

Activity Recognision using Machine Learning Techniques

Lisna K T, Zainul Abid T P

M.tech Cse Department MES College of Engineering, KuttipuramKerala, India Assistant Professor,Cse Department MES College of Engineering,Kuttipuram Kerala, India Corresponding Author: Lisna K T

Date of Submission: 26-07-2020

Date of Acceptance: 06-08-2020

ABSTRACT—Activity recognition is considered as an important task in many applications, particularly in healthcare services. Among these applications include medical diagnostic, monitoring of users daily routine and detection of abnormal cases. This paper presents an approach for the activity recognition using an accelerometer sensor embedded in a smartphone. This approach uses a publicly available accelerometer dataset as the raw input signal. The features of the signal are selected based on the time and frequency domain. Then, Principal Component Analysis (PCA) is used to reduce the dimensionality of the features and extract the most significant ones that can classify human activities. A comparison process is performed between the original raw data and PCAbased features and additionally, time and frequency-domain features are also compared using several machine learning classifiers. The obtained results show that the PCA-based features obtain higher recognition rate while frequency-domain features have higher accuracy, with the rate of 98 percent respectively.

Index Terms—Accelerometer dataset, Activities of daily living, Classification, Machine learning

I. INTRODUCTION

Activity recognition plays a vital role in healthcare services and has been studied as a part of solutions to reduce the costs and workloads currently being placed on professional caregivers . The capability of performing activities is usually associated with the physical and mental health of and can be considered as a primary people indicator to determine their quality of life . Activity recognition is regarded as a challenging task due to the fact that each activity has their unique characteristics. It is indeed a well-researched problem and can be associated with many applications. Among these include falling detection , abnormality detection and prediction of human behaviour.

Studies in this area are usually conducted

in a highly controlled environment. Often, the results do not represent the condition in a realworld application. However, activity recognition using mobile-based devices have shown to generate high quality results in a real-world setting. In particular, activity recognition using accelerometer sensor shows a good potential due to the ability of the sensors to consume low power which enables continuous sensing over a day. These sensors are usually embedded in various types of smartphones or it can also be strapped to human body using strip or belts. In fact, the computing capabilities of smartphones have increased in recent years, which allows the function to be extended to other applications such as capturing human body movement rather than supporting only voice communications . Using the accelerometer sensor data, a mobile phone device can analyze and interpret that a user is performing some activities such as running or walking. With the advancement of today's technologies, activity recognition can be used to monitor human daily activities and identify any unusual changes in their daily routine.

Aspect that needs to be considered is the number of sensors. The use of multiple sensors has resulted in the problem of movement obstruction as well as practicality in the long-term wearing . In addition, the cost will also be increased with the addition of more sensors. With this respect, more researchers are focusing to apply activity recognition approaches by using only one accelerometer sensor in order to collect the body movement signal. However, several issues are associated with the activity recognition approaches using accelerometer sensor. These include data processing, feature extraction methods and highperformance classification support techniques . For example, if the features are not properly selected from the raw signal, it will degrade the activity recognition accuracy and decrease the computational efficiency. Several studies have applied feature extraction methods to select the most signifi- cant features that can classify human



activities . Furthermore, dimensionality reduction process also can be applied to reduce the dimensionality of raw data and transform original features to a lower dimensional space. These processes are often expected to meet several requirements, such as high accuracy, short training time and real-time data generalization. paper presents an approach to recognize activities of daily living using a publicly available accelerometer sensor dataset [20]. It also highlights several issues such as signal pre-processing, feature dimensionality reduction selection, and classification. The comparison process is performed using several machine learning classifiers, which consist of Decision Tree (DT), Support Vector Machine (SVM) and Multi-Layer Perceptron Neural Network (MLP-NN).

II. LITERATURE SURVEY

A. State of the art

- The MobiFall Dataset: An Initial Evaluation of Fall Detection Algorithms Using Smartphones : Fall detection re- ceives significant attention in the field of preventive medicine, wellness provision and assisted living, especially for the el- derly. As a result, numerous commercial fall detection systems exist to date and most of them use accelerometers and/ or gyroscopes attached on a person's body as primary signal sources. These systems use either discrete sensors as part of a product designed specifically for this task or sensors that are embedded in mobile devices such as smartphones. The latter approach has the advantage of offering well tested and widely available communication services, e.g. for calling emergency if necessary, when someone has fallen. Apparently, automatic fall detection will continue to evolve in the fol- lowing years. The aim of this work is to introduce a human activity dataset that will be helpful in testing new methods, as well as performing objective comparisons between different algorithms for fall detection and activity recognition, based on inertialsensor data from smartphones. The dataset contains signals recorded from the accelerometer and gyroscope sensors of a latest technology smartphone for four different falls and nine different activities of daily living. Using this dataset, the results of an initial evaluation of three fall detection algorithms are finally presented.
- Perception of Smart Home Technologies to Assist Elderly People : In this paper, phones were placed in three different positions. Five daily behavior information has been collected

based on the synthetic acceleration, ten kinds of user activity features are extracted. The decision tree based on the features has been established. This paper studies the three kinds of modeling method, vector (activity, position) based modeling, position based modeling and activity based modeling respec- tively. Compare all these models, behavior based recognition model gain the highest accuracy and lest timeconsuming, which can effectively identify human behavior.

An Ontology-Based Hybrid Approach to 3) Activity Mod- eling for Smart Homes : It is worth noting that the research presented in this paper is based on single-user single-activity scenarios. While complex activity scenarios, e.g., interleaved and concurrent activities, pose many research problems, it is beyond the scope of this paper to address them all. In addition, the activities this research is concerned with are basic ADLs and instrumental ADLs which can be performed within home environments with clear model semantics, such as meal and drink preparation. Instrumental ADLs such as shopping and use of transportation which take place outside residential en- vironments, and money management and housekeeping which do not have meaningful computational models, require special treatment, and are therefore also considered to be beyond the scope of this paper. Activity monitoring in this study is based on dense sensing, i.e., one miniaturized sensor is attached to individual objects that are used for monitoring individual tasks within ADLs. As such, by analyzing an inhabitant's interactions with objects of interest, it is possible to infer the inhabitant's activity. This paper introduced a hybrid approach to creating complete, accurate activity models through incremental activity discovery and profile learning. We have described a three-phase process and discussed iterative the methodology of each phase of the lifecycle. While previous work reported the details of ontological activity modeling and recognition, this paper has presented the details of activity and profile learning methods by which activity models can be expanded, personalized, and adapted. The compelling feature of the approach is that it combines the strengths of traditional data mining based activity modeling with that of ontology based explicit activity modeling, making our approach flexible, applicable, and scalable in terms of reusability, rapid system development, and deployment. We have implemented our approach in a



feature-rich assistive system and conducted sys- tematic controlled experiments in a number of well-designed activity scenarios. Initial results have demonstrated that the approach and algorithms are technically correct, viable, and robust. Although the experimental dataset is not very large, it is representative and serves the purposes well. Our future work will focus on testing and evaluating our approach using publicly available activity datasets and also considering the exact impact of different noise levels on the performance of our approach.

4) Improving the Accuracy of Complex Activities Recog- nition Using Accelerometer-Embedded Mobile Phone Classi- fiers: This study is one of series of our works for recognizing the complex activity using mobile phone sensors. This study investigated recognizing of complex activities with common classifiers those using in recognizing human activities. Data were collect about subject prepares breakfast scenario. Those activities are categorized into three levels as hierarchy ing to the complexity. accord-The accelerometer of mobile phone was used to acquire data of the activities. Armband and waist- mounted positions were tested in this study using two mobile phones. The collected data was preprocessed by extracting two features: mean and standard deviation. The performance of the classifiers was evaluated in terms of recognition accuracy and time computation. The study concluded that those classi- fiers are good to recognize low level activities (simple), but their performance reduces when the complexity of activities increase. So classifiers are needed to deal with the complex activities as future work.

III. PROPOSED METHOD

This section provides the methodology involves in perform- ing activity recognition from the accelerometer sensor data, which has been embedded in a smartphone. This section is divided into two subsections, where each section describes how data is collected and steps taken in the data preprocessing method.

A. Data Collection

A publicly available dataset is used in this study. The dataset is composed of sensory data from a tri-axial accelerometer and a gyroscope. However, for this study, only accelerometer dataset is used to identify human activities. This is because previous studies show many disadvantages of using multiple sensors in identifying human activities [15]. Furthermore, it has been shown that one accelerometer is sufficient in analyzing human body movement. The dataset is composed of nine types of ADLs and four types of falls. Each signal is stored in time (ns), acceleration values (ms-2) in x, y and z- axis as well as the activity labels. The mean sampling rate for the signal is 87 Hz and the range of the acceleration value is between 20 to -20. For this study, six activities are chosen, namely Standing (STD), Sitting (SIT), walking(WAL).

B. Data Pre-processing



Fig. 1. Activity recognition method

Firstly, the segmentation technique is used to divide sensor signals into small time window segments so that the feature can be easily extracted in each segment. In this work, a sliding window with 50 percent overlap is chosen as the method of segmentation, since it has been proved as wellsuited in many studies. The features are computed from 600 sampling points, which represent a 3second time window. This duration is considered sufficient, as most existing studies use different size duration between one and three seconds.

Finally, the dimensionality reduction process is a technique to transform original features in high-dimensional data into a meaningful representation data in the form of reduced dimensionality. This facilitates process classification process and visualization of highdimensional data. PCA is consid- ered as one of the popular approaches that can reduce the dimensionality of data by converting original features into new mutually uncorrelated features . These new features are called as principal components, where they are arranged according to their variances and the components that contribute to the lowest variances are usually omitted. The steps taken in the PCA can be represented as below:

Normalize the data by subtracting the mean

i



value

- ii. Calculate the covariance matrix
- iii. Calculate the eigen vectors and eigenvalues of the covari- ance matrix
- iv. Choose the components and form a feature vector
- v. Derive a new dataset

IV. RESULTS AND DISCUSSION

In this section, the results from the conducted experiments in the methodology section are presented and discussed. Firstly, the results of the normality test are presented in Table 2. From this table, it can be seen that some features which are taken from the time and frequency-domain have probability values (pvalue) less than 0.05. Based on this result, the null hypothesis can be rejected and thus, it can be concluded that the acquired features are not fitted in a normal distribution with a 95% confidence.

The next process is to classify the activities and compare their performance. The comparison process are performed in terms of Precision, Recall, F-score and Accuracy. The first comparison is between the original features extracted from the raw data and PCA-based features. Additionally, time- domain and frequencydomain features are also compared. It uses several non-parametric machine learning classifier tools, namely DT, SVM and MLP-NN. These machine learning tools are chosen as they have been proven to give better results. The confusion matrix is performed between three classes of activities, namely standing (STD), sitting (SIT) and walking (WAL).

<pre>catat in version 0.12 and will be income in version 0.34. The on sens / Financian simulations and the imported from wilesame.example 185. Metrics is imported from wilesame.neurial_intensis is now part 185. File "Onlinesationsonician"Appletational Programs: Python Python Python ages atlantic is a sensitive and provide the intensis is depress wernings examinesses, Finandaming TearsRearing The eldersity preproteing table module is depress mouth intensi be reported from atlantic performance of the primer kill another the sensing and sensitive is the primer kill another (from examples module) / file "Online examples module) / meeting intense examples module) // meeting intense examples file file meeting intense examples intense examples file meeting intense examples intense examples intense examples intense meeting intense examples intense examples</pre>	TLANG	Anyte of	
<pre>Maring (from versings modules: Pric "in the solution price (Local Verogeness) Pythons Pythons Price "in the solution price (Local Verogeness) Pythons Pythons Segret account restances of the solution of the solution of the versings.currings.pythone (Local Verogeness), allocations of the Solution (Local De Education Allocation) Solution (Local De Education Allocation) Solution (Local De Education) Solution (Local De Education) Solution) Solution (Local De Education) Destingting Solution(Local De Education) Destingting Solution (Local De Education) Solution (Local De Education) Destingting Solution (Local De Education) Solution (Local De Education) Destingting Solution (Local De Education) Solution (Local De Education) Sol</pre>	tet in	ALTE -	
Hanning (from wearings module): file ~(\)TestprocessingleringProlices()Troprome(Tythus)Pythus Sept ellevinges(Pythus 100 DestWarning) BestWarning (Tythus to ingirable estimator labelHickaring, from ver	ter / E	spin h	1210 184 14 5
a denie verwich diffici. This wight lead to bleasing rock of inval	TYJANY RAUE J.	.19.0	ante atori Tert
at you can the. Merile (from warings schile))			
File "Colterstoesingure/Applete/Lonel/Frogress/Fythes/PythesT apst/stlearchase.py", 2008-318 Martheorem	112281	ntr-j	
Decomprising Trought to support the timeter Minister from very using verying 0.22.1. This might leaf to knowling outs of intenin 41 year own risk.	Lon. (); 4 (mm);	20.8 s 51.8. 1	ites
Blanding			

Fig. 2. Activity recognition for standing activity

🕞 Pythen 173 Shell File Edit Shell Delay Options Window Help	-	α	×
<pre>Berging (from warmings multiple) Tails -21/Description/inspire/AppGens/Local/Fromplans/Python/P</pre>	d in / du	ute p vessi actio	415 48 # 1
Berring (From warnings module): File *C)(Tees)(assign)(as)(AppCeta)(Loss)(Pyropeass)(Pyroon)(Pyroon)(T) appr)(addarn()ass.pp?. Lies 3.3 Descharged (Compared States)) Bertwarning: Tayling to emplotele series of Loss)(Loss)(Appl) Bertwarning: Tayling to emplotele series of Loss) Bertwarning reprint (C.T., This adapt lead to breaking only of Loss) of Typer may fish.	1101.s	20.0 20.0	with a Unre
<pre>Karning (Frim varmings module): Tile "Div(SectionsLongine)LggDets'Llobel/Programm/Python/Py</pre>	110%s 1.3 179911	110 p	ken av

Fig. 3. Activity recognition for walking activity

V. CONCLUSION AND FUTURE WORKS

This paper presents an approach for the recognition of activ- ities of daily living based on a publicly available accelerometer

Python 173 theil	⊨ □ ×
File Ball Shall Daking Gelicity Warman Help	
Provide rougs the adjustment and a present solution of the sound is repeated to be used in a comparison in solution of sound of factories through interest he encourted from shield a class sound for papertial from shielders. Areasa, writes a 401.	enderen wehile zu depri 28. The textemperatury can compare provery. Arythus a new plant of the provider
PARALLEL (THE MARLING BUILDED)	
File "In Developmentation deplete Long's Programming of agent at hear 4 years of any prostable of p ² , the set	address and a second
Patterning The shiners proproved in label and the	sectored the sector of the
0.22 and will be realwed in version blue, the convergence	damp sineses / functions
studid Lastand be impressed from subsemigroprocessing.	Deprinting that former for a
sperres the sticked preparation is no part of the p	minute Art.
Financias (How sensitive and the) - PLLs *Conferences and appletational forgeneric feet spectral and sensitive app*. Line : 110	an Armath Little and Sant
the starting of the second size and the starting of the second size of	A REAL PROPERTY OF A REAL PROPER
At your own that	e as anisital regular. The
estation chose experience however.	
Fale Artilleersteeringstin Gepland Long Charge and Peri	and a started life house of the
ager subsections gy*, tips with	
Orer=ection()	
Designation Trying to separate encourse differentiation	from receiver 2.20,0 place
hanny verying diling i this might lead to presence the	or several results. See
be pred non bine.	
E CITTER ATTAC	
GIVELING	





Fig. 5. Feature values of 3 activities

dataset. The dataset uses an accelerometer sensor which has been embedded in a smartphone. A number of features from the time-domain and



frequency-domain are extracted from the raw accelerometer signal. PCA is performed on the original features to distinguish low and high variances and reduce the dimensionality of data. This approach is evaluated by comparing the precision, recall, F-score and accuracy of four different types of machine learning classifiers.

In particular, this paper investigates which features that can contribute to the higher classification rate of activity recognition. Based on the normality tests, it is proven that the data is not in a normal distribution, therefore non-parametric classification tools are used to classify the activities. A con- siderable improvement can be observed by using PCA-based features which can better classify and improve the recognition rate rather than using original features extracted from raw data as the input classifiers. Furthermore, features that are selected from the frequencydomain have shown to have higher ac- curacy rather than the time-domain features. In another word, frequency-domain features have more robust performance than the selected time-domain features.

As for the future work, the activity recognition can be per- formed using another approach such as probabilistic methods and the accuracy can be compared with this classificationbased method. Moreover, the recognition of ADL can also be extended to other types of activities including context-based activities such as watching television, toileting and cooking. This application can be used to help caregivers in monitoring the health of elderly people, particularly the ones who are living independently in their own homes and identify any abnormalities regarding their daily lives.

REFERENCES

- S. Chernbumroong, A. S. Atkins, and H. Yu, "Perception of Smart Home Technologies to Assist Elderly People", 4th Int. Conf. Software, Knowledge, Inf. Manag. Appl. (SKIMA 2010), no. March 2016, pp. 1–7, 2010.
- [2]. J. Liming Chen, Member, IEEE, Chris Nugent, Member, IEEE, and George Okeyo, Member, IEEE, "An Ontology-Based Hybrid Approach to Activity Modeling for Smart Homes", IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS, VOL. 44, NO. 1, FEBRUARY 2014.
- [3]. W. Xiao and Y. Lu, Daily Human Physical Activity Recognition Based on Kernel Discriminant Analysis and Extreme Learning Machine, "Math. Probl. Eng., vol.

2015, 2015.

- [4]. F. Sposaro, G. Tyson, "iFall: an Android application for fall monitoring and response", IEEE EMBS, Mineapolis, Minasotta, USA, September 2–6, 2009. .
- [5]. Yuan and J. Herbert, "Context-aware Hybrid Reasoning Framework for Pervasive Healthcare", "Pervasive Ubiquitous Computing., vol. 18, no. 4, pp. 865–881, 2013.
- [6]. L. Chen, C. Nugent, and G. Okeyo, An Ontology based Ontologybased Hybrid Approach to Activity Modeling for Smart Homes, "IEEE Trans. Human-Machine Syst., vol. 44, no. 1, pp. 92–105, 2014.

International Journal of Advances in Engineering and Management ISSN: 2395-5252

IJAEM

Volume: 02

Issue: 01

DOI: 10.35629/5252

www.ijaem.net

Email id: ijaem.paper@gmail.com