An Approach for Accurate Pattern Recognition of Four Hand Gestures Based on sEMG Signals

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ABSTRACT
There are an increasing number of disabled people in the world. These people face many problems going about their day to day lives, in order to improve the day to day lives of these people, it is important to give much attention to the research of artificial lower and upper limb prostheses Conventionally, different pattern recognition and learning networks must be developed for EMG signals extracted from different people, but an exceptional method for pattern classification utilizing EMG signals from forearm muscles of the upper limb is introduced in this paper. This method allows the use of one network for different people without dropping the accuracy, overcoming the problem of individual difference during EMG signal collection. This can be achieved in 2 different ways. The first way, 6 different time domain feature extraction methods are combined using a regular pattern attaining 22 new features which are used with 6 different main classifiers with a total of 22 sub classifiers. This is done to identify which classifier gives the highest classification accuracy. In the second method, combining the feature extraction method using the sequence (X, XY, Y) provides high accuracy and makes it possible to use one network for classifying different people hand gesture without any drop in the accuracy.

CCS Concepts
Human-centered computing→Laboratory experiments

Keywords
EMG; random forest; gesture classification; individual difference

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1. INTRODUCTION
In the branch of nonindustrial robotics, rehabilitation robotics became an active branch of research in the last thirty years. Rehabilitation robotics is human centered and addresses different aspects such as user adaptation, medical compliance, flexibility, safety and gentleness, and humanoid appearance and behavior [4]. Artificial hands must be multi-functional, comfortable, easy to use, and compatible with the users. Prosthesis that depend on the sEMG are one of the natural types of interface among the human hand muscles and the prosthesis. sEMG signals are electrical voltages ranging from -5 to +5 (mV). They are always available, and their strength and variability depend on different movements and force levels. These signals can be acquired using suitable sensors and can be used as an input to the controller of the hand prosthesis to control the movements and force applied by the fingers. Since, most of the available prostheses employ the users' direct vision as a sensory feedback, they lack tactile or proprioceptive feedback for grasping [3]. The control of a multi-fingered artificial hand is extremely difficult as the nature of the human hand is a complex and nonlinear system with multi degrees of freedom [5]. as sEMG signals have been collected from the surface of the skin, the signals pass through many tissues before they are acquired by the sensors on the skin [6]. They are also subjected to crosstalk, obstructions and clamor. The sEMG could be temporal and spatially balanced signal.
Using of neural network-as classification system [7], [8], [9] with back prorogation (BP) also the use of fuzzy-as a classification system [10], [11] also probably not a good choice, because of their learning seems to be slow in most of the cases. the EMG map EMG decoding with of 150 ms window length, demonstrating a mean±SD testing performance of 94.21%±4.84% after voting was achieved by Y. Li, Q. Zhang, N. Zeng, J. Chen and Q. Zhang [12]. By using frequency domain features with double-layer neural network as pattern recognition with back propagation learning four hand motion have been classified. 75 - 80 percent accuracy have been achieved by Ferguson et al [13].A multi run independent component

analysis (MICA) and neural network with a back propagation as classification system to decrease cross talk and enhance the performance of the classification system introduced by Naik et al. [14].Wang et al. used six electrodes mounted on target muscles and a support vector machine was employed as a classifier with a success rate of 90% [15].MinKyu Kim et al by using supervised feature extraction which called (NFE) they achieved 91.54 % as initial accuracy and 91.71% as additional accuracy also with using another supervised feature extraction which called (CA-PCA) they achieved 91.44 % as initial accuracy and 80.40 % as additional accuracy [16]. K. Park and S. Lee introduced method based on CNN showed performances than SVM in both non-adaptation and adaptation, the adaptation performance based on CNN shows accuracy above 90% [17]. a model using a canonical correlation analysis (CCA) for the inter-user variability. to generate a new set of features which can project to the unified-style space. This method reported classification accuracies around 83%. Another approach to solving the inter-user variability has been achieved by Tommasi et al. [18].]. M. S. Park, K. Kim and S. R. Oh achieved classification accuracy 92% by suing supervised feature extraction method called (called class-augmented principal component analysis) with a fast learning classifier (extreme learning machine). even that still using different network for different people [19].

In this study, multi-channel-based EMG pattern recognition has been developed to provide an easy way to detect upper-limb motions. To detect the upper limb motion 4 muscles from the form arm are used. They are; Flexor digitorum superficialis of index finger and middle finger, Flexor digitorum superficialis of ring finger and little finger, Flexor digitorum flexor digitorum of ring finger and little finger, and Extensor digitorum, extensor pollicis longus and extensor pollicis brevis. The signals are detected from the muscles with the aid of multi-channel surface electrode. The purpose of this study is to provide a network that can classify the upper limb motion with high accuracy by using time domain features like (Root-Mean-Square (RMS), Mean Absolute Value (MAV), Integrated EMG (iEMG), Wave Length (WL), Variance of EMG (VAV), Simple square integral (SSI). This high accuracy is achieved by controlling the time of getting the raw data, choosing the right position to place the surface electrode, and mixing of features to get new feature characteristics that is able to describe obvious difference allowing the network to easily classify which motion the limb acts with high accuracy and low computational time. This enabled us to control prothesis hand.

This paper has been organized as follow in section II methodology of the work in section III the experimental work in section IV the result of the classification process and the validation of our work, in section V the conclusion of the work and in section VI the reference that used.

2. METHODOLOGY

In general, a pattern recognition will be divided into four main steps, as shown in Fig. 1. The feature information will be learned by the recognition algorithm during the training process and it will be used as reference class for predicting the identity of new signals from the non-training data.

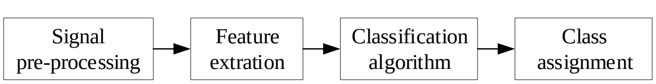

Figure 1. General approach of pattern recognition

2.1 Data Preprocessing Steps

In the raw data preprocessing step, first, the raw signals will be trimmed through a butterworth band pass filter, where the expected useful range of frequency will be followed by notch filter to prevent the light human interference.

2.2 Feature Extraction

In these step, 6 main feature extraction types (RMS, MAV, IEMG, VAV, SIS, WL) will be combined to obtain 22 new feature extractions shown in Tab. 2 which were applied to the data in time domain.

1) The Root-Mean-Square (RMS) a feature extraction method of sEMG signal in time-domain. The equation of RMS is:

$$RMS = \frac{1}{N}\sum_{i=1}^{n}|x_i|^2 \tag{1}$$

where i is the number of window length.

2) The Mean Absolute Value (MAV) is used to measure the average of absolute value of all the samples, which is important to determine the baseline of sEMG signal for the channel during upper -limb motions it's also considering as feature extraction method of sEMG signal in time-domain. The equation of MAV can express as:

$$MAV = \frac{1}{N}\sum_{i=1}^{n}|x_i| \tag{2}$$

where x_i is the potential at the ith sampling and the parameter N is the number of samples.

3) The Integrated EMG (iEMG): the integral of the absolute value of EMG normalized for the candidate segments is also considered as a feature extraction method of sEMG signal in time-domain. The equation of iEMG can be expressed as:

$$iEMG = \sum_{i=1}^{n}|x_i| \tag{3}$$

4) The Wavelength (WL) a feature extraction method of sEMG signal in time-domain. The equation of WL is:

$$WL = \sum_{i=1}^{n}|x_{i+1} - x_i| \tag{4}$$

5) The Variance of EMG (VAV) is a feature extraction method of sEMG signal in time-domain. The equation of (VAV) can be expressed as:

$$VAV = \frac{1}{N-1}\sum_{i=1}^{n}x_i^2 \tag{5}$$

6) The Simple square integral (SIS) is a feature extraction method of the sEMG signal in the time domain. The equation of (SIS) can be expressed as:

$$SSI = \sum_{i=1}^{n}|x_i^2| \tag{6}$$

2.3 Classification Algorithms

In the linear classifier app provided by MATLAB, there are Six main types (Decision Trees, Discriminant Analysis, Logistic Regression, Support Vector Machines, Nearest Neighbor Classifiers, and Ensemble Classifiers) each with its advantages and disadvantages such as Prediction Speed, Memory Usage and Interpretability. Each main classifier has sub algorithm which result in a total of 22 classifiers as shown in Tab. 3. These classifiers are used with the 22 different features to determine which feature is compatible with which classifier. After checking all the classifier results with all the 22 features, to check how can we get the best accuracy.

2.4 Random Forest

Random forests are one of the most recent competitive tools in the process of prediction. Due to the Law of Large Numbers can't be overfit. picking the right kind of randomness results in high accuracy in the classification process and regressors. Moreover, it shows the strength of the individual predictors and its correlations prove that the ability of the random forest in the prediction process. Also, Random forests are a collection of tree types of predictors. In this collection each tree has its own values of a random vectors which are sampled individually without depending on the other tree's random vectors, but the same distribution is kept for all trees in the same forest. The total error of the forest become near to the highest limit as the number of trees increases. The total error of the forest tree classifier relies on the strength of each tree in the forest. By choosing random features to divide the yield error of each node is favorable to Adaboost (Y. Freund & R. Schapire, Machine Learning: Proceedings of the Thirteenth International conference, ∗∗∗, 148–156), its more robust from the point of noise [20].

The mathematical model of the random forest is

$$ni_j = w_j c_j - w_{left(j)} c_{left(j)} - w_{right\,(j)} c_{right\,(j)} \quad (7)$$

where: nij= the importance of node j; wj = the weighted number of samples reaching node j; cj=the impurity value of node j; $lef(j)$=child node from the left split on node j; right(j) = child node from the right split on node j.

The importance of each feature on a decision tree is then calculated as:

$$fi_j = \frac{\sum j{:}node\ j\ splits\ feture\ i\ ni_j}{\sum k{\in}allnodes\ ni_k} \quad (8)$$

where: fi_j= the importance of feature I; ni_j =the importance of node j.

These can then be normalized to a value between 0 and 1 by dividing by the sum of all feature importance values:

$$norm\ fi_i = \frac{fi_i}{\sum j{\in}all\ feture\ fi_j} \quad (9)$$

The final feature importance, at the Random Forest level, is its average over all the trees. The sum of the feature's importance value on each tree is calculated and divided by the total number of trees:

$$RFfi_i = \frac{\sum j{\in}all\ trees\ norm\ fi_{ij}}{T} \quad (10)$$

where $RFfi_i$ = the importance of feature i calculated from all trees in the Random Forest model; $norm\ fi_{ij}$=the normalized feature importance for i in tree j; T = total number of trees.

3. EXPERIMENTAL

3.1 Data Acquisition

A total of 8 healthy male and female from different countries have different Wight and tall length (right-handed, left-handed) between the ages of 20-25 years participated in acquisition. Data has been collected by using (Surface EMG signal acquisition device utilizes NeuroCube-NSW308 surface EMG signal acquisition instrument manufactured by Neuracle company, Wi-Fi module) shown in Fig. 2, four surface electrodes were placed on the forearm four muscles as shown in the Fig. 3, Add to that, the ground was placed at (the end of radius) as a reference, as four types of motion as shown in Fig. 4, need to be classified by the proposed pattern recognition algorithm.

Figure 2. Surface EMG signal acquisition device utilizes. NeuroCube-NSW308 surface EMG signal acquisition instrument manufactured byNeuracle company, Wi-Fi module.

Figure 3. Figure forearm four muscles used to place the electrode.

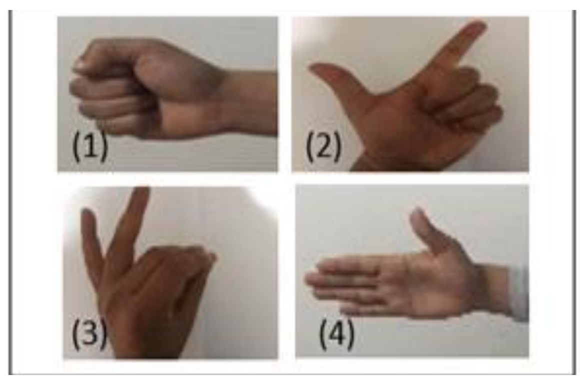

Figure 4. Fourmotion preformed during the experime.

3.2 Setup of the Experiment

During data collection, each motion lasts for four seconds with six seconds rest Tab. 1. The sEMG signals were collected with sampling rate (1000) HZ as shown in table. Also, the experiment preformed for each gesture consisted of 12 trials with each trial consisting of 4 runs.

3.3 Data Preprocessing Steps

In the raw data preprocessing step, first, the raw signals have been trimmed by butter band pass filter 5-480 Hz and then followed by notch filter between 48-52 Hz.

3.4 Feature Extraction

6 main time domain features with 150 window length. After that the features were also overleaped in series (side by side) as well. These feature arrangements are as shown in Tab. 2. in order to choose the result with best accuracy among all.

3.5 Classification Algorithms

As have been discussed in methodology Each main classifier has sub algorithm which result in a total of 22 classifiers as shown in Tab. 4. These classifiers are used with the 22 different features to determine which feature is compatible with which classifier. After checking all the classifier results with all the 22 features, the best accuracy was obtained from RMS and MAV. These classifiers were then combined in a matrix order as shown in table (3). A higher accuracy was observed with budget tree algorithm as shown in table (4) with the feature (RMS) with accuracy 97.9%. After that we checked the bugged trees algorithm with the proposed new feature sets and the result was as shown in table (3) with the highest accuracy regarding to the new set (X, [X Y], Y) with accuracy 99.6%.

Table 1. Hold the Hand Open for 4 Second then Take 2 Second to Perform the Feature then 4 Second Keep the Feature then Repeat It for 4 Times

Set position	Movement				Movement		
	rest	Move	close	Stop	rest	Move	Close
	4	2	4	2	4	2	4
							

Table 2 The Proposed Feature Applied to the Data

SUM	FEATURE NAME					
6	MAV	RMS	VAV	iEMG	SSI	WL
5	RMS	VAV	iEMG	SSI	WL	
4	VAV	iEMG	SSI	WL		
3	iEMG	SSI	WL			
2	SSI	WL				
1	WL					
1	(MAV, MAV_RMS, RMS)					
22	Sum of all the feature used					

Table 3 Result of Different Feature with Bugged Trees

Feature	Recognition Accuracy	Prediction Speed	Training Time
MAV	**97.8 %**	**56000 obs/sec**	**6.575 sec**
MAV, RMS	97.9%	65000 obs/sec	12.691 sec
MAV, VAV	97.6%	65000 obs/sec	13.182 sec
MAV, iEMG	97.6%	66000 obs/sec	12.841 sec
MAV, SSI	97.5%	60000 obs/sec	13.576 sec
MAV, WL	97.7%	67000obs/sec	12.39 sec
RMS	**97.8**	**54000obs/sec**	**6.094 sec**
RMS, VAV	97.7%	66000 obs/sec	13.201 sec
RMS, iEMG	97.7	68000 obs/sec	12.833 sec
RMS, SSI	97.7%	69000 obs/sec	12.225 sec
RMS, WL	97.6%	68000 obs/sec	12.544 sec
VAV	97.7%	57000 obs/sec	6.1817 sec
VAV, iEMG	97.1%	66000 obs/sec	12.854 sec
VAV, SSI	97.7%	70000 obs/sec	12.82 sec
VAV, WL	97%	65000 obs/sec	12.845 sec
iEMG	97.5%	54000 obs/sec	6.5364 sec
iEMG, SSI	**97.8%**	**69000 obs/sec**	**12.628 sec**
iEMG, WL	97.1%	67000 obs/sec	12.36 sec
SSI	97.7%	57000obs/sec	6.2839 sec
SSI, WL	97.6%	67000 obs/sec	12.711sec
WL	97.5%	80000obs/sec	6.1605sec
D= (MAV, [MAV RMS], RMS)	**99.6%**	**59000obs/sec**	**23.196 sec**

4. Result of Classification and Validation

The new matrix of features introduced in Tab. 2 were applied to each feature with all the algorithms of linear classifiers in MATLAB as example here the result of our new proposed feature with all the algorithms Tab. 4. We noticed that all the features are compatible with bagged tree. This validates the advantage of using bagged tree. Thus, bagged tree was used as the pattern recognition method. Here also a result of using bugged tress with all the 22 features proposed in the paper Tab. 3. The best results were obtained by the Confusion matrix helps us to understand how the currently classifying element performed in each class as shown in the second class (extension hand). All the class was right with a total number (11394) except 16 was wrong with the second class and zero with the third class and 2 with the fourth-class Fig. 5.We can notice in Fig. 6, that reflect in the prediction process during the training process and the validation of the model in Fig. 7, the number of right predictions was more than 99%. On the other hand, the number of wrong predictions was less than 1%. It reflects the stability, reliability of our algorithm, and the robustness of our algorithm. ROC Our result shows in the right angle to the top left of the plot, high prediction classification near to 100%. The Area Under the curve indicates the performance of our classifier network and shows there is no misclassified point in the prediction process Fig. 8.

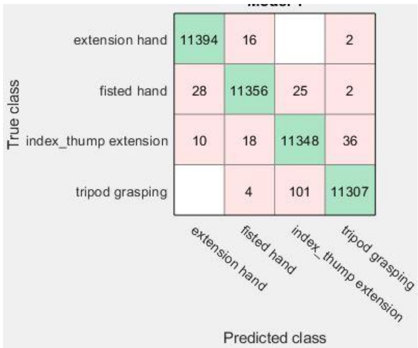

Figure 5. Confusion matrix the result of the classified targets.

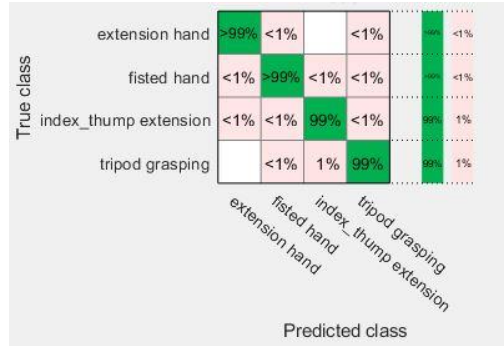

Figure 6. The prediction result during training process

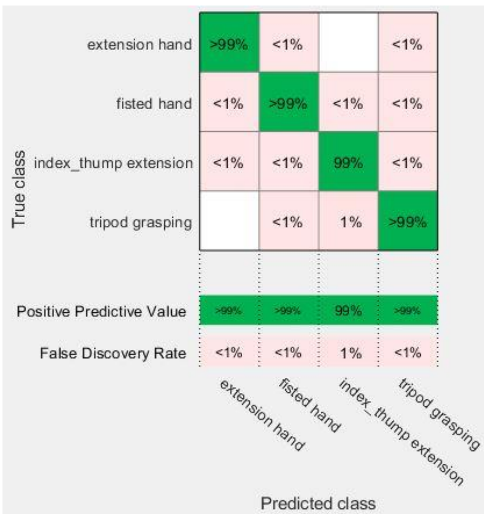

Figure 7. The true and false positive and negative rate classified Samples percentage

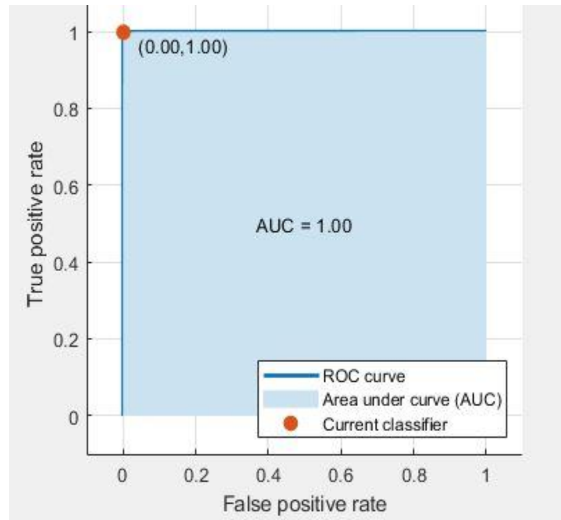

Figure 8. The Area Under the curve indicates the performance of our classifier

Table 4. Different Algorithms Applied on the Data Using (RMS) Feature as Data Input to Check and Validate with Algorithm Will Be Combatable with the Feature

Main classifier	**1**	**2**	**3**	**4**	**5**	**6**
Decision Trees	Coarse Tree (79.9%)	Medium Tree (92.9%)	Fine Tree (95.6%)			
Discriminant Analysis	Linear Discriminant (81.5%)	Quadratic Discriminant (88.8%)				
Logistic Regression	Logistic Regression					
Support Vector Machines	Linear SVM (90.2%)	Quadratic SVM (84.1%)	Cubic SVM (65.9%)	Fine Gaussian SVM ((96.9%)	Medium Gaussian SVM (95%)	Coarse Gaussian SVM (92.6%)
Nearest Neighbor Classifiers	Fine KNN (97.3%)	Medium KNN (97.1%)	Coarse KNN (94.8%)	Cosine KNN (94.4%)	Cubic KNN (97%)	Weighted KNN (97.4%)
Ensemble Classifiers	Boosted Trees (94.1%)	**Bagged Trees (97.9%)**	Subspace Discriminant (80.4%)	Subspace KNN (97.15%)	RUSBoost Trees (92.9%)	

Table 5 Result of Testing the Classification System Using People from Different Countries

Object name	Country	Accuracy (%)
1	El Salvador	99.56
2	Egypt	98.56
3	Pakistan	99.4
4	Egypt	99.15
5	Congo	99.4
6	Mexico	99.83

5. CONCLUSION

In this paper we proposed anew classification system that can solve the problem of individual difference in collecting EMG data with achieving 99.5% of classification accuracy. The network was tested with 6 people from different countries, with different height, and weight. The accuracy of the network didn't drop however, the features must be combined in the form (X, [X Y], Y) as shown in Tab5. so, we highly recommend the use of the budget tree algorithm with the proposed feature in the future research more than using the traditional way of neural network or fuzzy algorithm because it has medium prediction speed, high memory usage, hard interpretability, flexible, with high accuracy, adaptation with different kind of feature extraction that used in EMG classification methods.

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