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MOBILITY DETERMINATION AND ESTIMATION BASED ON SMARTPHONES-REVIEW OF SENSING AND SYSTEMS

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ABSTRACT

Smartphones devices, due to its complex sensory capability and comparable processing power, have proven their capability of handling mobility-related applications. This article aims at addressing the need for research on the development of mobility determination and estimation systems based on smartphones. Essentially, three main types of systems are addressed: human activity recognition (HAR), physical activity monitoring and evaluation, and indoor navigation. Some systems are developed as stand-alone smartphone application, while others are augmented with auxiliary sensors to improve functionality and performance. This article shows the main challenges that researchers aim at resolving in developing satisfactory smartphone based mobility determination and estimation systems.

Keywords: smartphone based systems, human activity recognition, human energy expenditure estimation, indoor navigation.

INTRODUCTION

The fast development and the decrease in the cost in wearable technology have enabled a lot of applications to be functioning on smart wearable devices (SWD), such as smartphones and tablets type devices [1-3]. Smartphones are equipped with a wide range of sensory capabilities (e.g., camera, accelerometers, gyroscope, proximity sensor, microphone, GPS, compass), high processing power, and user-friendly interface. Besides, in recent time, every human is more frequently attached to some type of SWD to connect with the world. All of these have made smartphones a strong candidate to replace a lot of stand-alone electronic devices. In addition, a variety of applications have been developed for smartphones to replace passé technologies such as are health-monitoring applications [4], indoor navigation [5], calorie-counting [6], and sleep-watching [7]. Moreover, smartphones are becoming key in interfacing with other different smart devices that can be found at home or in the office [8]. The advancement in sensory and processing power in smartphones have enabled the user to interact with the surrounding environment more efficiently.

Smartphone-based mobility perception is based on algorithms that can be developed and installed on the device to calculate motion-related action of the user. Typically, these algorithms can be built based on different sensory technology in smartphones such as wireless, vision, inertial sensing (accelerometers, and gyros), compass, and global positioning system (GPS) [9]. Numerous smartphone applications can be categorized under mobility determination and estimation. The goal of this article is to address mobility determination and estimation in smartphones from the sensory and systems perspectives.

MOBILITY SENSORS IN SMARTPHONES

Every smartphone is equipped with set of sensors that can be used in mobility application. The next three subsections present GPS, IMU, magnetometer, and camera as direct mobility sensors in smartphones.

Global Positioning System GPS

GPS, with the reduced in size and integrated easily in smartphones, is regarded as the most convenient navigation sensor due to its capability of providing exact positioning data [23]. Exact positioning means that there is no need to conduct further calculation to obtain position by using sensor data. Hence, GPS is considered as the main navigation sensor for many mobility application. Unfortunately, relying only on GPS is not possible because it can only be optimally used outdoors, depending on the line of sight to at least four satellites. In addition, GPS performance varies significantly according to the number of available satellites. Another problem in using GPS for mobility is its low accuracy in positioning, since its deviation can be at least 15 meters or more. Table-1 presents the pros and cons of GPS.

Table-1. GPS pros and cons.

Pros	Cons
Direct sensing of position	Requires Line of Sight to at least four GPS satellites
Easy to use for mobility sensing	Variability in performance according to the number of available satellites
Absolute sensing –no drifting because of integration	Restriction to outdoor application

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Inertial Measurement Unit IMU

Every smartphone is equipped with inertial sensors or IMU [10], which is composed of accelerometers and gyros. This unit belongs to the class of highly integrated silicon micro electromechanical systems (MEMS). The fundamental operational concept of the IMU is to take advantage of acting force that results from the acceleration or the rotation of the body where it is attached. This acting force is converted to electronic signal through transduction. The following subsections will further discuss the operation of accelerometers and gyroscopes.

Accelerometers

Acceleration is measured as units of gees (g), where every g is equivalent to 9.8 m/s^2. Most smartphones are equipped with 3-axis accelerometers, which means that the earth's gravity is projected in three axes, depending on the relative position of the sensor and its containing device. However, if the positioning with respect to the body is fixed, a rotation matrix can be built and used to subtract the projected values and keep the acceleration based on the actual motion of the body. Again, the operation of acceleration depends on the conversion of linear force to electrical charges (DC component) through transduction. Unfortunately, DC accuracy is sensitive to temperature and components lifetime. Thus, there is a natural deviation or bias in determining true value of acceleration, which is based on two components. Static bias is a fixed component that can be estimated and removed before a calculation is undertaken, which can be done through proper calibration. A proper calibration is performed by mounting the sensor on a turntable with controllable orientation, thus ensuring that the bias is estimated after cancelling the component of the earth's gravity. Removing the fixed bias before using the accelerometer is critical to ensure accurate estimation of motion, which can be affected by the drift on the position that happens when using a double integration process to obtain position and yields a quadratic error on time. On the other hand, accelerometers suffer from dynamic bias, which is represented by different type of noises: (1) white noise component caused from thermo-mechanical noise, which is modelled as zero mean random walk whose standard deviation grows proportionally to the square root of the time; (2) flicker noise, which happens to MEMS accelerometers, is observed at low frequency while at high frequency that tends to be overshadowed by white noise; and (3) other errors related to environmental heating that can affect calibration issues.

Gyros

The gyros, which comes from the classical gyroscope mechanical device, consists of a spinning wheel installed on two gimbals and provided with 3 axes of degree of freedom. MEMS gyros are relatively complex MEMS sensors. The function of MEMS gyros is to measure angular rate of rotation by using degree per second (dps) as unit of measurement. Typically, the rate of rotation is obtained by measuring the Coriolis acceleration. Similar to accelerometers, gyros are vulnerable to some measurement errors: (1) constant bias, which is defined as the average output of the gyro when it is not subject to any kind of rotation; (2) zero mean random walk, wherein the standard deviation grows proportionally to the square root of time; and (3) flicker noise, which can be observed at lower frequency. In addition, temperature effect and calibration errors can lead to added errors in gyros signal. Table -2 summarizes accelerometers and gyros error sources and their impact on position estimation.

Table-2. IMU error types**.**

Error type	Nature
Bias	Constant bias
White noise	Zero mean, fixed standard deviation
Flicker noise	Temperature dependent
Temperature effect	Deterministic such as scale factor
Calibration	Fluctuating

MEMS accelerometers and gyros are considered as low quality devices because of the different error that affects MEMS sensors. This is especially observed when the subject is navigating in low speed and accurate positioning is aimed. However, from a cost and practicability perspective, MEMS technologies are convenient for use as mobility applications, as long as high qualified algorithmic layer is used or incorporated. Also, it has an effective indoor positioning algorithms, since inertial sensing is optimal due to less energy consumption compared with other sensing types such as wireless or vision and the restriction of GPS to outdoor and open areas mobility.

Magnometers and vision

Smartphones are equipped with sensory systems that can be used to assist IMU in the application of mobility determination and estimation. The magnetometer [11] is one of the most important sensors in assisting mobility applications as it can be used for absolute direction determination. However, the magnetometer is sensitive to electromagnetic fields in the indoor environment. Vision is another important sensor for mobility determination and estimation. The camera, which is the most prominent mobility instrument for vision, provides a rich information about the surrounding environment. Also, the relative change in position of the

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subject with respect to his environment is reflected in the camera data. Unfortunately, using vision requires special holding of the smartphones, which makes it not practical in the long run. Besides, vision is highly sensitive to environmental lighting conditions [11]. Other hurdles in terms of vision include the dependence of performance on the obstacle configurations in the environment, which means that vision-based mobility algorithms behave better in structured environments as compared with unstructured environments. Based on these, camera can be used as assisting sensor for mobility determination and estimation with other sensors. Sensor fusion can be regarded as useful concept for estimation-type problems such as mobility estimation. Table -3 summarizes magnetometer and vision pros and cons in the context mobility estimation.

Table-3. Camera sensor pros and cons in mobility application.

Sensor	Pros	Cons
Magnetometer	Absolute direction determination	Sensitivity to electromagnetic fields
Vision	Rich information	Computational concern for processing information Sensitivity to lighting conditions Requires stable holding to the sensor by the user Performance variation according to obstacle configuration

WiFi sensing

WiFi is a common technology for mobility sensing [24]. The fundamental concept of WiFi mobility sensing is to map the change in signal strength to distance considering fixed infrastructure of known location of WiFi antennas. The wide spread of WiFi routers in most indoor environment has made it highly convenient to use for mobility determination and estimation. However, multi-path of signals and variability of signal attributes in indoor environments add difficulties in deriving accurate mobility estimation. In addition, WiFi is barely available in outdoor environment and its infrastructure is not installed in all indoor environments. Table-4 presents WiFi pros and cons in mobility determination and estimation.

Table-4. Pros and cons of WiFi sensing for mobility**.**

Pros	Cons
Availability of WiFi infrastructure is increasing	Requires infrastructure
No accumulated errors	Restricted to indoor environment
Capability of reaching high accuracy	Not straightforward

Auxiliary sensors

The big suitability of smartphones to handle the core of mobility determination and estimation application has encouraged a lot of researchers to integrate it with other assisting sensory devices for satisfying the functionality needs for further improvement of the performance. To address the concept of integrating smartphones with aiding sensory devices, we have to present the Bluetooth sensor in smartphones as an appropriate connectivity channel with aiding sensory devices. Next, we present RGBD –Kinect sensor as promising sensor for smartphone-based mobility determination and estimation if used as part of auxiliary sensing set.

Bluetooth

Bluetooth [11] provides wireless connectivity for exchanging information over short distance. This sensor provides flexibility for integrating auxiliary sensing to smartphones for any application. As stated earlier, the performance mobility determination and estimation increases by using sensor fusion. Bluetooth is regarding an efficient wireless channel to add sensing device to SWD.

RGBD-Kinect sensor

RGBD sensor is a type of camera that provides both color and depth information for the environment in two synchronized frames. This sensor used to be a high-cost sensor before Microsoft has embedded in its entertainment tool, the xbox360, in 2010 under the commercial name Kinect. This has attracted researchers to consider developing systems based on Kinect in different applications. Considering Kinect as an assisting sensing tool for SWD based navigation is efficient due to the following reasons. Firstly, depth data can complement information from classical vision data for sensing changes in the surrounding environment. Secondly, the frame rate of Kinect at 30 Hz is effective in capturing human movement in indoor environments. Thirdly, depth data processing is less computationally complex than color data, and is direct in telling motion related variables than classical imaging data. Fourthly, can provide longitudinal data such depth images vis a vis classical image data. All of these have recommended RGBD sensor as an efficient assisting sensor tool for navigational estimation when integrated with smartphones [12].

APPLICATIONS OF SMARTPHONES BASED MOBILITY DETERMINATION AND ESTIMATION

Numerous applications have been developed for smartphone based mobility determination and estimation. In the following subsections, we present some of the most active research trends under this topic.

Smartphone based HAR

Numerous smartphone-based systems have been developed for human activity recognition. Inertial data has been considered by researchers to be the key type of data to perform HAR. A smartphone's comparable processing power and small size has made it most suitable as host to the whole HAR system. Furthermore, some researchers have argued that the smartphone is recommended as a standalone device for HAR without the need to use other sensor or device as auxiliary set [14]. In [13] an Online Sequential Extreme Learning Machine (OSELM), it has been proposed to develop the smartphone for inertial-based HAR. The system has been tested on five activities: walking, walking upstairs, walking downstairs, sitting, standing, and lying down. The system was capable of providing a classification decision of the subject's activity with an overall accuracy 82%; for some activities, it reported a 99% accuracy. This work recommend to improve the performance of HAR in smartphones by considering some factors related to the nature of human being activities, such as the sequential nature action with respect to time. The OSELM classifier also has a more some random nature in selecting input-hidden layer weights, which makes it possible to develop an optimization criteria to assign the weights. Based on careful assessment, this can be further improved by taking advantage of smartphone-based implementation, which can feed the system with useful contextual information about the activity such as location or time. Taking an advantage of the comparable processing power of smartphones, many researchers have used the concept of ensemble classifier. For example in [15] J48 decision tree, Multi-Layer Perceptions (MLP) and Logistic Regression analysis techniques have been combined for acceleration-based HAR. This model has provided better performance than the MLP-based recognition approach suggested [16]. Extreme Learning Machine has been used by another work [6], wherein readings of acceleration along the three axes are combined, and 17 statistical features are extracted. Next, Principal Component Analysis (PCA) has been applied for determining the most important features. Other work has tested HAR by using smartphone placed in six different locations of the human body [17]. This work has applied Autoregressive technique for parameterizing 3D acceleration data. AR-coefficients are also augmented with Signal Magnitude Area (SMA). Finally, discriminative features have been extracted by using Kernel Discriminant Analysis.

Smartphone based measuring and evaluation of physical activities

Smartphones have been proposed by some researchers for serving in continuous monitoring and smart evaluation of physical activities. Different systems have been developed for estimating human energy expenditure by using smartphones to accurately quantify physical activity in terms of expended energy (EE). Acceleration data is good input to such system. In addition, heart-rate monitoring sensor can be used as an auxiliary sensor for improving the accuracy of the AR and EE estimation. In such cases, [20] the system has allowed the user to wear the smartphone freely on the body. The EE-estimation was enabled based on the detected location and orientation of the smartphone on the human body.

The work of [19] has proposed using the accelerometer and barometer body sensors of smartphones for EE. Accelerometer and barometer data was sampled at 2Hz only. Next, an Artificial Neural Network was trained on extracted and prepared features vector FV. The author has proposed training the model offline and enable it online to avoid slow training problem of ANN. According to the reported results, the system can yield up to 89% correlation and RMSE of 1.07.

Smartphone based indoor navigation

Indoor navigation is a difficult research problem due to non-availability of GPS signal in indoor environment [21]. Many pedestrians find difficulties in locating themselves or recognizing directions in big malls, airport terminals, or railway stations. This has attracted researcher to develop system provide accurate estimation of users location in indoor environment. The smartphone has been suggested strongly by many researchers as platform for carrying such application. Besides, it has all required sensing data and computational processing capability for performing such task [22]. Moreover, smartphone interfacing is very useful to provide real time feedback about the navigation information.

In [25] PERCEPT-II system has been developed for the blind people. The system was implemented as an Android app. Specific landmarks tagged with Near Field Communication tags have to be determined by the user in order to enable navigation instructions. The navigation instructions have been tested and an orientation and mobility survey tool was provided. The ultimate goal of this system was to be used by visually impaired users.

Other types of smartphone based navigation systems have been developed by using different auxiliary sensors. In [26] foot mounted IMU has been integrated with smartphone sensing for indoor navigation. The implementation is in Android operating system. The benefit of foot-mounted IMU is to add a constraint to reset the drift every time the foot touches the ground while walking. This system has to be evaluated more in different indoor navigation environments.

CONCLUSIONS

In this article, the research work of developing mobility determination and estimation systems on smartphones has been addressed. Smartphone devices, due to its wide sensing set and comparable processing power, have proved its capability of handling mobility related applications. From a research perspective, this article shows that smartphones are greatly appealing and demanded for mobility determination and estimation applications. Most importantly, three main types of systems are considered mobility-related applications in smartphone devices, i.e., HAR, physical activity monitoring and evaluation, and indoor navigation. In our opinion, more attention should be made to smartphone based mobility determination and estimation due to its high potentiality. Issues to be discussed are on the development of algorithms capable of execution in smartphone under real time constraints, and sensors to assist the core sensing system in smartphone for this application.

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