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Comparison of Hand Gesture Classification from Surface Electromyography Signal between Artificial Neural Network and Principal Component Analysis

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Abstract: The goal of this research is to detect Surface Electromyography (SEMG) signal from a person's arm using Myo Armband and classify his / her performed finger ges-tures based on the corresponding signal. Artificial Neural Network (based on the machine learning approach) and Principal Component Analysis (based on the feature extraction approach) with and without Fast Fourier Transform (FFT) were selected as the methods utilized in this research. Analysis results show that ANN has achieved 62.14% gesture classifying accuracy, while PCA without FFT has achieved 30.43% and PCA without FFT has achieved 48.15% accuracy. The three classifiers are tested using SEMG data from a set of six recorded custom gestures. The comparison results show that the ANN classifier shows higher classifying accuracy and more robust rather than the PCA classifier's classi-fying accuracy. Therefore, ANN classifier is more suited to be implemented in classifying SEMG signals as hand gestures.

Keywords: Bionic hand, surface electromyography, artificial neural network, principal component analysis, gesture classification

1. Introduction

The Surface Electromyography (SEMG) signal measures the difference of electrical potential in an arm's muscles during its contraction. Therefore, the signal is characterizing a muscular activity in doing so. However, the signal itself always has some degree of noise in it (Reaz et al., 2006). This particular noise can affect a gesture recognizer to an extent, making it characterize muscular activities not as well as it should be. Concurrently, characterizing muscular signals using EMG has become very useful in constructing a bionic hand. If the gesture recognizer is able to make out a custom gesture from its wearer, based on the EMG data and despite its noise, it could be very useful for the development of a fully functioning bionic hand.

Classifying custom gestures such as grabbing gesture or pointing direction gesture based on EMG data would be a quick example. However, to do that a gesture classifier software must be designed. The feature extraction and machine learning method will be used in this study as the method to classify EMG signals. Feature extraction is actually commonly used in computer vision applications, i.e. to classify objects and images (Nixon, 2013). On the other hand, ma-chine learning is commonly used in big data applications, i.e. stock market predictions, online surveys, etc (Oladipupo, 2010). The same concepts of either methods could also be applied in classifying EMG signals (Hai, 2002). The Principal Component Analysis (PCA) method is chosen from many other methods of feature extraction (such as partial least squares, kernel PCA, etc.) because it has relatively easier implementation method, does not need too many raw data and has considerably fast computation time (Keho, 2012). Also, Artificial Neural Network (ANN) method is chosen from many other methods of machine learning (such as Recurrent Neural Network, Convolutional Neural Network, etc.) to classify custom gestures in this thesis project because it has a lot of customizable parameters, simpler neural network model, has the capability to achieve a high classifying accuracy, robust, and very adaptive in many applications (Shanmuganathan, 2016).

2. Materials and Methods

This research's main focus is to find out the accuracy comparison between the two methods (PCA and ANN) to recognize hand gestures. To achieve the objective, a software package is constructed to work on the main tasks: recording the EMG data based on performed gestures, training a classifier model based on the recorded data and classifying a gesture dataset based on the trained classifier model. The classifier model is set to recognize a fixed amount of custom gestures. Then, experiments on tuning the parameters from each classifier model are taken to achieve the highest accuracy.

2.1. Myo Armband as EMG Sensor

Myo is a wearable gesture control (using eight EMG sensors) and motion control (using nine-axis IMU sensors) device that is very customizable and user-friendly (Smith, 2014). Myo Armband is designed by the company Thalmic Labs. It reads electrical activity of the wearer's muscles and the motion of their arm. It's also a device that could fit a wide range of arm sizes, because it is equipped with removable fitters. Myo's developers at Thalmic Labs already provided the community with an open source Software Development Kit (SDK). It allows EMG data recording and real-time EMG data streaming, which are the crucial parts in this research. See the Myo Armband device in Figure 1.

Figure 1: Thalmic Labs' Myo Armband (Good, 2018).

In this research, the raw data and filtered data streamed by the Myo will be recorded in separate sessions to be put into comparison in classifying the same custom gestures. Filtered data stream, in this case, will take out environment noise from the Myo, which will smooth out the signal. On the other hand, unfiltered data will be streamed as is, without any filter applied to it (raw data). The EMG data stream will be recorded in two separate datasets: training dataset and evaluation dataset. This is done to evaluate the classifier model that are created using the training dataset using the different evaluation dataset. The recording will be done for a fixed duration. See the recorded gestures in Figure 2.

Find the development computer specifications used in this research as reference in Table 1 below. This much processing power of the computer is needed to achieve faster model training so that it could reduce development time.

2.2. Principal Component Analysis

The main idea of PCA is to find out which of the sensor reading pairs are the main contributor of the characterization of the muscular activity, without needing much time to finish its computations.

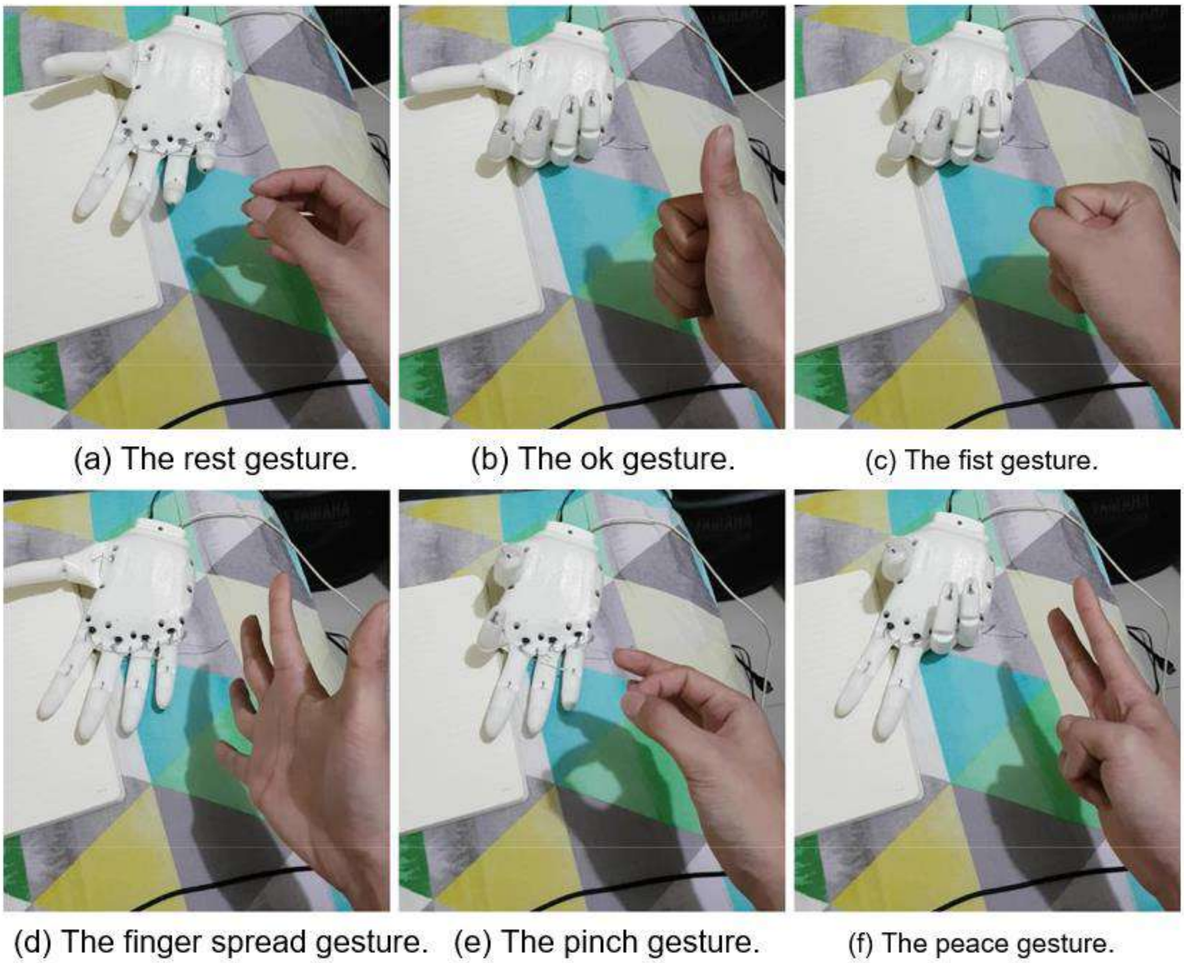

Figure 2: The set of 6 custom gestures.

Table 1: Computer specifications.

Components	Specifications
Processor	*Intel Xeon CPU E5-2630 v4 2.2GHz*
Graphics Card	*NVIDIA GeForce GTX 1060 6GB*
RAM	*DDR4 8 GB*

PCA uses a mathematically derived matrices to compute the features of the input data to classify gestures. The following subsections will explain more on how to process the eight EMG sensors' data to calculate the data's principal components using the PCA method. This matrix manipulation method is developed using the Karhunen-Loève transformation theorem (Webb, 2001), which is also an expansion of the PCA transformation. It is based on the concept of reduced dimension space, meaning that the total eight sensors are not all used to diff erentiate a set of gestures. Instead, only some of them that already describe the main 'features' are used (Shlens, 2005). To start the computation, firstly, samples of input data taken from Myo are collected and archived. These samples are kept at the same timeframe to minimize errors and redundant data in the calculations.

2.3. Artificial Neural Network

Neural network is currently being developed as the state-of-the-art system to classify data and solving control problems on non-linear systems. It is popular because of many reasons, some of them are its model's robustness and high classifying accuracy. With enough training data and good parameters setup of the network model, the system can achieve a high accuracy in classifying gesture data (Song et al., 2008). To construct a neural network model, many of open source libraries can be used, i.e.

Google's TensorFlow, Caffe, etc. An artificial neural network can also be constructed using MATLAB / Octave by deriving the forward and backward propagation equations. This research will utilize the well-documented and also open source Google's TensorFlow library to implement neural network for custom gesture classification (Ertam and Aydin, 2017). First a training EMG data is collected for custom gestures. All training data are kept at the same timeframe, to minimize errors and redundant data in the network model. Then, reference output is assigned to each of the training data to be the setpoint for the model's learning. These input data are then fed into the neural network model through forward propagation (Sandberg, 2001), and then evaluated back to recalculate the weights of the neurons inside the model through backward propagation.

3. Results and Discussion

The results of the gesture classifying experiments with parameters modification will be presented in this chapter. Each classifier method will have their each parameters and experiments setup.

3.1. PCA Classifier

The tests were basically done for different threshold values, which starts from 10% until 65%, with increments of 5%. The threshold values chosen were based on the sensitivity of the choosing results of the eigenvectors will have as minimal changes as possible for each experiment. Though, in some cases there are no difference at all when the threshold values are changed. For each threshold values, the tests were done with FFT and without FFT. See Table 2 for the accuracy means of FFT method and non-FFT method taken from all threshold values tests (sample size: 12).

Table 2: Accuracy average for FFT and non-FFT calculations in PCA evaluation.

Data Type	Method	Accuracy Average
Filtered data	FFT	25.77%
	non-FFT	20.83%
Unfiltered data	FFT	35.70%
	non-FFT	24.59%

The results show that on average, unfiltered data evaluation produces higher accuracy overall than filtered data evaluation. However, the impact of FFT is clearly shown in the unfiltered data tests (9.93% accuracy difference) rather than on filtered data tests (3.76% accuracy difference). In short, the results prove that the PCA classifier will have better classification results based on unfiltered data processing. This is supported by the fact that in unfiltered mode, the EMG data recorded does not have its signals filtered by removing spiked values, powerline noise, etc. Such filters oftentimes will remove some of the data itself that creates a feature that describes its own gesture. Table 2 shows that this does indeed occur in the EMG data filtering of the Myo. Lower results in the evaluation indicate that the classifier does not differentiate the gestures (classifying them from extracted features) properly.

3.2. ANN Classifier

The analysis on ANN classifier will be based on the data type (filtered or unfiltered data). ANN classifier is best trained with raw data, without having any signal processing done before it at all (Singh et al., 2014). Unlike the classifying method using PCA, it is advised to prepare information-rich raw data as much as possible for the ANN training node. The ANN model will then be fed by many different types of events occurred in the data, therefore it will make the network grow smarter as it receives more information. The experiments will be using two types of trained model (from filtered and unfiltered data), and the evaluation dataset will also use two types of data (filtered and unfiltered dataset) for each trained model. However, the ANN model's parameters themselves will also determine the accuracy of the evaluation tests. To summarize, the training results of both data types are represented in Table 3.

Table 3: Accuracy average for trained ANN model using filtered and unfiltered data.

Trained Data Type	Training Accuracy Average
Filtered	71.25%
Unfiltered	69.16%

On average, the evaluation tests using filtered evaluation datasets scored higher in both trained filtered and unfiltered ANN models. See the evaluation accuracy average summarized in Table 4.

Table 4: Average evaluation accuracy of ANN method.

Trained ANN Model	Evaluation Dataset	Average Evaluation Accuracy
Filtered model	Filtered data	45.75%
	Unfiltered data	31.49%
Unfiltered model	Filtered data	58.38%
	Unfiltered data	39.33%

From Table 4, it can be seen that filtered dataset tested on trained unfiltered ANN model pro-duces an overall higher accuracy than the other tests. This proves that the ANN model is better trained with unfiltered data, which contains more information than the filtered dataset. As have been illustrated before back in the EMG data logger node, the raw EMG data (unfiltered) logged more of the EMG data's characteristics including occassional signal spikes and other random events compared to the filtered EMG data.

3.3. Classifier Comparison

PCA classifier uses two methods overall, which are the FFT-method and non-FFT-method, to evaluate the gesture data. These two methods off er diff erent kinds of approach in classifying the evaluation data, in which also produces diff erent results for the accuracy. On the other hand, the ANN method presents one approach in classifying the data, however it is done by classifying diff erent data types. In this case, only the highest accuracy out of the two data types will be taken for comparison. In terms of accuracy, the ANN method scored higher than the PCA method. This could be analyzed from various diff erent point of views, in which one of them is the fundamental way of the data processing. Basically, PCA method uses the dimensional reduction concept, which eliminates information that are deemed unnecessary by doing the SVD calculation, and takes only important features that describe the gestures data to classify them. In reality, the extracted features did not always describe the gestures correctly. While in the ANN methodology, the neural network model learns about the characteristics of the EMG data by feeding raw data that contains many untinkered information about itself. This way, the model learns all about the data without having some reduced information and still, it gets better when it learns more data (requires more data logging time). To see the best and worst result from all evaluation experiments in all methods, see Figure 3.

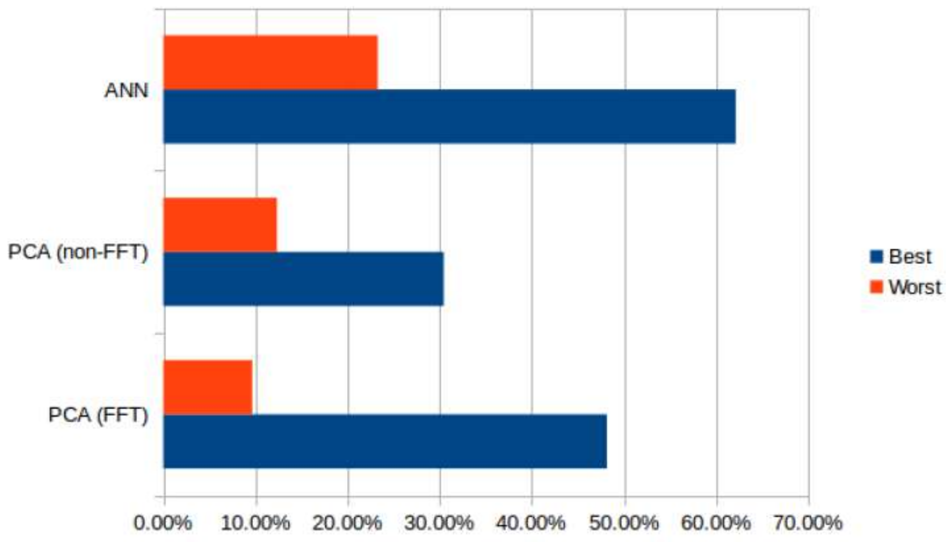

Figure 3: Best and worst evaluation accuracy comparison.

Statistically, both PCA methods (with and without FFT) tested on both filtered and unfiltered data types showed significant status at $p < 0:5$, with f-ratio value of 8.28403 and p-value of 0.000177 (using one-way ANOVA method). This shows that indeed the two methods (with and without FFT) are significant to each other in terms of independent methods. For ANN method, both trained filtered and unfiltered models' evaluation results tested on filtered and unfiltered datasets are also calculated statistically. It shows that indeed they are significant as independent methods at $p < 0:5$, with f-ratio value of 369.31296 and p-value < .00001.

4. Conclusion

The EMG data have been recorded and stored in the respective directories based on their data types. The gesture classifier software have also been developed using both methods (PCA and ANN) as a package to recognize custom hand gestures. The highest custom gesture classifying accuracy from the PCA method have been produced by using FFT and non-FFT methods. ANN method used filtered dataset evaluated on a trained unfiltered data model to produce the highest accuracy. PCA classifier with FFT reaches a classifying accuracy of 48.15%, PCA classifier without FFT reaches 30.43%, and ANN classifier reaches 62.14% accuracy. All stated accuracy percentages were taken from each methods' experiments' results.

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