Analyzing Human Activities Using Internet of Things Technology

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***Abstract*—Due to the widespread use of Internet of Things devices, a large volume of tracking data including location and daily physical activity becomes available on the Internet. Analyzing these data is key to a growing number of researches aiming at understanding human activities and management of complex phenomena that involve humans such as traffic management and urban planning. This paper reviews some methods that can be used to solve this problem and describes potential health care activities that could benefit from these studies. In addition, the paper reviews challenges that need to be addressed to ensure future success.**

1. INTRODUCTION

As shown by Kevin Ashton in [1], the term Internet of Things (IoT) was coined as the title of a presentation made in 1999 for Procter & Gamble (P&G). At that time, IoT was used to get P&G executive attention about the new idea of combining Radio-Frequency Identification (RFID) in P&G supply chain with the Internet. Two decades later, the phrase is used to describe an important technology that captured the interest of many scientists. IoT helps to connect common devices and industrial equipment onto the Internet, allowing communications between these physical objects and enabling them to collect and exchange data. Therefore, device efficiency is increased and new services appear. As IoT technology continues to evolve, IoT application has been introduced in many domains such as health care, automotive, and smart home.

One of the prominent research topics in the IoT field is Human Activity Regcognition (HAR). HAR provides valuable information about the behavior and actions of the human subjects [2]. This is usually accomplished by collecting signals from IoT sensors and processing them through data mining techniques for classification. HAR can be used to study daily physical a ctivity (PA) data which have great implications on diagnosis and treatment of many chronic diseases. In addition, monitoring and analyzing these data can shed new light on people's everyday activity patterns.

The main objective of this paper is to provide a short survey of methods and IoT technologies that have been used to analyzing human activities. The remainder of this paper is organized as follows. The next section introduces the Global Positioning System (GPS) tracking technology and some researches that leverages this information to understand the activity of a moving person. In Section 3, we take a look at some IoT technologies that have been used to study human behavior in the health care sector. After that, Section 4 gives a glance at some of the challenges in using IoT devices to speculating human action. Conclusion are given in Section 5.

2. ANALYZING HUMAN ACTIVITIES USING GPS TRACKING

2.1. GPS Technology

The GPS system is a satellite-based radio navigation system initially developed and currently maintained and operated by the U.S. Department of Defense (DoD). It consists of three segments: space, control, and user [3]. A constellation of at least 24 operational satellites in six equally-spaced orbital planes at an altitude of 20,200 km above the Earth make up the space segment. Each plane is occupied by four baseline satellites. This arrangement ensures that at any time, a minimum of four satellites will be available to users anywhere in the world. In June 2011, an expansion called "Expanse 24" was conducted by the Air Force, thereby increase the number of satellites in the constellation to 27 [4].

The control segment consists of a master control station, a substitute master control station, 11 command and control antennas, and 16 monitoring sites [5]. These ground facilities track the GPS satellites, monitor their transmissions, perform computation, and send commands and data back to the constellation. The last segment consists of processors, receivers, and antennas that allow users to pick up the GPS satellite signals.

The availability of IoT devices with GPS-enabled have grown enormously in the last decade and is still rising. Besides mobile phone, wearables such as Apple Watch [7] and Fitbit [8] now has a built-in GPS receiver that can detect, analyze, and transmit GPS information back to the users. Even though these devices are mainly used to collect user PA data, it can also be used to sense the movement of people and vehicles. This ability makes IoT devices useful to collect spatial-temporal data and serve as 'sensors' for observing and measuring the activities of people. Due to the increasing

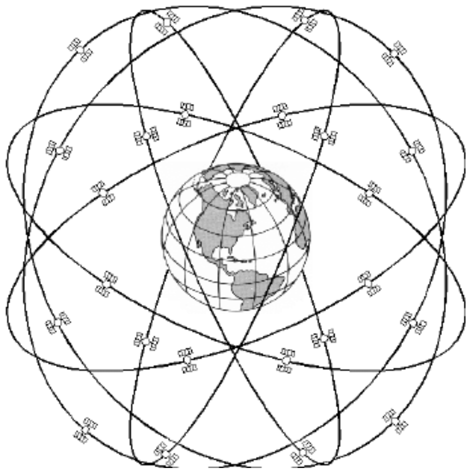

Figure 1. GPS satellite constellation. [6]

availability of movement data sets collected from IoT with GPS-enable devices, it becomes viable to studying people's activities from their movement traces. Many domains such as public transportation, traffic management, commercials, and urban planning will be benefitting from this.

It is worth mentioning that GPS is not the only technology for evaluating the location and activity of humans. Since the last two decades, mobile phone technology like multilateration of radio signals between cell towers and users phone, RFID and Bluetooth also provide easy-to-use sensing data on position and activity. The potential of using cell phone data for urban planning, tourism studies, and monitoring can be seen in [9] and [10]. Fu *et al.* using active RFID in combination with Inertial Navigation Systems (INS) for positioning in [11].

2.2. Methods to Analyzing Human Activities Using IoT

The identification of human activities is not new in the literature. Although the accuracy of GPS data collected from IoT devices are improving, the same can not be said for their quality in terms of semantic richness. This means that the raw data collected from IoT devices can not be used directly to speculate the personal activity that generated it. To solve this problem, a conceptual model for semantic trajectories have been proposed by Spaccapietra *et al.* in [12].

A trajectory is a user-defined record that captures the changing of the position of an object moving in space during a given time interval to reach a given goal. Semantic trajectories are defined as sequences of stops (where the object position stays fixed) and moves (where the position of the object changes).

Analysis methods on semantic trajectories have been proposed in [13], where authors introduce methods to compute stops from raw GPS trajectories. The approach in [14] based on supervised learning to automatically inferring the transportation modes such as walking and driving from trajectories recorded by personal GPS devices.

In [15] Baglioni *et al.* proposed a semantic enrichment process where raw data reinforce with semantic information and integrated with geographical knowledge encoded in an ontology. Then, the chosen ontology is exploited to reach a further semantic enrichment step that makes it possible to interpret patterns in terms of movement activities. After that, machine learning techniques are applied to classified human activities into different categories. For example, people stopping in museums and restaurants are classified as tourists.

A novelty approach to enriching people's movements, represented as trajectories, was introduced by Spinsanti *et al.* in [16]. A person that travels using a transportation means (e.g. car, train, and bus) associated with a traceable GPS-enable IoT device is represented as a moving object. The basic assumption is that the person stopped in a place because he or she is interested in visiting that place, so the geographical objects that could represent the goal of the stop are called Place of Interest (POI). Many spatial and temporal elements like the opening times and the stop duration are considered to associate a stop to POI. More than one POI can be associated with each stop.

The mapping activity to POI category is generated using the application programming interfaces available from both Google Map [17] and OpenStreetMap [18]. The result is shown in Table 1.

Activity	***POI Categories***
Services	ATM, Bank, Car rental, Dentist, Doctor, Hospital, Pharmacy, Finance, Insurance, Gas station, Travel agency, Post office, . . .
Food	Bakery, Bar, Cafe, Food, Meal takeaway, Restaurant, . . .
New Daily Shopping	Grocery or Supermarket, Shopping mall
Shopping	Book Store, Clothing Store, Electronics Store, Florist, Furniture Store, Home Goods Store, Jewelry Store, Library, Pet Store, . . .
Education	School, University
Leisure	Airport, Amusement park, Church, Gym, Museum, Night club, Park, Spa, Stadium, Zoo, . . .

TABLE 1. MAPPING POI-TO-ACTIVITY [19]

The approach presented by Spinsanti *et al.* is based on the analysis of the POI visited by the user during a stop. First, we need to identify the place that people travel to. Then, we associate these places to an activity that commonly happened in those places. Finally, we try to evaluate the overall activity of this person by analyzing the specific activities that occurred during people's stops. The methodology to analyze the activity performed by moving users is illustrated in Figure 2.

First, movement data is collected from IoT devices and trajectories are reconstructed from them [20]. The stops are computed using the trajectories where the user stops for a given time period and where we assume the user is performing some activity. It is important that we remove the outlier during this step. For example, the stops with a very short time duration such as waiting for the traffic light. We then pass the list of stops and POIs to "Visited POI component. It will generate a ranked list base on

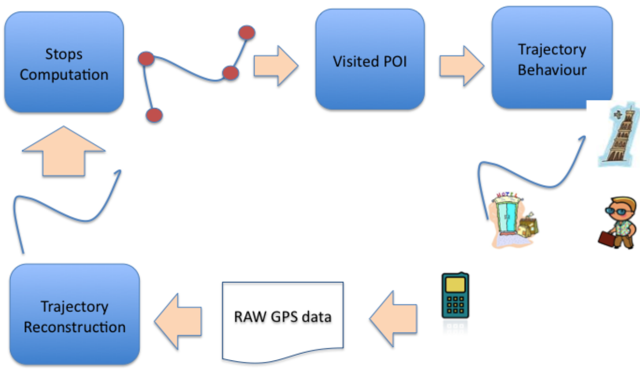

Figure 2. The schema of Spinsanti et al. approach [16]

probabilities of possible POI visited by the user. Next, ”Trajectory Behaviour” component will perform a deduction on the plausible behavior based on the ranked list. In the end, a trajectory is tagged with the most probable activity that occurred on this particular trip.

In this context, we can derive the activity of a person by looking at the sequence of places that he or she visited. For example, if a person visiting scenic spots, museums, restaurants, and eventually ending the day in a hotel then it can be speculated that this person is a tourist.

3. MONITORING PHYSICAL ACTIVITY IN HEALTHCARE USING IOT

According to the survey of World Health Organization (WHO) [21]:” Insufficient daily PA is a key risk factor for noncommunicable diseases such as cardiovascular diseases, cancer, and diabetes”. As mentioned in the first section, the widespread use of smart wearable devices can help us track and monitor people’s daily activities. In this section, we review the current research of PA Monitoring and Assessment (PAMA) technologies from an IoT layer-based perspective.

3.1. Sensing Technologies

Devices that are equipped with RFID or intelligent sensors for sensing and exchange information make up the sensing layer of IoT. Due to the characteristic of many IoT devices are low cost, low energy, and small in size, it makes them a great tool to measuring daily PA and health information related to individuals for many years.

The most important sensor in studying PA is the tri-axial accelerometer. It provides simultaneous measurements in three spatial directions (x, y, z) to calculate the tilt angle by measuring the linear acceleration of movement. In [23] and [24], accelerometers are used to recognizing and discovering human actions. Even though attaching multiple sensors to the human body can provide highly accurate data, it is too expensive and impractical in many cases. Therefore, most of the studies are using only a single accelerometer sensor attached to a certain part of the human body.

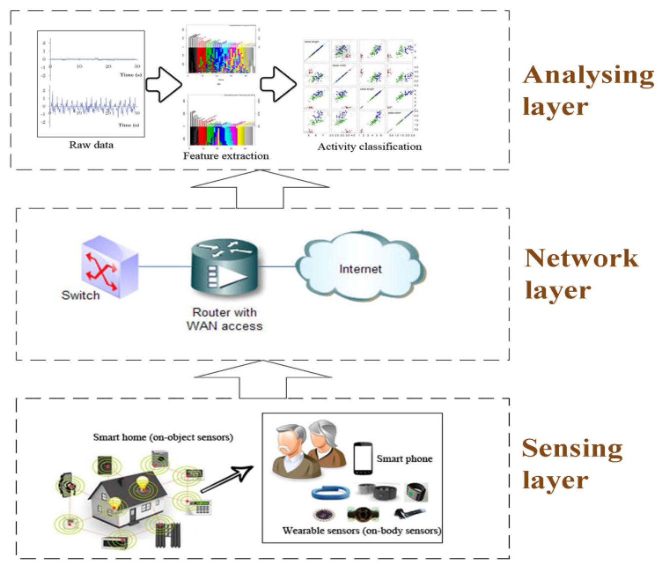

Figure 3. PAMA in IoT environments. [22]

Another popular wearable sensor is the gyroscope due to its high accuracy in determine ascending upstairs and descending downstairs. It can be used in combination with accelerometers to help gait rehabilitation and joint pathology through monitoring patient’s stairs climbing [25]. Elderly fall detection is one of the many applications that leverage the gyroscope sensor [26], [27].

Apart from the above sensors, Smartphone emerges as an important tool in many studies due to its portability. Because carrying a Smartphone is a daily necessity for most people, it can easily collect PA data in an unobtrusive way. One of its advantages is that sensor signals can be collected and processed locally [28].

3.2. Networking Technologies

The networking layer of IoT acts as an interface that links devices and applications together, allow them to exchange information with other devices and applications. In recent years, many studies have been focusing on incorporating wireless communication technologies such as RFID, Bluetooth, Wi-Fi, Zigbee. Karantonis *et al.* use Zigbee compliant transceiver modules for data transfer in [29]. In [30], Bluetooth was used for data exchange between wearable devices.

3.3. Analyzing Technologies

In this layer, we investigate some algorithms and methods that have been used by scientists to achieve high accuracy data. We divided analysis technologies into three main categories [22]: temporal segmentation, feature extraction, and learning methods.

3.3.1. Temporal segmentation. To recognize PA pattern, the sensor data set needs to be segmented because it contains the result of many activated sensors. In wearable computing scenarios, we can figure out activities such as walking and standing based on the data provided by body-worn acceleration sensors. However, most studies use only a single set of features, regardless of which activity to be recognized. Huynh *et al.* showed in [31] that careful selection of individual features for each activity can improve recognition rates.

3.3.2. Feature extraction. Feature extraction is a key procedure for analyzing human activity. It can be categorized into two domains with respect to the signal processing techniques: the time domain and the frequency domain.

Time-domain features cover some well-known extracted characteristics such as min, max, variance, magnitude, etc. Liu et al. [32] used mean and standard deviation to analyze and assess PA data with multiple sensors.

The frequency features refer to the analysis of mathematical functions or signals with respect to frequency, rather than time. The most common procedures are Fast Fourier Transform and Wavelet Transform.

3.3.3. Learning methods. Most studies using machine learning algorithms to train and categorized PA data into different subjects with different characteristics. For example, Artificial Neural Networks can be used for PA classification [33].

4. CHALLENGES AND OPEN ISSUES

Even though there is huge potential in using IoT technologies to study human behaviors, most researchers agree that the field is still in its infancy and faces many challenges. In this section, we take a look at some issues that need to be addressed to ensure future success.

4.1. Standardization

Machine to Machine (M2M) communication technologies that require no human involvement have been considered as the foundation of IoT. As the number of IoT devices reaches 50 billion in 2020 (Figure 4) [34], we need to deal with a massive number of M2M devices whose capabilities vary widely, ranging from tiny sensors with low resources to powerful storage and computation servers. Furthermore, they may have different communication patterns, from real-time communication for mission-critical applications to delay-tolerant communication for offline messaging. To solve this problem, we need standards to support a wide range of applications and address common requirements from a wide range of industry sectors. Several industrial, government agencies, and research bodies like European Telecommunications Standards Institute [35] and International Telecommunication Union [36] are currently involved in the activity of developing these standards.

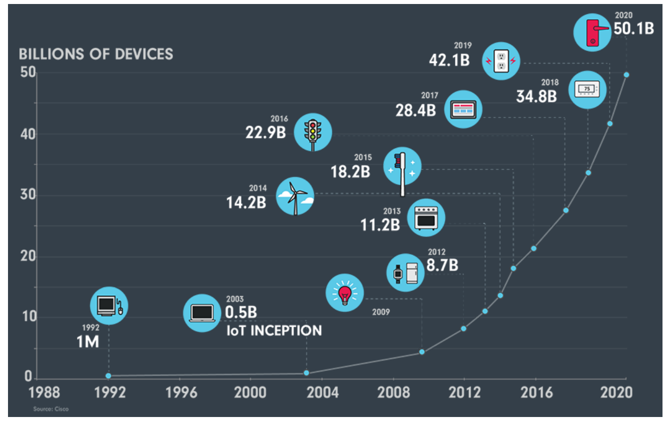

Figure 4. Growth In The Internet of Things. [34]

4.2. Security and Privacy

IoT devices are extremely vulnerable to attacks for many reasons. Since most of the communications are transfer through wireless networks, it very hard to avoid eavesdropping. Furthermore, because most of the IoT components are designed with low capabilities in terms of both energy and computing resources, it is not possible to implement complex security tactics. Some solutions have been proposed by scientists for RFID systems, nonetheless, they all have major problems as described in [37].

Another concern that has been proven to be a significant barrier against the implementation of IoT tracking technologies is privacy. GPS and PA data are considered sensitive information for many people. It is important to ensure that the personal data collected is used only to support authorized services by authorized providers. Further research is needed to address these concerns.

5. CONCLUSION

In the last few years, IoT technology has become a real game-changer in many domains from traffic management to tourist monitoring and urban planning. In this paper, we have introduced the GPS technology and its application in analyzing human activities. We also reviewed some important IoT technologies that have been used to study human behavior in the health care sector. Finally, we investigated challenges that need to be addressed to ensure future success. We believe that given the interest shown by industries and governments, IoT will become one of the leading research topics in the near future.

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