The Case for Ambient Sensing for Human Activity Detection

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ABSTRACT
Human activity detection using various sources of data is an important problem due to its application in various domains, such as health-care, elderly care, security/safety, etc. Traditionally, this activity detection is carried out using multimedia data, including audio and video resources. Recently, the Internet of Things (IoT) has led to highly-improved computation and communication capabilities even within the smallest devices, giving rise to wearable devices. These devices can collect useful data about movements and thus enable detecting human activities. However, both traditional methods (multimedia) and wearable device-based methods completely expose users, resulting in severe privacy issues. Thus, it is crucial to be able to still detect these activities without compromising the user's privacy. In this paper, we make a case where ambient sensing (sensors that collect data representing only environmental changes, such as temperature, lighting, etc.) can be used to detect human activities. Since the available data corresponds to only the status of the surrounding environment, the user privacy can be preserved. We demonstrate which aspects of ambient sensing methods are desirable and what types of applications can benefit from them.

Author Keywords
human activity detection; internet of things; privacy; wearable devices; ambient sensing

INTRODUCTION
Detecting the activities of a person in a specific environment can be both useful and crucial. Using the detected activities, an application can make changes to the surroundings to improve user comfort (e.g. adjusting the heating/air-conditioning temperature [16]), predict dangerous health conditions for the user (e.g. fall detection for the elderly [4]), or understand the safety/security condition of an environment (e.g. a burglary, fight, etc. [11]). Thus, activity detection will stay crucial for spaces with added intelligence (i.e. smart spaces), including offices [13], houses [7], classrooms [17]. This activity detection has usually been performed using audio/video surveillance because the multimedia data provide very accurate representations of human activities [15]. A recent method to obtain activity detection is using wearable devices [10]. Recently, wearable devices have become more widely-available to people. These devices provide data about the movement of different body parts, heart rate, skin temperature, etc. Then, applying machine learning methods on the available data, the physical activity of a user can be detected/predicted [6].

These activity detection methods, though effective, can have some serious disadvantages. First, both multimedia-based and wearable-based methods lead to privacy issues. The multimedia-based solutions completely expose user audio and/or video for a period of time. Similarly, each wearable device should be assigned to a single person, and thus, the user's privacy is compromised from the beginning. Second, multimedia-based solutions create big audio/video data sets, requiring ample data storage and considerable computation power. Third, wearable-based solutions can be uncomfortable for the users. It is very common among the users (such as children and elderly) to take off the wearable device for a randomly long time, which can hurt the activity detection capabilities. Thus, it would be ideal to perform activity detection without any user-identifying data and dependence on the users.

Ambient sensing is a well-known concept [1], which provides information regarding the surroundings, such as temperature, lighting, pressure, etc. The status of the ambient variables might change due to human activities taking place in a specific environment. For example, the position of a user can be determined because the user might be in front of some ultrasound sensors [3], or the activity of a user can be inferred using a thermal sensor [3]. In all these cases, an activity detection framework does not have any identifying information about the user in the environment, and since the user does not carry any sensor, the system does not depend on user's cooperation.

In the rest of this paper, we give more in detail examples of existing methods and their shortcomings. Afterwards, we demonstrate a case for activity detection using ambient sensing and example applications that can benefit from it.

MULTIMEDIA-BASED ACTIVITY DETECTION
Multimedia-based human activity detection generally focuses on using images or videos. These methods have been popular

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	Multimedia-based	Wearable-based	Ambient sensing-based
Data source	Image, audio, video	Data from various wearable sensors	Data from ambient sensors
Preprocessing	Necessary	Might be necessary	Usually not necessary
Classification	SVM, ANN, DT, BN, etc.	SVM, ANN, DT, BN, etc.	SVM, ANN, DT, BN, etc.
Applications	Surveillance, security, etc.	Health care, fitness, fall detection, etc.	Smart spaces, elderly care, smart classrooms, etc.
Computation overhead	High	Low to medium	Low
Ground truth data	Easy to obtain	Easy/medium difficulty to obtain	Difficult to obtain
Multiple people	Suitable	Not very suitable	Suitable
Privacy	Low	Low	High

Table 1. Comparison among different methods with respect to different system parameters

because the data provide significant information about the human activity, increasing the activity detection accuracy. The video-based detection is very common as continuous activity demonstration is available in video data [12]. It is also possible to detect the activities from streaming real-time videos [14]. Recent efforts include activity detection using rgbd images/videos [15], reducing the data size and making the identification of the user more difficult. For both image and video-based detection, the raw data is usually preprocessed to extract features using some transformation algorithms (e.g. discrete Fourier transform, scale invariant feature transform, etc.) and then the processed data is fed into some classification algorithms to label the activities (e.g.hidden Markov models, support vector machines, neural networks, etc.) [8]. To aid the work in this domain, researchers have released large-scale databases that include video-based activity benchmarks [5].

The advantage of image/video-based activity detection is the potential high accuracy. Also, since the activities can be observed in images/videos, it is easier to obtain the ground truth before constructing a model. In contrast, there are several disadvantages, including 1) the size of data: image/video data may require significant storage, 2) computation overhead: image/video data need pre-processing, making it difficult to obtain real-time results, 3) privacy issues: the user is completely or partially exposed in image/video data.

WEARABLE-BASED ACTIVITY DETECTION

Another method to detect human activities is to use wearable devices, such as wristbands. The wearable devices include a variety of sensors, e.g. accelerometer, heart rate sensor, skin temperature sensor, etc. The activity detection framework collects data from these sensors (features), and applies machine-learning algorithms to classify the observed activities [10]. Depending on the system setup and the activities to be detected, one or more wearable devices are placed on different parts of the body (wrist, ankle, thigh, elbow, hip, chest, etc.) [9]. The classification algorithms used are similar to multimedia-based ones, including support vector machines, Bayesian networks, hidden Markov models, etc.).

The advantage of wearable-based systems is that the activity detection can be personalized since the collected data come from a specific person. This is especially useful for health-related applications [2]. Also, the data features have more variety, directly representing the human body conditions and thus, can be related to activities more easily. The disadvantages of this method include that 1) obtaining the ground truth might be difficult as the actual activities need to be monitored and cross-correlated with the collected data; 2) the study might be difficult scale up for multiple people, requiring a lot of devices; 3) the variety of wearable sensors and the fact that the user has to wear or carry them might create discomfort to the user [18], and hence hurting the continuity and longevity of the study; 3) since the wearable devices are user-specific, the data can be easily linked to the user, exposing their identity, and hence creating privacy issues.

AMBIENT SENSING-BASED ACTIVITY DETECTION

Based on the disadvantages of the multimedia-based and wearable-based activity detection method, in this section, we are going to present the case for ambient sensing-based activity detection. The work-flow of an ambient sensing-based system is very similar to the other ones, i.e. there is data collected through some sensors and data sources, and using machine learning, the connection between the data and human activities is established. First, we look into the types of data that can be collected with ambient sensing. The ambient data come from sensors placed in the surrounding, such as temperature, pressure, lighting, etc. For activity detection, we can use a variety of sensors. For example, we can use ultrasound sensors to locate a person; vibration sensors to decide if a person is sitting or standing on a specific point; passive infrared sensors to detect people entering in an area; microwave sensors to detect small movements; and thermal sensors to detect temperature changes in a space which can be tied to specific activities.

Second, all collected data should be analyzed using a machine-learning algorithm that can map multiple-featured data points to discrete human activities. Similar as before, we can use support vector machines, neural networks, random forests, decision trees, or simple Bayesian networks [3]. The chosen algorithm would depend on the underlying system and application requirements, i.e. what type of accuracy is needed, what type of computation delay is acceptable, etc. The advantage over the previous methods is that usually this way, preprocessing is not required.

The biggest advantage of using ambient sensing is that there is no connection to the user in the environment, and thus the user is not exposed. This is an important step towards preserving the privacy in an activity detection setup. Another advantage is that the dependency on the user is minimized, e.g. the user does not have to wear or carry anything with them during data collection and detection phases. The computation overhead is usually low after the learning model is set [3] since there is not preprocessing involved. Furthermore, the removed dependency on the user makes the system easily scalable to multiple people, i.e. the system does not require additional hardware to detect activities of multiple people.

Such an activity detection system can be used in elderly care, smart childcare or classroom, etc. where it is difficult to use wearable devices and also not preferable to use multimedia.

Despite the advantages, there are some challenges that need to be addressed with ambient sensing-based method. The biggest challenge is to obtain the ground truth data. Since this requires observing the users for a while with the corresponding ambient sensor variables, it requires manual operation and is difficult to automate. However, this is usually a one-time effort. Another possible issue is the amount of hardware. There is no one specific design that would work for all different spaces. The system setup should be adjusted for each environment, adding up to the initial setup overhead. Again, this is a one-time effort, that can be minimized with experience from previous setups.

CONCLUSION

In summary, human activity detection can be performed with a variety of methods that have different requirements, capabilities, and issues. In this paper, we present a case for activity detection using only ambient sensing, i.e. why it might be desirable to use compared to other methods. Ambient sensing-based frameworks are especially useful when 1) the users have privacy issues and do not want to be directly linked with data, 2) the system does not want to depend on the users to carry devices, and 3) the system design should be lightweight with small amount of hardware and computation overhead.

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