International Journal of Information Sciences and Application (IJISA). ISSN 0974-2255, Vol.11, No.1, 2019, (Special Issue)

HUMAN ACTIVITY RECOGNITION USING SMARTPHONE SENSORS

Neetish Singh, Rajat Yadav, Harshit Kumar Singh, Shivani Agarwal

Department of Computer Science and Engineering, IMS ENGINEERING COLLEGE, GHAZIABAD**.**

Abstract:

In the world, the human activities recognition, which use sensors to recognize human actions, have been studied for a long time to produce the simpler system with high precision [1]. Smartphones, nowadays have become an essential gadget in human's life. These smartphones have embedded sensors like Gyroscope, GPS, Accelerometer, Compass sensor etc. These sensors can be used to predict the state of the user. To get results we applied machine learning to the dataset provided by various embedded sensors. We used SVM and RNN algorithms to train classifiers; With SVM [2], we got results with an accuracy of 74% whereas with RNN we got results with accuracy of 92%. We have designed an Android system through which one user will be able to know what activity other user is doing through an offline (in short range)/online, real-time activity recognition system for Android.

Introduction:

Human activity recognition is an important yet challenging research area with many applications in healthcare, smart environments, and homeland security. Computer vision-based techniques have widely been used for human activity tracking, but they mostly require infrastructure support, for example, installation of video cameras in the monitoring areas. Alternatively, a more efficient approach is to process the data from inertial measurement unit sensors worn on a user's body or built in a user's smartphone to track his or her motion. We aim to develop a model that is capable of recognizing multiple sets of daily activities under real-world conditions, using data collected by a single triaxial accelerometer built into a cell phone (in our study, an Android smartphone). A triaxial accelerometer is a sensor that returns an estimate of acceleration along the x y and z axes from which velocity and displacement can also be estimated. Activity recognition is formulated as a supervised classification problem, whose training data is obtained via an experiment having human subjects. Our data has been collected in an experiment having four users each performing one of the following six physical activity patterns: Walking, Running, Stairs-Up, Stairs-Down,[i] and Standing. In the last decades, there were several machine learning methods that can use for classifier and recognition of human physical activities including Naïve Bayes, Support Vector Machines (SVMs), Threshold based and Markov chain [3]. In the following sections, we discuss the related work, describe our data collection methodology and our approach to recognize activity from accelerometer data, and results of our experiment.

Literature Review:

S. No.	Topic of Paper	Author	Year of Publication	Publication	Technologies Used	Accuracy
1.	Human Activity Recognition using Android Smartphone	Usharani J.	2017	International Journal of Advanced Networking & Applications (IJANA)	KNN classification	92%
2.	Human Activity Recognition: A Review	Ong Chin Ann	Nov 2014	IEEE International Conference on Control System, Computing and Engineering	RGB cameras, depth sensors and wearable devices	Significant
3.	Human Activities Recognition in Android Smartphone Using Support Vector Machine	Duc Ngoc Tran	2016	International Conference on Intelligent Systems, Modelling and Simulation	Support Vector Machine (SVM)	89.59%
4.	An unconstrained Activity Recognition Method using Smart Phones [4]	Naciye C.	2012	The Scientific and Technological Research Council of Turkey	K-Star	98%
5.	Automatic Annotation for Human Activity Recognition in Free Living Using a Smartphone	Federico Cruciani	2018	MDPI Open Access Journals	Random Forests	84%

System Overview:

We designed an android application [5][6] which dynamically recognizes current state of the user and send this state to the server from where the state can be accessed by any other member who is permitted by admin. The application already consist of classifier model file and dynamic state is state is classified by values provided by embedded accelerometer.

Firebase:

Firebase provides a real time database and backend as a service. The service provides application developers an API that allows application data to be synchronized across clients and stored on Firebase's cloud. The developer can use it to store images, audio, video, or other user-generated Firebase Storage provides secure file uploads and downloads for Firebase apps, regardless of network quality content. Firebase Storage is backed by Google Cloud Storage.

TensorFlow:

TensorFlow is a free and open source software library for dataflow and differentiable programming across a range of tasks. It is symbolic math library and is also used for machine learning applications such as neural networks. It is used for both research and production at GOOGLE. It is a standard expectation in industry to have experience in TensorFlow to work in machine learning.

Building the Proposed Model:

Our LSTM model expects fixed-length sequences as training data. We have used a familiar method for generating these. Each generated sequence contains 200 training examples.

Our model contains 2 fully-connected and 2 LSTM layers with 64 units each.

N_CLASSES=6 N_HIDDEN_UNITS = 64

Classification Task:

Number of examples: 5,424
Number of attributes: 46
Missing attribute values: None
Class distribution: {
    Walking -> 2,082 -> 38.4%,
    Jogging -> 1,626 -> 30.0%,
    Upstairs -> 633 -> 11.7%,
    Downstairs -> 529 -> 9.8%,
    Sitting -> 307 -> 5.7%,
    Standing -> 247 -> 4.6%
}

	user	activity	timestamp	x-axis	y-axis	z-axis
0	33	Jogging	49105962326000	-0.694638	12.680544	0.503953
1	33	Jogging	49106062271000	5.012288	11.264028	0.953424
2	33	Jogging	49106112167000	4.903325	10.882658	-0.081722
3	33	Jogging	49106222305000	-0.612916	18.496431	3.023717
4	33	Jogging	49106332290000	-1.184970	12.108489	7.205164

Figure1: -Attributes required to classify an activity as Jogging

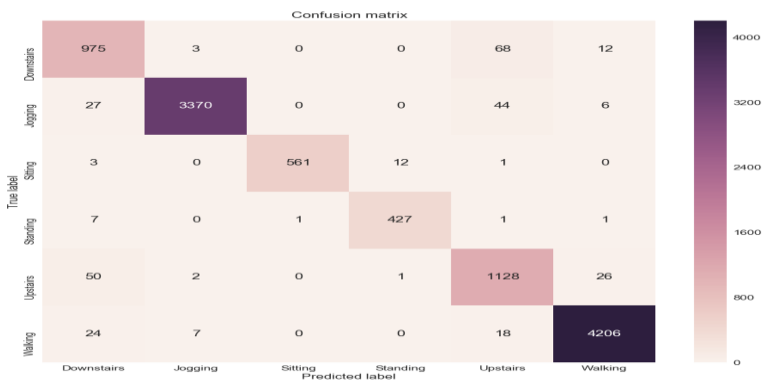


Figure 2: Confusion Matrix for all the Activities

Technologies Used:

Recurrent Neural Network Using Python: -

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence [7]. This allows it to exhibit temporal dynamic behavior for a time sequence. Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition.

Libraries Used:

OPENCV, IMUTILS, KERAS, NUMPY, TENSORFLOW

Data Acquisition:

The dataset is created by 4 users (2 male, 2 female) each recording every activity for 30 seconds. Our dataset consists of 8000 instances and 5 attributes. The data is taken when keeping the phone in the front right pocket of pants. The dataset records triaxial accelerometer values (values of x, y, and z-axes), one feature and label. We are generating magnitude feature which is:

$M=\sqrt{a*a+ b*b+ c*c}$

Where:

M=Magnitude (feature)

a= x-axis value of accelerometer

b= y-axis value of the accelerometer c= z-axis value of accelerometer

Working Methodology:

Training the Classifier:

The classifier is trained using the generated dataset. The algorithm used is RNN and SVM. The classifier is tested on a test dataset of 561 instances and gives 92% accuracy. This classifier is exported using weka Serialization helper and a ". model" file is generated.

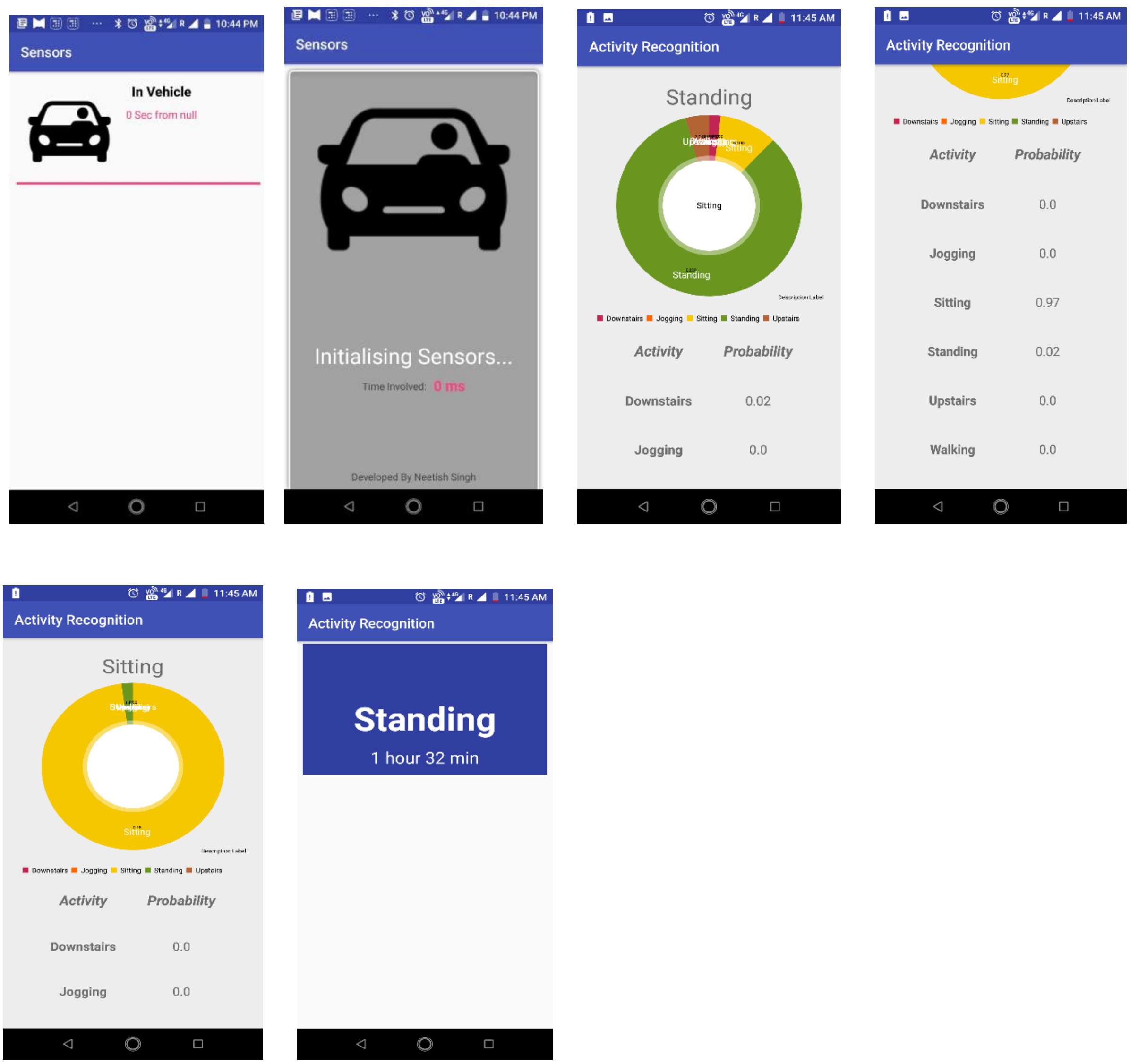
Getting the Sensor Values:

Sensors in android can be accessed by using Sensor Event Listener Interface in android [8]. The current values are taken and magnitude is generated and this data is written to a file "accelerometer.csv" stored in the phone's internal storage.

International Journal of Information Sciences and Application (IJISA). ISSN 0974-2255, Vol.11, No.1, 2019, (Special Issue)

Classifying the Activity:

The model file is stored in the assets folder in the android project directory. It is imported using Asset Manager class in Android. The model file is imported and the data from "accelerometer.csv" is read and converted into an instance. This instance is given to imported classifier and appropriate activity is displayed.



Results:

The current activity is being correctly recognized and displayed. Data available to the other user is being correctly displayed. The accuracy for classification is 92% and step count and calorie count are also fairly accurate. The application fulfills all its objectives almost to the fullest.

Fig: Comparison between Accuracy of SVM and RNN Classification.

Conclusion:

The data were acquired from multiple subjects under real-world conditions for two most common phone positions: smartphone in hand and smartphone in pants pocket. A new set of features was taken into account and different classifiers were used for evaluating recognition performance. Combining the three best classifiers using the average of probabilities method turned out to be the best classifier for activity recognition, outperforming all individual classifiers. We further showed that our recognition method can detect activities independent of smartphone's position. For future work, we plan to extend our activity recognition task in several ways. First, we intend to recognize additional activities, such as sleeping or walking. Second, we would like to collect data from more users of various ages. Third, we plan to extract more features that could better discriminate different activities.

References:

[1] T. Starner, B. Rhodes, J. Weaver, and A. Pentland, Every day-use Wearable Computers. 1999.

[2] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "Human Activity Recognition on Smartphones Using a Multiclass Hardware-Friendly Support Vector Machine," in Ambient Assisted Living and Home Care, J. Bravo, R. Hervás, and M. Rodríguez, Eds. Springer Berlin Heidelberg, 2012, pp. 216–223.

[3] A. Mannini and A. M. Sabatini, "Machine Learning Methods for Classifying Human Physical Activity from On-Body Accelerometers," Sensors, vol. 10, no. 2, pp. 1154–1175, Feb. 2010.

[4] Naciye C, elenli, Kamile Nur Sevis, Muhammed F. Esgin, Kemal Altunda˘g, Umut Uluda˘g, "An unconstrained activity recognition method using smartphones", 2014 International Conference of the Biometrics Special Interest Group (BIOSIG), IEEE .

[5] http://developer.android.com/guide/index.html.

[6] https://developers.google.com/places/android- api/start
[7] Williams, Ronald J.; Hinton, Geoffrey E.; Rumelhart, David E. (October 1986). "Learning representations by back-propagating errors". Nature. 323 (6088): 533–536.
[8] Ozlem Durmaz Incel," Analysis of movements, orientation and rotation-based sensing.",5th October 2015 conference and published in mdpi.com.