Human Activity Identification Using Smartphone Data

Nilesh Patel[1*], Tushar Dubey[2], Shashwat Singh Tomar[3], Manish Kumar Sharma[4]
[1,2,3]*Student, Department of Computer Science and Engineering, Galgotias College of Engineering and Technology, Greater Noida, India*
[4]*Assistant Professor, Department of Computer Science and Engineering, Galgotias College of Engineering and Technology, Greater Noida, India*
*Corresponding author: nileshpatel231302@gmail.com

***Abstract*: Mobile phones are pervasive, specialized gadgets that have an effective and capable handling power enveloped with smaller segments that can do efficient and powerful calculations. One of the components that is built into the mobile phones to make it more robust are the sensors. Mobile phones are encompassed with several sensors, for example, proximity sensors, temperature sensors, accelerometers, gyroscopes and many more. These sensors have opened up ways to different fields in data mining and data analytics. The existence of these sensors has empowered people to control its information to perform different tasks. One such task is movement detection which is termed as activity recognition. In this paper, a novel automated method for classification of human activities, using wearable sensors which are also found interfaced within most of the modern mobile phones, is developed. The features are extracted from the recordings of data from individual as well as combination of sensors. The publicly available dataset is used for experimentation.**

***Keywords*: Accelerometer, Gyroscope, KNN, NB, SVM, C-Tree, J48, RF.**

1. Introduction

Smartphones have become ubiquitous. They have various sensors embedded in them like accelerometer, gyroscope, light sensors, proximity sensors and so on. The values from the accelerometer can be used to detect activity being performed by the user. The accelerometer values for different activities exhibit a specific pattern. We have trained a classifier to recognize these patterns. We have used KNN (K-Nearest Neighbours) Algorithm using three nearest neighbours. We are currently detecting sitting, standing, walking, sleeping and jumping with an accuracy of 94%. We can train the model to recognize more activities. HAR has applications in healthcare, monitoring, and user identification. We are developing the application for healthcare where we are calculating calories burnt based on the activity recognized.

Although there are already various applications in the market, most of them do not make full use of the smartphone embedded inertial sensors. The granularity of such applications is also not sufficient. In some applications, only the activities of walking and motionless are recorded. Some applications that only use GPS signals fail to function in indoor environments.

Since we believe that various types of human-carried sensors might discourage older adults from participating in an activity recognition-based system, we focus on one sensor-based ubiquitous piece of technology, namely smartphones, which are far more than just communication devices. They are packed with high-end hardware and features for every type of user. Additionally, a large number of sensors can be found inside them, including motion sensors. Therefore, this paper studies human activity recognition and how it can be achieved using the sensors available on a smartphone.

A full study as well as developing human activity recognition applications under the supervised learning scheme is demanding. Collecting and recording smartphone sensor readings for different human activities in real scenarios is the preliminary of this work. With regard to this, the effectiveness of various features extracted from raw sensor data will be investigated.

2. Literature Review

Human activity recognition has been studied for years and researchers have proposed different solutions to attack the problem. Existing approaches typically use vision sensor, inertial sensor and the mixture of both. Machine learning and threshold-base algorithms are often applied. Machine learning usually produces more accurate and reliable results, while threshold based algorithms are faster and simpler. One or multiple cameras have been used to capture and identify body posture. Multiple accelerometers and gyroscopes attached to different body positions are the most common solutions. Approaches that combine both vision and inertial sensors have also been purposed. Another essential part of all these algorithms is data processing. The quality of the input features has a great impact on the performance. Some previous works are focused on generating the most useful features from the time series dataset. The common approach is to analyze the signal in both time and frequency domain.

A. HAR using Accelerometer and Gyroscope Sensors

Mobile phones are robust devices which are implanted with various sensors and in the meantime are affordable. The accessibility of these sensors has demonstrated open entryways for data mining and data analytics. The presence of sensors has made it possible to understand the data collected from it, to recognize various mundane tasks performed by humans which is labeled as activity recognition.

B. Data Mining and Machine Learning

Data mining and machine learning techniques are utilized to discover patterns in data and make future predictions. To better understand how to adopt a machine learning approach in a specific problem, we need to define a training set {x1, ..., xN} that contains N instances to train and tune the parameters of a model. The categories (or labels) of each instance in the training set are known in advance. In most cases, the categories are labelled manually during the data collection stage. The category of each instance in the training set can be expressed as the target vector t. The output of running a machine learning algorithm can be expressed as computing a function f(x) that takes a new instance as input and outputs a vector y, where y is in the same form as the target vectors. The form of the function f(x) can be determined in the training (or learning) phase based on the training set. Once the model is generated, we can utilize it to make predictions on the test set.

C. Classification Algorithms

1) Naive Bayes

One of the supervised classifiers is the Naive Bayes classifier which is based on the Bayesian theorem. The advantages of the Naive Bayes classifier are that it is fast to train and make classifications, it is not sensitive to irrelevant features, and it can handle real and discrete data. However, the Naive Bayes classifier assumes features are independent, which is one of its drawbacks.

2) k-Nearest Neighbours (kNN)

The k-Nearest Neighbours algorithm is a non-parametric technique for classification and regression. It is also among one of the simplest machine learning algorithms. The kNNs is a kind of instance-based classifier, which means it does not abstract any information from the training data during the training stage. For an unknown instance, it is labelled as the same class as that of the majority of its k nearest neighbours. The nearest neighbours are measured by a distance function. The most commonly used distance functions are the Euclidean distance, the Manhattan distance, and the Minkowski distance.

3) Artificial Neural Networks (ANNs)

ANNs are models that are composed of many nonlinear computational nodes in parallel and perform like biological neural networks. The best known model of ANNs is the feedforward neural network, which is also known as the multilayer perceptron. The nodes or neurons in the neural network are connected via weights and updated during the learning process.

4) Human Activity Recognition based on Supervised Learning

Human activity recognition (HAR) has been widely studied in the literature. Research in machine learning developed a number of inference methods. Probabilistic methods are widely used for human activity systems, such as Hidden Markov Models (HMMs), Conditional Random Fields (CRFs), and Bayesian networks. Discriminative approaches, such as Support Vector Machines (SVMs), it decision trees, and neural networks, are also successfully applied in the area of HAR.

3. Problem Formulation

Human Activity Recognition (HAR) is the problem of identifying a physical activity carried out by an individual dependent on a trace of movement within a certain environment. Activities such as walking, laying, sitting, standing, and climbing stairs are classified as regular physical movements and form our class of activity which is to be recognized. To record movement or change in movement, sensors such as triaxial accelerometer and gyroscopes, capture data while the activity is being performed.

The challenge arises as there is no explicit approach to deduce human actions from sensor information in a general manner. The large volume of data produced from the sensors and use of these features to develop heuristics introduces the technical challenge. Storage, communication, computation, energy efficiency, and system flexibility are some of the aspects which need to be analyzed in detail to build a robust activity recognition system. Conventional pattern recognition methods have made tremendous progress in discovering significant information from scores of low-level readings.

4. Proposed Work

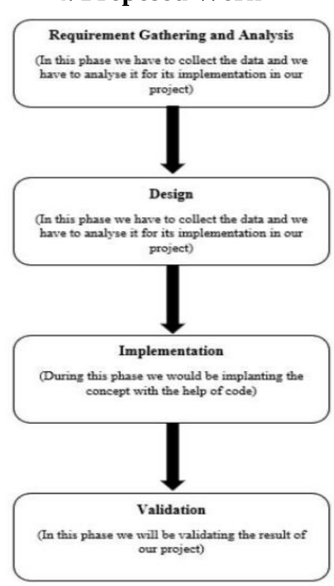

Fig. 1. Work flow

The previous work done in this area does not support a proper mathematical model to properly verify the methodology.

Although they provide all the details of the necessary factors, which can help in detecting human activity. Here we suggest a mathematical databased approach to solve this problem.

We detect here Human Activity with the help of user data by comparing with system defined flags. It is a mathematical factor. It is the sum of all mathematical value of all the factors and parameters which is assigned by the system by comparing the user data and system flags. The figure 1 describes the work flow of the project.

5. System Design

The below given figure 2 describes the architecture of our system. It is a recommendation system. The architecture is a combination of database, CSS and the data from the user.

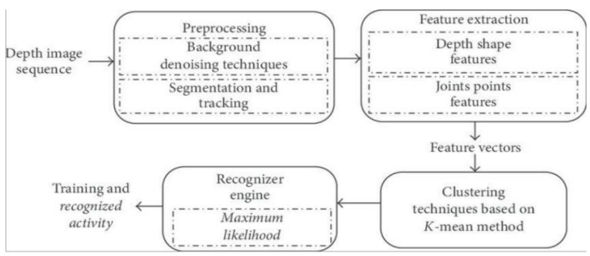

Fig. 2. System Architecture

6. Implementation

This section contains a step-by-step description of the proposed solution.

A. *Data Collection*

The data collection can be separated into two groups: training data and testing data. Moreover, the testing data collection is also divided in half: one part for the data we gathered our using an application specifically created for this purpose (the "internal dataset") and the other one for an external dataset. This partitioning of the testing data was necessary because the two datasets used data from different sensors (as shown in Table 1).

Table 1
Sensons registered in each dataset

Dataset	Sensors
Internal dataset	Accelerometer, Gyroscope, Gravity
External dataset	Accelerometer, Gravity, Linear Acceleration, Magnetometer

B. *Feature Extraction*

After collecting the data, it had to go through a transformation process in order to extract features that provide all the necessary information to the algorithm used for ML. For every set of readings, we computed five types of features, each generating a number of inputs for the learning algorithm. A brief description of the features can be found below.

1) Average

There were nine inputs for this feature, which represented the average value of readings per axis, computed as follows (where N is the number of readings for each sensor per 10 s, for this and all the following equations):

$$\frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

2) Average Absolute Difference

This feature (also with nine inputs) is the average absolute difference between the value of each of the readings and the mean value, for each axis.

3) Standard Deviation

The standard deviation was employed to quantify the variation of readings from the mean value, for each axis (resulting in nine inputs):

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i - \mu} \tag{2}$$

4) Average Resultant Acceleration

This feature, having the inputs, was computed as the average of the square roots of the sum of the squared value of each reading:

$$\frac{1}{N}\sum_{i=1}^{N}\sqrt{x_i^2 + y_i^2 + z_i^2} \tag{3}$$

5) Histogram

Finally, the histogram implies finding the marginal values for each axis (minimum -maximum), dividing that range into ten equal-sized intervals and determining what percentage of readings fall within each of the intervals (resulting in 90 inputs):

$$\frac{1}{N}\sum_{i=1}^{N}\left[\left(x_i \ in \ b_j\right) \rightarrow 1, j = 1 \dots 10\right] \tag{4}$$

7. Conclusion and Future Work

A. *Conclusion*

In this paper, we have presented the general architecture utilized to build human activity recognition systems and emphasized the design issues such as selection of sensors, obtrusiveness, flexibility, etc. which are independently evaluated based on the kind of system which is being developed. The paper further focuses on the importance of selecting important features from the data and provides a quantitative analysis of the metrics of execution time and accuracy. Tree-based and L1-based feature selection methods were utilized to select important features and were evaluated over four classification models. The results indicate that without a compromise in accuracy, the execution time and computational cost are greatly reduced with the use of feature selection methods. Better feature selection methods and improvement in tuning the parameters can assist further to improve accuracy and decrease computational cost. The research paper also provides a solution to reduce and eliminate the dependency of the requirement of domain knowledge to create hand-crafted features from the raw signals obtained from the sensor data.

B. Future Work

For HAR systems to reach their full potential, more research is required. Comparison between HAR systems is hindered and becomes unquantifiable as each researcher uses a different dataset for activity recognition. A common public dataset would help researchers benchmark their systems and evolve the system altogether. Activities recognized in existing systems have been simple and atomic, which could be a part of more complex composite behaviors. Recognition of composite activities can enrich context awareness. There is also a great research opportunity to recognize overlapping and concurrent activities. Expanding on the work carried out on deep learning algorithms, one dimensional and two-dimensional convolutional neural networks, hybrids of convolutional networks and LSTMs should be further studied to determine their suitability to solve the problem of human activity recognition from raw signal data.

References

[1] R. Kavitha Kavitha, Warren Triston D'souza Human Activity Recognition Using Accelerometer and Gyroscope Sensors, 2017.
[2] George Vavoulas, Charikleia Chatzaki, Thodoris Malliotakis, Matthew Pediaditis, and Manolis Tsiknakis. The MobiAct dataset: Recognition of activities of daily Living using smartphones, 2016.
[3] Junker H., Amft O., Lukowicz P., Tröster G. Gesture spotting with body-worn inertial sensors to detect user activities. Pattern Recogn. 2008.
[4] Shoaib M., Bosch S., Incel O.D., Scholten H., Havinga P.J.M. Complex human activity recognition using smartphone and wrist-worn motion sensors. Sensors. 2016.
[5] Kwapisz J. R., Weiss G.M., Moore S.A. Activity recognition using cell phone accelerometers. SIGKDD Explor. Newsl. 2011.
[6] Su X., Tong H., Ji P. Activity recognition with smartphone sensors. Tsinghua Sci. Technol. 2014.
[7] Stefan Dernbach Barnan Das, Narayanan C. Krishnan, Brian L. Thomas, Diane J. Cook Simple and Complex Activity Recognition Through Smart Phones. 2012
[8] C. Medrano, I. Plaza, R. Igual, A. Sánchez, and M. Castro. The effect of personalization on smartphone-based fall detectors. 2016.
[9] Charlene V. San Buenaventura, Nestor Michael C. Tiglao. Basic Human Activity Recognition based on sensor fusion in smartphones, 2017.
[10] Cuong Pham. MobiRAR: Real-Time Human Activity Recognition Using Mobile Devices, 2015.