Human Activities Recognition Using Four Accelerometer Sensors

Xuan Li
School of Public Health
University of Pittsburgh
PA, USA
xul23@pitt.edu

En-Chi Lo
School of Industrial Engineering
University of Pittsburgh
PA, USA
enl12@pitt.edu

ABSTRACT

There is an increasing trend of using wearable devices to detect human activities recognition and monitor people's daily activities and health condition. Our project is mainly using 4 accelerometers sensor data. As customers, we are also curious about how the devices actually works. Our project goal is to correctly classify the human activities using experiment datasets.

Keywords

Data mining, Clustering, Classification, Wearable device, Accelerometer, Activity recognition

1. INTRODUCTION

Human activity recognitions is an important yet challenging research area with many applications in healthcare, smart environments, and homeland security. Early researchers tried to use computer vision-based techniques to do human activity tracking. However, it require expensive infrastructure support and not convenient for daily use. Alternatively, a more efficient approaches have been developed to track his or her motion in real time. Accelerometer Sensors worn on a user's body has been widely used in recent studies.

2. Related Works

Bao and Intille [1] have done some researches that using five biaxial accelerometers on the user's right hip, dominant wrist, non-dominant upper arm, dominant ankle, and non-dominant thigh to monitor 20 types of activities with 20 users using classifiers of C4.5 and Naive Bayes. Krishnan et. al. [2]used data from three wearable accelerometers to detect lower body motions. Our interest is to detect the activities by exploring more features and developing more sophisticated classification method based on previous work. We will consider the pattern of each activities and use combined classifiers to get higher accuracy results in this project.

3. Innovation Point

We use Random Forest to do feature selection on four sensors' accelerometers datasets.

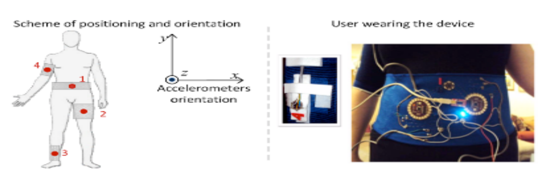
4. DATA COLLECTION

There are totally 165634 cases in our dataset with no missing value. Our dataset contains approximately 8 hours of accelerometer data for each of 4 individuals. Records represent 3-axis acceleration measurements taken from 4 accelerometers worn on the waist, left thigh, right arm, and right ankle. The position of those four sensors are shown in the following figure. The x axis represent the left and right movement, y axis shows the up and down movement while z axis represents the forward and backward movement. Each measurement is taken over a time window of 150ms and presented in temporal order, without a time stamp. The activity of each participant is categorized into 5 classes; sitting, sitting-down, standing, standing-up, and walking.

We also collect some basic information of users including age, gender, and weight and body mass index.

The original data we collected from sensors are:

x_1 = x axis acceleration measurement in waist
y_1 = y axis acceleration measurement in waist
z_1 = z axis acceleration measurement in waist
x_2 = x axis acceleration measurement in left thigh
y_2 = y axis acceleration measurement in left thigh
z_2 = z axis acceleration measurement in left thigh
x_3 = x axis acceleration measurement in right arm
y_3 = y axis acceleration measurement in right arm
z_3 = z axis acceleration measurement in right arm
x_4 = x axis acceleration measurement in right ankle
y_4 = y axis acceleration measurement in right ankle
z_4 = z axis acceleration measurement in right ankle



Position of four sensors

5. FEATURE EVALUATION

To further explore the acceleration data, we used line chart try to find the pattern among different axis and different positions for Debora.

The following figure shows how X, Y, Z axis differed for different activities on Debora waist sensor. It is easy to see that every activity has their distinct pattern.

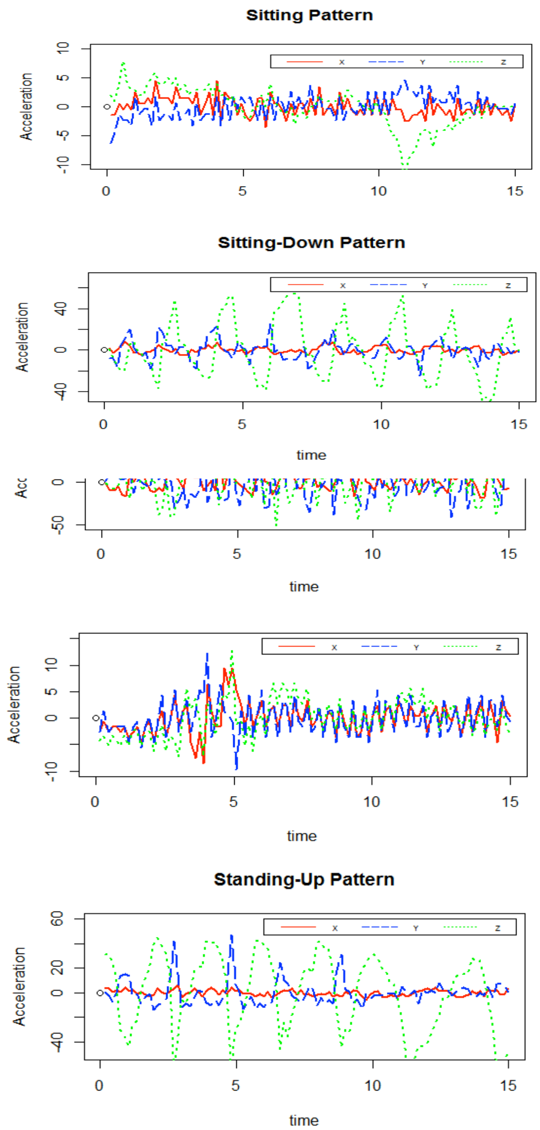


Figure 1 Acceleration Data of X,Y and Z axis from Debora Waist Sensor. Each graph shows a periodic behavior and has a special pattern.

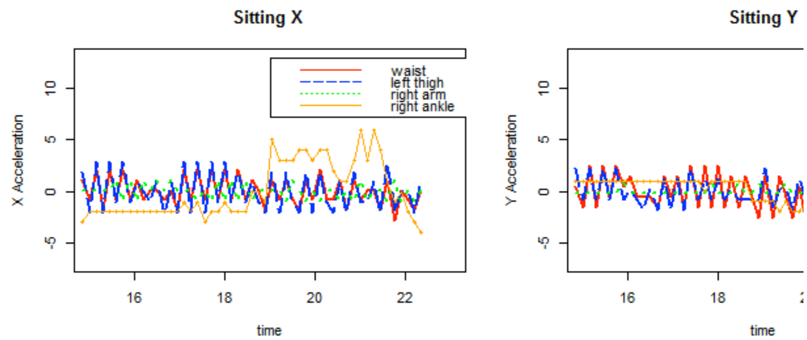


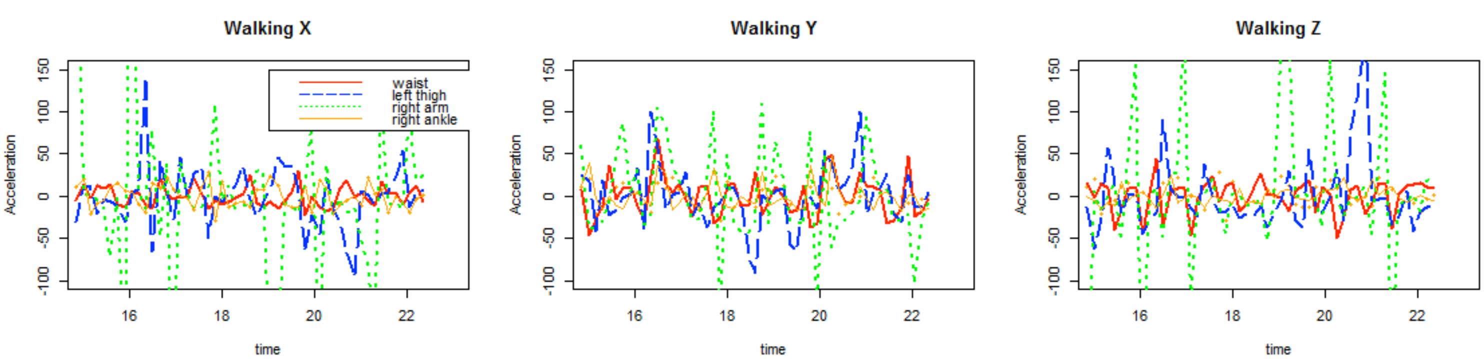
Figure 2 Acceleration Data of X,Y Z on walking and sitting from four sensors

From the Figure 1 ,three-axis have different performance for different actvities. For example, for standing-up and sitting-down activities, the z-axis of forward and backward and y-axis of upward and forward directions have changed siginificant while x-axis hold stable.Moreover, standing and sitting don't have obvious period for movement while all other three activities show a strong periodic pattern.

Besides, since the moving pattern of different positions in human body are different, the patterns in different position are further explored .Figure 2 shows the differences of four sensors in three axis for walking and sitting actvities. For example, for walking ,the right arm and left thigh have larger changes than other sensors due to human walking mechanisim.

6. FEATURE EXTRACTION

Classification methods cannot be directly applied to raw time-series accelerometer data since it don't capture the activities pattern. We divided the data into 6-second segments which corresponding to 40 samples with 50% overlapping in order to better capture activities pattern. Features are generated based on the segments. The reason we choose 6 second is that we believe that 6 seconds is enough to capture the 2-3 cycles of activities movement and can be used to detect pattern based on Figure 3.



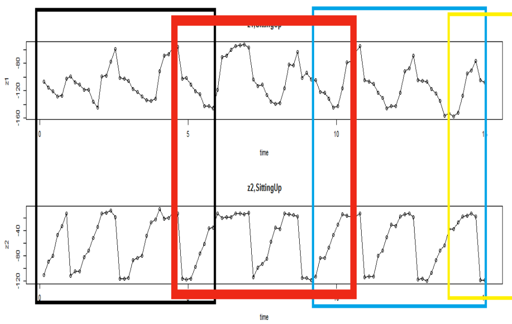


Figure 3.The periodic movement of standing up.

Based on previous paper, the features we are generated are: Average value of one cycle for each axis/sensors, Standard deviation of one cycle for each axis/sensors , Range (Max-Min) of one cycle for each axis/sensors, Correlation between each axis for each sensors, Average Absolute Differences and Average Distances.

Here the Average Abosolute Differences is calculated by each axis and each sensors, first calculate the absolute differences between the two points (previous one point and current one point) and then take average of these value in one time window (40 points).

The Average distances is calculated by: For each sensors, calculating the 3-dimensional distances between two points(previous one and current one) and then take average of this value in one time window(40 points).

Each Average, Standard Deviation, Range, Correlation and Average Absolute Different generates 12 feature columns for us. Average distance generates four features for the model.

7. Feature Selection and Classification Methods

In the raw data, there was a matrix with 165634 instance and 25 feature columns. After feature extraction, the dataset became 5513 instance with 64 columns. It is obvious that too many features will cause high computational cost and noise. We use Random forest to do feature selection. The list of importance of variables is returned (Table 1).From this table, we could find Average Absolute Distances and mean value of z are the most important factors .Correlations are not important features. To test how many features we should select, we also use the inner cross-validation methods in Random Forest. The graph shows that 10 features are enough for highest accuracy .However, to get more evidence, we set three different groups and ensemble with classification methods and Cross-Validation results to make final decision. Three settings are (1) top 10 variables, (2) top 20 variables and (3) all features.

Features	Sensors	Axis	Importance
AAD	right arm	x	137.81
Average	waist	z	124.24
Average	left thigh	z	115.24
AAD	right ankle	y	112.51
Range	waist	z	110.28
Average	left thigh	y	109.9
Distances	waist	All	106.99
AAD	waist	y	104.67
AAD	waist	x	99.24
AAD	right arm	x	97.83
AAD	waist	z	93.67
SD	right arm,	x	92.16
SD	waist	y	91.22
AAD	right arm	y	88.45
AAD	right arm,	z	87.85
SD	right ankle	x	87.49
Range	right arm	z	84.28
AAD	left thigh	z	82.42
Distances	right arm	All	82.33
SD	waist	z	82.21

Table 1 the importance value of each features. AAD is average absolute differences

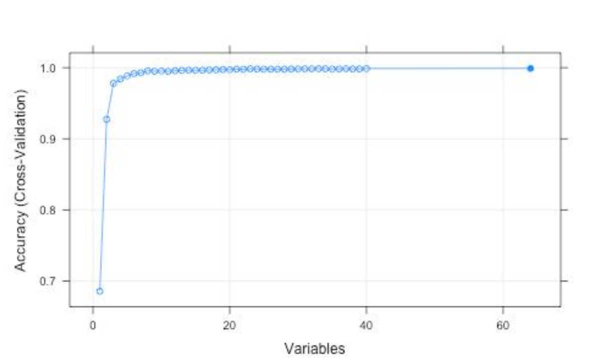


Figure The Cross-Validation Results for feature numbers

We choose several classification methods that have been proven by many other papers. Because the response is a categorical variable, we plan to use general classification method: KNN(K=1to 15), Decision tree, SVM with no kernel (avoid high computational cost) and Random Forest(complexity range from 1 to 500) . After classification, we will use 10-fold Cross Validation to evaluate the model based on Accuracy and Kappa Statistics.

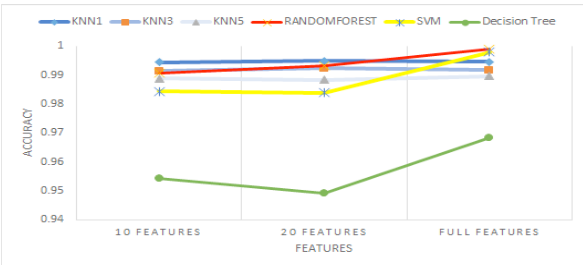


Figure 2 Accuracy for each classification method

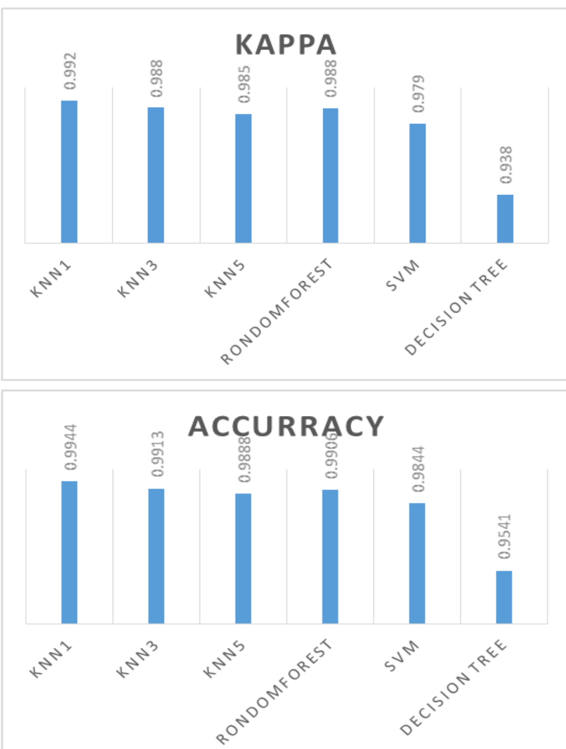


Figure3 Accuracy and Kappa value for each classifier with 10-fold CV

Based on the accuracy of 10 Cross-Validation with different classification methods and different feature groups, we finally choose the 10 features group as the accuracy don't improve significant from 10 features to all features. 10 features are enough to reach a high accuracy with low computational cost.

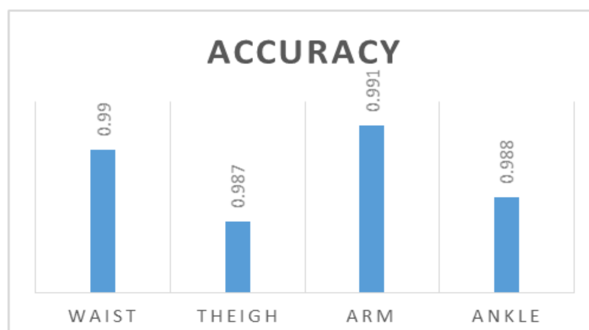
The analysis result of using different classification method is shown in figure 2. Based on the accuracy and kappa results, KNN1,3 and Random Forest have better performances in this datasets. However, KNN is sensitive to the data distribution and often overestimated. We plotted the MDS plot and found that the reason that KNN performs good is that there is some "sandwich" structure in data. However, a more sophisticated choice is to use random forest which the Random Forest algorithm itself optimization by controlling OOB and also have a good performances in accuracy and kappa value in 10-fold Cross Validation.

The confusion matrix for each activities using Random Forest with Top 10 features is listed as below

		Reference				
	Activity	sit	Sit down	stand	Stand up	w
Prediction	sit	1685	0	0	0	0
	Sit down	0	368	0	23	0
	stand	0	0	1577	0	2
	Stand up	1	25	0	388	0
	walk	0	0	0	1	14

Table 2 confusion matrix for each activities using Random Forest with 10 features

Based on the confusion matrix, it is obviously to find that the stand-up and sit-down are the two activities hard to classify. This is because they have very similar pattern.



Figue N Accuracy for each sensor classification using Random Forest with 16 features

One more interesting questions we want to explore is that which single sensors have best performance in classification. We use random forests with all features (each sensor has 16 features) and 10-folf Cross Validation. The results show that the sensor on arm have the highest accuracy 0.994. Other sensors also have high accuracy. This results suggest that one arm sensor is enough for further classification task.

8. Conclusion

The definition for a good classifier is high accuracy, stable and computational efficient. Under these criteria, Random Forest performs as best classifier with accuracy 0.99. 10 features can help reduce computational cost and reduce over-fitting and noisy information. Among all these features, Average Absolute

Differences, distances, average, and standard deviation are important features. The model overall have high performances and shows a good potential to be applied to real life practice.

However, there are some limitation in this study. We have only four users' data and it is hard to evaluate whether this model can be generalized to more users. Stand-up and Sit-down are hard to differentiate because they have similar motion pattern. We may need to consider like gravity to differentiate the two activities

In the future, we hope the model can also recognize user by our data. It is hard to generalize by only using this dataset because it has only four users. Besides, we also want to include more activity for recognition and try to find a way to reduce error made by similar activities like sit down and stand up. If we can get more detail in data collection process, it will still helpful for better understand the motion mechanism.

9. ACKNOWLEDGMENT

Our dataset are from the GitHub.
Below is the link of GitHub

https://github.com/dentrado/machine-learning-project/blob/master/dataset-har-PUC-Rio-ugulino.csv

10. REFERENCE

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