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A Review Paper on Mobile Technology for Activity Recognition

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Abstract: Today is the world of smart phones. Almost everyone now uses smart phones. A large amount of data is communicated via these smart phones. These smart phones save some of the user's data without the knowledge of the user. These data can be analysed and can be used into different things which can show the behaviour of the person who owns the smart phones. This survey study, basically deals with some of the different types of data that is collected by the smart phones and can be used in such a way that is useful for the user of the smart phones. I have surveyed some papers on human activity recognition with smart phones and will use the phone data to analyse the reactions of user for some applications that are installed in the smart phone.

Key words: Activity recognition, ADL, HAR, mobile communication, smart phone, applications

INTRODUCTION

In today's era, mobile phones have become basic necessity for human beings. Earlier the phones were just used for communication purpose but the introduction of smart phones has change the way of telecommunication. The data from cellular phones can be used for Human Activity Recognition (HAR). HAR is currently a hot topic amongst researchers and can be applied to a wide domain of research. Another reason that scalable data technology is hotter than ever is the amazing explosion of mobile communication devices around the world. Although, this trend primarily relates to the individual use of future phones and smart phones it's probably more accurate to as think of this trend as centered on a user's identity and device dependence. If you regularly use both computer and have a smart phone, it's likely that you have the ability to access same personal data from either device. Because of the incredible task of dealing with the data needs of the world wide web and its users, research organizations realized that a new approach of collecting and analyzing data was necessary.

LITERATURE REVIEW

Bayat *et al*. (2014) researched purely on human activity recognition system that recognize certain types of human physical activities. The data was captured by a user's cell phone. They obtained accuracy up to 91.15% using a single triaxial accelerometer on various day today activities. The acquired data from smart phones for two different main positions: smart phone in hand and smart phone in pants pocket. Here researcher has not briefly described the activities as dancing, fast walking, aerobics, etc., though focuses on less sensory input than previous work yet obtaining a good accuracy rate. The complete research was divided into four different steps: data collection, feature evaluation, feature extraction, classification. The researcher used triaxial accelerometer to collect data from android smart phones. This accelerometer generates three different time series along x-z-axis. The researcher used Weka toolkit to evaluate the performance of the classifier. They evaluated multilayer perceptron, LMT, LogitBoost, SVM, random forest and simple logistic classifiers available in Weka toolkit. They proved that accuracy and efficiency can be improved by combining different good classifiers. In this the researcher proved that random forest demonstrated high accuracy. Then the author used majority voting and average of probabilities for combining multiple good classifiers from the previous step (Fig. 1).

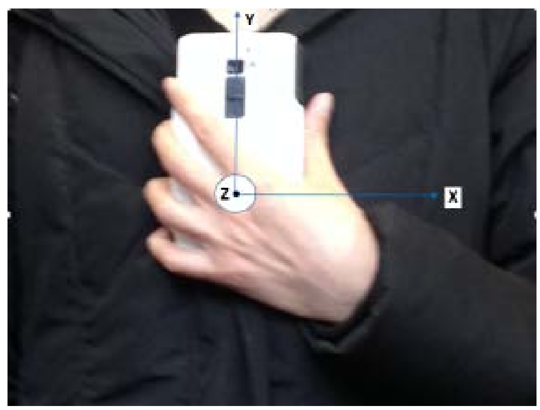

Fig. 1: Android smart phone with its axis direction for accelerometer (Bayat *et al*., 2014)

Table 1: Comparison of classification results using different feature sets Reiss *et al*. (2013)

Features	C4.5 decision tree (%)	AdaBoost. M1 (%)	ConfAdaBoost. M1 (%)
"Small" feature set	92.79	97.63	98.30
"Large" feature set	94.14	98.91	99.17
"Full" feature set	93.55	98.67	99.29

Table 2: Confusion matrix of the classification results the multiclass SVM Anguita *et al*. (2013)

Variables	WK	WU	WD	ST	SD	LD	Recall (%)
Walking	492	1	3	0	0	0	99
W. upstairs	18	451	2	0	0	0	96
W. downstairs	4	6	410	0	0	0	98
Sitting	0	2	0	432	57	0	88
Standing	0	0	0	14	518	0	97
Laying down	0	0	0	0	0	537	100
Percision	96%	98%	99%	97%	90%	100%	96

Reiss *et al*. (2013) also developed an approach for activity recognition. The research was made over a publicly available data set using smart phone sensors. The researcher introduces a new classification algorithm ConfAda-Boost.M1. The researcher has proved that ConfAda-Boost.M1 algorithm is more accurate than that of C4.5 decision tree and Ada Boost.M1 classification algorithm. Here researcher only provides the subject dependent training which can be in future can be done with subject independent training. Table 1 shows comparison of classification results using different feature sets tested by the researcher.

Rasekh *et al*. (2011) worked in areas like in medical research and human survey system. They collected time series signal with 3D smart phone accelerometer. They used four basic classifiers: quadratic classifier, k-nearest neighbor, support vector machine and Artificial Neural Network. The data was collected with HTC smart phones used by three persons. As a result, they successfully recognized five different types of activities: walking, jogging, limping and going up and down stairs. Here the author couldn't distinguish between the walking up and down stairs. Support vector machine showed the best classification rate of 84.4% in subset space (Fig. 2).

Anguita *et al*. (2013) describes various activities of daily living performed by 30 subjects with waist mounted smart phones with embedded inertial sensors. The experiment was done to collect a database for human activity recognition. There were six different ADL's: sitting, standing, walking, laying down, walking upstairs and downstairs. The experiment was conducted in two circumstances: first with smart phone on the left side of the belt and second as preferred by the user. Each task had a gap of 5 sec. Triaxial linear acceleration and angular velocity signals were collected from the sensors and the noise reduction was done. Table 2 shows confusion matrix of classification results by the researcher.

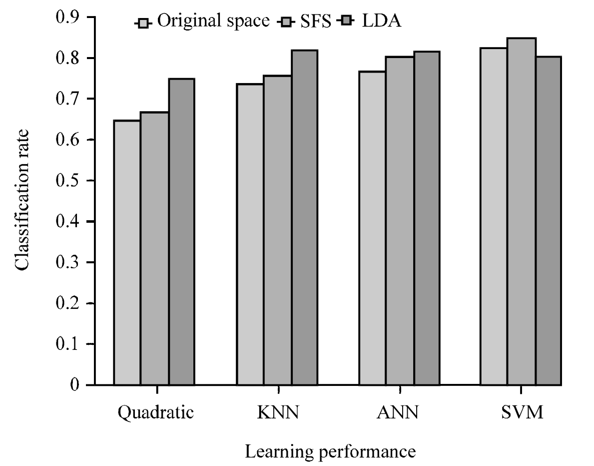

Fig. 2: Passive learning performance in original space, subset space (SFS) and LDA subspace (Reiss *et al*., 2013)

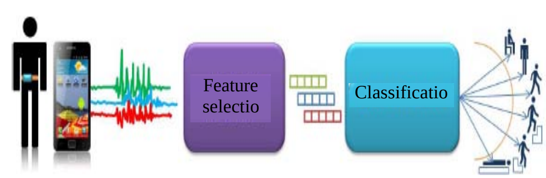

Fig. 3: Activity recognition process pipeline (Anguita *et al*., 2012)

Here, rows represent the actual class and columns the predicted class. Activity names on top are abbreviated.

Anguita *et al*. (2013) used inertial sensors to study human physical Activity Recognition (AR). This helps in the daily health monitoring for old aged people. They used support vector machine and exploits fixed point arithmetic for computational cost reduction. The experiment was performed over 30 persons of age group 19-40 years and performed six different activities. The data base formed was divided into two groups. About 70% of the data was used for training purpose and rest 30% of the data was used as test data. Through, experiments they showed that multiclass-HF-SVM exhibits a lower generalization error (Fig. 3).

Shoaib (2013) researched over some problems like inferring activity/state from heterogeneous and incomplete sensor data, detecting human context from smart phones (resource limited) in an energy efficient way, how to use different sensors in a cooperative way? For this they used three sensors: accelerometer, gyroscope and magnetometer. The data was collected from four male participants at university of Twente. The smart phones were placed on belt, right pocket, arm and wrist. They

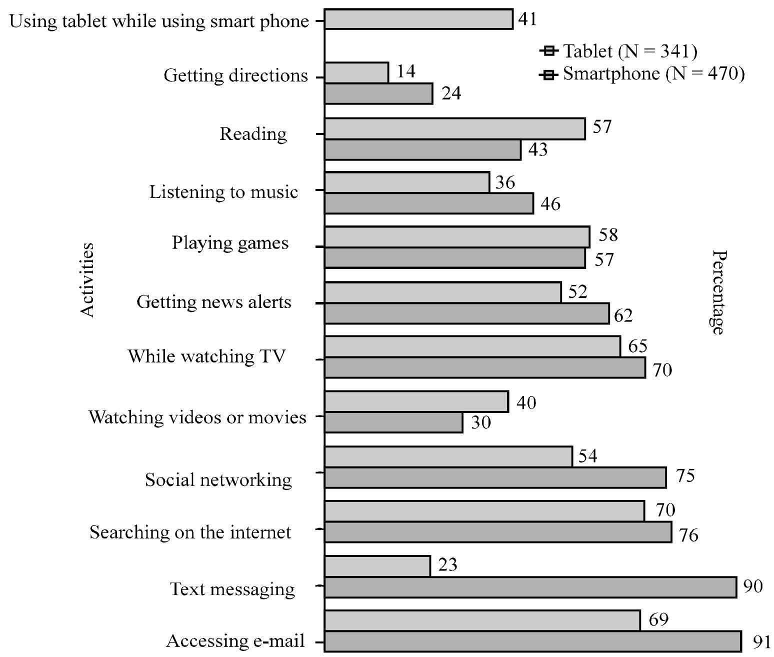

Fig. 4: Activities performed at least once a day smartphone vs. tablet

used WEKA classification method as classifiers. Blondel *et al*. (2015) researched on mobile phone dataset. This was basically a survey paper. This dataset can be used to make social networks by using the call dataset of people contacting each other. This can be analysed for creating communities, topological properties and social analysis thus, analyzing human behavior. A large amount of study has already been done on analysis of social networks based on CDRs. They surveyed new ways of using mobile phones for the use of society. They can be used for urban sensing: sensing traffic from mobile data. It is used for transport planning applications. Mobile phones can also be used for monitoring and preventing epidemics. They also surveyed the concept of viral marketing. Viral marketing focuses on identifying a person in society who has a great impact on his society as neighborhood has great influence in ones decision.

Gebauer (2008) studied technological requirements as the functional and non-functional for mobile professionals. The experiment included four research studies mobile email in a company, online user content analysis, various mobile technology devices and series of interviews. Through this they were able to understand success factors, mobile technology and impact of user satisfaction and performance. They tried to relate their understanding with business users of mobile technology, satisfaction level of users and their improvement in performance. They studied empirical survey of mobile e-mail, content analysis of online user reviews, empirical survey of mobile technology user and interviews of mobile professionals (Fig. 4).

Salesforce carried a survey over 470 volunteers for one month to study their usage of mobile phones for mobile apps. They find out that about 3.3 h on an average was spend by a volunteer on mobile phone. About, 73% of the volunteers surveyed also carried tablets. Most of the tablets are basically used for email and online search (approx. about, 70% both) where as smart phones are used basically for emails and messaging (approx. 90%). They also find that location sharing gives them better results for the search. The report basically uncovers perceptions and preferences, behavior patterns, evaluated assumptions, explored relationship with brands and also accessed impact on consumer's life.

Moser *et al*. (2016) researched about the user attitude at the meal time differs at any other time and about the design of the mobile technologies. Total of 1163 persons participated in an online survey. They focused on social awareness features, incorporated into the mobile, so as to ease tensions around conlicting mealtime behavior. The research can benefit health researchers for mapping the relationship between them. The data was analysed using paired-t test. They found that usage of social media was inappropriate at mealtime than calls and texting.

Pham (2015) represented a real time human activity system named as MobiRAR. This device sences the data from accelermeter in smart phones. They used data processing, segmentation, feature extraction and classification for activity recognition. They performed experiment on Samsung GalaxyNote II. The 17 subjects

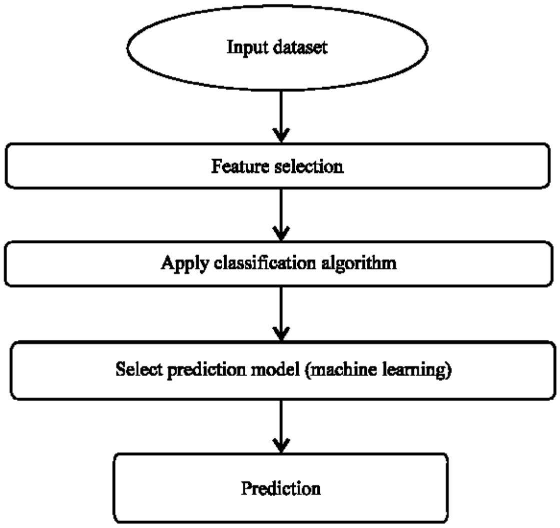

Fig. 5: Flowchart for our proposed approach

aged from 19-54 got involved in their study. Each subject was asked to perform 10 activities: running, walking, sitting, standing, jumping, kicking, going-up stairs, going down-stairs, laying and unknown activities. Overall, with 93.35% precision and 94.03% recall HMM performs better than decision tree C4.5 (with 89.67% precision and 91.84% recall).

Prabowo *et al.* (2016) worked on handleing missing data handling for human activity recognition. They tested some algorithms like Bayesian network, Multilayer Perceptron (MLP), C4.5 and k-Nearest Neighbour for handling missing data. Based on their experiments they found that optimal result based on accuracy is obtained by kNN with 89.4752%. From this study we can learn that the data from mobile phones get lost due, to small memory and computational capacity. So, there is also a need to handle this missing data during human activity recognition.

OUR APPROACH

From the work done, so far we are able to know the different methods of collecting the data via smart phones. Most of the people about 85% say that mobile is a necessary part of life. These data are used for human activity recognition for several purposes. We will be taking an offline dataset that has already been tested and will apply regression to compute the activity of the user and test the accuracy of the algorithm. We also concentrate on capturing data related to different mobile usage like timings of different applications accessed by the user, type of contents accessed by the user. These data can be analysed and can be used for future prediction work (Fig. 5).

CONCLUSION

The researcher conclude that, there is still need of more research on human activity analysis. The smart phone pays a great help in collecting data. A human activity recognition system can automatically recognize physical activities which is a key research problem domain in mobile and ubiquitous computing. The HAR collects and recognizes tasks that are simple as well as complex. The sensors involved in HAR system can be video sensors, inertia sensors or environment sensors. These collected data need to be analysed more and more for getting more accurate results in activity recognition. The availability of such a huge dataset may lead to help society in much greater way. Data can be used for the beneficiary of old peoples, health practitioners, improving mobile technologies. From the above researches, we can find some bottleneck to develop an efficient HAR system:

RECOMMENDATIONS

- To improve the prediction accuracy, we need to use efficient classifier
- Sensors involved in HAR system must be wearable by the person, hence activity recognition is completely dependent on how sensors are wore, i.e., irrespective moving of sensors also effect the prediction accuracy
- Using historical data, we improve the performance, hence we need to store the training data into device which will reduce the performance of HAR as well as the device
- Online HAR system is not so efficient as it uses complex mathematical computations

Thereby, we need to an approach which will increase the accuracy of HAR and can improve the device performance, so we have proposed the HAR system based on machine learning by using multiple regression model that also decreases the mathematical complexity.

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