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Using Sensors to the Smartphone Functionality

G.Sumantha
M.Tech,
Dept of Computer Science and Engineering,
G.Pulla Reddy Engineering College (Autonomous),
Kurnool - 518 007, AP, India.

Dr.S.Zahoor-ul-Huq
Professor,
Dept of Computer Science and Engineering,
G.Pulla Reddy Engineering College (Autonomous),
Kurnool - 518 007, AP, India.

ABSTRACT:

Provided that the motion sensor embedded smartphones Activity inference of a new platform. These sensors, At the beginning of the development of the cell phone feature can be useful, now being Used for a variety of applications. Providing information to cell phone users About their own physical activity as a means to Format to allow users to make more informed and healthy Lifestyle choices. In this work, we have built a smartphone application It is to track the users' physical activities and provide feedback No user input is required during normal operation. Application Estimates of calories, burned through physical break Activities. The most notable physical activity, running, walking, Descending the stairs, cycling, climbing stairs, driving and being inactive. We evaluated a number of classification algorithms Naive Bayes, Decision Tree area, including machine learning, K- nearest neighbor and support vector machine classifier. For Classification of training and certification, we collected a dataset Using sensors that tracks the activity of the cell phone 510. We have developed a Suggests that the implementation of the smartphone app The need for any user intervention. Classification of execution At the presentation of the true positive rate than the average Android app More than 95% false positive rate of less than 1.5% and an ROC area More than 98%.

I.INTRODUCTION:

The last decade witnessed a virtual explosion of mobile communication infrastructure and services. With the technological advancement of cell phones a new platform for computing is quickly gaining popularity. These state of the art mobile phones are becoming more popular than computers as they wireless computers of the new era. The current smart phones are not just communication devices rather it's a personal computer packed into a small gadget.

Smartphones are now equipped with a number of embedded sensing devices such as an accelerometer, gyroscope, digital compass, microphone, GPS and camera. These sensors are now being used in various fields for human gesture and activity recognition based applications which are opening the doors to new areas of research and significantly impacting our daily life. Thus, the recognition of human physical activities from cell phone sensor measurements is formulated as a detection problem.Our proposed approach is to develop a classifier while adhering to best machine learning practices. We collect a large data set for classifier training and verification. We target the recognition of 7 different activities, which include walking, running, climbing stairs, descending stairs, cycling, driving and remaining inactive. Cell phone physical sensor readings were collected while performing all these activities, while the cell phone was kept in different orientations. The data set so collected was pre-processed to extract a number of features from the data that have not been explored in previous studies. The most informative features were chosen for further use by ranking features according to information gain. The data set was partitioned into 10 sets for 10-fold cross validation.

Various classification algorithms were trained using the training set and then evaluated using the test set, iterating over all 10 data sets. The best performing classifier was chosen for implementation in the Android app. Accuracy rates of up to 91% have been reported if phones are allowed to be carefully positioned in predetermined locations ([1], [2], [12], [15]). Sun et al. [16] investigated orientation and position independent classification schemes whereby a separate classifier is implemented for each position. This approach yielded an accuracy of 93% but is not practically feasible as it requires high computational resources. Some recent studies show behavioral analysis based applications using activity recognition techniques. In [17] the fluctuations in the signal strength of GSM signals are used to infer activities like sitting, walking and driving.

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The use of GSM signals is not a very efficient approach as there are sudden spikes and troughs that cause complexity in GSM cell strength and visibility. Real time activity inferences also leads to accuracy and privacy issues. Recently, smartphone GPS sensor data was also exploited to establish mode of transport used to commute over duration of time. Consolvo et al. [18] used a mobile sensing platform called UbiFit for activity recognition which transfers data to a Nokia smartphone which uses blooming flowers to encourage increase in physical activity. Similarly, Denning et al. [19] worked on BALANCE which estimates the calorie expenditure in routine life. Nevertheless both these solutions rely on additional body sensors.

II.RELATED WORK:

Activity recognition has a number of leading application areas. Wearable accelerometer based body sensors have been used to infer human mobility levels. These sensors have favorable have small size and high level of accuracy. Earlier works explored the use of multiple on-body sensors placed at the waist, arms, knees and ankles [1] to accurately determine physical activities ([5]–[8]). Other works investigated activity recognition outside laboratory conditions but lacked accuracy ([9], [10]). The positioning of sensors was crucial for precise inference, e.g. eating, typing and brushing teeth were easier to determine if placed at the wrist and arm with an accuracy of 96.67%. However, if the same activity is performed with sensors on waist or knee, detection accuracy drops to 66% ([6], [10]). Other disadvantages of using multiple accelerometers include discomfort of numerous wires attached to the body as well as the irritability that comes from wearing sensors for a long duration. A few works have been performed whereby only one triaxial accelerometer located at the waist or back is used for movement recognition. However accuracy drops to 35% in comparison to 5 on-body sensors ([7], [8], [11]). Nevertheless using single sensor is more preferable and convenient in real world scenarios. These sensors were capable of recognizing basic activities such as lying, walking and running. Reduction in sensors requires analysis of fewer signals thus reducing computational power. Restricting the user to or adopt a particular lifestyle will result in a low adoption / acceptance rate. Recent studies have shown the use of a single device fitted with multiple sensors on a Multi-modal Sensor Board (MSB) ([12], [13]).

Lester et al. used a MSB for activity recognition and a Bluetooth device to send the data to a hand held device or laptop for offline analysis [14]. On the downside these devices have limited battery power. Accuracy rates of up to 91% have been reported if phones are allowed to be carefully positioned in pre-determined locations ([1], [2], [12], [15]). Sun et al. [16] investigated orientation and position independent classification schemes whereby a separate classifier is implemented for each position. This approach yielded an accuracy of 93% but is not practically feasible as it requires high computational resources. Some recent studies show behavioral analysis based applications using activity recognition techniques.

In [17] the fluctuations in the signal strength of GSM signals are used to infer activities like sitting, walking and driving. The use of GSM signals is not a very efficient approach as there are sudden spikes and troughs that cause complexity in GSM cell strength and visibility. Real time activity inferences also leads to accuracy and privacy issues. Recently, smartphone GPS sensor data was also exploited to establish mode of transport used to commute over duration of time. Consolvo et al. [18] used a mobile sensing platform called UbiFit for activity recognition which transfers data to a Nokia smartphone which uses bloomingflowers to encourage increase in physical activity.

Similarly, Denning et al. [19] worked on BALANCE which estimates the calorie expenditure in routine life. Nevertheless both these solutions rely on additional body sensors. In the last few years attempts have been made to implement activity recognition for limited sets of activities using mobile phones. The CenceMe system developed by Miluzzo et al. [20] explored basic level activities like idle walking and running for continuous mobile sensing with the help of back-end classifiers using accelerometer data along with conversation data. This approach achieved an overall classification accuracy of 72%. Hausmann [21] classified idle, walking and running into activity levels using median thresholds which are validated by empirical experimentation (rather than using Machine Learning algorithms).

III. SYSTEM PREMELIRIES:
A. Motivation & Problem Statement:

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With the technological advancement of cell phones a new platform for computing is quickly gaining popularity. These state of the art mobile phones are becoming more popular than computers as they wireless computers of the new era. The current smart phones are not just communication devices rather it's a personal computer packed into a small gadget. Smartphonesare now equipped with a number of embedded sensing devices such as an accelerometer, gyroscope, digital compass, microphone, GPS and camera. These sensors are now being usedin various fields for human gesture and activity recognition based applications which are opening the doors to new areas of research and significantly impacting our daily life. Thus, the recognition of human physical activities from cell phone sensor measurements is formulated as a detection problem.

B. Limitations of Prior Art:

The explosive growth in the global penetration rate of cell phones and, more recently, smartphones has led to interest in leveraging this connectivity for the delivery of health care services to the most remote regions. One of the many health care applications that cell phones are being leveraged for is activity recognition. Prior works on automated activity recognition, like Bao and Intille [1], required the use of dedicated on-body sensors. Prior approaches that rely only on cell phone sensors such as ours either required calibration or require users to keep their phones in a particular way. Kwapisz, Weiss and Moore [2] require the phone to be in a pant pocket. A recent study by Lane et al. [3] implements jigsaw continuous sensing [4] to develop an application based on physical health, sleep and emotional well being. The physical activity section of this application focuses only on three main activities walking, sitting and running. Another drawback of the system is that the report of the activity classification can only be viewed on a desktop web portal.A basic level mobile application uses graphical user interface to display physical well being along with a score which is computed using Metabolic Equivalent of Task (MET). Classification is performed using a split and merge technique [4]. Although classification accuracy of more than 90% is achieved, the downside of using the split and merge method is that the classifier is designed offline and merged at runtime. Another drawback is the development of multiple classifiers for various activity subclasses which adds to the classifier's complexity.

Most apps available on app marketplaces today that seek to track calorie consumption require extensive user input.

C. Proposed Approach:

Our proposed approach is to develop a classifier while adhering to best machine learning practices. We collect a large data set for classifier training and verification. We target the recognition of 7 different activities, which include walking, running, climbing stairs, descending stairs, cycling, driving and remaining inactive. Cell phone physical sensor readings were collected while performing all these activities, while the cell phone was kept in different orientations. The data set so collected was pre-processed to extract a number of features from the data that have not been explored in previous studies. The most informative features were chosen for further use by ranking features according to information gain. The data set was partitioned into 10 sets for 10-fold cross validation. Various classification algorithms were trained using the training set and then evaluated using the test set, iterating over all 10 data sets. The best performing classifier was chosen for implementation in the Android app.

D. Experimental Results & Findings:

We designed four separate classifiers, namely C4.5 Decision Tree, Na¨ıve Bayes, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). For verification, 10-fold cross validation was carried out. It was determined that the C4.5 Decision Tree classifier outperforms the other classifiers on average with a true positive rate of 95.2%, false positive rate of 1.1%, precision of 94.4% and recall rate of 94.2%.

E. Key Contributions:
Our contributions are three-fold:

1) We created a data set comprising 510 activity traces. These comprise of measurements taken from cell phone physical sensors collected while their carriers were engaged in various physical activities.
2) We developed four different classifiers for the task of activity detection, the best of which provides excellent average performance in terms of hit, false alarm, precision and recall rates.
3) We developed an Android app that implements the classifier and performs live activity detection and reporting.

IV. CONCLUSIONS:

In this paper we reported the design, development and performance evaluation of a smartphone app that performs live detection of physical activities. This app differentiates itself from previous works on activity recognition in the following: 1) It requires no user interaction post-setup, 2)It requires no additional sensing hardware and relies solely on the physical sensors that are standard on even low-end smartphones, 3) It requires no calibration, 4) It supports the detection of 7 different physical activities, including walking, running, climbing stairs, descending stairs, cycling, driving and remaining inactive, and 5)The Decision Tree classifier used by the Activity Diary app is accurate. The average area under the ROC curve exceeds 0.99.

This application letsusers monitor their daily physical activity and enables them to make healthier and more informed choices that can lead to healthier habits and lifestyle. Live updates are specifically targeted to encourage decisions based on a healthier lifestyle. We are currently field testing the Activity Diary app and are working to make it available to the public through the Google Android marketplace.

In the future, we would like to extend this app further to: 1) Support more physical activities, 2)Infer modes of transportation and provide users with feedback in terms of their estimated carbon footprint, and 3) Develop an app function that uses historical information about physical activities and contextual information to gives users pro-active suggestions for lifestyle choices.

REFERENCES:

[1] L. Bao and S. Intille, "Activity recognition from user-annotated acceleration data," Pervasive Computing, pp. 1–17, 2004.
[2] J. Kwapisz, G. Weiss, and S. Moore, "Activity recognition using cell phone accelerometers," ACM SIGKDD Explorations Newsletter, vol. 12, no. 2, pp. 74–82, 2011.
[3] N. Lane, M. Mohammod, M. Lin, X. Yang, H. Lu, S. Ali, A. Doryab, E. Berke, T. Choudhury, and A. Campbell, "Bewell: A smartphone application to monitor, model and promote wellbeing."
4] H. Lu, J. Yang, Z. Liu, N. Lane, T. Choudhury, and A. Campbell, "The jigsaw continuous sensing engine [for mobile phone applications," in Conf. on Embedded Networked Sensor Sys. ACM, 2010, pp. 71–84.
[5] G. Chambers, S. Venkatesh, G. West, and H. Bui, "Hierarchical recognition of intentional human gestures for sports video annotation," in Intl. Conf. on Pattern Recognition, vol. 2. IEEE, 2002, pp. 1082–1085.
[6] S. Lee and K. Mase, "Activity and location recognition using wearable sensors," Pervasive Computing, IEEE, vol. 1, no. 3, pp. 24–32, 2002.
[7] P. Lukowicz, H. Junker, M. Staeger, T. von Bueren, and G. Troester, "Wearnet: A distributed multi-sensor system for context aware wearables," Ubiquitous Comp., pp. 361–370, 2002.
[8] M. Mathie, A. Coster, N. Lovell, B. Celler, S. Lord, and A. Tiedemann, "A pilot study of long-term monitoring of human movements in the home using accelerometry," Journal of telemedicine and telecare, vol. 10, no. 3, pp. 144–151, 2004.
[9] J. Bussmann, W. Martens, J. Tulen, F. Schasfoort, H. van den Berg- Emons, and H. Stam, "Measuring daily behavior using ambulatory accelerometry: the activity monitor," Behavior Research Methods, vol. 33, no. 3, pp. 349–356, 2001.
[10] F. Foerster, M. Smeja, and J. Fahrenberg, "Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring," Computers in Human Behavior, vol. 15, no. 5, pp. 571–583, 1999.
[11] D. Karantonis, M. Narayanan, M. Mathie, N. Lovell, and B. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," Info. Tech. in Biomedicine, IEEE Trans. on, vol. 10, no. 1, pp. 156–167, 2006.
[12] J. Yang, "Toward physical activity diary: motion recognition using simple acceleration features with mobile phones," in Intl. workshop on Interactive multimedia for consumer electronics. ACM, 2009, pp. 1–10.
[13] S. Lau and K. David, "Movement recognition using the accelerometer in smartphones," in Future Network and Mobile Summit. IEEE, 2010, pp. 1–9.
[14] J. Lester, T. Choudhury, G. Borriello, S. Consolvo, J. Landay, K. Everitt, and I. Smith, "Sensing and modeling activities to support physical fitness," in Ubicomp Workshop: Monitoring, Measuring, and Motivating Exercise: Ubiquitous Computing to Support Fitness, Tokyo, Japan, 2005.
[15] T. Brezmes, J. Gorricho, and J. Cotrina, "Activity recognition from accelerometer data on a mobile phone," Distributed Comp., Artificial Intelligence, Bioinformatics, Soft Comp., and Ambient Assisted Living, pp. 796–799, 2009.