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Classifier Algorithms-Based Activity Recognition In Cell Phone Accelerometers

Saritha Banoth
Asst. Professor
Department of CSE
Siddhartha Institute of Technology and Sciences
Narapally, Hyderabad, Telangana, India

Vaddepally Santhosh
Asst. Prof.
Department of CSE
Siddhartha Institute of Technology and Sciences
Narapally, Hyderabad, Telangana, India

Abstract **- Mobile devices have been increasingly sophisticated in recent years, and the latest generation of smart phones includes a powerful and numerous sensor. Some of the sensors found in mobile devices include GPS sensors, vision sensors, audio sensors, light sensors, temperature sensors, direction sensors, and acceleration sensors. In this study, the Naive Bayes algorithm is utilized to recognize user behaviors, and a system is shown that uses mobile phone-based acceleration sensors (i.e., accelerometers) to do activity recognition, a task that entails describing a user's physical activity. It will be necessary to collect marked accelerometer data from twenty-five users while they were doing daily activities such as walking, jogging, ascending stairs, sitting, and standing in order to deploy the suggested system. The acquired data is then translated into examples that detail user activities over 10-second intervals. Because the suggested activity recognition methodology allows us to passively draw useful knowledge about the behaviors of thousands of users, this work is critical. The experimental results (described in section 4) suggest that the proposed system performs better.**

Key words:Classification algorithms, Accelerometer based mobile phone and Activity recognition, Accelerometer

1. INTRODUCTION

Mobile devices with advanced functions have been increasingly popular in recent years. Audio sensors, air humidity sensors, acceleration sensors, image sensors, light sensors, proximity sensors, temperature sensors, direction sensors, and GPS sensors have lately been integrated into mobile devices such as cellular phones, smart phones, and tablet computers. The size of these smart mobile gadgets is modest. These smart gadgets can open up exciting new domains for data mining research and applications due to their enormous computational power and ability to transmit and receive data. The main goal of the Wireless Sensor Data Mining project [1] is to identify current research difficulties related to mining sensor data from smart mobile devices in order to develop useful applications. The aim of the accelerometer (i.e., acceleration sensor) is investigated in this study in order to recognize the activity conducted by the users. Activity recognition is the name given to this task. Android-based mobile phone devices are used as the platform in this study because the Android operating system is free, open-source, and easy to program, and it is expected to become the most powerful entry in the mobile phone industry.

Initially, accelerometer sensors were utilized in some devices to support advanced game play and to enable the automated screen rotation application, but they have many other uses. If accelerometer sensors can be used to identify a user's activities, more beneficial applications can be developed. The activity data can be used to automatically customize the behavior of a mobile phone. To deal with the activity identification challenge using supervised learning, twenty-five users' accelerometer data were collected while performing various activities such assitting, standing, ascending stairs, descending stairs, walking and jogging.

The proposed work differs from most earlier studies in that it employs a commercial market device that is primarily a research device; a single device that is held in the user's pants pocket rather than multiple smart devices distributed throughout the body. The user is not required to perform any extra activities in this case. The proposed models were then constructed and evaluated with more than twenty-five users than in past studies, and this number is expected to grow significantly as the data gathering expands.

The proposed effort establishes numerous contributions, one of which is data collecting, i.e., data is collected and continues to be collected in order to construct a public database in the future. Because we are unable to observe such publicly available data sets on our own, this collected data can serve as a resource for researchers. The transformation of raw time series accelerometer data into examples that can be used by conventional classification algorithms is performed. It is possible to do activity identification with commonly available equipment while still obtaining more accurate test findings. Finally, it is concluded that the suggested effort will draw attention to the possibilities for wireless sensor data mining and will result in additional work in this field.

The rest of this paper is organized as follows: Sections 2 and 3 address related work, while section 4 illustrates the process for dealing with the activity identification task, which includes data collection, preprocessing, and transformation phases. The experimental results are shown in Section 4. Section 5 contains the conclusion part.

2. RELATED WORK

Bao &Intille [3] used five biaxial accelerometers on the user's right hip, dominant wrist, non-dominant upper arm, dominant ankle, and non-dominant thigh to collect data from 20 people. To distinguish twenty daily activities, instance-based learning, C4.5, and Nave Bayes classifiers are used to generate model’s decision tables. Finally, their findings show that a biaxial accelerometer worn on the non-dominant thigh is the most effective at distinguishing between activities. This finding supports the conclusion that the test subjects (i.e., participants) should carry their smart phones in the most appropriate place, such as their jeans pocket.

Krishnan et al. [4] collected data from three users using two accelerometers to identify five activities: walking, sitting, standing, running, and lying down. They concluded that data from the accelerometer implanted in the thigh was insufficient for distinguishing behaviors such as sitting, lying down, walking, and running. As a result, many accelerometers are required for this study.

Tapia et al. [5] used five accelerometers put on various parts of the body to collect data from twenty-one individuals and used this information to create a real-time system that identified thirty gymnasium activities. In order to marginally improve performance, a heart monitor is added to the accelerometer data.

Mannini and Sabitini [6] used five tri-axial accelerometers on thirteen users to identify twenty behaviours at the hip, wrist, arm, ankle, and thigh. Three "positions," such as lying, sitting, and standing, and five "motions," such as walking, cycling, running,stair climbing was identified using a variety of learning strategies.

Parkka et al. [7] created a system that used twenty non-identical sensors, one on the chest and one on the wrist, to identify activities such asstanding, walking, jogging, lying, swinging, playing ball, football, croquetand using the toilet in specific areas.

Using a proposed sensor module that consisted of an angular velocity sensor and a biaxial accelerometer placed in the pants pocket with a digital compass placed at the user's waist, Lee and Mase [8] developed a system to identify the locations and activities of users such as sitting, standing, walking upstairs, and walking downstairs, walking on level ground.

Subramayana et al. [9] dealt with similar activities by developing a model that used data from tri-axial accelerometers, two microphones, phototransistors, temperature and barometric pressure sensors, and GPS to distinguish between a stationary state and other states like walking, jogging, driving a vehicle, and climbing up and down stairs.

3. PROPOSED ACTIVITY RECOGNITION SCHEME

The activity recognition task, as well as the process for performing it, is detailed in this segment. The suggested procedure for acquiring raw accelerometer data is explained in subsection 3.1, and the feature Extraction operation and the transformation of raw accelerometer data into examples are explained in subsection 3.2. In section 3.3, classification is briefly discussed.

3.1 Data Collection

The dataset was obtained from the WISDM database, and the data collection phase was based on a supervised learning task that required many users to hold Android-based smart phone devices while performing daily tasks. Twenty-five volunteers are engaged in the study, who use android-based smart phones to complete a set of tasks. These participants were instructed to walk, jog, sit, stand, ascend stairs, and descend stairs for a length of time while wearing the android devices in their front pants pockets. A new application was designed and installed on the smart phone devices to control the data collection task. This application uses a simple GUI (Graphical User Interface) to gather user data such as the user's name, the start and stop times for data collection, and the activity that the user is performing. The accelerometer data is captured every 60ms in each scenario, for a total of 25 samples per second.

3.2 Feature Extractionphase

Standard classification algorithms are employed in this study, which cannot be directly applied to raw time-series accelerometer sensor data. This is accomplished by converting the raw time series accelerometer data into various examples [10]. To do so, the time series data is separated into 10-second parts, and then features are produced based on on the 200 values included inside each 10-second segment. The duration of each time segment is designated as "ED" (Example

Duration), and a 10-sec ED is ideal because it allows for more motion repeats.

3.3 Classification

Users were requested to walk, jog, ascend stairs, drop stairs, sit, and stand for particular time periods while using Android-based mobile phones in their front pants leg pockets exclusively. A total of 400 instances of this front pants leg pocket location were made. The cases were gathered into a dataset with a 20% and 80% margin, with 20% being the untrained dataset used for testing the classifiers and 80% being the dataset used for training the classifiers. The 10-fold cross-validation approach was used to train for this pants pocket position. Testing was subsequently carried out using the untrained datasets to assess the trained classifier's accuracy.

4. RESULT AND DISCUSSION

4.1 Experimental description

The experimental findings of Nave Bayes, Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Random Forest and Hidden Markov Model (HMM), is compared with the proposed activity identification algorithms. Some parameters are measured for each system, such as proper classification, precision, and recall values. Because it is incredibly scalable and requires a handful of linear parameters in the number of variables in a learning problem, the Naive Bayes algorithm is used to recognize the activities in this study. The naive Bayes classifier has several characteristics that make it extremely useful in real-world applications. The proposed Naive Bayes scheme yields 91.4 percent correct classification, as seen in the table above. This result is so high when compared to other typical classification algorithms because the suggested system is run unsupervised. The suggested Naive Bayes strategy achieves precision and recall rates of 89 percent and 95.6 percent, respectively, which are quite high when compared to other existing strategies.

5. CONCLUSION

The operation of smart phone devices that can be used to perform activity detection processes by simply gripping a user's jeans pocket is reported in this study. The suggested classification training approach has excellent accuracy rates, with most activities accurately detected 91.4 percent of the time. Furthermore, because each example takes only 10 seconds to generate, these actions are easily recognized. In the future, the proposed activity recognition system will need to be improved in the following ways: identifying additional activities such as bicycling and driving, collecting training data from more users, developing more sophisticated features to aggregate the raw time series, and measuring the impact of holding mobile phones in various locations such as shirt pockets and belt loops.

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