

HUMAN ACTIVITY RECOGNITION AND SMART PHONE DATASET: A LITERATURE SURVEY

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Abstract—Mobile devices are flattering 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. 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 study different methods of human activity recognition real time as well as offline processing and we will discuss how we can improve the accuracy of human action recognition system.

Keywords—HAR;SVM;GPS

I. INTRODUCTION

A Human Activity Recognition (HAR) system can automatically recognize physical activities, which is a key research issue in mobile and ubiquitous computing. An HAR system performs tasks of recognizing different human daily activities from simple to complex. The sensors involved in an HAR system can be video sensors, inertia sensors, and environment sensors. The GPS receiver can also be used for activity recognition but is limited to outdoor environments.

Depend on the putting in of sensors, HAR systems can be separated into three categories: wearable devices based sensing systems, smart phone sensing systems, and smart living environments. Although wearable devices and smart living environments can deliver good activity detection results, smart phone based applications are an increasingly prominent solution as smart phones have become an indispensable part of our daily life. Especially with the rapid evolution of hardware, ever-increasing computing and networking capacity, and rich embedded sensors, smart phone based HAR systems can tell us different kinds of human activities in real time using machine learning techniques. In addition, using smart phones for human activity recognition has a wide range of applications including healthcare, daily fitness recording, anomalous situation alerting, personal biometric signature identification, and indoor localization and navigation. All this benefits from the fast development of mobile phone software and hardware.

In the Android environments, the most commonly used and installed sensors can be categorized as follows [Google, “Android API description”]:

- Motion sensors: the motion sensors are based on inertial force.
- Environmental sensors: these sensors measure environmental parameters, like temperature and pressure, using barometers or thermometers.
- Position sensors: these sensors include orientation sensors and magnetometers, measuring the physical position of the device.



Fig.1 Compass sensor on Smart phone

There are already plenty of mobile sensing applications in Google's Play store as:

App Index	Vendor	App Name
1	Fitness Keeper Inc.	Run keeper-GPS Track Run Walk
2	Google Inc.	Google Fit
3	ITER S.A	Fade: fall detector
4	Map My Fitness Inc.	Map My Fitness Workout Trainer
5	Microsoft Corporation	Microsoft Health
6	Noom Inc.	Noom Walk Pedometer

Table-1 Mobile Apps

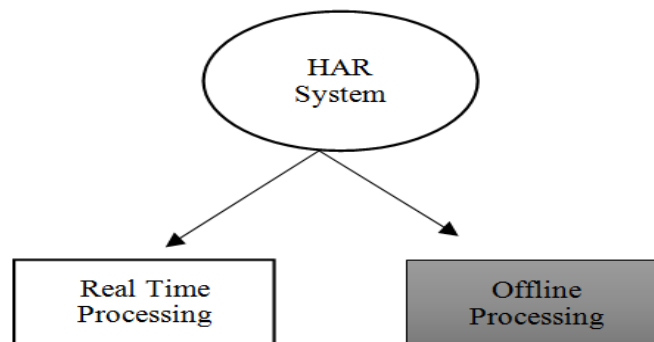


Fig.- HAR System

Furthermore we can see in fig.2 activity recognition system involved five phases, in data collection phase we need to input the data collected from mobile phone sensors for training of dataset, feature selection involved algorithm applied on collected dataset for selection feature which are meant for activity recognition process (dimension reduction), classifier model used to evaluate the effectiveness of different classifiers, cross validation is used as the evaluation method. The performance metrics selected to evaluate the classification methods are precision and recall. Precision (P) is defined as the number of true positives (Tp) over the number of true positives and the number of false positives (Fp):

$$P = \frac{Tp}{Tp + Fp} \quad \dots\dots\dots(1)$$

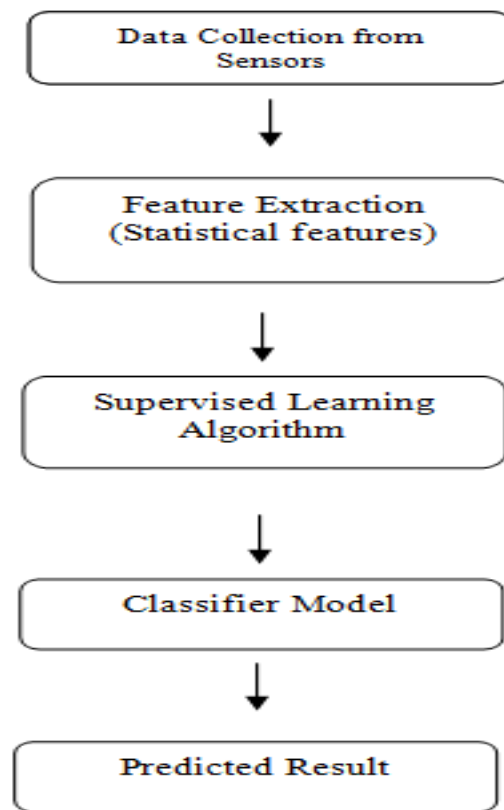


Fig.2. - Activity Recognition Process

Recall (R) is defined as the number of true positives (Tp) over the number of true positives and the number of false negatives (Fn):

$$R = \frac{Tp}{(Tp + Fn)} \quad \dots\dots\dots(2)$$

Accuracy is also used for comparing the classification results, which is defined as:

$$\text{Accuracy} = \frac{(Tp + Tn)}{(Tp + Tn + Fp + Fn)} \quad \dots\dots\dots(3)$$

In next section of this paper we will go through literature survey, section III will describe about how we motivated towards research, section IV we will discuss about Weka tool meant for machine learning, in section V we will provide comparative table among different literature at end of paper in section VI we will conclude our survey.

II. 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%.

Muhammad Shoaibet. al. [Sensors 2015]review the studies done so far that implement activity recognition systems on mobile phones and use only their on-board sensors. We discuss various aspects of these studies. Moreover, we discuss their limitations and present various recommendations for future research. In this paper, we reviewed the work done so far on online physical activity recognition using mobile phones. We consider studies that use only mobile phone sensors and that do the classification locally on mobile phones in real time.

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.

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.

Davide Anguita et. 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.

Jie Yin, Qiang Yang [IEEE 2008] propose a novel approach for detecting a user's abnormal activities from body-worn sensors. To deal with the scarcity of training data for abnormal activities, we propose a two-phase abnormality detection algorithm. In the first phase, a one-class SVM is built on normal activities, which helps to filter out most of the normal activities. The suspicious traces are then passed on to a collection of abnormal activity models adapted via KNLR for further detection. A major advantage of our approach is that it can achieve a better tradeoff between detection rate and false alarm rate. We demonstrate the effectiveness of our approach using real data collected from sensors attached to a human body. A potential limitation of our approach is that there is a risk of generating a large number of abnormal models when abnormal activities suddenly becomes the norm. This may happen when a user being monitored repeats a certain behavior repeatedly after a certain time point.

Charissa Ann Ronao et. al. [IEEE 2014] shown that a two-stage continuous HMM classifier is a feasible method towards universal activity recognition on smart phones. Continuous HMMs are able to specifically handle time series data such as accelerometer and gyroscope sensor values, and the two-stage architecture enabled us to use a significantly smaller number of features at the same time utilizing the most effective ones. We have also demonstrated that random forest variable importance measures, in combination with proper domain knowledge, is an effective approach in uncovering the most useful features from a large feature set. The proposed method consists of first-level CHMMs for coarse classification, which separates stationary and moving activities, and second-level CHMMs for fine classification, which classifies the data into their corresponding activity classes. Random Forests (RF) variable importance measures are exploited to determine the optimal feature subsets for both coarse and fine classification. Experiments show that with the use of a significantly reduced number of features, the proposed method shows competitive performance in comparison to other classification algorithms, achieving an over-all accuracy of 91.76%.

III. 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 HAR calculations.

The features and functionalities of these mobile apps can be summarized

Features	App Index (Table 1)
Burned Calorie Calculation	1, 4, 5
Chart/Graph Activity Records	1, 2, 4, 5
Fall Detection	3
Food Log	4, 5
Health & Fitness Knowledge	5
Pedometer	2, 6
Routes on Map	1, 4, 5
Social Networking	1, 4, 6

Table 2- Mobile Apps ant their feature

IV. WEKA TOOL

The WEKA project delivers functions that investigators can use to attempt out and matchdissimilar machine learning methods on datasets. Furthermore, APIs are delivered for tailored solutions and examinations. Classification, clustering, regression, and attribute selection are integrated in the workbench. The main GUI of WEKA is call the "Explorer" which has six components: Preprocess, Classify, Cluster, Associate, Select attributes, and visualize. The "Preprocess" panel is used for data preprocessing. Different preprocessing tools are called "filters" in WEKA.

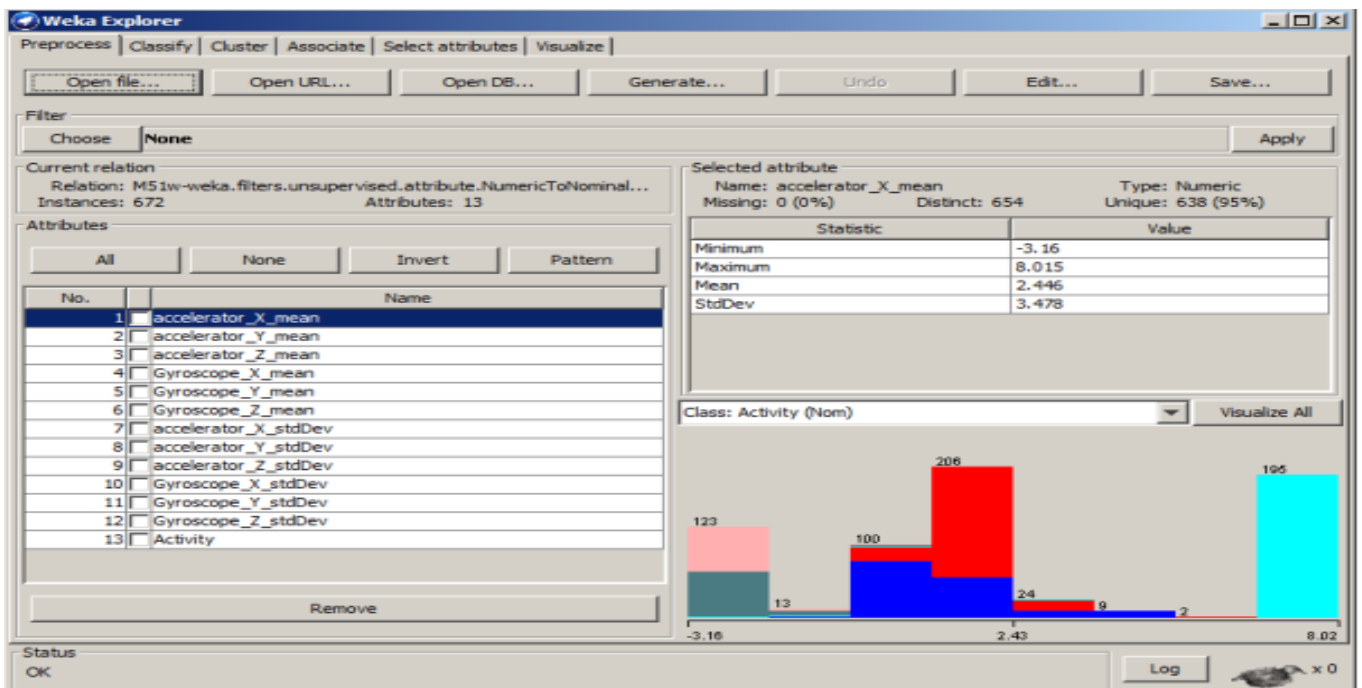


Fig.-2 Weka GUI

The second panel called "Classify" includes various classification and regression algorithms. Validation methods as well as evaluation visualization like ROC curves can be drawn in this panel. In addition, WEKA also supports unsupervised learning algorithms. Evaluation and visualization of the clustering algorithms are provided in the third panel. The fourth panel enables the methods for association rule mining, which is used for discovering interesting relations between items in datasets. Attributes selection is another important task in practical machine learning and data mining. The "Select attributes" panel gives access to some attribute selection algorithms, such as principal components analysis (PCA), information gain evaluation, and gain ratio attribute evaluation. The last panel is the data visualization, which provides the color scatter plot of the data matrix that can be visualized.

V. COMPARISON

S. No	Author/Paper title/Year	Name of Algorithm/Tool/Method(discussed/Implemented)	Description	Accuracy
1	BishoySefen, Sebastian Baumbach et. al. / Human Activity Recognition Using Sensor Data of Smart phones and Smart watches/ ICAART 2016[1]	Naive Bayes Classifier	In this paper, a platform to combine sensors of smart phones and smart watches to classify various human activities was proposed. It recognizes activities in real-time Moreover, this approach is light-weight, computationally inexpensive, and able to run on handheld devices	87%
2	ZhinoYousefi/ Human Activity Recognition Using Time Series Classification/ T Space 2015[2]	Modified Dynamic Time Warping Distance	Propose a system that learns activity trends using only the data from an accelerometer sensor, which is the most common motion sensor in smart phones. The system uses raw traces in a training set to build a predictor that assigns the proper label to new traces.	90%
3	Muhammad Shoaib et. al./ A Survey of Online Activity Recognition Using Mobile Phones/ Sensors 2015[3]	SVM, Decision Tree, Naive Bayes, KNN	Review the studies done so far that implement activity recognition systems on mobile phones and use only their on-board sensors.	-
4	Oscar D. Lara and Miguel A. Labrador / A Survey on Human Activity Recognition using Wearable Sensors/ IEEE 2013[4]	Decision tree, Fuzzy Basis Function and Fuzzy Inference System Regression methods, Hidden Markov Models and Conditional Random Fields	Propose a two level taxonomy in accordance to the learning approach (either supervised or semi-supervised) and the response time (either offline or online). Then, the principal issues and challenges are discussed, as well as the main solutions to each one of them. Twenty eight systems are qualitatively evaluated in terms of recognition performance, energy consumption, obtrusiveness, and flexibility, among others.	-
5	Davide Anguita et. al. / Energy Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic/ JUCS 2013[5]	SVM, Fixed-Point Arithmetic	Propose a novel energy efficient approach for the recognition of human activities using smart phones as wearable sensing devices, targeting assisted living applications such as remote patient activity monitoring for the disabled and the elderly. The method exploits fixed-point arithmetic to propose a modified multiclass Support Vector Machine (SVM) learning algorithm	89%
6	Jie Yin et. al./ Sensor-Based Abnormal Human-Activity Detection/ IEEE 2008[6]	Kernel nonlinear regression (KNLR)	Employs a one-class support vector machine (SVM) that is trained on commonly available normal activities, which filters out the activities that have a very high probability of being normal. We then derive abnormal activity models from a general normal model via a kernel nonlinear regression (KNLR)	84%
7	Charissa Ann Ronao et. al./ Human Activity Recognition Using Smartphone Sensors With Two-Stage Continuous Hidden Markov Models/ICNC 2014[7]	Two-stage continuous hidden Markov model (CHMM)	Propose a two-stage continuous hidden Markov model (CHMM) approach for the task of activity recognition using accelerometer and gyroscope sensory data gathered from a smart phone	91.76%

VI. CONCLUSION

With the purpose of developing more truthful activity recognition (AR) systems independent of smart phone models, effects of sensor alterations across several smart phone models are scrutinized.

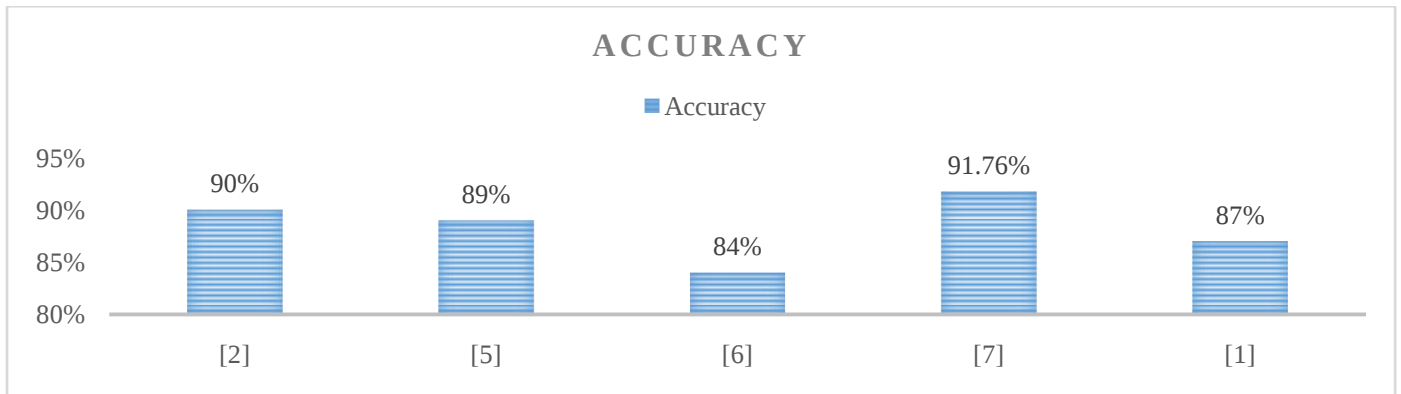


Fig.3 Comparison

From fig.-3 comparison we can conclude that there is need of need of improvement over existing system to increase the accuracy.

HAR system involves five phases, from different literature concluded that to improve the prediction accuracy there is need of efficient method for dimension reduction, feature selection.

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