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Classification Algorithms in Human Activity Recognition using Smartphones

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***Abstract*—**Rapid advancement in computing technology brings computers and humans to be seamlessly integrated in future. The emergence of smartphone has driven computing era towards ubiquitous and pervasive computing. Recognizing human activity has garnered a lot of interest and has raised significant researches' concerns in identifying contextual information useful to human activity recognition. Not only unobtrusive to users in daily life, smartphone has embedded built-in sensors that capable to sense contextual information of its users supported with wide range capability of network connections. In this paper, we will discuss the classification algorithms used in smartphone-based human activity. Existing technologies pertaining to smartphone-based researches in human activity recognition will be highlighted and discussed. Our paper will also present our findings and opinions to formulate improvement ideas in current researches' trends. Understanding research trends will enable researchers to have clearer research direction and common vision on latest smartphone-based human activity recognition area.

***Keywords*—**Classification algorithms, Human Activity Recognition (HAR), Smartphones

I. Introduction

NOWADAYS, computers and humans have converged into one inseparable entity in daily life. Computers' existence has become ubiquitous in human's daily life. This factual reasoning has led into emerging computing perspective so called pervasive computing where computing process is already existing everywhere and every time in everyday objects. One of the central elements of pervasive computing is the ability to recognize and understand its users dynamically. That ability can be provided by obtaining the current and updated information about the user. The recent information about users is basically the information about context of users. Context of users can be any information and status in regards to users' status, user's location, user's environment, and so on. Context-aware computing is then introduced to address the challenges to recognize and to understand them more especially under dynamic changes from users.

There are growing interests on recognizing context generated from human notably known as human activity recognition.

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Recognizing human activity covers several lower-level bodily actions happening in coarse-grained perspectives ranging from falls detection, gait and posture-derived information, metabolic energy expenditure, up to monitoring physical activity. A research in physical activity recognition is basically a research aimed at an ability to identify a series any bodily movement of an object. In regard to human activity recognition, it is aimed to identify physical activity performed by human as an object of research.

By involving smartphones, researchers aim towards successful human activity recognition with users being comfortable in mind. With their advantageous characteristics compared to wearable sensors, human activity recognition of particular users is expected to be performed unobtrusively when observing people behaviors and their surrounding environments. Additionally, being different from wearable sensor-based systems which require separated processing unit, by using smartphone it is expected to have context processing integrated into one device where data has been collected. This will promise faster and more reliable decision result as it no longer requires specific communication medium between processing unit and sensor. Response with particular services once recognition is successful also now being possible as smartphone has wide range of connectivity options. With those several possibilities, eventually, smartphone-based system will enable human activity recognition being portable even during intense users' mobility activities or movements.

II. Related Works

A. Human Activity Recognition

One of the contexts that researchers want to recognize is users' activity. Activity recognition (AR) is a more specific field in context-aware computing where researchers aim to recognize any actions from users. Typical activities to detect vary from mechanical process like activities of daily livings (ADL) until socio-spatial processes like meetings. The advances in activity recognition will enable computer systems to bring better services and user experiences towards their users such as in healthcare services and living services.

Activity recognition basically concerns about the users and/or their surrounding environment. In socio-spatial process like meetings, an activity recognition system must be able to address both users and their environment. In a facet of activity recognition, Human Activity Recognition (HAR) solely focuses on humans as users in its concern. In practical, activity recognition can be conducted aiming to detect single user activity recognition from recognizing ADL of a person up until multi-user activity recognition like in surveillance and monitoring situation.

Human Activity Recognition researches mostly observe human actions to obtain understanding on types of activities that humans perform within a time interval. Human Activity Recognition dominantly observes a series of physical actions that construct one physical activity. Physical activity is the essential human activity that mainly garners attention from many researchers to recognize. It is defined in [31] as any bodily movement produced by skeletal muscles that result in energy expenditure beyond resting expenditure. Activity itself is a sequence of actions while recognition is an ability to identify of something from previous knowledge or sensing or achievement. Due to the rapid advancement of mobile phone technology, there exists a new category for mobile phone categorized as smartphone. Smartphone is a more advanced mobile phone that is capable to perform computing process just like a personal computer, but with smaller resources capability. Smartphone is equipped with embedded built-in sensors that enable it to sense the smart pone users' context to deliver more personalized user experience. The emergence of smartphone excites many researchers to open a research possibility to have smartphone involved into unobtrusive activity recognition research especially pertaining to human as the object of research. Comparing wearable sensor-based HAR systems with smartphone-based HAR systems, smartphone has several unique advantages to prominently appear as cutting-edge device for activity recognition in daily life. Smartphones have several built-in sensors embedded into one integrated device. Smartphones are also able to provide wide range of connectivity option in one integrated device. Furthermore, smartphones also possess computing capability, although they are not as powerful as dedicated processing unit as used in wearable-sensor systems. Ultimately, smartphones have been very personalized devices in human's daily life so that implementation using smartphone will edge wearable sensor-based systems in the most critical issue: interaction with users. Wearable sensor-based systems have been reported to create discomfort to their users as being odd devices to be embedded to humans. In contrast, smartphone will be unobtrusively acting as the device as it has been very common and usual to wear and bring smartphone in our daily life. HAR using smartphone has been mainly approached by using motion sensor like accelerometer such as in Table [32][33]. Besides sensory motion, HAR has also been studied so interestingly through multimedia sensor like image-based sensor in [28] which recognizes human activity through image tagging and also in [34] using audio-based sensor like microphone based on noise in trousers. The most common physical activity being active interest among researchers is Activity of Daily Livings (ADL). Activity of Daily Living (ADL) is a way to describe the functional status of a person. Monitoring and observing ADL of a person through his physical activity recognition is essential in healthcare application. Abnormality in ADL may indicate serious health problem. In other case, patients in post-operative surgery require supervision to ensure whole process of a surgery is carried out well.

As for smartphones, they have been popularly incorporated as tools for encouraging and monitoring physical activity and healthy lifestyles such as activity daily livings and diets, for assistive and supporting patient undergoing health rehabilitation and treatment, and for many other health problems. For example, text messaging services have been used in college smoking cessation [32], and to provide diabetes education [35].

B. Applications of Human Activity Recognition

Increasing interest from researchers in human activity recognition field has various underpinnings. There are several possible applications that can be developed with human activity recognition enhancing the service significantly. Application examples can vary from application in smart homes, on-demand information systems, surveillance and monitoring systems, interactive interfaces for mobile services and games, up to healthcare application for both inpatient and outpatient treatment.

Human activity recognition is mainly targeted towards development of intelligent healthcare system. Health problem is ultimately the critical issue that motivates researches to conduct researches in human activity recognition. Researches for healthcare having the most significant attention is presented as in [1], [2], [3], and [4]. W. H. Wu et al. in their paper [1] propose MEDIC: a patient monitoring and medical diagnosis system architecture by using physiological body-worn and wireless contextual sensors network. X. Long et al. in their paper [2] measure daily energy expenditure in daily activities and sport activities as a base on physical activity classification. Bartalesi et al. [3] interestingly use kinesthetic wearable sensor for stroke patients to detect their upper limb gesture where this works followed up in Tognetti et al. [4] that also interestingly use garment-based sensors like upper limb kinesthetic garment (ULKG) and sensing gloves.

Besides healthcare application, human activity recognition is also made use in smart homes application. Smart homes enable intelligent control by residential occupants to various automations in residences. Smart homes are equipped with various sensors to capture contexts in their surroundings and with intelligence to process the contexts so that they can respond flexibly according to the contexts. Human activity recognition in smart homes mainly employs contexts' identification and recognition from multimodal features using multiple types of sensors. Tae-Seong Kim in [5] uses multimodal features that later being fused together. He obtains contexts from video sensor-based HAR system up to motion sensor-based HAR system. One interesting fact from his project named Smart homes: Personal Life Log is that he realized the potential of smartphone in human activity recognition in smart home perspectives. Therefore, he also has experienced using smartphone in his smart home project. This is interesting because smartphone is implemented in smart home application most dominantly as merely the remote controller. Liang-Wang et al. present their work in [6] which focus more in low-level activity features like human-environment interaction in multimodal contexts using multiple wearable sensors.

More specifically, a group of researchers in [7] focus more on data fusion techniques for many types of sensors deployed. However, there are still researches conducted that focus on solely vision-based approaches using video/image-based system. In [8], researchers use both real-time video feeding and stored video files as input to reveal contexts in human recognition. Researchers in Stanford [9] propose an idea that multi-view from multiple cameras fusion for whole area observation has yielded reasonable performance for human activity recognition in their smart studio laboratory. Yi-Ting Chiang et al. formulate coarse-grained description encapsulating multiple sensory inputs into a framework as in [10] for activity recognition in a smart home.

In surveillance and visual monitoring technology, there is also strong demand to equip surveillance infrastructure becoming more intelligent. Common implementation of surveillance and monitoring technology is still requiring human as controlling subject which is very costly to achieve consistent monitoring thus still prone and vulnerable towards negligence of duty. Human activity recognition is gaining momentum pertaining to this demand. Mostly, to cater the demand, vision-based approaches in video and image are used as in [11], [12], and [13]. Another exciting application using human activity context-aware ideas is interactive interfaces aimed to multimedia visualization guidance, entertainments, games, and even advertisements. Researchers in [14] and [15] have aimed to develop a tour guidance benefitting from context-aware ideas. The popular Nintendo Wii remote controller and infamous Kinect for X-Box have clearly highlighted how context-aware ideas have successfully leveraged entertainment devices for better and interactive interfaces enriching user experience. Additionally, with Wii controller, a group of researchers [16] has begun studying gait recognition. Researchers have proposed in [17] about context-aware advertisement inside public transportation, especially in taxi. Their opinion is that context-aware can enhance accurate advertisements delivered towards correct target of advertisements considering contextual information such as gender, group of age, weather, and location-based from starting point, current location, up to passengers' destination.

C. Wearable Sensors in Human Activity Recognition

Currently, mainstream researches in human activity recognition involve many types of wearable sensors decoupled with separated processing units. They are mainly computers like dedicated servers, to process collected data from sensors and perform sequential process like feature extraction and classification. However, due to emergence of smartphone, there has been significant interest generated to implement smartphone in human activity recognition.

Human activity recognition can be approached through multiple perspectives. In terms of sensory input media, HAR has been mainly approached by using motion sensor like accelerometer such as from [18] and [19] up until [20]. Besides accelerometer-only input sensor, accelerometer is recently also combined altogether both with gyroscope such as in [21] and also with wearable camera as in [22] as input sensors.

Considering the weakness of accelerometer in recognizing activities little movement, Sung-Ihk Yang and Sung-Bae Cho in [23] also combine accelerometer with physiological sensor worn in human arms to obtain human physiological signals such as galvanic skin response, skin temperature, heat flux, energy expenditure, and metabolic equivalents. HAR is also researched using vision-based sensor especially via video camera either by emulating condition for surveillance and neighborhood monitoring like in [11], [12], and [13], by constructing 3D modeling from several motion images like in [24], or by studying motion context such as tennis match in [25]. Ultimately, Teixeira et al. in [26] study HAR with a fusion of multimodal features using multiple sensory inputs from obtaining visual input with camera nodes until motion input by placing accelerometer, gyroscope, and magnetometer on arms of research's subjects.

D. Human Activity Recognition Frameworks

In this paper, we introduce several existing human activity recognition frameworks using smartphone. Human activity can be inferred using smartphone through its multiple sensors embedded inside. Before having the ability to sensing, Emiliano Miluzzo et al. [27] argues that the phone itself must have its current sensing context. Phone sensing context here is a context of phone prior to performing sensing task. It's essential to detect phone sensing context because it can determine limitation of sensing and as well as the fidelity in such a situation where such a sensor works best while others not. Hence, the accuracy is better achieved with usage of correct sensor in each different situation. For example, to achieve air-quality sensing, Emiliano Milluzo et al. stress out the importance of determining phone sensing context as such if a phone is in owner's pocket or not. Such situation is important because air-quality sensing will not represent real situation well during it being inside pocket. This phone sensing capability is presented through a framework of human activity and its sensor in Discovery Framework. In that framework, they obtain 23-dimensional feature vector from an audio clip. They use microphone in iPhone and Nokia N95 to perform research. Using FFT power computation over a threshold T, they argue that they can determine whether the current phone position is inside pocket or not. Chuan Qin et al. [28] proposed another way of using smartphone camera to introduce image tagging framework called TagSense that senses images about people, contexts, and their activity via image processing. TagSense basically tries to address issues to extract information from images such as who are in the picture, what they are doing, and when and where the picture was taken. Another framework is introduced by Hache, G. et al. [29] that addresses healthcare issue under patient rehabilitation program. The Wearable Mobility Monitoring Systems (WMMS) framework is designed for patients' mobility monitoring in those who have physical disability. Using Blackberry phone combined with external board, mobility monitoring at a patient is done via several sensors embedded in both phone and external board that sense multimedia context and biomechanical context of a patient. In addition, Heng-Tze Cheng et al. [30] present idea of beyond using single phone to sense contexts of users by consolidating multiple smartphone sensing capabilities into one concurrent sensing group. Under the framework named as OmniSense, they are able to group all nearby phones and then to sub-sequentially extract the data from all smartphones' sensors. The framework offers also inference capability on users' contexts from those multiple smartphone through a pre-trained model.

III. Feature Extraction

Raw data from sensors and devices contain many hidden information and noise. Feature extraction could find the useful hidden information from the raw data. Moreover, it could eliminate the noise in the raw data from data collection process or sensors. Selecting suitable features will reduce the amount of time and memory required by classification process. Therefore, it may improve the performance of the classification algorithm. Classification algorithm with minimum classification time and memory is very beneficial for implementation of HAR using smartphones. We have made a comparison among researchers' work regarding the feature extraction. Fig. 1 shows the number of features used by researchers to classify human activities. Moreover, Table 1 shows the feature group used based on the references.

According to Fig. 1, researchers use different number of features from 3 to 148 for classification process. There is a thread of between number of features and classification accuracy. Ville Könönen et al. mentioned in [17] that bigger number of features normally tends to provide higher classification accuracy because it contains most of the values about a particular class. However, it requires high computation resources such as time and memory. On the other hand, smaller number of features requires small computation resources and provides lower classification accuracy because it contains a small number of values for a certain class.

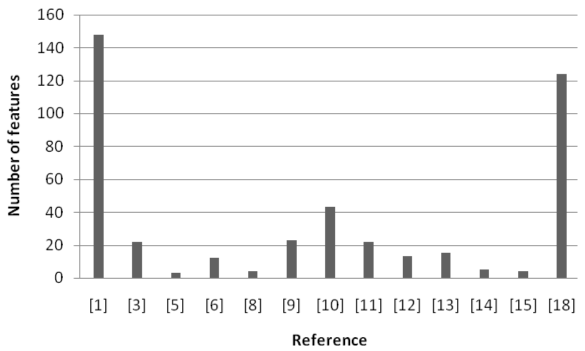

Fig. 1 Number of features used in the references

TABLE I
Feature Group used in References

Feature Group	Reference
Magnitude	[36–50]
Frequency	[27], [34], [38], [40], [41], [43], [46–50]
Correlation	[37], [38], [40], [49]
Other	[51], [52]

Pedro Canotilho Ribeiro and Jose Instituto Santos-Victor in [20] have proposed two large feature groups for HAR from video. The first feature group is used for storing the instantaneous position and velocity of the tracked subject. The second feature group is based on the instantaneous pixel motion inside a certain region in a video. Thus, based on our survey, we have grouped all features used by researchers for HAR using smartphone into four categories; magnitude-based, frequency-based, correlation and others. Below is the explanation of each category.

1) *Magnitude-based features*. This category contains features that are based on the magnitude values of sensors. Features in this category are mainly based on the raw values from sensors. There are x-axis, y-axis, z-axis, axes means, axes standard deviation, axes minimum, axes maximum, axes min minus max, axes max minus min, kurtosis, average absolute difference, zero crossing rate and 75% percentile.
2) *Frequency-based features*. This category contains features that are based on the frequency values of sensors. Most commonly used feature is from Fast Fourier Transform (FFT). Other features in this category are frequency-domain entropy, maximum frequency, FFT energy, FFT mean and FFT standard deviation.
3) *Correlation features*. Many researchers use correlations between axes or between features as part of their features.
4) *Other features*. Some works proposed new features that are not in the three previous categories. Eladio Martin et al. [5] proposed five novel metrics. A. M. Khan et al. [8] used autoregressive coefficient and signal magnitude area for their kernel discriminant analysis.

The usage of the features groups in researchers' work is shown in Fig. 2. Nearly 80% of works use magnitude-based features since the values are easier to be calculated. Based on our survey, few researchers explore correlation as their feature for classification.

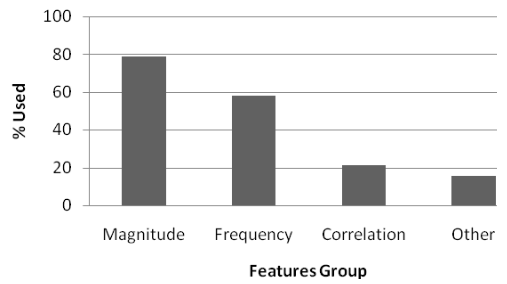

Fig. 2 Percentage of features group used for HAR classification

Many works have explored the usage of other than smartphone's sensors data for HAR classification. The integration with smartphone's sensors data could improve the performance the algorithm. Daniele Riboni and Claudio Bettini implement their COSAR in [2] by integrating ontology of possible activities that can be done at a particular location.

Moreover, their model takes activities' histories into consideration for prediction of current activity. Another work by Nicola Bicocchi et al. [14] considered time features of sliding windows in their instance-based algorithms. Moreover, they use majority voting on the classification of sliding windows. Other interesting data that has been examined for HAR classification is heart rate [17]. The authors get the heart rate signal from the ECG electrodes attached to the users. T. Scott Saponas et al. [19] used Nike+iPod Sport Kit to get additional data from classification. It consists of a sensor placed in the shoe to track user's running pace and distance during a workout.

IV. Classification Algorithms

One of the important components in HAR is classification algorithm used to classify different activities and actions based on the user inputs. The algorithm usually is executed either on a workstation or user's smartphone. The selection of classification algorithm is based on the capability of the processing platform to execute the algorithm. Moreover, the evaluation method is used to measure the performance of the classification algorithm. This section compares three components that include classification algorithms, evaluation methods and processing platform. Table 1 summarizes the three components for recent works in HAR. Most researchers use supervised classification algorithms. The algorithms are trained with labeled samples to generate classification model. Then the model will be used for classification of input data. From the survey, the most popular algorithms are Decision Trees, k-Nearest Neighbor, Naïve Bayes, Support Vector Machine and Neural Network. Brent Longstaff et al. in [5] introduce algorithms using semi-supervised and active learning methods. They investigated two semi-supervised learning methods which are self-learning and co-learning. Self-learning use one classifier to classify unlabeled data. If the confidence level of the prediction by the classifier is high, the data will be labeled with the prediction. Another semi-supervised learning method called co-learning that uses multiple classifiers to classify unlabeled data. Since supervised classification algorithms need intensive computation to generate models from training data, thus most of the implementations are being done in servers. There are some implementations in smartphones [1], [15], [12], [6], [18], [21].

They use instance-based classification algorithms, such as k-Nearest Neighbors, to classify human activity based on the user's environment inputs. These kinds of algorithms are suitable to be implemented in smartphone because its need less computation resources. On the other hand, some researchers [13], [23] generate classification model by executing the algorithm at a workstation. Then bring the model into smartphones for classification of input data.

Evaluating the classification algorithms used for HAR is very important since it shows which algorithm performs better. From our survey, the popular evaluation methods are n-fold cross validation (commonly 10-fold), precision and recall measures, F-measures and accuracy. Claudia Nickel et al. in [14] used error rates from biometric matching, which are False Non-match Rate (FNMR) and False Match Rate (FMR) to evaluate their method. FNMR may be compared with false positive and FMR with false negative.

V. Discussion

There are a lot of rooms for improvement in the area of HAR research. We suggest a list of actions to all researchers for the betterment of HAR research.

Explore towards phone-based processing platform: Current technological advancement has increased the smartphones capability in term of speed and memory size. It enabled many new applications in wide variety of domains. HAR classification algorithms should exploit the capability. The processing of the HAR algorithms can be done in smartphones. Thus, it could reduce the network traffic since the smartphones will process the input data itself.

Standardize the performance evaluation matrices: Researchers use different methods to measures the performance of their methods and algorithms. Moreover, they need to compare the performance with other existed methods. It is encouraged to use standardized evaluation matrices for easier and better comparison. The most popular methods based on our survey are 10-fold cross validation, precision and recall, and F-measures.

Fuse other available context-aware data for better HAR classification: Based on this survey, most researchers use accelerometer embedded in smartphones as input for HAR classification methods. Currently smartphones are equipped with many other sensors [25] such as digital compass, gyroscope, GPS, microphone, and camera.HAR research can take an advantage of the smartphones' sensors to improve the classification methods by fusing all available sensors' data as input.

Explore adaptive models for HAR classification: Current researches focus to static classification system. The classifier learns using training data to generate a classification model. The model then is used to classify activities perform by users. Adaptive classifiers should be explored to produce better HAR system. The classifiers should learn continuously about the users' activities behavior. The output from the classification system should become the feedback input for the adaptive classifier. Thus the classifier will understand more about the user's activities' pattern.

TABLE II
COMPARISON OF CLASSIFICATION ALGORITHMS IN HAR

Year	Ref	Classification Algorithms	Evaluation Method	Processing Platform
2011	[39]	Hidden Markov Models	4-fold cross validation and precision/recall measures	Phone
2011	[37]	Multiclass Logistic Regression	4-fold cross validation and precision/recall measures	Server
2011	[40]	Transfer learning Embedded Decision Tree	10 times 10-fold cross validation	Server
2011	[51]	Hidden Markov Chain	Not applicable	Server
2011	[38]	Decision Tree, Naïve Bayes, Random Forest, Logistics Regression, RBF Network, Support Vector Machine	10-fold cross validation	Server
2011	[53]	Smoothed Single-layer Hidden Markov Models	F-measure	Server
2011	[34]	Decision Tree	Not applicable	Phone
2011	[36]	Hidden Markov Model	false non match rate (FNMR), false match rate (FMR)	Server
2010	[43]	Support Vector Machine	F-measure, precision and recall	Server
2010	[42]	Decision Tree, Logistic Regression and Multilayer Neural Networks	10-fold cross validation	Server
2010	[44]	Recurrent Fuzzy Inference Systems	Accuracy	Server
2010	[45]	k-Nearest Neighbour, Direct Density, Class Local Outlier Factor, Local Classification Factor	Precision and recall	Phone
2010	[52]	Artificial Neural Network	Accuracy	Server
2010	[41]	Active Learning, Self-learning, and Co-learning	10-fold cross validation	Server and phone
2010	[47]	Decision Tree, Bayesian Network, Naïve Bayes, k-Nearest Neighbour, Support Vector Machine	10-fold cross-validation, mean and 95% confidence interval	Server
2010	[46]	Decision Tree, k-Nearest Neighbours and Sequential Minimal Optimization	Accuracy	Server
2010	[27]	Gaussian Mixture Model (GMM) and Support Vector Machine	Accuracy and Error	Phone
2009	[54]	K-Nearest Neighbour	Accuracy	Phone
2009	[55]	Artificial Neural Network	F-measure	Server and phone
2009	[49]	Decision Trees, Naive Bayes, k-Nearest Neighbour and the Support Vector Machine	Accuracy	Server
2008	[48]	k-Nearest Neighbour, Support Vector Machine, Adaptive Minimum-distance	Accuracy	Phone
2008	[50]	Naïve Bayes	Accuracy	Server and phone

Explore the privacy and security of sensitive context-aware data: Context-aware data that are transferred between smartphones and server contain sensitive user information. For example the data related to the location, activities and health of the users. Thus the data should be secured during the transmission. Most researchers didn't aware the importance of preserving the privacy and security of context-aware data because there are too little considerations in their research works.

VI. CONCLUSION

This survey paper regarding the classification algorithms used in human activity recognition using smartphone is very important for researchers to get clearer picture of the current trends of research in the area of human activity recognition. Moreover, it helps researchers to know other works being done in the area.

Researchers will benefit the comparison being done among other researchers by improving the current works and exploring new suggested area.

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