

Synopsis

*submitted in partial fulfilment of the requirements
for the award of the degree*

of

**Bachelor of Technology
in
ELECTRONICS & COMMUNICATION ENGINEERING**

ACTIVITY RECOGNITION FROM EMBEDDED SENSOR DATA SET USING DATA MINING TECHNIQUES



**DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING
INDIAN INSTITUTE OF INFORMATION TECHNOLOGY
UNA, HIMACHAL PRADESH (INDIA)**

SUBMITTED BY:

Saurabh Yadav (IITU15201)

Deepanshu Yadav (IITU15202)

Dipanshu Sharma (IITU15209)

SUBMITTED TO:

Miss Minakshi Shastri (CSE Dept.)

Table of Contents

Introduction3

Literature Survey.....4

Problem Statement5

Motivation.....6

Objective7

References8

Introduction:

The aim is to identify the actions carried out by a human, from the data collected from the sensors and the surrounding environment. The movement of a human can be recorded through sensors with the help of which activities and events can be recognized. Automatic recognition of activities and events is possible by processing this sensor data with appropriate machine learning and data mining approaches. We will examine several new machine learning and data mining approaches based on decision trees and ensemble learning techniques including random forests and random committee, and compare them with traditional naive Bayes classifier and K-Means clustering approaches for processing sensor signals for activity recognition.

Literature Survey:

In this paper we have gone through several literature for (HAR) human activity recognition, some concentrated upon real time processing and some of the approach uses offline processing.

Bishoy Sefenet. al. [ICAART 2016] said that In order to achieve the best tradeoff between the system's computational complexity and recognition accuracy, several evaluations were carried out to determine which classification algorithm and features to be used. Therefore, a data set from 16 participants was collected that includes normal daily activities and several fitness exercises. The analysis results showed that naive Bayes performs best in our experiment in both the accuracy and efficiency of classification, while the overall classification accuracy is 87%.

Subhas Chandra Mukhopadhyay [IEEE 2015] has reviewed the reported literature on wearable sensors and devices for monitoring human activities. The human activity monitoring is a vibrant area of research and a lot of commercial development are reported. It is expected that many more light-weight, high-performance wearable devices will be available for monitoring a wide range of activities. The challenges faced by the current design will also be addressed in future devices. The development of light-weight physiological sensors will lead to comfortable wearable devices to monitor different ranges of activities of inhabitants. Formal and Informal survey predicts an increase of interest and consequent usages of wearable devices in near future, the cost of the devices is also expected to fall resulting in of wide application in the society.

Davide Anguitaet. al. [JUCS 2013] presented a novel energy efficient approach for the classification of Activities of Daily Living using smart phones. It has been constructed based on a modified Support Vector Machine model that works with fixed-point arithmetic. The proposed model was supported in terms of Structural Risk Minimization principles, where simpler models are always preferred if they have (almost) equivalent ability to learn when compared to more complex approaches. The scope of this work is to apply the current technology for ambient intelligence applications such as in remote patient monitoring and smart environments (e.g. in long term smart phone-based activity monitoring systems). Its advantages include faster processing time, and the use of less system resources which in result provide savings in energy consumption while maintaining comparable recognition performance when compared with other traditional approaches.

Oscar D. Lara and Miguel A. Labrador [IEEE 2013] surveys the state-of-the-art in human activity recognition based on wearable sensors. A two-level taxonomy is introduced that organizes HAR systems according to their response time and learning scheme. Twenty eight systems are qualitatively compared in regards to response time, learning approach, obtrusiveness, flexibility, recognition accuracy, and other important design issues. The fundamentals of feature extraction and machine learning are also included, as they are important components of every HAR system. Finally, various ideas are proposed for future research to extend this field to more realistic and pervasive scenarios.

Problem Statement:

The main motive of this project is to detect the movements that a human is doing which will be done with the help of sensor data and applying suitable programming and mining techniques to it. The problem is being studied upon by various people but the accuracy that is achieved is still not up to the mark (nearly 94%). We want to contribute from our side to increase the accuracy of the motions detected.

Motivation:

Though there are previously several applications in the arcade as demonstrated in the introduction section, most of them do not fully utilize the smart phone embedded inertial sensors. The granularity of such applications is also not adequate. In some applications, only the events of walking and motionless are documented. Certain apps that only use GPS signals fail to function in indoor environments. The adequacy of utilizing machine learning systems on cell phone based sensor information is set apart to be researched, with the motivation behind perceiving human exercises. Distinctive space components and information handling systems should be contemplated. The unsupervised plan for action acknowledgment on cell phones is infrequently explored in the writing. What's more, there have been not very many reviews on lightening the effects of versatile detecting execution contrasts over numerous gadgets. Our examination is roused by the request of satisfying the absence of studies on those themes keeping in mind the end goal to grow more precise Human Activity recognition calculations.

Objective:

Mobile devices are flatterring more refined with every new model release. Nowadays, smart phones normally incorporate many diverse and influential sensors for example GPS, microphones, light sensors, temperature sensors, magnetic compasses, gyroscopes, high-resolution camera sand accelerometers. Human activity recognition (HAR System) has empowered innovative applications in divergent regions such as healthcare, entertainment and safety. Activity recognition is an important technology in pervasive computing because it can be applied to many real-life, human-centric problems such as eldercare and healthcare. Successful research has so far focused on recognizing simple human activities. Recognizing complex activities remains a challenging and active area of research. Specifically, in HAR, the trade-off between accuracy, system latency, and processing power always exist. There are abundant research which works upon real time processing which causes more power consumption of mobile devices as we know mobile phones are resource-limited devices and moreover, it is a thought-provoking task to implement and evaluate different recognition systems on mobile devices. Therefore offline processing is vital over smart phone dataset. In this paper we will develop an efficient method of human activity recognition and we will develop a human action recognition system with improved accuracy and better processing power.

References:

- [1] Davide Anguita Energy Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic/ JUCS 2013.
- [2] ZhinoYousefi, “Human Activity Recognition Using Time Series Classification”/ TSpace 2015.
- [3] Muhammad Shoaib,”A Survey of Online Activity Recognition Using Mobile Phones/ Sensors” 2015.
- [4] Oscar D. Lara and Miguel A. Labrador / “A Survey on Human Activity Recognition using Wearable Sensors”/ IEEE 2013.
- [5] “Jie Yin Sensor-Based Abnormal Human-Activity Detection”/ IEEE 2008.
- [6] Charissa Ann Ronaoet. “Human Activity Recognition Using Smartphone Sensors With Two-Stage Continuous Hidden Markov Models”/ICNC 2014.
- [7] Bishoy Sefent, Sebastian Baumbach Human Activity Recognition Using Sensor Data of Smart phones and Smart watches/ ICAART 2016.
- [8] O. D. Lara, A. J. Perez, M. A. Labrador, and J. D. Posada, “Centinela: A human activity recognition system based on acceleration and vital sign data,” Journal on Pervasive and Mobile Computing, 2011.
- [9] Charissa Ann Ronaoet. Human Activity Recognition Using Smartphone Sensors With Two-Stage Continuous Hidden Markov Models/ICNC 2014.
- [10] A. J. Perez, M. A. Labrador, and S. J. Barbeau, “G-sense: A scalable architecture for global sensing and monitoring,” IEEE Network, vol. 24, no. 4, pp. 57–64, 2010.
- [11] Y. Jia, “Dietetic and exercise therapy against diabetes mellitus,” in Second International Conference on Intelligent Networks and Intelligent Systems, pp. 693–696, 2009.
- [12] J. Yin, Q. Yang, and J. Pan, “Sensor-based abnormal human-activity detection,” IEEE Trans. Knowl. Data Eng., vol. 20, no. 8, pp. 1082– 1090, 2008.
- [13] O. X. Schmilch, B. Witzschel, M. Cantor, E. Kahl, R. Mehmke, and C. Runge, “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.
- [14] 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.
- [15] E. Kim, S. Helal, and D. Cook, “Human activity recognition and pattern discovery,” IEEE Pervasive Computing, vol. 9, no. 1, pp. 48–53, 2010