Gesture Recognition Using MyoBand

Chethan Kumar Kolar Ananda Kumar
Arizona State University
Tempe, AZ, 85281 USA
ckolaran@asu.edu

***Abstract*— Gesture Recognition has been a topic of interest in the field of computer science. Gestures have been seen as a very important way towards machines understanding human body language. Many machine learning algorithms and statistical methods have been proved efficient in recognizing gestures. Gesture recognition has found its applications in the field of medicine, robotics, automation, automobile etc. Surface electromyography (sEMG) signals collected using the MyoBand can be statistically analyzed to recognize gestures.**

***Index Terms*—MyoBand, Fast Fourier Transform, Decision Tree, Neural Network, Support Vector Machines.**

I. Introduction

The aim of the project is to develop a gesture recognition mechanism from the sEMG data collected using the MyoBand. The time series data collected from MyoBand was subjected to various statistical measures like Fast Fourier Transform, Variance, Mean, Standard Deviation, Min and Max of a given range of a feature in order to select the most important features that help differentiating eating action from other action. In this phase, we aimed to distinguish 'eating action with a spoon' from 'eating action with a fork' and build various Machine Learning algorithms to classify the action. For this phase we were given a different dataset containing 'MyoBand' data collected from 32 users. However, the type of features of the collected data remain same as previous phase. By applying the same statistical analysis, we were able to extract features which were used to train Machine Learning algorithms such as SVM, Decision Tree and Neural Network to check Precision, Recall, Accuracy and F1-Score.

II. Developed Solution

A. Data Analysis

We were provided raw data collected from 30 users in folders named userxx, each such folder with 2 files inside. One file consists of data from EMG sensors and the other has IMU data which internally has readings of Accelerometer, Gyroscope and Orientation sensors. The files contained data corresponding to activities other than fork and spoon as well and hence needed to be filtered and readied before applying any transformation. There were two folders: 'groundtruth' and 'Myodata'. GroundTruth folder contained frame information of the activities performed by each user for fork and spoon actions. It contained start time and end time of the time frame of the actual fork and spoon activity. The rest of the activities were to be interpreted as non-fork or non-spoon action. This helped as a mapper file. We applied the following formula to map from the grounding file to the fork and spoon eating activity rows in the EMG and the IMU files.

R = Round (Frequency ratio * Si)

Where R = Index of the data element and Si = start time or end time in Nano second.

Frequency Ratio for IMU sample data = 1.68

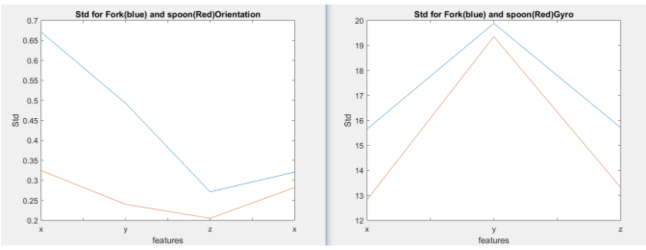
Frequency ratio for EMG sample data = 3.4

For example, given the data element from the helper file of 'groundTruth' folder for userxx spoon data: 163, 185, and 2 is mapped to a spoon/fork activity using start time Si = 163. So the first row of eating activity of IMU files starts at row: Round (163 * 1.68) = 274. The end time for the first activity = 185. Hence the activity ends at row number: Round (185 * 1.68) = **311.** So the first data of eating activity of IMU files for spoon for user09 is between rows (274, 311).

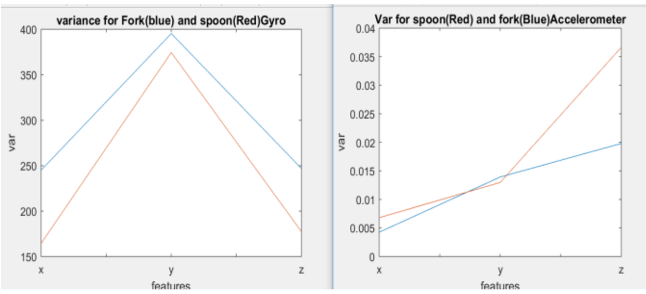
We did this for all activities mentioned in the spoon file of the user to get the true spoon gesture data of userxx. And repeated it for all EMG files and fork data of this user and subsequently all users. The MATLAB code for data processing is given in the file 'MapSplit.m'

B. Feature Selection

For feature selection we applied the following statistical methods like variance, mean, min, max and Entropy to segregate the two actions (Spoon, Fork). The plots below are for variance measure and standard deviation measures of various sensors of the MyoBand for the time series data for eating actions with fork and spoon.



The intuition for using variance as a feature extraction method is because we expect to see high variance with respect to certain sensors for one action or the other. We applied the variance function on the given data, the variance for the orientation shows clearly the difference in variations in angular velocity between spoon and fork action.The intuition for using mean is that there is usually a noticeable difference between the mean values for two actions. For certain sensors like Orientation data we anticipate that the sensor values for the two actions will be skewed differently with respect to the medians.



For the sensor like orientation we found the difference between the spread of the data which helped us to identify the important features. As we can see in the plot for mean of spoon and fork data using the Orientation Sensor, the actions show different mean values for each of the orientation sensors. Similarly, we can see for EMG and gyro. The Intuition behind using min is to find the values that can help to distinguish different activities how the min values differ for them. The Intuition behind using maxis to find the values that can help to distinguish different activities how the max values differ for them. We applied the max function on the data and identified the difference between max value of various sensors, we observed the noticeable difference in the two actions for gyro and orientation sensor. We used standard deviation to see the dispersion of the data points, the standard deviation on orientation sensor shows the noticeable difference between the two activities. The entropy is measure of uncertainty in the data, after observing entropy over the two actions, we found noticeable difference in entropy of orientation sensor for both the actions.

C. *Data Transformation: Applying Principal Component Analysis(PCA)*

From the statistical analysis done in step B above, we concluded that our dataset has 56 interesting features. As a part of phase 2 task we had to apply Principal Component Analysis and try to transform and reduce features. However, we found that the transformed feature matrix performed poorly on all the Machines: SVM, Decision Trees and Neural Networks. The accuracy and precision were quite low when compared with non-transformed feature matrix for most users. We conclude that PCA is not helpful in our case.

D. *Applying Models for Classification*

We used three algorithms: Support Vector Machine (SVM), Decision Trees (DT) and Neural Network (NN). The algorithms are coded in MATLAB using available MATLAB libraries. In Phase 2, for each of the above model, the 60% data of each user is used to train the model. The rest of the 40% is used to test the model. In Phase 3, the split was the same, however the data of the selected 60% users was combined in a single file and the remainder 40% user's data in another file, used to test the models.

Support Vector machines are classifiers that maximize the margin of the classification. It utilizes the training instances that are closest to the decision boundary as "support vectors" and thus trains the parameters based on these "support vectors" and not on instances that lie far away from the boundary. Decision Tree returns a fitted binary classification decision tree based on the input variables contained in matrix X and output Y. The returned binary tree splits branching nodes based on the values of a column of X. fitnet (hiddenSizes) returns a function fitting neural network with a hidden layer size of hiddenSizes.

III. Results

In this section, we discuss the results of the statistical data analysis for feature selection, performance of the three models namely SVM, NN and Decision Trees used for gesture recognition.

TABLE I. Summary of Features selected

	EMG	Orientation	Accelerometer	Gyroscope
Min	2, 8	X, Y	Y	X, Y, Z
Max	1, 4	Z, W	X, Y, Z	X, Y
Variance	1,8	X, Y	X, Z	X, Y, Z
Mean	1, 4, 5, 6	X, Y, Z, W	None	X, Y, Z
Entropy	4, 5	Z, W, Y	Y, Z	X, Y, Z
Standard Deviation	5	Y, Z, W	Y, Z	X, Z

A. *Feature Selection*

After performing different statistical analysis calculations like variance, mean, min, max and Entropy to segregate the two actions (Spoon, Fork) on the collected data from the sensors of the MyoBand, we finalize different parameters of the four sensors EMG, Orientation, Accelerometer and Gyroscope as shown in Table 1.

B. *SVM*

Support Vector machines are classifiers that maximize the margin of the classification. It utilizes the training instances that are closest to the decision boundary as "support vectors" and thus trains the parameters based on these "support vectors" and not on instances that lie far away from the boundary. The MATLAB call for SVM is: fitcsvm(x_train, y_train, 'KernelFunction', 'Gaussian', 'KernelScale', 'auto'); The performance metrics accuracy, precision, recall and F1 score for the SVM model for phase 2 and phase 3 of the project are as shown in Fig 1. For phase 2, Precision = 0.9286, Accuracy = 0.9000, Recall = 0.8667, f_score = 0.8966 and for phase 3 Precision = 0.3750, Accuracy = 0.3333, Recall = 0.5000, f_score = 0.4286.

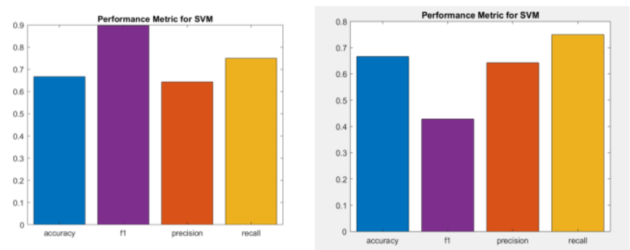


Fig. 1. Performance Metric for SVM in Phase 2 and Phase 3

C. *Neural Network*

fitnet (hiddenSizes) returns a function fitting neural network with a hidden layer size of hiddenSizes. The performance metrics accuracy, precision, recall and F1 score for the Neural Network model for phase 2 and phase 3 of the project are as shown in Fig 2.

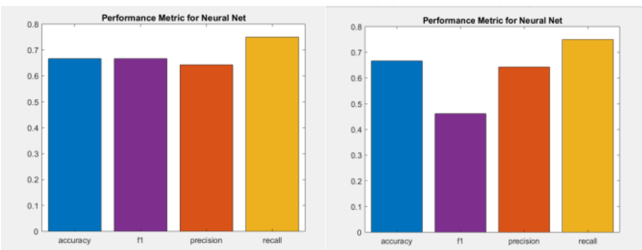


Fig. 2. Performance Metric for NN in Phase 2 and Phase 3

For phase 2, Precision = 0.7037, Accuracy = 0.6833, Recall = 0.6333, f_score = 0.6667 and for phase 3 Precision = 0.5455, Accuracy = 0.5333, Recall = 0.4000, f_score = 0.4615.

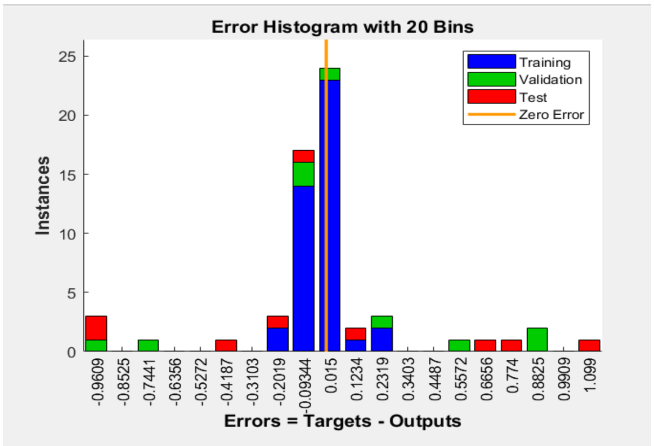


Fig. 3. Error Histogram for Neural Network Model

D. Decision Tree

Decision Tree returns a fitted binary classification decision tree based on the input variables contained in matrix X and output Y. The returned binary tree splits branching nodes based on the values of a column of X. The performance metrics accuracy, precision, recall and F1 score for the Decision Tree model for phase 2 and phase 3 of the project are as shown in Fig 4. For phase 2, Precision = 0.6765, Accuracy = 0.7000, Recall = 0.7667, f_score = 0.7188 and for phase 3 Precision = 0.6429, Accuracy = 0.6667, Recall = 0.7500, f_score = 0.6923.

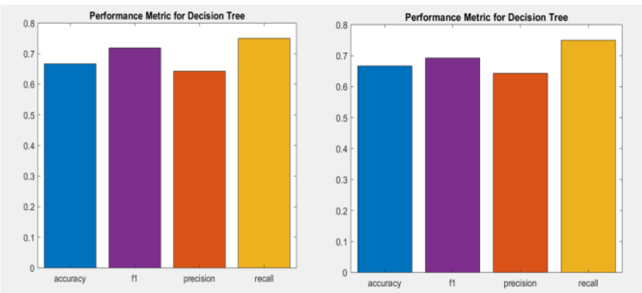


Fig. 4. Performance Metric for Decision Tree in Phase 2 and Phase 3

E. Conclusion

Analyzing the above graphs from phase 3, we can conclude that the models predicted better for individual users in phase 2 than with a combined data. More data is needed to achieve a better classification. PCA was not effective in our case to achieve better results. Analyzing the results from assignment 2 and assignment 3, we see that the performance metrics are higher for users whose eating activities data was trained using the models. In assignment 3 as we are testing completely on a new user, the performance metrics tend to be a lower compared to assignment 2. For both the assignments PCA was also used and tested. The performance of SVM, Decision Trees and Neural Networks were all higher when the feature matrix without the application of PCA was used rather than when using the feature matrix with PCA applied on it.

IV. Contribution

In the first phase of the project, I was involved in collecting the data by wearing the MyoBand and recording data while performing different activities like cooking, biking, eating etc. The collected data was to be used for the phase 2 and phase 3 of the project. Instead in phase 2, Prof. Ayan Banerjee provided us alternate data collected by MyoBand performing eating food with a fork and eating food with a spoon. The task of phase 2 was to use this time series data and subject it to various statistical measures like Fast Fourier Transform, Variance, Mean, Standard Deviation, Min and Max of a given range of a feature in order to select the most important features that help differentiating eating action from other action. I worked on analyzing the time series data using Variance, Entropy and standard deviation. In the third phase of the project, applying the same statistical analysis, we were able to extract features which were used to train Machine Learning algorithms such as SVM, Decision Tree and Neural Network to check Precision, Recall, Accuracy and F1-Score. My contribution was training and executing the SVM model.

V. *Learnings*

The project helped me obtain a great understanding on the numerous techniques employed in the field of data mining. The different phases of the project involved employment of many data mining techniques in the process of Data retrieval, preprocessing, data analysis and building models like neural networks, decision trees and SVM for recognizing gestures. The entire project was coded extensively using Matlab and henceforth led me to learn an entirely new language. Many libraries of Matlab were also learnt. The second phase of the project involved data collection and feature selection. For feature selection process, I learnt analyzing time series data using different features.

I like to thank Prof. Ayan Banerjee for his assistance, availability and guidance for this project. At last, I thank my teammates – Aikya Shah, Manjunath Darshan Shantigrama Rangaswamy, Sanjay Narayana and Varun Singh for their immense contribution to the project in a timely and efficient manner.

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