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Seminar Report

On

Classification of human posture and movement using accelerometer

Submitted By

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CERTIFICATE

This is to certify that, the Seminar entitled "**Classification of human posture and movement using accelerometer**" submitted by **Vandan Rathod** is a bonafide work completed under my supervision and guidance in partial fulfillment for award of Bachelor of Technology (Computer Science and Engineering) Degree of Dr. Babasaheb Ambedkar Technological University, Lonere.

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Abstract

Patient compliance is important when assessing movement, particularly in a free-living environment when patients are asked to don their own accelerometers. Reducing the number of accelerometers could increase patient compliance. The aims of this study were (1) to determine and compare the validity of different accelerometer combinations and placements for a previously developed posture and dynamic movement identification algorithm. Custom-built activity monitors, each containing one tri-axial accelerometer, were placed on the ankles, right thigh, and waist of 12 healthy adults. Subjects performed a protocol in the laboratory including static orientations of standing, sitting, and lying down, and dynamic movements of walking, jogging, transitions between postures, and fidgeting to simulate free-living activity. When only one accelerometer was used, the thigh was found to be the optimal placement to identify both movement and static postures, with a misclassification error of 10%, and demonstrated the greatest accuracy for walking/fidgeting and jogging classification with sensitivities and positive predictive value (PPVs) greater than 93%. When two accelerometers were used, the waist-thigh accelerometers identified movement and static postures with greater accuracy than the thigh-ankle accelerometers (with a misclassification error of 11% compared to 17%). However, the thigh-ankle accelerometers demonstrated the greatest accuracy for walking/ fidgeting and jogging classification with sensitivities and PPVs greater than 93%. Movement can be accurately classified in healthy adults using tri-axial accelerometers placed on one or two of the following sites: waist, thigh, or ankle. Posture and transitions require an accelerometer placed on the waist and an accelerometer placed on the thigh.

Keywords: accelerometer, movement analysis, posture detection, monitor placement

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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.

Developing tools to accurately assess posture and movement in a free-living environment is of great importance. However, many studies have reported patient compliance issues using activity monitors to assess physical activity in free-living environments. One of the main issues which can affect patient compliance in assessments are requesting them to wear multiple sensors which can be too cumbersome for long-term use. Using numerous activity monitors per subject can provide information on the movement of a greater number of body segments. For more complex postural orientation and movement classifications, this can generate results of superior accuracy . However, reducing the number of activity monitors would increase the user-friendliness of such assessments. This could increase participation willingness in activity assessments and reduce the possibility of user error as instructions would be simpler.

LITERATURE SURVEY

Bodor et al. developed a novel method for employing image-based rendering to extend the capability of the human movement classification . 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) . 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 nanomanufacturing 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. This project utilizes the same set of data but a different set of models to compare classification performance.

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

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

Brief on System

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.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.

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.

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 Eigen values and the associated eigenvectors are used. The data is represented above. 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).

Gaussian Discriminant Analysis

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:

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

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

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

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.

h(x) = arg $\max_y$ p(xjy)p(y);   where y belongs {1; 2; 3; 4; 5}

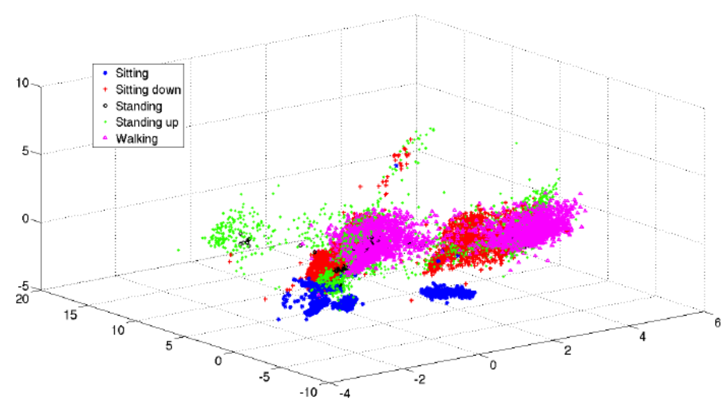

Figure 1: Data projected onto first 3 principal eigenvectors

Support Vector Machine

A support vector machine builds a model that seeks to maximize the margin between the separating hyperplane and data points. More specically, 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

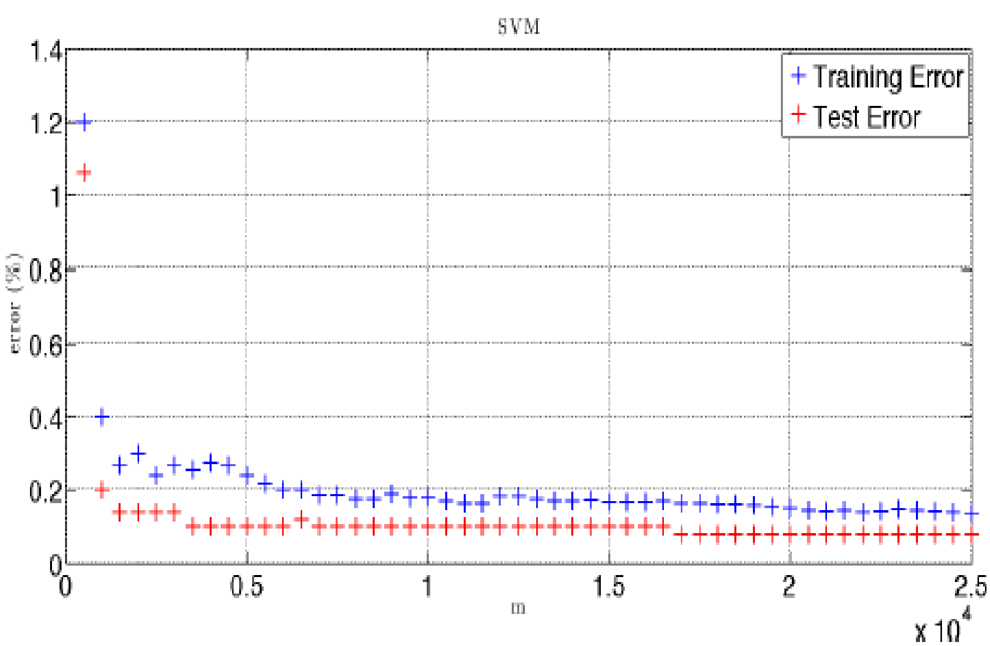

Figure 3: SVM learning curve

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 below. 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.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.

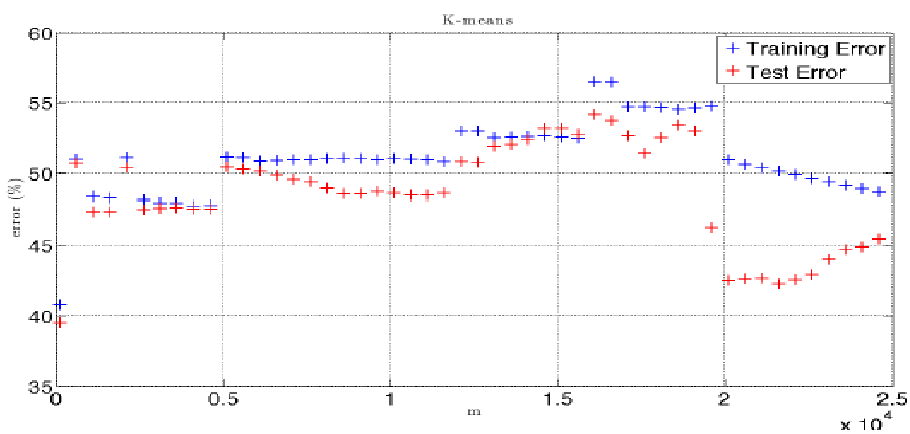

Figure 4: K-means learning curve

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

CONCLUSION

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. This project utilizes the same set of data but a different set of models to compare classification performance.

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.
The results from this study show that there is a trade-off between reducing the number of accelerometers per subject, choosing their locations and accuracy. The data suggests that researchers should carefully choose accelerometer numbers and their locations depending on the information required while considering patient preferences. For posture-related tasks, we recommend using a waist and thigh accelerometer combination. For redundancy, an extra thigh accelerometer should be added. For eddynamic tasks, we recommend using a thigh accelerometer. For redundancy, an ankle accelerometer should be added. While this study involves a simulated protocol conducted in a laboratory environment, the results suggest that the proposed analysis methods are suitable for posture and movement classification in healthy adults in a free-living environment

Applications: Watches like fitbit; mobile phones applications like healthcare, Health, in various medical fields such as for handicap patients, for diabetic patients, for asthma patients etc.

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Signature of Student
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