Smartphone Data Analysis using Random Forests Model for Human Activity Recognition

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Abstract: Human Activity Recognition is the process of classifying the activity of a person using sensors, particularly gyroscopes and accelerometers, that are affected by human movement. The study aimed to construct a model that utilized the data that can be retrieved from smartphone sensors to successfully recognize human activity as well as predict the user based on their unique walking patterns. The study utilized a Random Decision Forest model and achieved a 93.8% accuracy when classifying between 6 activities and 98% accuracy in identifying the participant when walking.

Keywords:

Human Activity Recognition, Random Forests, Smartphones, Accelerometer, Gyroscope

1 Introduction

1.1 Background of the Study

A considerable number of research on gait recognition is being conducted to supplement as a biometric tool. However, the acquisition of data is through video cameras to see the repeating pattern in specific regions. This study on the other hand relies only on two devices: an accelerometer and a gyroscope; which is found inside a smartphone. The utilization of a smartphone and the increasing number of users will allow a personal data acquisition which results in the identification of individualistic tendencies and the classification between one person to another.

1.2 Objectives of the Study

The study aims to analyze the activity labels performed by the partipants in the dataset through the application of a machine learning model. The study also aims to determine whether or not one can predict the participant performing certain activities. In particular, the study aims to:

- To accurately classify activities based on data given by a smartphone's gyroscope and accelerometer.
- To determine the time it takes for the smartphone to gather enough meaningful data for an accurate classification.
- To determine the attributes that provide the most meaningful data to the model.

1.3 Significance of the Study

Human activity recognition is important for managing human interaction. It lends the accessible and extensive capability of computers to aid in a variety of situations, from fitness to surveillance. For instance, classification of smartphone user activities has been focused on different activities (Kozina, Gjoreski, Gams, & Luštrek, 2013). worked on fall detection using an accelerometer. Fall detection can be life-saving for certain groups like the elderly. Currently, there are devices that detect when the user has found themselves in danger (falling down the stairs, kitchen accidents, etc.), and they only need a button press to alert emergency responders, thus offering convenience and quick resolutions. HAR has gained importance in the fields of health, security and surveillance, entertainment, and intelligent environments as well. The human ability to recognize another person's activity is an important subject in the field of computer vision and machine learning. A development in this field can help real life, human centric problems such as healthcare and eldercare, improve performance in sports, and pattern discovery.

1.4 Scope and Limitations

The experiment is held in a closed environment with 30 volunteers within an age bracket of 19-48 years old. A total of 6 movements were performed: walking, walking upstairs, walking downstairs, sitting, standing, and laying. The data was gathered through the built in accelerometer and a gyroscope which was inside a smartphone (Samsung Galaxy SII) while being strapped on their waist.

1.5 Definition of Terms

Accelerometer. Devices that measure acceleration in meters per second squared or in G-forces.

Angular acceleration. The time rate of change of angular velocity, usually in radians per second squared.

Butterworth low-pass filter. First described by Stephen Butterworth in 1930, it is sometimes called as a maximally flat magnitude filter due to the fact that it is a type of signal processing filter intended to have a frequency response as flat as possible in the passband (a band of frequencies that pass through a filter or some filters).

Fixed-width sliding windows. They contain fixed-width spans of data, and also implicitly delete the data when it moves past the window scope.

Gyroscope. Devices used to measure and/or maintain orientation and angular velocity, in degrees per second or revolutions per second.

Linear acceleration. Also known as tangential acceleration, are changes in the magnitude of velocity moving along a straight line, and is measured in meters per second squared.

Noise filters. Devices or processes that remove unwanted noise from data signals.

2 Related Work

2.1 PMAP Multi-Sensor Ensemble Approach

A multi-sensor ensemble approach to human physical activity recognition (Feng, Mo, & Li, 2015) used data gathered from PAMAP (Physical Activity Monitoring for Aging People) which is a standard, publicly available database. Their studies depict that their multi-sensor ensemble method based on Random Forest algorithm performs better than other known classification algorithms and non-ensemble classifiers in terms of accuracy and stability with higher calculation speed.

2.2 Human Activity Recognition in Sports

HAR is not limited to daily activities but in sports as well. A project was conducted (Michahelles & Schiele, 2005) with professional skiers and their trainers wherein wearable sensors were utilized to improve observations and impressions. The wearable sensors were accelerometers to measure motion, force-sensing resistors to measure force applied to the skiers feet, and a gyroscope to measure rotational motion. A study (Mandha, LavanyaDevi, & Row, 2017) used a weight lifting exercise dataset which contains data from dumbbell lifts done correctly and incorrectly. Sensors were strapped to the participants' arm, forearm, and waist, a sensor was placed on the dumbbell as well. They used different classification methods and their Random Tree model predicted over the test dataset with a 99.97% accuracy compared to KNN (K-Nearest Neighbor) and CART (Classification and Regression Tree) model.

2.3 Medical Applications of Human Activity Recognition

In the medical field, HAR can be utilized in practices such as rehabilitation. To monitor progress of patients in a unique way, (Deutsch et al., 2011) made use of the Nintendo Wii console and the game Wii Fit. The game makes use of a special balance board that measures the user's weight, strength, center of balance and more. Their study shows that the game provides a greater amount of feedback (knowledge of results and knowledge of performance).

3 Methodology

3.1 Human Activity Recognition Dataset

The dataset consists of signals from a smartphone carried by 30 individuals performing 6 different activities. Activities performed are listed below in Table 1 with their corresponding numerical label after undergoing LabelEncoder, we use this to encode target labels with value between 0 and nclasses-1. In our case it was used to transform non-numerical labels (activities were labelled as WALKING, LYING, WALKING UP, WALKING DOWN, etc.) to numerical labels to simplify the work for the Random Forest classification model. (Reyes-Ortiz, Anguita, Ghio, Oneto, & Parra, 2012). The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore a filter with 0.3 Hz cutoff frequency was used. From each window, a vector of features was obtained by calculating variables from the time and frequency domain. For each record in the dataset it is provided: triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration, triaxial angular velocity from the gyroscope, a 561-feature vector with time and frequency domain variables, the activity label, and an identifier of the subject who carried out the experiment. Label Encoder was implemented in the model and thus the non-numerical labels were transformed into numerical labels (refer to Table 1).

3.2 Random Forest Model Application

It was determined that since the characteristic of the data set was a continuous time-series, all features were used for constructing the machine learning model. Stratified splitting was performed to generate training and test sets (80% and 20% of the data set, respectively), The classifier used in this study is the Random Decision Model Classifier (RandomForestClassifier), an ensemble of decision trees that was

Table 1: The numerical equivalents of the non-numerical labels.

Non-Numerical Label (prior to using Label Encoder)	Transformed Numerical Label (using Label Encoder)
Laying	0
Sitting	1
Standing	2
Walking	3
Walking Downstairs	4
Walking Upstairs	5

utilized from the SciKit-Learn library. 100 trees with the maximum depth set to expand until all leaves contain less than the minimum number of samples required to split an internal node (set at 2). The classifier model was then fitted on the training set. After training, predictions were generated on the test set. A confusion matrix was then generated to calculate the metrics accuracy. precision, recall, and f1-score to assess the model's performance.

4 Results and Discussions

4.1 Activity and Participant Visualization using t-SNE

Since the data was geared towards classifying the activities of each participant, t-distributed Stochastic Neighboring Embedding (t-SNE) was used to visualize the dataset. Based on Figure 1, six clusters were identified. The locomotive activities (walking, walking upstairs, walking downstairs) were found to be the activities that appeared to be the more separable clusters, as compared to non-locomotor activities such as laying, standing, and sitting. We deduced that this was because locomotive activities provided more meaningful data to interpret since it provided data for the accelerometer and the gyroscope. In Figure 2, t-SNE was used again this time to plot each activity of each subject. It is clear that the participants had a unique and thus a separable walking style. Therefore the smartphone should be able to detect the activity of the subject holding the phone, as well as who the subject is, assuming they are in motion.

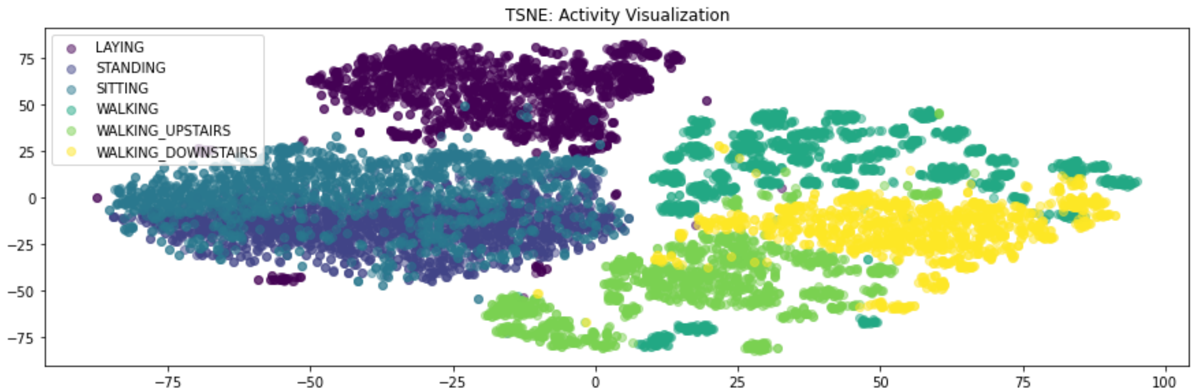

Figure 1: The t-SNE plot based on the activities from the data collected by the gyroscope and the accelerometer.

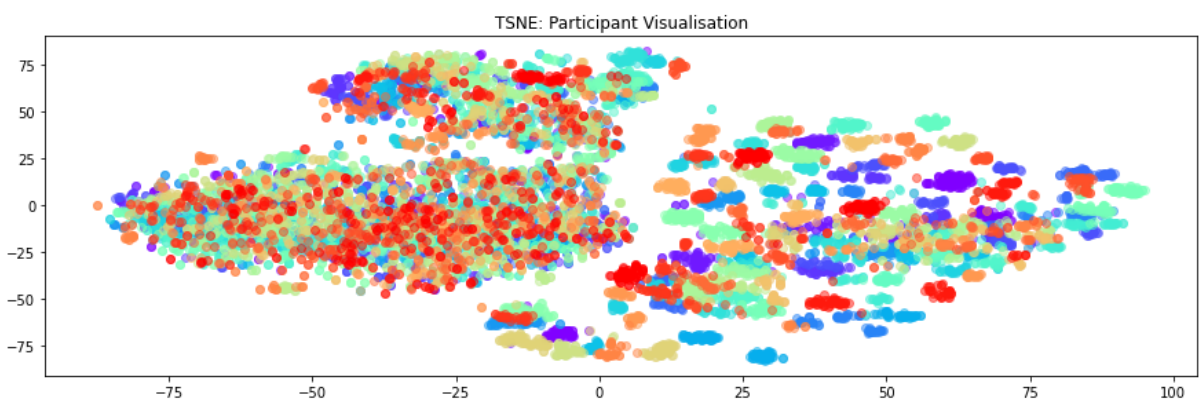

Figure 2: The t-SNE plot based on the different activities of each participant

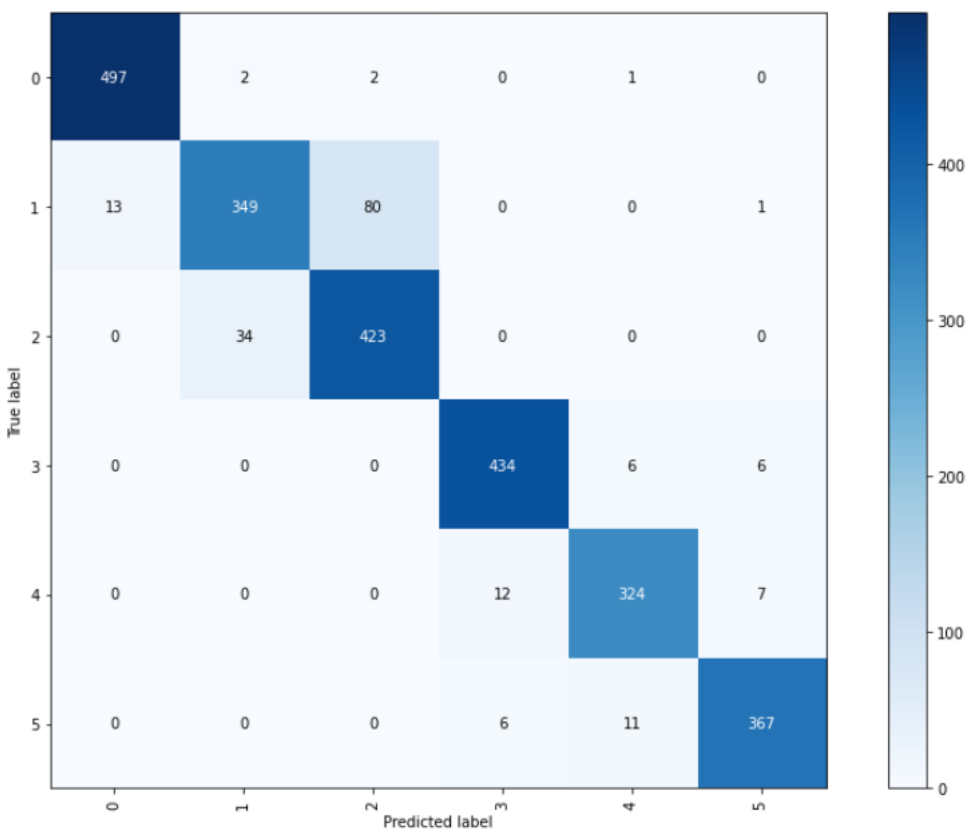

Figure 3: Confusion matrix of activity classification using Random Decision Forest model.

4.2 Quantitative Analysis of the Random Forests Model's Performance

After the dataset was subjected to our Random Forest Model, the confusion matrix of our model is presented in Figure 3. Results from the test set returned an accuracy of 93.8%. For the attributes Laying, the precision, recall, and f-1 score were 98%, 99%, and 98%, respectively. The attribute Sitting had a score of 90%, 82%, and 86%. The Standing attribute scored an 86%, 93%, and 89%. The Walking attribute scored an 97%, 97%, and a 97%. The attribute for Walking Downstairs scored 96%, 97%, and 96%. Walking Upstairs scored 96%, 95%, and 96% respectively.

Table 2: Classification Report generated to measure the model's performance on the test set.

Class	Precision	Recall	F-1 Score
Laying	0.98	0.99	0.98
Sitting	0.90	0.82	0.86
Standing	0.86	0.93	0.89
Walking	0.97	0.97	0.97
Walking Downstairs	0.96	0.97	0.96
Walking Upstairs	0.96	0.95	0.96

From Figure 2, we were challenged to determine whether or not it was possible to classify the participant based on the data alone. To do this, the activities were split into different groups and the Random Forest model was applied, this time to predict who the participant was based on each activity. It was found based on Table 3, that standing, laying, and sitting, all non-moving activities, had the lowest percentage of accuracy in the test set, with standing having the lowest accuracy (49.66%). Meanwhile, moving activities such as walking, walking upstairs, and walking downstairs had high accuracy percentages with walking having the highest (98.14%). Based on Figure 4, we can gather that the walking duration of the participants were more or less the same, with participant # 1 being the sole outlier. This reinforces the claim that we can successfully identify an individual based on their walking pattern since their walking duration was the same.

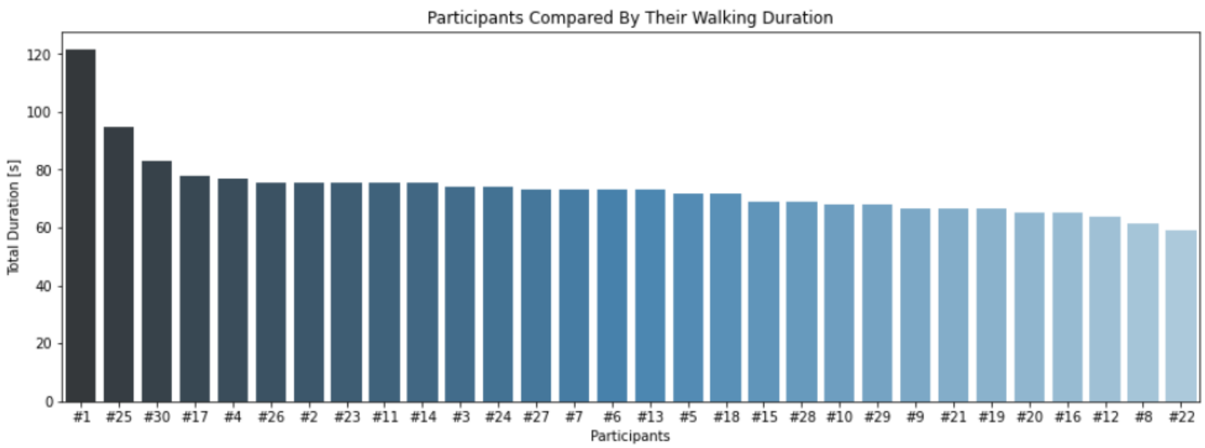

Figure 4: Barplot of the walking duration of each participant.

Table 3: The accuracy of predicting a participant for each activity.

Activity	Accuracy of the test set
Laying	68.52 %
Sitting	55.56 %
Standing	49.66 %
Walking	98.14 %
Walking Upstairs	95.85 %
Walking Downstairs	94.03 %

4.3 Smartphone Data Gathering Duration

To determine the amount of data the smartphone needs to gather to reach the respective accuracy per activity, we refer to the details of the dataset in 3.3, where it stated that there was a fixed-width sliding window of 2.56 sec and 50% overlap for each datapoint. We can determine that a single datapoint is gathered at around every 1.28 sec. It was found based on Table 4, that it takes around 60-74 seconds to gather enough data to produce an accurate classification for walking-related activities.

4.4 Feature Importance Sum

The walking data was then fitted into the model and the feature ranking analysis was performed by grouping the 17 features in the dataset according to the measuring device (accelerometer, gyroscope). It was revealed that the accelerometer had a higher feature importance score than the gyroscope. Although

Table 4: The duration of the smartphone gathering enough data to classify an activity.

Activity	Accuracy	Duration (in seconds)
Laying	68.52 %	82.94
Sitting	55.56 %	81.32
Standing	49.66 %	75.82
Walking	98.14 %	73.47
Walking Upstairs	95.85 %	65.88
Walking Downstairs	94.03 %	59.99

the gyroscope still provides meaningful data to the model since the feature ranking difference as seen in Figure 5 only separates them by a small margin. It should also be noted that this is the feature importance analysis of walking styles and thus the outcome of feature analysis rankings may differ among other labels.

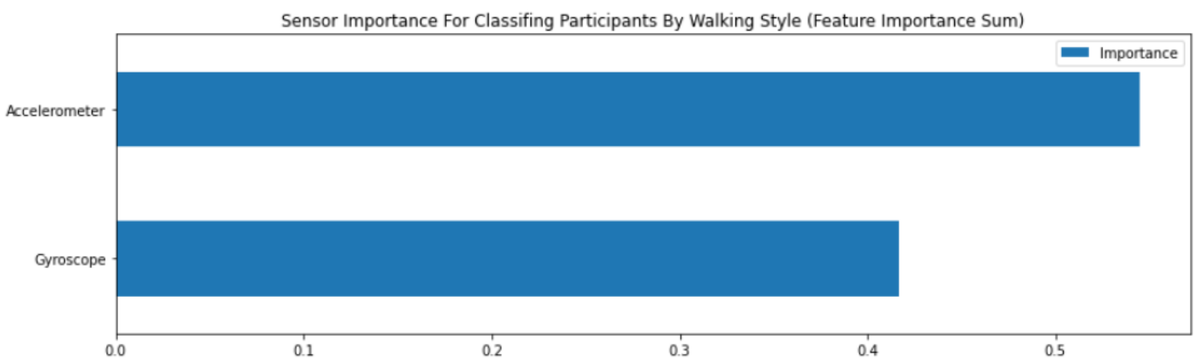

Figure 5: Barplot of the summed feature importance of the two measuring devices.

5 Conclusion and Recommendations

5.1 Conclusion

In this article, we were able to successfully construct a Random Forest Model that classifies the activity labels of the dataset with 93.8% accuracy using measurements from a smartphone's accelerometer and gyroscope. We were also able to correctly classify participants with 98.14% accuracy when basing on the attributes of their walking style. We were also able to determine that it takes around 59-82 seconds to gather enough data to accurately classify the activity being performed by a participant. Despite the accelerometer having a larger feature importance in terms of contributing data for the model, the gyroscope still provided meaningful data that helped the model classify the activity labels.

5.2 Recommendations

The dataset used in this study contained data generated only from accelerometer and gyroscope signals. The study could be improved by increasing the number of activities such as falling, which could prove beneficial to the development of fall detection apps on the smartphone. New smartphones now also contain more sensors such as light sensors, proximity sensors, heart pulse monitor, etc. that can be used to increase the number of activities for future datasets to classify much more complex activities and situations. Further research would involve investigating unsupervised learning approaches as model building in real time on resource constrained smartphones could be restrictive.

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