Classification of Human Posture and Movement Using Accelerometer Data

Huafei Wang
huafei@stanford.edu
Dept. of Electrical Engineering
Stanford University

Jennifer Wu
jwu46@stanford.edu
Dept. of Aero/Astro
Stanford University

1 Introduction

Human activity classification has wide reaching applications, such as in providing medical assistance to disabled or elderly persons. This project implements several machine learning algorithms to classify human posture and movements. The different activities being classified are:

Sitting, Sitting down, Standing, Standing up and Walking

The difference between "Sitting" and "Sitting down" is that the former is the static posture, whereas the latter is the transitional movement from standing to sitting.

Past work

Bodor et al. developed a novel method for employing image-based rendering to extend the capability of the human movement classification [1]. Sminchisescu et al. have developed algorithms for recognizing human motion in monocular video sequences, based on discriminative conditional random fields (CRFs) and maximum entropy Markov models (MEMMs) [2].

However, vision-based systems have issues in camera installation, lighting, picture quality, privacy and etc., which may render the system impractical in certain applications. As a branch of movement classification techniques, wearable sensor-based system could solve the above problems thanks to the development of nano-manufacturing technologies and ultralow-power embedded systems, which makes the wearable sensors cheap, small and compact. Ugulino et al. collected human movement data from 4 ADXL335 accelerometers, utilized C4.5 tree, Iterative Dichotomiser 3 (ID3) and AdaBoost to classify the human movements and have obtained high recall and precision [3]. This project utilizes the same set of data but a different set of models to compare classification performance.

2 Data

The data is made publicly available on UCI's Machine Learning Repository. It can be accessed at: `http://groupware.les.inf.puc-rio.br/har#dataset`.

The dataset contains the following features

Age, Weight, Body Mass Index, Height
x,y,z axis readings from 4 different accelerometers

Table 1: Frequency of each class

Class	**Frequency**
Sitting	50631
Sitting down	11827
Standing	47370
Standing up	12415
Walking	43390

3 Features

3.1 Description

The features used in our models are the 12 accelerometer readings. Although the original data also contains age, weight, body mass index and height, they are neglected in this preliminary analysis and classification because they are less relevant in determining human movement compared with the 12 accelerometer readings.

3.2 Preprocessing

In the initial implementation without any preprocessing of the data, precision and recall were very low. To improve performance, different ways to scale the data was investigated. More specifically, we tried *Z-score scaling* and $0-1$ *scaling* and tested the resulting effects on performance.

Table 2: Effect of scaling data on performance

	GDA		SVM	
	Precision(%)	Recall(%)	Precision(%)	Recall(%)
Unscaled	78.94	69.56	85.83	51.40
Z-score scaling	75.49	70.42	98.76	98.76
$0-1$ scaling	99.90	99.90	99.90	99.90

Randomizing the data Since the raw data is presented as a series of sampled outputs from the accelerometers, it was important to randomize the order of the data sets, especially when we were performing smaller tests where only a small constant number of training example were chosen. Due to the physical nature of the data, consecutive training examples are largely dependent, thus reducing the rank of the training matrix. It was found that randomizing the order of the training sets improved precision and recall.

3.3 Principal Component Analysis

Since the feature data is of dimension 12, which makes it impossible to directly visualize the data, Principal Component Analysis (PCA) is used to reduce the dimension for the feature dataset from 12 to 3. Three principal eigenvalues and the associated eigenvectors are used. The data is represented in figure 1. The horizontal data distribution corresponds to human lateral movements (moving forward, backward, left, right) while the vertical data distribution corresponds to human longitudinal movements (standing up, sitting down).

4 Gaussian Discriminant Analysis

4.1 Binary classification

GDA models the input features as a multivariate normal distribution, with the class label as a Bernouilli variable. For each class, the class's data is used as positive training examples, while data from each of the other classes are concatenated to be used as negative training examples. After constructing the training set, model parameters are calculated with the following formulas:

$$\phi = \frac{1}{m}\sum_{i=1}^{m} 1\{y^{(i)}=1\}$$

$$\mu_0 = \frac{\sum_{i=1}^{m} 1\{y^{(i)}=0\}x^{(i)}}{\sum_{i=1}^{m} 1\{y^{(i)}=0\}}; \quad \mu_1 = \frac{\sum_{i=1}^{m} 1\{y^{(i)}=1\}x^{(i)}}{\sum_{i=1}^{m} 1\{y^{(i)}=1\}}$$

$$\Sigma = \frac{1}{m}\sum_{i=1}^{m}\left(x^{(i)}-\mu_{y^{(i)}}\right)\left(x^{(i)}-\mu_{y^{(i)}}\right)^T$$

4.2 Multi-class classification

For a testing example, in order to make a prediction into 1 of the 5 classes, the posterior distribution is calculated for each class, and the predicted label is chosen depending on the largest posterior.

That is

$$h_\theta(x) = \arg\max_y p(x|y)p(y); \quad \text{where } y \in \{1,2,3,4,5\}$$

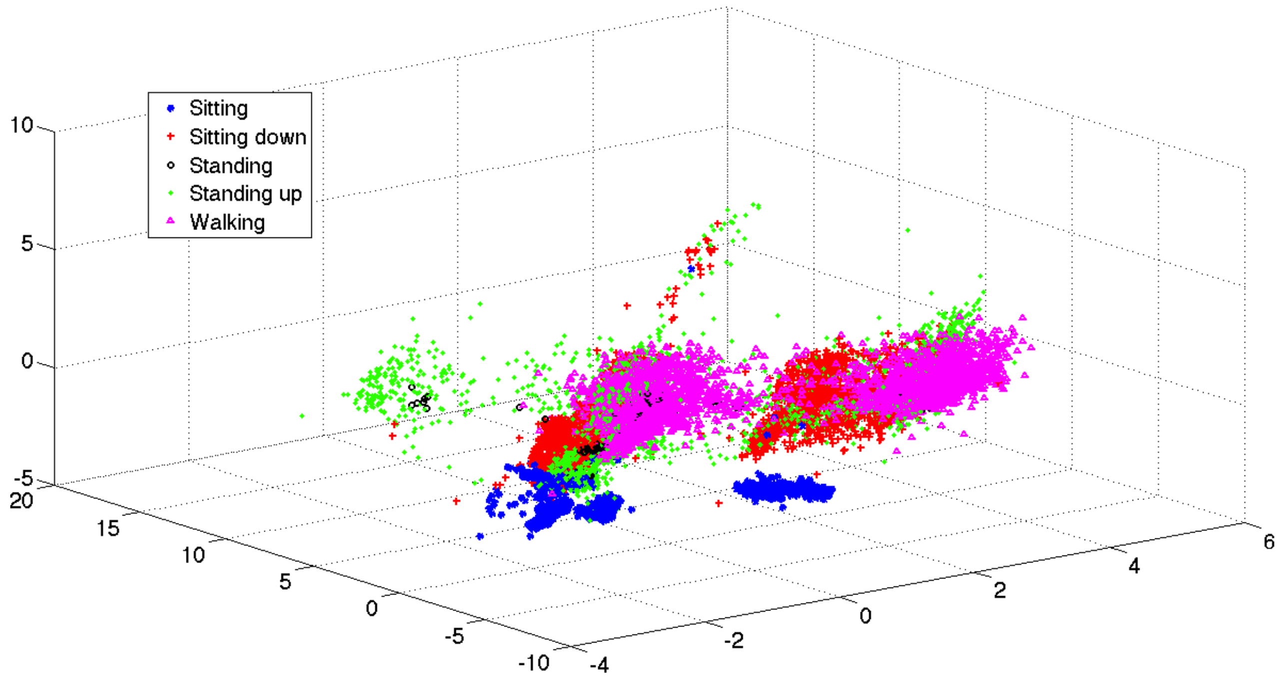

Figure 1: Data projected onto first 3 principal eigenvectors

Learning Curve

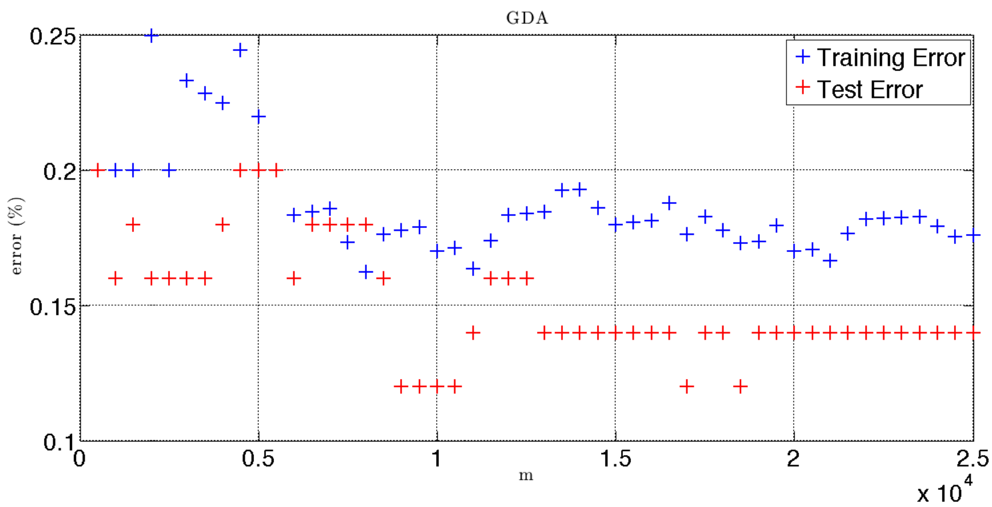

Figure 2: GDA learning curve

The learning curve shows significant improvement in performance only up to the first 2000 training examples. Thus SVM is efficient in terms of training set size.

5 Support Vector Machine

A support vector machine builds a model that seeks to maximize the margin between the separating hyperplane and data points. More specifically, the model parameters are found by solving the following optimization problem[4]:

$$\begin{aligned} \min_{\gamma,w,b} \quad & \frac{1}{2} \parallel w \parallel^2 + C\sum_{i=1}^{m} \xi_i \\ s.t. \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i, i = 1, .., m \\ & \xi_i \geq 0, i = 1, \ldots, m \end{aligned}$$

To implement SVM, we used LIBSVM [5].

Learning Curve

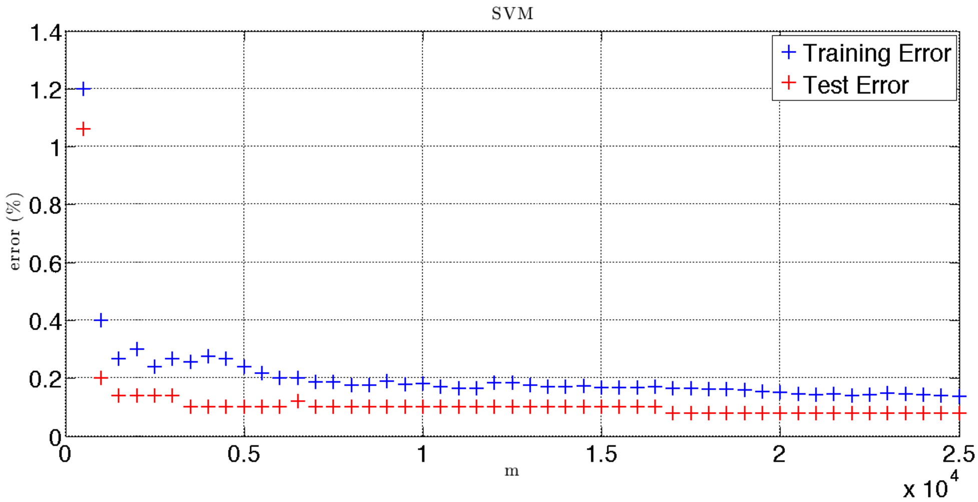

Figure 3: SVM learning curve

6 K-means

Since a particular human movement usually requires a harmonious coordination among different parts of the body, accelerometer readings would exhibit clustering properties. Therefore, K-Means has been attempted to classify the human postures and movements.

Learning Curve

The K-means learning curve is shown in figure 4. K-Means has a poor overall classification performance and the learning curve for the K-Means does not exhibit a typical decreasing pattern as most of the supervised learning algorithms do. One reason is that K-Means is not a supervised learning method and the clustering algorithm does not necessarily correspond to how human accelerations of a movement are coordinated and clustered. Therefore, K-Means could only roughly classify non-movements from the accelerometer readings while detailed movements classifications need to be done by using supervised learning methods like GDA and SVM. Therefore, it is concluded that unsupervised learning algorithms like K-Means may not be suitable in a supervised learning context.

7 Results

For the final results, training was done on taking 90% of the data from each class and testing was done on the remaining 10% of the data. The following table shows the precision and recall for each model.

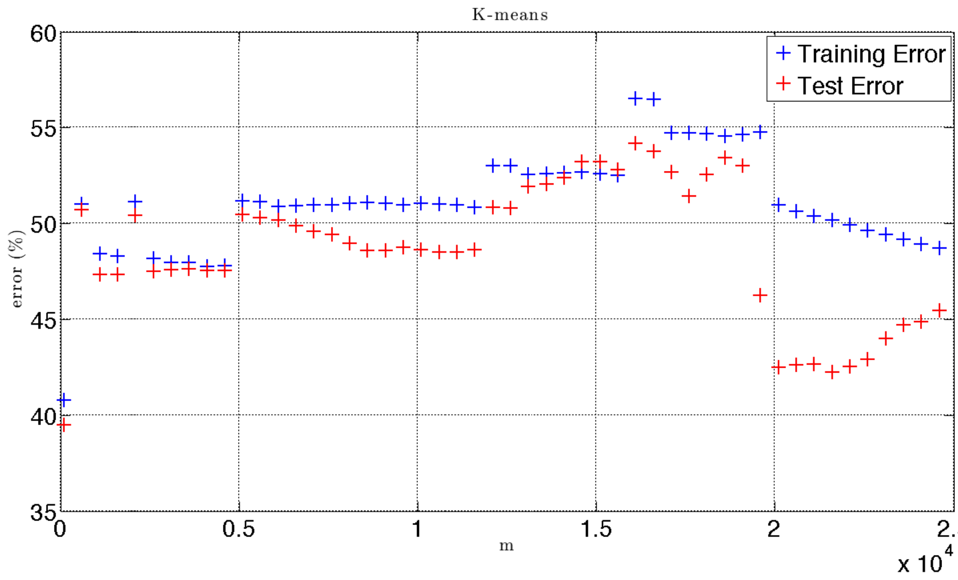

Figure 4: K-means learning curve

Table 3: Testing results for all three models

	GDA		SVM		K-means	
	Precision(%)	Recall (%)	Precision(%)	Recall (%)	Precision(%)	Recall (%)
Sitting	99.94	99.96	99.98	99.96	82.0	100.0
Sitting down	99.83	99.75	99.83	99.75	0.0	0.0
Standing	99.81	100.00	99.96	100.00	44.7	100.0
Standing up	100.00	99.12	99.92	99.84	39.7	37.3
Walking	99.95	100.00	99.98	100.00	2.9	1.4

8 Future Work

The algorithms exhibited have shown high precision and recall. The next step would be to integrate the algorithm into a portable embedded system that has limited computation capability, memory space and/or battery life to classify the movements to make the system practical. With the development of the cloud technology, the wearable devices could also just collect the accelerometer data and send it wirelessly to a data processing server to carry out the processing and classification work. This would enable the devices to work longer and more reliably given the limited resources available.

References

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