TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 02/11 pp235-249
Volume 19, Number 3, June 2014

Activity Recognition with Smartphone Sensors

Xing Su, Hanghang Tong, and Ping Ji*

Abstract: The ubiquity of smartphones together with their ever-growing computing, networking, and sensing powers have been changing the landscape of people's daily life. Among others, activity recoginition, which takes the raw sensor reading as inputs and predicts a user's motion activity, has become an active research area in recent years. It is the core building block in many high-impact applications, ranging from health and fitness monitoring, personal biometric signature, urban computing, assistive technology, and elder-care, to indoor localization and navigation, etc. This paper presents a comprehensive survey of the recent advances in activity recognition with smartphones' sensors. We start with the basic concepts such as sensors, activity types, etc. We review the core data mining techniques behind the main stream activity recognition algorithms, analyze their major challenges, and introduce a variety of real applications enabled by activity recognition.

Key words: activity recognition; mobile sensors; machine learning; data mining; pattern recognition

1 Introduction

Smartphones are ubiquitous and becoming more and more sophisticated, with ever-growing computing, networking, and sensing powers. This has been changing the landscape of people's daily life and has opened the doors for many interesting data mining applications, ranging from health and fitness monitoring, personal biometric signature, urban computing, assistive technology, and elder-care, to indoor localization and navigation, etc.

Human activity recognition is a core building block behind these applications. It takes the raw senor reading as inputs and predicts a user's motion activity. Many main stream smartphones are equipped with various sensors, including accelerometers, GPS, light sensors, temperature sensors, gyroscope, barometer, etc. These sensors have become a rich data source to measure various aspects of a user's daily life. The typical activities include walking, jogging, sitting, etc. Due to its unobtrusiveness, low/none installation cost, and easy-to-use, smartphones are becoming the main platform for human activity recognition. Figure 1 shows a typical process for activity recognition with smartphone sensors.

Activity recognition is important in many real applications. Let us elaborate this using the following examples. To begin with, as one branch of human-computer interaction, it makes the computer even "smarter", that is, it could provide the corresponding services based on what the user is doing. For example, suppose that the phone detects that the user is about to leave the room and its weather application indicates that it will rain later, a reminder will pop up with a message "Bring an umbrella. It is going to rain with a high probability". Another important application of activity recognition techniques is in both indoor and outdoor localizations for building navigation or

• Xing Su is with Computer Science Department, Graduate Center, the City University of New York, New York, NY 10016, USA. E-mail: sunnyxing@gmail.com.
• Hanghang Tong is with Computer Science Department, City College, CUNY, New York, NY 10031, USA. E-mail: hanghang.tong@gmail.com.
• Ping Ji is with Computer Science Department, Graduate Center, the City University of New York, New York, NY 10016, USA. E-mail: pj.ping@gmail.com.
* To whom correspondence should be addressed.
Manuscript received: 2014-04-01; revised: 2014-04-15; accepted: 2014-04-17

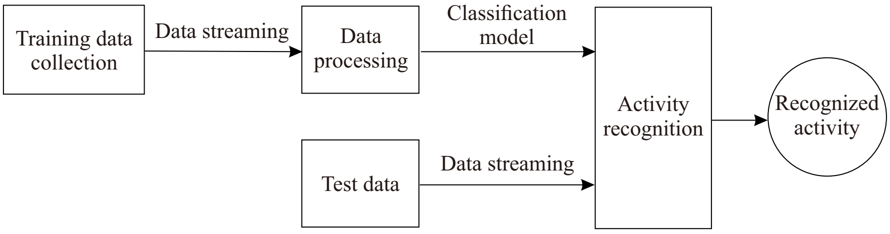


Fig. 1 Activity recognition process.

augmenting the precision of context-aware services[1,2]. Finally, as smartphones become as essential as keys and the wallet for a user's pocket stuff nowadays, the activity recognition techniques could help in assisting life in healthcare. It could help in the prevention of dangerous activities, such as elder people's fall detection[3], youth Autism Spectrum Disorder (ASD) detection in a classroom, etc. It could also help in a proactive way. For example, in order to help the user form a healthy fitness habit, the smartphone can send a reminder if it detects that she/he has been sitting too long. Several recent popular fitness trackers such as Fitbit One[4] are built upon wearable sensors and activity recognition techniques. They track people's steps taken, stairs climbed, calorie burned, hours slept, distance travelled, quality of sleep, etc.

There are several survey works on activity recognition using mobile sensors and related topics such as Refs. [5-8]. Reference [5] summarizes the application and process of activity recognition using inertial sensors in the healthcare and wellbeing fields. Reference [6] describes and categorizes the activity recognition based applications. References [7, 8] are the most recent ones that both contribute on taxonomy in activity recognition. Survey work on smartphone related sensing and applications can be found in Refs. [9,10]. In this paper we aim to summarize the recent advances of activity recognition with mobile sensors so that (1) for those who have no background in this area they could obtain a comprehensive review on how the experiment is conducted and how the problem is tackled; and (2) for those who work on similar research topics we provide a summary of the technical challenges and corresponding solutions in literatures, as well as the latest applications.

2 Background

An activity recognition application takes the raw sensor reading as inputs and predicts a user's motion activity. Before we dive into the algorithmic details in the next section, let us review these basic concepts in this section.

2.1 Inputs: Sensors

Sensors are the source for raw data collection in activity recognition. We classify sensors into three categories: video sensors, environmental-based sensors, and wearable sensors. Video sensors are basically cameras that are installed in the fixed places such as the entrance/exit of the public places (to detect people's appearance and actions), or in the living rooms or bedrooms[11] (to track the users' daily life). Cameras are also embedded in robots for a more active visual data capture. Visual monitoring for activity recognition is used in many applications such as surveillance, anti-terrorists, and anti-crime securities as well as life logging and assistance.

Environmental-based sensors are used to detect the users' interaction with the environment. They are radio-based sensors like WiFi, Bluetooth, and the infrared sensors. These sensors are usually deployed in indoor places such as office buildings or homes. They passively monitor the appearance of users at a certain location, or the users' interaction with objects that are also equipped with sensors. Their limitations are that (1) they can only be applied to certain fixed locations, and (2) the cost for the full deployment of such sensors is often very high.

Wearable sensors are the mobile sensors that are in small size and designed to be worn on human body in daily activities. They can record users' physiological states such as location changes, moving directions, speed, etc. Such sensors include accelerometers, microphones, GPS, barometers, etc. Most of the mobile sensors are equipped on smartphones. Table 1 summarizes a set of sensors that are provided in current mainstream smartphones. Please refer to the Android document for a detailed description of all the supported sensors and their interface definitions on Android smartphones in Ref. [12]. Next, we will introduce several important sensors that are commonly used in the mobile activity recognition applications. Compared

Table 1 A set of mobile phone sensors.

Sensor	Description
Accelerometer	Measure the acceleration force that applied to the device, including force of gravity
Ambient temperature sensor	Measure the ambient room temperature
Gravity sensor	Measure the force of the gravity that applied to the device, in three axes (x, y, z)
Gyroscope	Measure the device's rotation in three axes (x, y, z)
Light sensor	Measure the ambient light level (illumination)
Linear acceleration	Measure the acceleration force that applied to the device, force of gravity is excluded
Magnetometer	Measure the ambient geomagnetic field in three axes (x, y, z)
Barometer	Measure the ambient air pressure
Proximity sensor	Measure the proximity of an object relative to the view screen of a device.
Humidity sensor	Measure the humidity of ambient environment
Gyroscope	Measure the orientation of a device in pitch, roll and yaw.

with sensors like light sensors and proximity sensors, these sensors' reading reveals the actual motion status and their features are more related to activity recognition.

2.1.1 Accelerometer

Accelerometer sensors sense the acceleration event of smartphones. The reading includes three axes whose directions are predefined as in Fig. 2. The raw data stream from the accelerometer is the acceleration of each axis in the units of g-force. The raw data is represented in a set of vectors: $\text{Acc}_i = < x_i, y_i, z_i >$, $(i = 1, 2, 3, \cdots)$. A time stamp can also be returned together with the three axes readings. Most of existing accelerometers provide a user interface to configure the sampling frequency so that the user could choose a best sampling rate through experiments.

Accelerometer has been used heavily in smartphone sensors based activity recognition. Its popularity is due to the fact that it directly measures the subject's physiology motion status. For example, if a user changes his/her activity from walking to jogging, it will reflect on the signal shape of the acceleration reading along the vertical axis — there will be an abrupt change in the amplitude. Moreover, the acceleration data could indicate the motion pattern within a given time period, which is helpful in the complex activity recognition.

2.1.2 Compass sensor

Compass is a traditional tool to detect the direction with respect to the north-south pole of the earth by the use of magnetism. The compass sensor on smartphones works with a similar functionality. Figure 3 shows the compass reading display screen on a smartphone. The raw data reading from a compass sensor is the float number between 0° and 360°. It begins from 0° as the absolute north and the actual reading indicates the angle between current smartphone heading direction and the

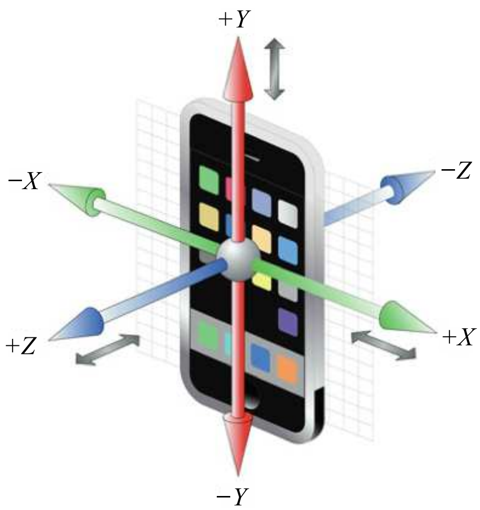


Fig. 2 Accelerometer axes on smartphones[13].

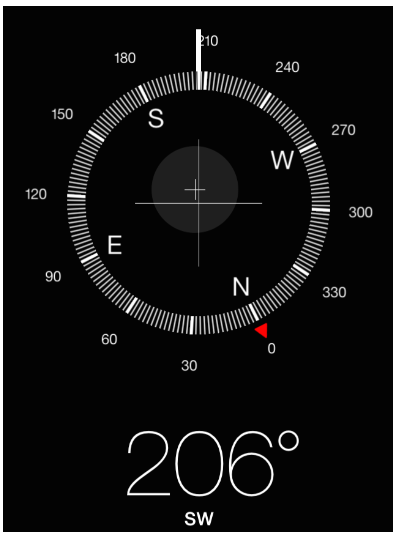


Fig. 3 Compass sensor on smartphones.

absolute north in clockwise. For example, the reading of heading to absolute East is 90° and heading to absolute West is 270°. The data stream returned from compass sensors is a set of floating numbers indicating the angel, $\text{comp}_i, (i = 1, 2, 3, \cdots, 0° \leqslant \text{comp}_i \leqslant 360°)$. Compass reading can be used to detect the direction change in the user's motion such as walking.

2.1.3 Gyroscope

Gyroscope measures the phone's rotation rate by detecting the roll, pitch, and yaw motions of the smartphones along the x, y, and z axis, respectively. The axes directions are shown in Fig. 4. The raw data stream from a gyroscope sensor is the rate of the rotation in rad/s (radian per second) around each of the three physical axes: $\text{Rotation}_i = <x_i, y_i, z_i>, (i = 1, 2, 3, \cdots)$. Gyroscope is helpful in the navigation applications as well as some smartphone games which use the rotation data. In activity recognition research, gyroscope is used to assist the mobile orientation detection.

2.1.4 Barometer

Barometer is one of the latest sensors equipped on some advanced smartphones (e.g., Samsung Galaxy S4 and Google Nexus 4/10). It measures the atmospheric pressure of the environment that the sensor is placed in. The air pressure varies with different altitude or even with places of the same altitude but having different structures (e.g., narrow and wide hallways) inside a building. Thus, barometer reading can be used to indicate the user's position change in localization related activity recognition[14].

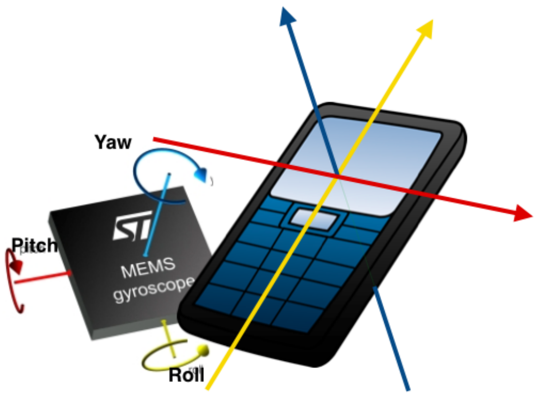


Fig. 4 Three axes of gyroscope on smartphones.

2.2 Outputs: Activities

Activities recognized by the sensor's data can be classified in different ways. For example, they can be classified in terms of the complexity of activities. A simple locomotion could be walking, jogging, walking downstairs, taking elevator, etc. The complex activities are usually related to a combination of a longer period of activities (e.g., taking bus and driving). The activities may only correspond to the movements of certain parts of the body (e.g., typing and waving hand). There are several healthcare related activities, such as falling, exercise, rehabilitations, etc. Location-based activities include dining, shopping, watching movies, etc. Vision-based activities include leaving or entering a place. Activities detected by an infrared sensor could be a user moving or being still, and the activities recognized by a home assisting robot could be sleeping, taking pills, or doing cleaning. The latest versions of Android and iOS both provide an API to detect a user's current activity in one of the four activities: Walking, Stationary, Running, and Automotive. Table 2 summarizes the different categories of activities in the current literatures. Different ways to categorize activities could also be found in Refs. [5, 7].

3 Core Techniques

In this section, we review the core data mining techniques for activity recognition, including raw data collection, data pre-processing, feature computation, model training, and classification. Accordingly, these are the main steps in the activity recognition process.

3.1 Raw data collection

The way to collect the raw data will directly impact

Table 2 Type of activities.

Category	Activity type
Simple activities	Walking, Jogging, Sitting, Standing, Lying, Walking upstairs, Walking downstairs, Jumping
	Taking escalator up, Taking escalator down, Taking elevator up, Taking elevator down
Complex activities	Shopping, Taking buses, Moving by walking, Driving a car
Living activities	Brushing teeth, Vacuuming, Typing, Eating, Cooking, Washing hand, Meditation, Clapping
	Watering plants, Sweeping, Shaving, Dry blowing the hair, Washing dishes, Ironing, Flushing the toilet
Working activities	Working, Relaxing, Cleaning, On a break, Meeting, Home talking, Home entertaining
Health activities	Exercising, Fall, Rehabilitation activities, Following routines

the accuracy in the recognition period, as well as the adaptivity of the classification models. According to Refs. [15, 16], the recognition model trained from one subject's data has a lower accuracy in recognizing another subject's activities, and the sensor position and orientation on the body, if different from how the model is trained, will decrease the accuracy. The number of sensors and the variety of sensors also impact the recognition results[17], so does the location where the activity is taken. In Table 3 we summarize the experiment settings in terms of sensors and subjects in the majority of the literatures in activity recognition using mobile sensors.

There are various experiment settings to minimize the effect of the location sensitivity and the identity sensitivity. For example, in Ref. [17], multiple sensors are used to remove the gravity effect on the accelerometer readings and convert the accelerometer reading from the body coordinate system to the earth coordinate system. By doing so, the trained model becomes sensors-orientation-independent. In Ref. [15], the authors experimented to collect the data from different users and put sensors on the different body parts of subjects. They concluded that with a larger training set obtained under different settings, the location and identity sensitivity could be alleviated.

Another subtle issue in raw data collection is the sampling rate. Almost any sensors provide APIs to allow the user to configure the sampling rate. Although data collected at a higher rate provides more information of the user, it may also introduce more noise. Therefore, a higher sampling rate does not always lead to a higher accuracy.

3.2 Preprocessing: De-noising and segmentation

After collecting the raw data from different sensors, the next step is to preprocess it before performing any further calculation. One purpose of the data preprocessing is to reduce the noise from the users and the sensors themselves. References [23, 30] use an average smoothing method. They replace each raw data by its average with the two adjacent data points to reduce the noise like a sudden spike that may be caused by cellphone's accidentally falling to the ground. In Ref. [3], two filters are used for data preprocessing. The band-pass filter is used to eliminate the low-frequency acceleration (gravity) that captures the information about the orientation of the sensor with respect to the ground data, and the high-frequency signal components generated by noise. Thus it preserves the medium-frequency signal components generated by dynamic human motion. The low-pass filter aims to eliminate the noise generated by the dynamic human motion and to preserve the low-frequency components.

Another important preprocessing step is data segmentation, which is to divide the (preprocessed) continuous data streaming into small segments for feature extraction and model training. The segmentation

Table 3 Experiment setting for data collection in the literatures.

<table>
<tr><th>Element</th><th colspan="2">Setting</th><th>Papers</th></tr>
<tr><td rowspan="2">Subjects</td><td colspan="2">Single subject</td><td>[18]</td></tr>
<tr><td colspan="2">Multi subjects</td><td>[16,19-22]</td></tr>
<tr><td rowspan="7">Sensor amount</td><td rowspan="2">Single sensor (Accelerometer)</td><td>Single accelerometer</td><td>[19-26]</td></tr>
<tr><td>Multiple accelerometers</td><td>[16]</td></tr>
<tr><td rowspan="5">Multi modality</td><td>Accelerometer, Gyroscope, Magnetometer</td><td>[17,27]</td></tr>
<tr><td>Accelerometer, Microphone, Magnetometer, Compass, Barometer, Light sensors</td><td>[15]</td></tr>
<tr><td>Accelerometer, RFID Radar</td><td>[28]</td></tr>
<tr><td>Accelerometer, GPS</td><td>[2]</td></tr>
<tr><td>Accelerometer, Bluetooth</td><td>[1,29]</td></tr>
<tr><td rowspan="7">Sensor location</td><td colspan="2">On the back</td><td>[23]</td></tr>
<tr><td colspan="2">Multi locations such ase Knee, Waste, Wrist, Ankle, Elbow, Shoulder, Chest</td><td>[3,15,16,28]</td></tr>
<tr><td colspan="2">Grasp with hand (holding)</td><td>[18,21,24]</td></tr>
<tr><td colspan="2">Pelvic area</td><td>[19]</td></tr>
<tr><td colspan="2">Belt</td><td>[30]</td></tr>
<tr><td colspan="2">Pants pocket</td><td>[20]</td></tr>
<tr><td colspan="2">Waist</td><td>[31]</td></tr>
<tr><td rowspan="2">Location of activity</td><td colspan="2">Single location</td><td>[1,2,32]</td></tr>
<tr><td colspan="2">Multiple locations</td><td>[15,22]</td></tr>
</table>

can be classified into two categories: (a) segmentation with overlapping, and (b) segmentation without overlapping. The fixed-size no-data-overlapping window segmentation method is commonly used in most activity recognition systems. It reduces the computation complexity of segmentation and hence is a good approach when data is continuously retrieved over time. However, the selection of the window size might have a big impact on the final recognition accuracy. In Ref. [28], the authors conducted experiments to estimate the recognition performance with each algorithm based on different window sizes. The result shows that for each algorithm they test, the accuracy decreases as the window size increases. Another no-data-overlapping window solution is to use a dynamic window size. In this method, its window size depends on the actual time when all the active sensors are triggered. This method is good for multi-modality sensors' data. However, it imposes the same weight on different sensors, which may be sub-optimal. Another method is to use the sliding window with data overlapping, i.e., 10 timeticks of data overlapping between two segments in adjacent windows. The sliding window with overlapping is helpful when there are transitions between different activities. By applying the segmentation with data overlapping, it reduces the error caused by transition state noise[3, 19].

3.3 Feature computation

As in any other data mining tasks, extracting the "right" features is critical to the final recognition performance. For activity recognition, we can extract features in both time and frequency domains.

3.3.1 Time-domain features

Time-domain features contain the basic statistics of each data segment and those of different segments.

- *Mean*. The mean value of each segment in each dimension.
- *Max, Min*. The maximum and minimum values of each segment in each dimension.
- *Standard deviation, Variance*. The variance (and standard deviation) of each segment.
- *Correlation*. Correlation is calculated between each pair of axes of the acceleration data.
- *Signal-Magnitude Area (SMA)*. SMA is calculated as the sum of the magnitude of the three axes acceleration within the segment window[23]. Besides SMA, there exist similar features to combine the three axes readings. *Average Resultant Acceleration* is the average of the square root of the sum of the values of each axis. Another similar feature is the deviation of the sum of the square of acceleration along three axes[33]. The square root of the sum of the acceleration is used as the movement intensity feature in Ref. [30].

3.3.2 Frequency-domain features

Frequency-domain features describe the periodicity of the signal, which are typically calculated based on the FFT.

- *Energy*. The energy feature is calculated as the sum of the squared discrete FFT component magnitudes. Ravi et al.[19] used the normalized energy divided by the window length.
- *Entropy*. The entropy feature is calculated as the normalized information entropy of the discrete FFT components, and it helps in discriminating the activities with the similar energy features[16].
- *Time between peak*. This feature is the time between the peaks in the sinusoidal waves[32].
- *Binned distribution*. This feature is essentially the historgram of the FFT and it is calculated as follows[32]. First, determine the range of values for each axis (e.g., maximum and minimum). Then, divide this range into 10 equal sized bins, and calculate the fraction of the values falling within each of the bins.

3.4 Classification

From data mining perspective, activity recognition is a multi-class classification problem. Many existing classifiers can be plugged in. In this subsection, we review those popular classifiers which have been used in the literatures of activity recognition.

3.4.1 Base-level classifiers

Base-level classifiers have been widely used in activity recognition.

Decision tree. Due to its low complexity in implementation and excellent interpretation, decision tree is adopted as the main classifier in many activity recognition researches. Reference [34] uses decision tree to build the hierarchical classification model for background sound analysis. Reference [35] adopts decision tree as the classifier in the two-stage activity recognition process. They first classify the activity into two categories: active (e.g., walking, running, and cycling) and inactive (e.g., driving and idling); then each activity is further classified within the first level category. Reference [36] generates a lightweight and efficient tree model. Carós et al.[37] presented a binary decision tree to discriminate between standing/sitting and lying by using data collected from an accelerometer located on the body thorax.

Weka Toolkit[38] is a machine learning toolbox with many existing algorithms. It is commonly used as an off-line training tool in activity recognition. One of decision tree algorithms C4.5[39] is implemented with Java and is named as *J48* in *Weka*. *J48* is used by many activity recognition researches as an off-line classification model. A comparative study of classifiers, including *J48*, can be found in Refs. [30, 32, 40, 41]. Martín et al.[41] found that *J48* outperforms both Decision Tables and Naive Bayes Classifier in their activity logging system.

The disadvantage of decision tree lies in model updating. Once the decision tree model is built, it might be costly to update the model to accommodate the new training examples. Thus, in the online learning settings, decision tree is not a popular classifier for activity recognition.

Decision table. Decision table is a table of rules and classes. Given an unlabelled example, it searches for the exact match in the table and returns the majority class label among all matching instances, or reports no matching is found[42]. Bao and Intille[16] and Ravi et al.[19] tested different classifiers including decision table in daily activity recognition. Compared with decision tree, decision table is easy to program and maintain because of its straight-forward structure. However, unlike decision tree, decision table does not have a hierarchical structure. In the context of activity recognition, the activities are sometimes classified with a hierarchy. For example, an activity can be first classified into still vs. moving, and then within each category, a more detailed category is generated. Decision table is not able to capture such a hierarchy.

KNN. KNN is an instance-based classifier based on the majority voting of its neighbours[43]. In general, KNN is one of the most popular algorithms for pattern recognition[24] and is par with Decision Tree in terms of performance and the computational complexity. In Ref. [44], Lombriser et al. developed a dynamic sensor network combining KNN and decision tree algorithm for activity recognition. According to their test, KNN and *J48*/C4.5 are identified as "the classifiers with the least complexity but rendering acceptable performance". In a comparative study[40], Maguire and Frisby compared the performance between KNN and *J48*/C4.5 using *Weka Toolkit* for activity recognition. By using 10-fold cross validation in different experiment settings, they found that KNN achieves a better overall accuracy. Reference [17] uses KNN as the classifier in the user and device orientation independent activity recognition. In Ref. [24], Kaghyan and Sarukhanyan adopted KNN in the desktop application of activity recognition using acceleration data recorded by smartphones. They observed that the choice of a good training set is the key factor in the recognition accuracy. Kose et al.[45] developed *Clustered KNN* for their online activity recognition system.

HMM. Using HMM to recognize activities has its unique advantage in capturing the transition among different types of activities[15]. In Ref. [18], Lee and Cho proposed a two-layered smartphone application to recognize the users' activities and actions based on the hierarchical HMMs. Zappi et al.[46] proposed a manipulative activity recognition system for assemble line workers. Multiple accelerometers are equipped on different parts of the body and for each sensor's data one HMM model is trained. Then by competing the accuracy of different HMMs, the system would dynamically choose the sensor that achieves the highest accuracy. In Ref. [47], Oliver and Horvitz conducted a comparative analysis of a layered architecture of HMM and Dynamic Bayesian networks for identifying human activities from multi-modal sensor information.

SVM. SVM is a maximum margin classifier. Anguita et al.[31] proposed a hardware-friendly multi-class SVM for a smartphone activity recognition application that is used in healthcare. By using the fixed-point algorithm, its computational cost is reduced to be comparable to a traditional SVM.

Other classification methods used in activity recognition with mobile sensors include Gaussian Mixture Models[48, 49], Artificial Neural Networks (ANN)[50-52], Naive Bayes (NB)[53], Rule-Based classifier[54], and a fuzzy inference system[55].

3.4.2 Meta-level classifiers

Ravi et al.[19] clustered meta-level classifiers into three categories: voting (using bagging or boosting), stacking, and cascading. In voting, each base-level classifier gives a vote for its prediction. The class label receiving the most votes is the final decision. In stacking, a learning algorithm is used to learn how to combine the predictions of the base-level classifiers. In cascading, a multi-stage mechanism is used based on several classifiers. The output from a given classifier is collected as additional information for the next classifier. Cascading generally gives sub-optional results compared to the other two schemes[19].

In Ref. [19], Ravi et al. conducted a comparative study in terms of classifying eight activities. They evaluated an exhaustive set of classifiers: Boosting, Bagging, Plurality voting, Stacking with Ordinary-Decision Trees (ODTs)[56], and Stacking with Meta-Decision tress (MDT)[56]. All the base-level classifiers (e.g., NB, SVM, KNN, Decision Tree, and Decision Table) and all the meta-level classifiers mentioned above were evaluated with four different experiment settings. The Plurality Voting classifier outperforms other classifiers in most cases and hence is recommended as the best classifier for activity recognition from a single accelerometer. One of the meta-level voting classifier, Bag-of-Features (BoF), is used in Ref. [57]. Authors used BoF to build activity recognition models using histograms of primitive symbols, and then validated experimentally the effectiveness of the BoF-based framework for recognizing nine activity classes. Their framework is adopted in Ref. [30] for a long-term activity recognition system based on accelerometer data.

Meta-level classifiers can also be used in feature selection. A modified version of AdaBoost proposed in Ref. [58] is used for feature selection in Ref. [15]. Given the maximum number of features that the activity recognition system aims to use, it automatically chooses the most discriminative sub-set of features and uses them to learn an ensemble of discriminative static classifiers for activity recognition.

Another boosting algorithm based on the AdaBoost is introduced by Reiss in Ref. [59]. By using the information on how confident the weak learners are to estimate the class of instances, the algorithm allows the voting weights of the weak learners to vary in response (decrease or increase in the weight) to the confidence. Thus the new instance is classified based on weighted voting.

4 Challenges

Although the research on activity recognition is beneficial from the mobile sensors' unobtrusiveness, flexibility, and many other advances, it also faces challenges that are brought by them. In this section, we review the major, common challenges for activity recognition using mobile sensors, and the corresponding solutions to alleviate them in the current literature.

4.1 Subject sensitivity

The accuracy of activity recognition, especially those based on the accelerometer data, is heavily affected by the subjects participated in training and testing stages. This is mainly due to the fact that different people have different motion patterns. Even for the same subject, she/he may have different patterns at different time. In Ref. [19], the comparative experiments show that training and testing on the same subject achieves the highest accuracy. Training and testing on the same group of multiple subjects has the second highest accuracy. The accuracy decreases when the test data is collected from same subject but on different days. The lowest accuracy is in the setting where the training data is collected from one subject on one day and testing is conducted on another subject on a different day. Reference [17] reports a high accuracy in user dependency test based on an activity recognition system using 20 subjects' data.

Various solutions have been discussed to address the subject sensitivity. Lester et al.[15] suggested collecting the activities over longer periods of time and of people with different ages and body types. A recognition model trained on such a diversified dataset works more reliably when it is tested on data from new individuals. Deng et al.[60] proposed a cross-person activity recognition model to eliminate the effect of user sensitivity. The model training stage consists of two parts: The initial model is trained off-line and the adaptive model is updated online. For new users in the online phase, the algorithm selects those high confident recognition results in order to generate the new training dataset. Based on this new training dataset, the algorithm will update the recognition model to alleviate the subject sensitivity.

4.2 Location sensitivity

Due to the property of accelerometer both in wearable sensors and smartphones, its raw reading heavily depends on the sensors' orientation and positions on the subject's body. For example, when a user is walking while holding a phone in his/her hand, the moving data reading is quite different from the data reading if the phone is in his/her pocket.

One solution is proposed in Ref. [17] to address the orientation sensitivity by using another sensor: magnetometer. The magnetic field sensor provides the magnetic vector along three axes of the device's coordinate system in the orthogonal directions. Hence, it could be utilized to derive the devices' azimuth angle. Then the accelerometer reading can be converted to the earth coordinating axes reading. Park et al.[61] presented a device pose classification method based on the regularized kernel algorithm. It provides a way of how to estimate the smartphone's pose before doing any motion data analysis.

4.3 Activity complexity

The complexity of user activities also brings an additional challenge to the recognition model. For example, the motion during transition period between two activities is difficult for the underlying classification algorithm to recognize. People performing multiple tasks at the same time might also confuse the classifier which is trained under one-activity-per-segment assumption. In addition, culture and individual difference might result in the variation in the way that people perform tasks[5], which in turn brings the difficulty in applying the activity recognition models globally.

HMM is a natural solution to address the activity complexity by "smoothing" the error during the activity transition period[15]. Different classifiers and rule-based strategies are used for different activity recognitions in Ref. [3]. In Ref. [62], the transition states (such as Sit-Stand, Sit-Lie, Walk-Stand, etc.) are treated as additional states, and the recognition model is trained with respect to these states too.

4.4 Energy and resource constrains

Activity recognition applications require continuous sensing as well as online updating for the classification model, both of which are energy consuming. For the online updating, it might also require significant computing resources (e.g., mobile phone memories).

Yan et al.[63] introduced an activity-sensitive strategy, i.e., the Adaptive Accelerometer-based Activity Recognition (A3R) strategy. Based on the observation that the required sampling frequency differs for different activities, A3R adaptively makes the choices on both sampling frequency and classification features. In this way, it reduces both energy and computing resource cost. Liang et al.[64] designed the activity recognition algorithm with a lower sampling frequency. It also removes the time-consuming frequency-domain feature calculation.

4.5 Insufficient training set

As mentioned in the subject sensitivity challenge part, it is highly desirable that the training data must contain as many varieties of the subjects as possible. However, it is not easy to coordinate people of different ages and body shapes to collect data under a controlled lab environment, not to mention the varieties of the environment itself.

Semi-supervised learning is applied to address this issue. In many classification tasks, the unlabelled data, when used in conjunction with a small amount of labelled data, can produce considerable improvement in learning accuracy. For activity recognition, the collection of unlabelled data is easy and requires near zero users' effort. In Ref. [65], Guan et al. extended the co-training method[66] by ensemble and proposed the *en-co-learning* method. Instead of using two different labelled datasets for the initial training, the en-co-learning semi-supervised learning method uses only one labelled dataset and three different classifiers. In this way, it bypasses the time consuming confidence calculation and eliminates one labelled dataset. Mahaviani and Choudhury[67] presented an efficient semi-supervised learning for parameter estimation and feature selection in Conditional Random Fields (CRFs) in activity recognition. By combining semi-supervised learning with virtual evidence boosting (EVB) method, it reduces the human labelling cost as well as improves the efficiency for feature selection.

Besides the traditional semi-supervised learning method, the scale-invariant classifier with "R" metric (SIC-R) proposed by Xie and Beigi[68] could also be applied to solve this issue. Based on the image process method SIFT[69], SIC-R is designed to recognize multi-scale events of human activities. The introduced feature descriptor of time-scale invariance allows the feature from one training set to describe events of the same semantics class which may take place over varying time scales. In this way, it reduces the demand on training set.

5 Applications

Activity recognition is a core building block behind many interesting applications. Lockhart et al.[6]

classified the applications of mobile activity recognition according to their targeted beneficial subjects: (1) application for the end users such as fitness tracking, health monitoring, fall detection, behaviour-based context-awareness, home and work automation, and self-managing system; (2) applications for the third parties such as targeted advertising, research platforms for the data collection, corporate management, and accounting; and (3) applications for the crowds and groups such as social networking and activity-based crowd-sourcing. In this section, we review some representative applications.

5.1 Daily life monitoring

Applications in daily life monitoring usually aim to provide a convenient reference for the activity logging or assisting in exercise and healthy life styles. Recently, a very popular product is the Fitness Stats Tracking gadget, such as Nike Feulband, Fitbit One, Bodymedia, etc. These devices are equipped with the embedded sensors such as accelerometer, gyroscope, GPS; and they track people's steps taken, stairs climbed, calorie burned, hours slept, distance travelled, quality of sleep, etc.[4] An online service is provided for users to review data tracking and visualization in reports. Compared with smartphone sensors, these devices are more sophisticated, since their sensors are designed specifically for the activity detection and monitor. The drawback is that they are much more expensive.

Smartphone applications with activity recognition techniques have been shown up in recent years as an alternative solution. These applications usually have similar roles as above specialized devices. They track users' motion logs such as jogging route, steps taken, and sleeping time. By mining the logged data, they may offer the user a summary on his/her life style and report the sleeping quality. Such applications include *ilearn*[54], *Personal Life Log* (PLL) system[70], the popular iphone application *Nike + iPod*[71], *myHealthAssistant*[29], and *sleepcycle*[72]. Compared to the devices mentioned above, these applications are easier to use and less or zero cost because they are installed on smartphones and do not need extra sensors or devices.

5.2 Personal biometric signature

A subject's motion pattern is usually exclusive and unique. For example, when people raise their hands, it is almost impossible for two people's hands to share the exactly same motion patterns. Even in a successful imitation, the differences still exist because of the difference in the motion related bones and muscles on human bodies. Sensors such as accelerometers can capture those differences. The activity recognition techniques provide a possible solution for human biometric signature with patterns in motion/gestures. In these applications, pattern recognition methods are used to obtain the unique motion patterns, which are in turn saved in the database. It is convenient and feasible because of the pervasive usage of mobile devices. The biometric signature using mobile sensors is proposed in Refs. [20, 21].

On the other side, the motion signature could also be used in a malicious way. For example, people could use the learned patterns to crack users' behaviours, such as smartphone keyboard typing, or other spying activities. Such applications are discussed in Refs. [73, 74], where the user's typing pattern is learned via accelerometer reading and the learned patterns will be used to infer the user's typing on the screen.

5.3 Elderly and youth care

There is a growing need in elderly care (both physically and mentally), partially because of the retirement of the baby boomer generation. A major goal of the current research in human activity monitoring is to develop new technologies and applications for elderly care. Those applications could help prevent harms, e.g., to detect older people's dangerous situations. In Ref. [3], an architecture on the smartpphone is developed with the purpose of users' fall detection. Activity recognition and monitor sensors could help elders in a proactive way such as life routine reminder (e.g., taking medicine), living activity monitoring for a remote robotic assist[59]. Si et al.[75] proposed a prototype system that provides elderly people the personalized guidance to complete daily life activities by learning their living patterns using mobile sensors.

The youth care is another field that benefits from the activity recognition research. Applications include monitoring infants' sleeping status and predicting their demands on food or other stuff. Activity recognition techniques are also used in children's (ASD) detection. For example, Ref. [22] presents a solution to use sensors to detect the stereotypical motor movements on children with ASD in classrooms.

5.4 Localization

Activity recognition on mobile phones could help in context-awareness and hence can be applied in localization. One reason to use mobile sensors rather than GPS for localization is that GPS signal is usually very weak inside buildings and underground. On the other hand, the activity recognition techniques with mobile sensors could assist in locating the position. In addition, GPS localization is 2-D-based positioning which has no information of a user's altitude. Activity recognition techniques on mobile phones could fill in this gap. Song et al.[76] proposed a floor localization system to find 9-1-1 caller in buildings by inferring the current floor level using activity recognition techniques. A similar system is proposed in Ref. [1] for infrastructure-free floor localization. A third reason to use mobile sensors for localization is that GPS accuracy decreases inside cities with tall buildings surrounded. In this situation, GPS-based localization might confuse between a movie theatre and a restaurant, which might be just too close to each other in terms of the distance. Activity recognition related applications can alleviate this kind of mistakes by augmenting the positions with people's current activity type. Reference [2] proposes an application (*AAMPL*) to help positioning the context based on the learned activity signatures in certain environments.

5.5 Industry manufacturing assisting

The activity recognition techniques could also assist workers in their daily work. One example is Ref. [77]. This work (*wearIT@Work*) introduces wearable sensors into work — "wearable computing" is a kind of extension of the body that allows a worker to perform "extraordinary tasks"[78]. Other applications based on activity recognition include smart cameras that can understand people's gestures in film shooting field, robot assistance in car production, etc.

6 Conclusions

Smartphones are ubiquitous and becoming more and more sophisticated. This has been changing the landscape of people's daily life and has opened the doors for many interesting data mining applications. Human activity recognition is a core building block behind these applications. It takes the raw sensors' reading as inputs and predicts a user's motion activity. This paper presents a comprehensive survey of the recent advances in activity recognition with smartphones sensors. We introduce the basic concepts of activity recognition (such as sensors, activity types, etc). We review the core data mining techniques behind the main stream activity recognition algorithms, analyze their major challenges, and introduce a variety of real applications enabled by activity recognition.

The activity recognition based on smartphone sensors leads to many possible future research directions. Besides the applications mentioned in Section 5, an even novel way could be equipping smartphones with intelligent applications to replace the traditional devices such as remote control, traffic controlling, and tracking devices. Smartphone applications that can recognize users' gestures could send corresponding command to home electronics. Thus, instead of keeping different remotes in one's cabinet, we can just install one application that has the remote functions. The cross field research could be developed in many fields because of the mobile activity recognition techniques. For example, scientists in diseases field could conduct experiment with computer scientist based on the patients' activities records to infer the cause or pre-symptom of certain disease like Alzheimer or stroke.

Acknowledgements

This material is based upon work supported by the National Science Foundation (Nos. IIS1017415 and CNS-0904901). Research was sponsored by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-09-2-0053. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on. Funding was provided by Defense Advanced Research Projects Agency (DARPA) under Contract Number W911NF-11-C-0200 and W911NF-12-C-0028. The content of the information in this document does not necessarily reflect the position or the policy of the Government, and no official endorsement should be inferred. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on.

References

[1] H. Ye, T. Gu, X. Zhu, J. Xu, X. Tao, J. Lu, and N. Jin, Ftrack: Infrastructure-free floor localization via mobile phone sensing, in *Proc. Int. Pervasive Computing and Communications Conf.*, Lugano, Switzerland, 2012, pp. 2-10.

[2] A. Ofstad, E. Nicholas, R. Szcodronski, and R. R. Choudhury, Aampl: Accelerometer augmented mobile phone localization, in *Proc. 1st Int. Mobile Entity Localization and Tracking in GPS-Less Environments Workshop*, San Francisco, USA, 2008, pp. 13-18.

[3] S. Kozina, H. Gjoreski, M. Gams, and M. Luštrek, Efficient activity recognition and fall detection using accelerometers, in *Evaluating AAL Systems Through Competitive Benchmarking*, Springer, 2013, pp. 13-23.

[4] Fitbit, Sensors overview, http://www.fitbit.com/one, 2014, Mar. 17.

[5] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, and P. Havinga, Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey, in *Proc. 23rd Int. Architecture of Computing Systems Conf.*, Hannover, Germany, 2010, pp. 1-10.

[6] J. W. Lockhart, T. Pulickal, and G. M. Weiss, Applications of mobile activity recognition, in *Proc. 14th Int. Ubiquitous Computing Conf.*, Seattle, USA, 2012, pp. 1054-1058.

[7] O. D. Incel, M. Kose, and C. Ersoy, A review and taxonomy of activity recognition on mobile phones, *BioNanoScience*, vol. 3, no. 2, pp. 145-171, 2013.

[8] O. D. Lara and M. A. Labrador, A survey on human activity recognition using wearable sensors, *Communications Surveys & Tutorials, IEEE*, vol. 15, no. 3, pp. 1192-1209, 2013.

[9] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, A survey of mobile phone sensing, *Communications Magazine, IEEE*, vol. 48, no. 9, pp. 140-150, 2010.

[10] H. F. Rashvand and K.-F. Hsiao, Smartphone intelligent applications: A brief review, *Multimedia Systems*, pp. 1-17, 2013.

[11] H. Becker, M. Borazio, and K. Van Laerhoven, How to log sleeping trends? A case study on the long-term capturing of user data, in *Smart Sensing and Context*, Springer, 2010, pp. 15-27.

[12] Google Android, Sensors overview, http://developer.android.com/guide/topics/sensors/sensors_overview.html, 2014, Mar. 01.

[13] Apple, UIAcceleration class reference, https://developer.apple.com/library/ios/documentation/uikit/reference/UIAcceleration_Class/Reference/UIAcceleration.html, 2014, Mar. 17.

[14] K. Muralidharan, A. J. Khan, A. Misra, R. K. Balan, and S. Agarwal, Barometric phone sensors– more hype than hope! http://www.msr-waypoint.com/en-us/people/sagarwal/hotmobile14.pdf, 2014.

[15] J. Lester, T. Choudhury, and G. Borriello, A practical approach to recognizing physical activities, in *Pervasive Computing*, Springer, 2006, pp. 1-16.

[16] L. Bao and S. S. Intille, Activity recognition from user-annotated acceleration data, in *Pervasive Computing*, Springer, 2004, pp. 1-17.

[17] Y. E. Ustev, O. Durmaz Incel, and C. Ersoy, User, device and orientation independent human activity recognition on mobile phones: Challenges and a proposal, in *Proc. 13th Int. Pervasive and Ubiquitous Computing Adjunct Publication Conf.*, Zurich, Switzerland, 2013, pp. 1427-1436.

[18] Y.-S. Lee and S.-B. Cho, Activity recognition using hierarchical hidden markov models on a smartphone with 3d accelerometer, in *Hybrid Artificial Intelligent Systems*, Springer, 2011, pp. 460-467.

[19] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, Activity recognition from accelerometer data, *AAAI*, vol. 5, pp. 1541-1546, 2005.

[20] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, Cell phone-based biometric identification, in *Proc. 4th Int. Biometrics: Theory Applications and Systems Conf.*, Washington DC, USA, 2010, pp. 1-7.

[21] J. G. Casanova, C. S. Á vila, A. de Santos Sierra, G. B. del Pozo, and V. J. Vera, A real-time in-air signature biometric technique using a mobile device embedding an accelerometer, in *Networked Digital Technologies*, Springer, 2010, pp. 497-503.

[22] F. Albinali, M. S. Goodwin, and S. Intille, Detecting stereotypical motor movements in the classroom using accelerometry and pattern recognition algorithms, *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 103-114, 2012.

[23] A. M. Khan, Y.-K. Lee, S. Y. Lee, and T.-S. Kim, A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer, *Information Technology in Biomedicine*, vol. 14, no. 5, pp. 1166-1172, 2010.

[24] S. Kaghyan and H. Sarukhanyan, Activity recognition using *k*-nearest neighbor algorithm on smartphone with tri-axial accelerometer, *International Journal of Informatics Models and Analysis (IJIMA), ITHEA International Scientific Society, Bulgaria*, vol. 1, pp. 146-156, 2012.

[25] T. Brezmes, J.-L. Gorricho, and J. Cotrina, Activity recognition from accelerometer data on a mobile phone, in *Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living*, Springer, 2009, pp. 796-799.

[26] E. Mitchell and D. Monaghan, Classification of sporting activities using smartphone accelerometers, *Sensors*, vol. 13, no. 4, pp. 5317-5337, 2013.

[27] T. Choudhury, S. Consolvo, B. Harrison, J. Hightower, A. LaMarca, L. LeGrand, A. Rahimi, A. Rea, G. Bordello, B. Hemingway, et al., The mobile sensing platform: An embedded activity recognition system, *Pervasive Computing, IEEE*, vol. 7, no. 2, pp. 32-41, 2008.

[28] L. Wang, T. Gu, X. Tao, and J. Lu, A hierarchical approach to real-time activity recognition in body sensor networks, *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 115-130, 2012.

[29] C. Seeger, A. Buchmann, and K. Van Laerhoven, Myhealthassistant: A phone-based body sensor network that captures the wearer's exercises throughout the day, in *Proc. 6th Int. Body Area Networks Conf.*, Beijing, China, 2011, pp. 1-7.

[30] E. Garcia-Ceja and R. Brena, Long-term activity recognition from accelerometer data, *Procedia Technology*, vol. 7, pp. 248-256, 2013.

[31] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine, in *Ambient Assisted Living and Home Care*, Springer, 2012, pp. 216-223.

[32] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, Activity recognition using cell phone accelerometers, *ACM SigKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74-82, 2011.

[33] S. Wang, J. Yang, N. Chen, X. Chen, and Q. Zhang, Human activity recognition with user-free accelerometers in the sensor networks, in *Proc. 2005 Int. Neural Networks and Brain Conf.*, 2005, pp. 1212-1217.

[34] Y. Wang, J. Lin, M. Annavaram, Q. A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh, A framework of energy efficient mobile sensing for automatic user state recognition, in *Proc. 7th Int. Conference on Mobile Systems, Applications, and Services Conf.*, Kraków, Poland, 2009, pp. 179-192.

[35] P. Siirtola and J. Röning, Recognizing human activities user-independently on smartphones based on accelerometer data, *International Journal of Interactive Multimedia & Artificial Intelligence*, vol. 1, no. 5, pp. 38-45, 2012.

[36] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell, Sensing meets mobile social networks: The design, implementation and evaluation of the cenceme application, in *Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems*, ACM, 2008, pp. 337-350.

[37] J. S. Carós, O. Chételat, P. Celka, S. Dasen, and J. CmÃral, Very low complexity algorithm for ambulatory activity classification, presented at the 3rd European Medical and Biological Conference, Prague, Czech, 2005.

[38] S. R. Garner, Weka: The waikato environment for knowledge analysis, in *Proc. 2nd New Zealand Computer Science Research Students Conf.*, Hamilton, New Zealand, 1995, pp. 57-64.

[39] J. R. Quinlan, *C4. 5: Programs for Machine Learning*, vol. 1. Morgan Kaufmann, 1993.

[40] D. Maguire and R. Frisby, Comparison of feature classification algorithm for activity recognition based on accelerometer and heart rate data, presented at the 9th IT & T Conference, Dubrin, Ireland, 2009.

[41] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar, Activity logging using lightweight classification techniques in mobile devices, *Personal and Ubiquitous Computing*, vol. 17, no. 4, pp. 675-695, 2013.

[42] R. Kohavi, The power of decision tables, in *Machine Learning: ECML-95*, Springer, 1995, pp. 174-189.

[43] Wikipedia, k-nearest neighbors algorithm, http://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm, 2014, Mar. 17.

[44] C. Lombriser, N. B. Bharatula, D. Roggen, and G. Tröster, On-body activity recognition in a dynamic sensor network, in *Proc. 2nd Int. Body Area Networks Conf.*, Florence, Italy, 2007, pp. 17-22.

[45] M. Kose, O. D. Incel, and C. Ersoy, Online human activity recognition on smart phones, in *Workshop on Mobile Sensing: From Smartphones and Wearables to Big Data*, Beijing, China, 2012, pp. 11-15.

[46] P. Zappi, C. Lombriser, T. Stiefmeier, E. Farella, D. Roggen, L. Benini, and G. Tröster, Activity recognition from on-body sensors: Accuracy-power trade-off by dynamic sensor selection, in *Wireless Sensor Networks*, Springer, 2008, pp. 17-33.

[47] N. Oliver and E. Horvitz, A comparison of hmms and dynamic bayesian networks for recognizing office activities, in *User Modeling*, Springer, 2005, pp. 199-209.

[48] R. K. Ibrahim, E. Ambikairajah, B. G. Celler, and N. H. Lovell, Time-frequency based features for classification of walking patterns, in *Proc. 15th Int. Digital Signal Processing Conf.*, Wales, UK, 2007, pp. 187-190.

[49] F. R. Allen, E. Ambikairajah, N. H. Lovell, and B. G. Celler, An adapted gaussian mixture model approach to accelerometry-based movement classification using time-domain features, in *Proc. 28th Int. Engineering in Medicine and Biology Society Conf.*, California, USA, 2006, pp. 3600-3603.

[50] N. Győrbíró, Á. Fábián, and G. Hományi, An activity recognition system for mobile phones, *Mobile Networks and Applications*, vol. 14, no. 1, pp. 82-91, 2009.

[51] I. Anderson, J. Maitland, S. Sherwood, L. Barkhuus, M. Chalmers, M. Hall, B. Brown, and H. Muller, Shakra: Tracking and sharing daily activity levels with unaugmented mobile phones, *Mobile Networks and Applications*, vol. 12, no. 2-3, pp. 185-199, 2007.

[52] J.-Y. Yang, J.-S. Wang, and Y.-P. Chen, Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers, *Pattern Recognition Letters*, vol. 29, no. 16, pp. 2213-2220, 2008.

[53] N. D. Lane, M. Mohammod, M. Lin, X. Yang, H. Lu, S. Ali, A. Doryab, E. Berke, T. Choudhury, and A. Campbell, Bewell: A smartphone application to monitor, model and promote wellbeing, in *Proc. 5th Int. ICST Conference on Pervasive Computing Technologies for Healthcare Conf.*, Dublin, Ireland, 2011, pp. 23-26.

[54] T. Saponas, J. Lester, J. Froehlich, J. Fogarty, and J. Landay, Ilearn on the iphone: Real-time human activity classification on commodity mobile phones, University of Washington CSE Tech ReportUW-CSE-08-04-02, 2008.

[55] M. Berchtold, M. Budde, D. Gordon, H. R. Schmidtke, and M. Beigl, Actiserv: Activity recognition service for mobile phones, in *Proc. 9th Int. Wearable Computers Conf.*, Shanghai, China, 2010, pp. 1-8.

[56] L. Todorovski and S. Džeroski, Combining classifiers with meta decision trees, *Machine Learning*, 2003, vol. 50, no. 3, pp. 223-249.

[57] M. Zhang and A. A. Sawchuk, Motion primitive-based human activity recognition using a bag-of-features approach, in *Proc. 2nd Int. Health Informatics Symposium*, Miami, USA, 2012, pp. 631-640.

[58] P. Viola and M. Jones, Rapid object detection using a boosted cascade of simple features, in *Proc. 17th Int. Computer Vision and Pattern Recognition Conf.*, Kauai, USA, 2001.

[59] A. Reiss, Personalized mobile physical activity monitoring for everyday life, PhD dissertation. Dept. CS. Technical University of Kaiserslautern, Kaiserslautern, German, 2014.

[60] W.-Y. Deng, Q.-H. Zheng, and Z.-M. Wang, Cross-person activity recognition using reduced kernel extreme learning machine, *Neural Networks*, 2014.

[61] J.-G. Park, A. Patel, D. Curtis, S. Teller, and J. Ledlie, Online pose classification and walking speed estimation using handheld devices, in *Proc. 14th Int. Ubiquitous Computing Conf.*, Pittsburgh, USA, 2012, pp. 113-122.

[62] M. Khan, S. I. Ahamed, M. Rahman, and R. O. Smith, A feature extraction method for realtime human activity recognition on cell phones, in *Proc. 3rd Int. Symposium on Quality of Life Technology Conf.*, Toroto, Canada, 2007.

[63] Z. Yan, V. Subbaraju, D. Chakraborty, A. Misra, and K. Aberer, Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach, in *Proc. 16th Int. Wearable Computers Symposium*, Newcastle, UK, 2012, pp. 17-24.

[64] Y. Liang, X. Zhou, Z. Yu, and B. Guo, Energy-efficient motion related activity recognition on mobile devices for pervasive healthcare, *Mobile Networks and Applications*, pp. 1-15, 2013.

[65] D. Guan, W. Yuan, Y.-K. Lee, A. Gavrilov, and S. Lee, Activity recognition based on semisupervised learning, in *Proc. 13th Int. Embedded and Real-Time Computing Systems and Applications Conf.*, Daegu, Korea, 2007, pp. 469-475.

[66] A. Blum and T. Mitchell, Combining labeled and unlabeled data with co-training, in *Proc. 11th Int. Computational Learning Theory Conf.*, Wisconsin, USA, 1998, pp. 92-100.

[67] M. Mahdaviani and T. Choudhury, Fast and scalable training of semi-supervised crfs with application to activity recognition, in *NIPS*, 2007, vol. 20, pp. 977-984.

[68] J. Xie and M. S. Beigi, A scale-invariant local descriptor for event recognition in 1d sensor signals, in *Proc. Int. Multimedia and Expo Conf.*, New York, USA, 2009, pp. 1226-1229.

[69] D. G. Lowe, Distinctive image features from scale-invariant keypoints, *International Journal of Computer Vision*, vol. 60, no. 2, pp. 91-110, 2004.

[70] A. M. Khan, Human activity recognition using a single tri-axial accelerometer, Ph.D dissertation, Dept. Computer Engineering, Kyung Hee University, Seoul, Korea, 2011.

[71] Apple: Nike + iPod application, http://www.apple.com/ipod/nike/, 2014.

[72] Sleepcycle, http://www.sleepcycle.com/, 2014.

[73] M. Goel, L. Findlater, and J. Wobbrock, Walktype: Using accelerometer data to accomodate situational impairments in mobile touch screen text entry, in *Proc. Human Factors in Computing Systems*, 2012, pp. 2687-2696.

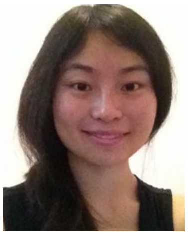
[74] P. Marquardt, A. Verma, H. Carter, and P. Traynor, (sp) iphone: Decoding vibrations from nearby keyboards using mobile phone accelerometers, in *Proceedings of the 18th ACM Conference on Computer and Communications Security*, ACM, 2011, pp. 551-562.

[75] H. Si, S. J. Kim, N. Kawanishi, and H. Morikawa, A context-aware reminding system for daily activities of dementia patients, in *Proc. 27th Int. Distributed Computing Systems Conf.*, Toroto, Canada, 2007, pp. 50-50.

[76] W. Song, J. Lee, H. G. Schulzrinne, and B. Lee, Finding 9-1-1 callers in tall buildings, http://academiccommons.columbia.edu/item/ac:156057, 2014.

[77] L. Mo, S. Liu, R. X. Gao, D. John, J. Staudenmayer, and P. Freedson, Zigbee-based wireless multisensor system for physical activity assessment, in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, 2011, pp. 846-849.

[78] Wearit sensors overview, http://www.wearitatwork.com/home/discovering-ubiquity/, 2014.



Xing Su received the BS degree in computer science from Shanghai Jiaotong University in 2007 and MS degree in computer science from Zhejiang University in 2010. She is currently pursuing PhD studies at Computer Science Department in Graduate Center of the City University of New York. Her current research interests include data mining, machine learning, mobile computing, mobile sensor techniques, and smartphone intelligence.

Hanghang Tong is currently an assistant professor at Computer Science Department, City College, City University of New York. Before that, he was a research staff member at IBM T. J. Watson Research Center and a post-doctoral fellow in Carnegie Mellon University. He received his MS and PhD degrees from Carnegie Mellon University in 2008 and 2009, both majored in machine learning. His research interest is in large scale data mining for graphs and multimedia. He has received several awards, including best paper award in CIKM 2012, SDM 2008, and ICDM 2006. He has published over 80 referred articles and more than 20 patents. He has served as a program committee member in top data mining, databases, and artificial intelligence venues.

Ping Ji received her BEng degree in computer science and technology from Tsinghua University, Beijing, China, and her PhD degree in computer science from the University of Massachusetts at Amherst in 1998 and 2003, respectively. Since fall 2003, she has been a faculty member, and currently a full professor of the Mathematics and Computer Science Department of John Jay College of Criminal Justice of the City University of New York (CUNY), and an active faculty member of the Computer Science PhD Program of CUNY Graduate Center. Dr. Ji is an awardee of a number of PSC CUNY Research Awards, NSF research grants, and US army research grants. Her research interests include the broad aspects of computer networks, network security and digital forensics, wireless and sensor networks, and distributed network signaling architectures and performance evaluation.