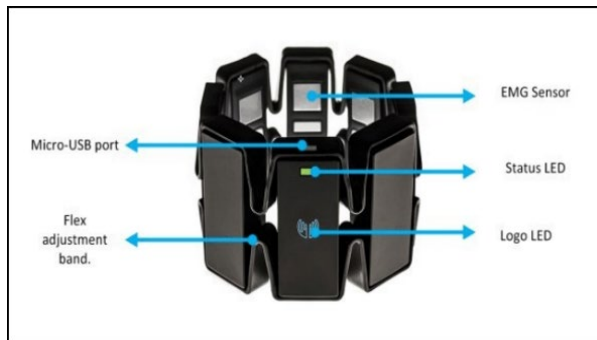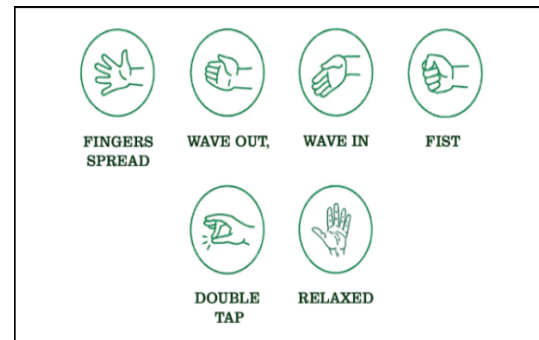

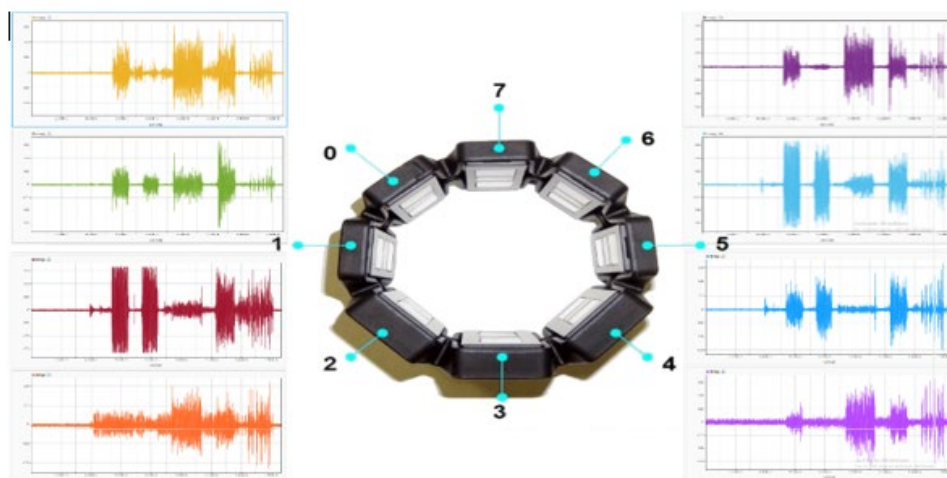Figure 2. Myo armband [21]

Figure 3. Types of hand gestures

Figure 4. Eight different signatures from the respective EMG channels

Noise is removed from the EMG of each channel using 4th-order Butterworth filter [23]. Sliding window method is then applied to the signal to extract features from the respective segments. The features include thirty-one statistical descriptors in time and frequency domain. These are mean, median, standard deviation, mean absolute deviation, lower quartile, upper quartile, inter-quartile range, skewness, kurtosis, Shannon's entropy, spectral entropy, power spectrum (maximum frequency), power spectrum (maximum magnitude), frequency ratio, enhanced mean absolute value, enhanced wavelength, mean absolute value, slope sign change, zero-crossing, wavelength, root mean square, average amplitude change, difference absolute standard deviation, log detector, modified mean absolute value 1, modified mean absolute value 2, Myopulse percentage rate, simple square integral, variance of EMG, Willison amplitude and maximum fractal length.

NCA is implemented as a non-parametric feature selection method that aims to maximize accuracy of classification models. As shown by (1), a multi-class training set with n observations can be considered. $x_i \in \mathbb{R}_p$ represents the feature vectors, $y_i \in \{1, 2, \ldots, c\}$ denotes the designated class labels, and c indicates the number of classes.

$$S = \{(x_i, y_i), i = 1, 2, \ldots, n\} \tag{1}$$

The main objective is for the classification model $f : \mathbb{R}_p \rightarrow \{1, 2, \ldots, c\}$ to learn a feature vector and predicts $f(x)$ for the correct label y of x. Consider a classification model that arbitrarity selects and assigns $Ref(x)$, from S as the reference point for x. The probability $P(Ref(x) = x_j|S)$ that point x_j is selected will be higher if x_j is nearer to point x as measured by distance function d_w. This is shown by (2), where w_r are the feature weights,

$$d_w(x_i, x_j) = \sum_{r=1}^{p} w_r^2 |x_{ir} - x_{jr}| \tag{2}$$

assuming $P(Ref(x) = x_j|S)$ is proportional to $k(d_w(x, x_j))$, and k is a kernel function that exhibit a reciprocal relationship with $d_w(x, x_j)$. Now, $k(z)$ can also be expressed by (3) [23],

$$k(z) = \exp\left(-\frac{z}{\sigma}\right) \tag{3}$$

the reference point for x can, therefore, be selected from S, so that $P(Ref(x) = x_j|S)$ equals to 1 for all j. Hence, the probability can be rewritten into (4),

$$P(Ref(x) = x_j|S) = \frac{k(d_w(x, x_j))}{\sum_{j=1}^{n} k(d_w(x, x_j))} \tag{4}$$

consider a leave-one-out approach for this randomized classifer. The label of x_i is predicted based on data S_{-i}, and the training set S that excludes (x_i, y_i). The probability of x_j being chosen as reference point x_i can then be expressed by (5),

$$p_{ij} = P(Ref(x) = x_j|S) = \frac{k(d_w(x, x_j))}{\sum_{j=1, j \neq i}^{n} k(d_w(x, x_j))} \tag{5}$$

subsequently, the probability p_i that an arbitrary model accurately classifies observation i using S_{-i} is considered as the average leave-one-out probability of correct classification. These can be mathematically expressed by (6),

$$p_{ij} = \sum_{j=1, j \neq i}^{n} P(Ref(x) = x_j|S)I(y_i = y_j) = \sum_{j=1, j \neq i}^{n} p_{ij} y_{ij} \tag{6}$$

meanwhile, the pre-defined conditions for y_{ij} are given by (7),

$$y_{ij} = I(y_i = y_j) = \begin{cases} 1 & , \quad \text{if } y_i = y_j \\ 0 & , \quad \text{otherwise} \end{cases} \tag{7}$$

therefore, the average probability of accurate classification by the model can be simplified to (8).

$$F(w) = \frac{1}{n} \sum_{i=1}^{n} p_i \tag{8}$$

As shown by (9), the expression for $F(w)$ is relies on the weight vector w. Hence, NCA is used to maximize $F(w)$ with regards to w. λ is the regularization parameter, and most of the weights are driven to 0 by the regularization term,

$$F(w) = \frac{1}{n}\sum_{i=1}^{n} p_i - \lambda \sum_{r=1}^{p} w_r^2 = \frac{1}{n}\sum_{i=1}^{n} \underbrace{\left[\sum_{j=1,j\neq i}^{n} p_{ij}y_{ij} - \lambda \sum_{r=1}^{p} w_r^2 \right]}_{F_i(w)} = \frac{1}{n}\sum_{i=1}^{n} F_i(w) \qquad (9)$$

the parameter σ in p_{ij} can be set to 1, and the weight vector w can then be determined through the minimization problem shown in (10). Do note that $f(w) = -F(w)$ and $f_i(w) = -F_i(w)$.

$$\hat{w} = \underbrace{\text{argmin}}_{w} f(w) = \underbrace{\text{argmin}}_{w} \frac{1}{n}\sum_{i=1}^{n} f_i(w) \qquad (10)$$

In this study, Gaussian function has been selected as kernel for optimum stability [24], [25]. As shown by (11), Gaussian function on samples x and x' are feature vectors in an input space. The γ parameter defines the extent of influence of the training samples.

$$K(x,x') = \exp(-\gamma\|x - x'\|^2) \qquad (11)$$

Additional parameter that controls generalization ability of the SVM is the box constraint. It manipulates maximum penalty imposed on observations that violate the margin and helps to prevent over-fitting [22]. Classification performance is then assessed in terms of classification accuracy, sensitivity, and positive predictivity. The parameters are expressed by (12), (13), and (14), respectively,

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \qquad (12)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \qquad (13)$$

$$\text{Positive Predictivity} = \frac{TP}{TP+FP} \times 100\% \qquad (14)$$

TP, TN, FP, and FN each denotes true positive, true negative, false positive and false negative classifications. 80% of the data is used for training, and 20% for testing.

3. RESULTS AND DISCUSSION

As elaborated earlier, each of the subject are required to perform specific hand gestures in sequential order. During each session, EMG is recorded from the eight electrode channels that are equally spaced around the forearm. The following number of EMG samples were obtained for each gesture class: 103 samples for fingers spread, 76 samples for wave out, 80 samples for wave in, 77 samples for fist, 103 samples for double tap, and 95 samples for relaxed state.

Subseqently, NCA is used to select the best features as input to the SVM classification model. To avoid overfitting, features with higher weightage for determining the model parameters are being selected. These requires that data from all eight sensor channels to be studied, where its influence on each other can be determined. Figure 5 shows that the majority of feature components do not constitute any significant weight in determining the model hyperparameters. A k-fold cross examination is conducted using configuration parameter λ. A uniformly distributed linear spaced vector is utilised to generate a finite set of λ. The plot in Figure 6 shows variation of classification loss with respect to varying λ values. The λ value with least classification loss is selected and used in a regressive NCA. Based on the results obtained, the loss is minimum at λ of approximately 0.2284. Therefore, the configuration parameter value is adopted for feature selection process.

Based on the regression analysis, any feature that can provide classification less that that of the optimized λ value is selected. In this case, features with weight exceeding 0.0351 is used for the next phase of the study. Based on the plot shown, the 248 features from eight Myo armband channel are effectively reduced to only fourteen features. These features are then used to develop the SVM classification model. The fourteen features and its corresponding EMG channels are summarized in Table 1.
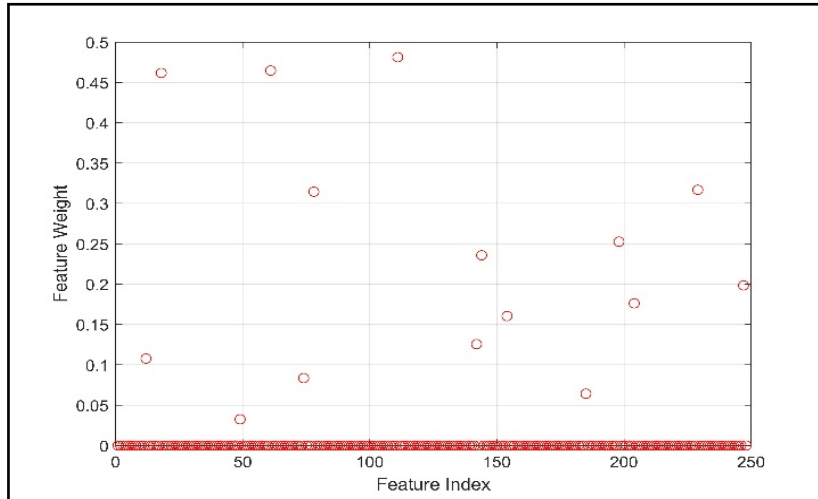
Figure 5. Feature weights with optimized λ

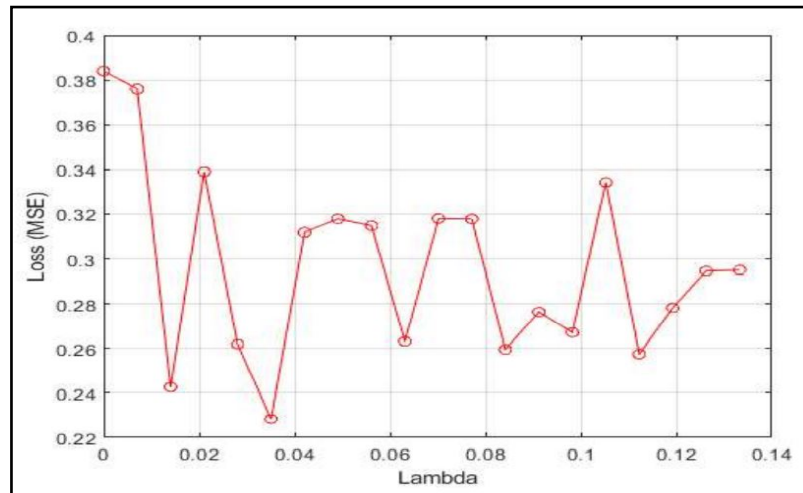Figure 6. Classification loss versus varying λ

Table 1. Selected features and the corresponding EMG channel

Feature	Channel
Power spectrum (maximum magnitude)	1
Wavelength	1
Willison amplitude	2
Power spectrum (maximum magnitude)	3
Enhanced wavelength	3
Wavelength	4
Wavelength	5
Slope sign change	5
Willison amplitude	5
Willison amplitude	6
Power spectrum (maximum magnitude)	7
Wavelength	7
Power spectrum (maximum magnitude)	8
Willison amplitude	8

      To avoid biased results, splitting of the dataset is performed randomly. Biases tend to occur due to frequency differences between the label classes. Table 2 shows the number of samples used for training and testing of each label class. During training, the data is used to compute the hyper parameters of the model. Subsequently, the fully developed SVM model performs hand gesture prediction based on the unseen testing

dataset. The results are compared to actual labels where the model performance is assessed. The SVM classification model has yielded excellent training accuracy of 97.4%. Table 3 shows the training accuracy, sensitivity and positive predictivity for each of the hand gesture classes. Meanwhile, the SVM classification model reduced accuracy of 88.0% during the testing. Table 4 illustrates the testing accuracy, sensitivity and positive predictivity for each of the hand gesture classes.

Table 2. Distribution of samples in training and testing datasets

Hand Gesture	Training Dataset	Testing Dataset
Fingers spread	103	26
Wave out	76	18
Wave in	80	19
Fist	77	19
Double tap	103	26
Relaxed state	95	25
Total	534	133

Table 3. Training accuracy, sensitivity and positive predicitivity for each gesture class

Hand Gesture	Predicted						Sensitivity (%)
	Fingers spread	Wave out	Wave in	Fist	Double tap	Relaxed state	
Fingers spread	97	1	0	0	4	0	95.1
Wave out	2	74	0	0	0	0	97.4
Wave in	0	1	75	0	4	0	93.8
Fist	0	0	0	76	1	0	98.7
Double tap	0	0	0	0	103	0	100.0
Relaxed state	0	0	0	0	0	95	100.0
Positive Predictivity (%)	98.0	97.6	100.0	100.0	92.0	100.0	97.4

(Target)

Table 4. Testing accuracy, sensitivity and positive predicitivity for each gesture class

Hand Gesture	Predicted						Sensitivity (%)
	Fingers spread	Wave out	Wave in	Fist	Double tap	Relaxed state	
Fingers spread	22	2	0	1	1	0	84.6
Wave out	4	13	0	0	1	0	72.2
Wave in	0	0	16	1	2	0	84.2
Fist	0	0	0	17	2	0	89.5
Double tap	0	0	0	0	26	0	100.0
Relaxed state	0	1	0	0	1	23	92.0
Positive Predictivity (%)	84.6	81.3	100.0	89.5	78.8	100.0	88.0

(Target)

4. CONCLUSION

This study has explored a new dimension of EMG signals analysis, specifically in the development of classification model for different hand gestures. A total of 32 healthy subjects have participated in the study in which 248 features were successfully extracted from the EMG signals. NCA has successfully reduced the number of features from 248 to fourteen significant features. These are then used to develop the SVM classification model, yielding excellent accuracies of 97.4% for training, and 88.0% for testing. Despite attaining excellent results, the model has yet to be implemented in real-time prosthetic control. Further investigation is still required to increase its sensitivity for fingers spread, wave out, wave in, and fist gestures. These will require increasing the sample size as the lack of variability in feature patterns may lead to its relatively low sensitivity.

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