International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

HUMAN ACTIVITY RECOGNITION USING SMARTPHONE ACCELORO METER

M.Swathi Reddy, Professor, Department Of AIML, SICET, Hyderabad
Kaki Reddy Vamshidar Reddy,Mulakalapalli Naveen Kumar
UG Student, Department Of AIML, SICET, Hyderabad

Abstract

Smartphones are now almost everywhere. Their numerous builtin sensors enable continuous measurement of activities of daily living, making them unique for health research. Researchers have proposed various huma n activity recognition (HAR) systems designed to interpret smartphone measurements for different types of physical activity. In this review, we summarize existing methods for smartphonebased HAR. To this end, we searched Scopus, PubMed, and Web of Science for peerreviewed publications up to December 2020 on the use of smartphones for HAR. For the recognition study, we extracted information regarding the physical loc ation of the smartphone, its sensors, and the type of physical activity examined, as well as the data transfer p rocess and classification process. We therefore analyzed 108 articles and described the various methods used for data collection, preliminary data extraction and classification, identifying relevant applications and their choices. We conclude that smartphones are good for HAR research in health research. For public interventio ns, future research should focus on improving data quality, addressing missing data, and more participants a nd activities. This should provide sufficient rest for the placement of mobile phones and provide more infor mation for participants to complete and share data. Source code for the implementation of methods and algor ithms.

Introduction

Education has always been driven by data. By 20201, more than 5 billion mobile phones with multiple senso rs (such as accelerometers and GPS) will be in use, capturing detailed, continuous and objective measureme

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

nts of all aspects of our lives, including physical activity. The increasing prevalence of smartphones worldwide presents an unprecedented opportunity to collect data to study human behavior and health.With sufficient storage space, powerful processors and wireless transmission, smartphones can collect large amounts of personal data over a long period of time without the need to add or measure hardware Data collection tools for

the purpose and remeasurement of normal and emerging risks to humans. Related behaviors, including but not limited to sedentary behavior, sleep, and physical activity, can be monitored in real time via a smartphone, for personal effort or for subsistence purposes. More importantly, unlike some watch games 2, smartphones are not niche products but have become universal and are increasingly used by people of all ages, both in terms of design and marketing. Versions 3 and 4 are used by users.

Their adoption in health research is further supported by other portable devices, primarily accelerometers, showing a link between physical activity and health outcomes (including obesity, diabetes, and various cardiovascular diseases), mental health, and health problems. mortality rate 59. However, there are some important limitations to the use of wearable devices in public health research: (1) ownership of these devices is lower than that of smartphones 10 ; (2) most people do not use wearable devices after 6 months of use11 (3) Wearable devices generally cannot receive raw data. This last point often forces researchers to rely on specialized equipment, reducing the efficiency of current biomedical research12 and making uncertainty in measurements almost impossible. Human Activity Recognition (HAR) is a technique designed to classify human behavior in real time based on individual measurements (speed, rotation rate, area of control, etc.) taken by individual digital devices. This topic has emerged in the machine learning community in recent years; As of this writing, more than 400 articles have been published regarding smartphone use of HAR. This is an increase compared to several publications published several years ago (Figure 1). As it becomes easier to collect data using smartphones, analysis of the collected data is considered important in health research13-15. To solve the analytical problems of HAR, researchers have proposed various algorithms that differ in the data used, the way it processes the data, and the classification process used individually for reflection and/or distribution. Published studies use existing methods and offer new ways to collect, perform, and classify act

Index in Cosmos
March 2024, Volume 14, ISSUE 1
UGC Approved Journal

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

ivities of daily living. Authors often discuss data filtering and custom selection techniques and compare the accuracy of various machine learning classifiers with existing data or data they collected for specific studies. Results are usually calculated using the accuracy of classification for different activity groups (e.g. walking, sports and exercise). annoyed. The procedure must be adapted to the physiology (e.g.

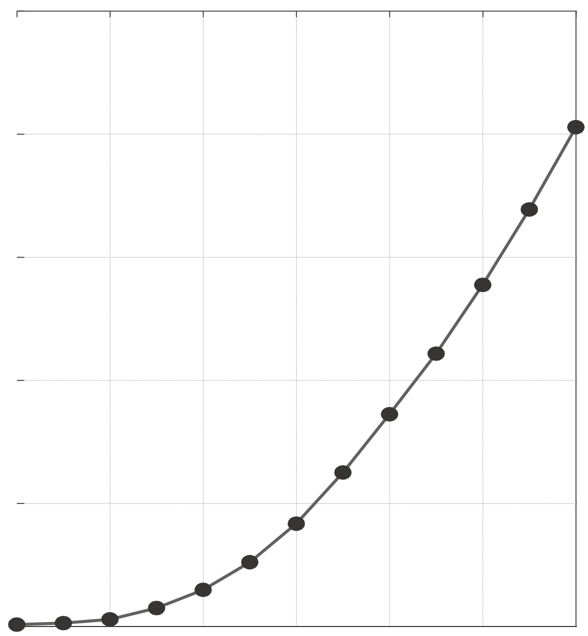

Fig. 1 Cumulative number of peer-reviewed articles on human.

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

Differences in smartphone users' characteristics (e.g. body type, mobility, walking speed) and characteristics (e.g. body type, mobility, walking speed) as well as differences in production sites (such as buildings and green spaces) that provide physical and social support for human activities. Additionally, data collection and statistics often used in HAR can be affected by de vice location (where the user's phone is on their body) and orientation (16), making it difficu lt to translate the collected data into terms and interpret the obtained results. Given that the m ain challenge in the study is to move from data collection to data analysis, we focus our analy sis on the methods used in data collection, data processing, extraction and classification. We use smartphones to gain insight into the complexity and diversity of HAR, the types of data c ollected, and the methods of translating digital measurements into human activities. We discu ss the generalizability and reproducibility of a method, that is, features that are important and relevant to a large number of diverse studies. Finally, we identify challenges that need to be a ddressed to enable broader use of the HARbased smartphone in public health research. article s, 2020, PubMed, Scopus and Web of Science databases. Filter data for “action” ANDphrases (“analysis” or “prediction” or “classification”) AND (title, summary, and subject) — smartphone — OR — mobile phone — OR —
mobile phone . The search was limited to all articles written in English. After removing dupli cates, we read the names and contents of additional posts. Studies that did not investigate the HAR pathway were excluded from further analysis. We then filtered out studies that used assi stive devices, such as portable devices or media, and studies that required more than one smar tphone. Only for consumer smartphones (personal orDebtor) read all the letters. We did not in clude studies that used smartphones or cameras for classification because these can collect inf ormation about one's surroundings, including information about those who disagree, which m ay hinder broad use of the road. To focus on studies based on free space, we excluded studies that used devices attached or attached to a fixed location on the body. review (Figure 2). 108 documents were included after removing items that did not discuss HAR algorithms (n = 793), used additional devices (n = 150), or used a body-
mounted microphone, camera, or smartphone (n = 149)Most HAR methods have four stages:

data collection, preliminary data, extraction and classification (Figure 1). 3). Here we will des cribe these steps and briefly describe the main criteria of the reviewed studies for each step. F igure 4 shows the characteristics of each subject. Essentially, we break down the data collecti on process into sensor type, test environment, performance analysis, and smartphone location We show which research uses corrections, the noise filter process, and the dynamic changes we write a research paper on before writing the test data. features are extracted according to t he type of signal and we show the use of feature selection, methods of classification of the rec eived work, the classification used and of course the applications eventually published, we m ake an effort to promote production and general research; We provide a brief description of th e issues before moving on to the results. In the studies reviewed, it was seen that the informat ion was generally obtained from fewer than 30 people.

We analyzed the data selected for study to learn details about population research, measurem ent, effectiveness, and smartphone configuration. Do this in a nearby open area. In such an en vironment, research participants are asked to perform various activities in a specified manner and related to the specified object. The time and duration of the study are usually determined by the study, and participants are monitored by members of the research team. A less commo n method is to observe in a free environment where people work without specific instructions . These studies will lead to a deeper understanding of individual behaviors and unimaginable activity patterns that arise from real life. Freerange studies also allow researchers to evaluate behavior at 22 weeks or 23 months compared to the laboratory. A. The studies in our review f ocused on a variety of smaller activities, such as sitting, standing, walking, running, and clim bing stairs. Infrequent activities that include various movements, sports, exercise and daily ho usehold activities such as slow walking, normal walking and brisk walking24; various types o f transportation, such as cars, buses, trains, subways and ferries25. Quick turns26 and househ old chores activities such as sweeping the floor or walking with shopping bags27. Recent stu dies have focused solely on cognitive walkability28,29. As shown in Figure 4, the various me asurements in the study were divided into several groups: “Posture” refers to lying, sitting, sta nding, or a combination of water. This activity "Mobility" refers to walking, climbing stairs a

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

nd turning. , taking the elevator or escalator, running, cycling, or any of these activities; a game. At the time of this writing, smartphone models are equipped with a variety of hardware and systems that can be used for activity monitoring, including accelerometers, gyroscopes, magnetometers, GPS, proximity and light sensors, including collecting information about the environment. pressure, humidity and temperature (Figure 6). It is difficult to accurately predict the use of sensors over time due to the multitude of smartphone manufacturers and models and differences in adoption across countries. Accelerometers, gyroscopes, magnetometers, GPS, and proximity and light sensing had greatly improved by 2010, according to international data on smartphone market share 30 and specifications of the flagship model 31 announced a few years later. Other smartphone sensors. For example, the Samsung Galaxy S III, released in 2012, includes a thermometer, while the Samsung Galaxy S4, released in 2013, includes a thermometer and a hygrometer. instrument and Some studies have taken advantage of the extensive capabilities of smartphones. For example, in addition to location measurements such as the distance between the smartphone and the person's body, some researchers also use proximity sensors and light to detect changes in the pocket and its contents depending on the change in illumination. 37. Sensor selection is also influenced by secondary research objectives such as ease of deployment and reduction of battery consumption. In these studies, data collection is done using a single sensor (e.g., accelerometer22), a group of sensors (e.g., accelerometer and GPS38), or by deliberately varying the sample frequency or pattern (e.g., switching between written and non-written). time) reduces the cost of written and processed information39. Due to the lack of indoor GPS reception, another information sensor is used to supplement the information. The GPS satellite signal will be absorbed or attenuated by walls and ceilings17 up to 60% of the time in the home and up to 70% of the time in the home. time. It's 23 o'clock in the subways. Short time. The choice of sampling frequency is usually a tradeoff between measurement accuracy and battery consumption. In the studies reviewed, sample frequencies are generally between 20 and 30 Hz for inertial sensors and between 1 and 10 Hz for barometers and GPS. The most significant changes occur in studies where limited electricity is important (e.g., accelerometer sampling at

1 Hz40) or where researchers conduct research using art methods (e.g., timefrequency decom position method). or active models that require higher sampling frequency (e.g., accelerometer sampling at 100 Hz41). Some studies have shown that inertial sensor sampling at 20 Hz provides sufficient information to distinguish different types of traffic42, while a sampling rate of 10 Hzis sufficient to distinguish different types of motion43. One study showed that reducing the sampling rate from 100 Hz to 12.5 Hz tripled the data acquisition time on a battery at position 44 alone. This is important due to the lack of reallife situations and the huge impact it has on smartphone inertial sensors. The main challenge of freeliving HAR is that the data recorded by the accelerometer, gyroscope and magnetometer sensors differ between the upper and lower body because the device is not fixed in a specific location or direction45. Therefore, studies need to collect information from as many institutions as possible to ensure good results. In the literature reviewed, study participants were frequently asked to put the device in their pocket (front or back) and were asked to place the smart device on their phone, although most studies also considered another location such as a pocket, purse, or backpack. It can be placed in the hand (49) or in the cup holder (50). However, we also remember the many ways to ensure that this process operates in a controlled and free manner; for example, via smartphones 22 or built-

in pedometers 53 with GPS data. GPS data produces "poor" data. Annotations are also made using builtin microphones (54), cameras (18, 20) or additional body wear (29), but all HAR pipes are used by the mobile phone; external (remote) server using a cellular, WiFi, Bluetooth, or wired connection. > Data PreprocessingWe use the term data preprocessing to refer to the process of editing, cleaning and converting parameters into HAR data. This step is necessary for three reasons: (1) Measurements on smartphones are often less stable than the researchlevel data obtained, so the compared data limit may be uneven or lost, or the current peak may not affect the individual. ; (2) The spatial orientation of the device (e.g., how the phone is placed in a person's pocket) affects the triaxial measurement of the inertial sensor, thus potentially degrading the performance of the HAR system; Data collection time Despite careful planning and execution, data quality may be affected by other unforeseen factors such as noncomplia

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

nce of study participants, time inconsistencies in assessment activities (e.g., unequal data), or learning issues. For example, to reduce the discrepancy between the proposed and effective m odel, researchers suggested using linear interpolation 55 or spline interpolation 56 (Figure 8). Such services work with a variety of sensors, primarily accelerometers, gyroscopes, magneto meters and barometers. Additional time domain preprocessing takes into account data prunin g to remove redundant data components. For this purpose, the beginning and end of each acti vity, that is, the short period for an activity type, are designed so that they do not represent th at activity. Time calculations are sometimes specified for complex processes such as deep. N eural networks20,82,111 and learning environments112, with symbolic representation85,86 a nd comparative analysis46. As discussed below, comparison of results is difficult or impossib le. The literature review provides a detailed description of key aspects such as data collection, data preprocessing, extraction and classification. The studies were conducted with one or mo re objectives in mind, such as limiting inefficiencies (e.g., no GPS signal reception at home), minimizing requirements (e.g., performing online data directly on the device), and completin g accurate classification cation. (e.g. no GPS signal reception at home). Our review highlights the most common methods and offers alternatives. Importance of the algorithmhealth issues are taken into account

specific conditions of the study group (e.g. age distribution, use of technology, and the natur of the disability Although most of the data is collected in clinical settings, algorithms trained using data collected in these control areas are free There is little evidence that it leads to life. In a free environment, the time, frequency and specificity that the environment and individual 's ability meet and these degrees of freedom should be taken into account when creating the H AR system. It is important that this information be made available in a free environment, bec ause the public health reality of the HAR system will be seen through a portable and scalable application in longterm studies or interventions around the world. Being able to volunteer. Th is facilitates the process of data processing and distribution, but also limits the width of the pa th to different cultures. This last point has been recognized in two studies. In the first study, t he authors found that the performance of the employee trained on the younger group was sign ificantly reduced when applied to the older group 18. Similar conclusions can be drawn from secondary studies where observations made in healthy individuals have not been replicated in other countries. Individuals with Parkinson's disease 21. These facts demonstrate responsibili tyThe concept of algorithmic fairness (or fairness in machine learning) is that the performanc e of an algorithm should not depend on differences such as race, ethnicity, gender, age, and di sability. A clear example of this is when some large companies, including IBM, decided not t o provide facial recognition technology to police station 115, while the European Commissio n decided to ban the use of facial recognition in public places116. These decisions were made after it became clear that facial recognition algorithms performed poorly when applied to peo ple with dark skin. It has a solid aspect. However, this is rarely seen in real life and these stud ies should be considered more than proof of concept. Developments can assume that these ac tivities are general patterns of behavior, including when the smartphone is not in one's hand, or measure the uncertainty associated with the classification of each type of action84. This ca n also provide a flexible approach leading to assessments/interventions targeting various aspe cts of health, including reducing sedentary behavior, increasing transportation (e.g., walking, cycling, or public transit), and improving circadian/sleep patterns. The importance of this pro blem is explained in a recent paper that demonstrates a method for estimating missing smartp hone data. The GPS authors found that interpolation reinforcement reduced the average error of all daily movements by 0%, relative to linear interpolation, a simple method for resolving missing data. factor of ten 118. The upside of missing data is the need to report uncertainty in a statistical way, from inconsistencies in the original data to the conclusions researchers are c onfident to draw from the data. Dealing with missing data and accounting for uncertainty is i mportant because it means you don't have to exclude study participants because their data doe sn't follow a success story; Everyone is important, every little piece of information about ever yone is important.

REFERENCES

[1] Sachin Kumar, Durga Toshniwal, "A data mining approach to characterize road accident locations", J. Mod. Transport. 24(1):62–72..

[2] Tessa K. Anderson, "Kernel density estimation and Kmeans clustering to profile road accident hotspots", Accident Analysis and Prevention 41,359–364.

[3] Shristi Sonal and Saumya Suman "A Framework for Analysis of Road Accidents" Proceedings of International Conference on Emerging Trends and Innovations in Engineering and Technological Research (ICETIETR)

[4] Analysis of road accidents in India using data mining classification algorithms- E. Suganya,S. Vijayrani.

[5] Hao, W., Kamga, C., Yang, X., Ma, J., Thorson, E., Zhong, M., & Wu, C., (2016), Driver injury severity study for truck involved accidents at highway-rail grade crossings in the United States, Transportation research part F: traffic psychology and behavior, 43, 379-386.

[6] Li, L., Shrestha, S., & Hu, G., (2017), Analysis of road traffic fatal accidents using data mining techniques, In Software Engineering Research, Management and Applications (SERA), IEEE 15th International Conference on (pp. 363-370). IEEE.

[7] El Tayeb, A. A., Pareek, V., & Araar, A. (2015). Applying association rules mining algorithms for traffic accidents in Dubai. International Journal of Soft Computing and Engineering.

[8] Bahram Sadeghi Bigham ,(2014),ROAD ACCIDENT DATA ANALYSIS: A DATA MINING APPROACH, Indian Journal Of Scientific Research 3(3):437-443.

[9] Divya Bansal, Lekha Bhambhu, "Execution of Apriori algorithm of data mining directed towards tumultuouscrimes concerningwomen", International Journal of AdvancedResearch in Computer Science and Software Engineering, vol. 3, no. 9, September 2013.

[10]S. Krishnaveni, M. Hemalatha, "A perspective analysis of traffic accident using data mining techniques", International Journal of Computer Applications, vol. 23, no. 7, pp. 40-48, June 2011.