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A pedestrian tracking algorithm using grid-based indoor model

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ABSTRACT

Pedestrian tracking is widely required by location-based services, e.g. indoor navigation, mobile advertising, and guidance for emergency response, etc. But indoor localization and tracking are still challenging due to the complexity of indoor environments and low positioning accuracy or/and precision. This paper presents an indoor pedestrian tracking approach that utilizes indoor environment constraints in the form of a grid-based indoor model to improve the localization of a WiFi-based system. The indoor space is subdivided into grid cells with a specific size and corresponding semantics. The algorithm recursively computes the location probability over these cells based on the indoor model and magnetometer measurements on a mobile phone. Our experiments prove that the proposed tracking approach can compensate for tracking errors such as improper locations, wrong headings and jumps between consequent locations, which significantly enhance the tracking performance.

1. Introduction

Over the past decades indoor tracking and positioning of humans are becoming increasingly important [1,2]. A number of surveys on indoor localization have been presented in the literature [3–7]. In the past, various technologies such as dead reckoning [4,6,8,9], WiFi [3,6,10,11], RFID [3,6,12], Bluetooth [6] have been used for indoor pedestrian localization and tracking. Most reported approaches provide localization at meter level [6], and a few systems can reach centimeter level [6,13]. Those very accurate methods often require specific signal receivers, the deployment of new infrastructure, or exhaustive fingerprinting of the environment to represent the spatial distribution of signal strength [14]. Localization at a centimeter level is hardly needed for pedestrian tracking and navigation [6]. Humans can observe and estimate the environment and therefore for many applications the accuracy of the localization is not that critical, i.e. localization in a room could be sufficient [15–17]. Path computation for humans is also more approximate. Obstacles in rooms are not considered and a detailed path avoiding the obstacles is left to the judgment of humans [18].

WiFi-based approaches are in the focus of many researchers because a lot of indoor and enclosed environments (e.g. mines) are equipped with WiFi networks. The cost of WiFi-based localization systems is relatively low because they make use of the existing infrastructures and do not rely on extra hardware except the mobile devices of users. Moreover, the number of private and public access points (APs) is increasing and the WiFi coverage is getting denser, hence higher precision can be provided [19]. Based on WiFi network, the location can be calculated through Cell identity, range-based methods such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) and fingerprinting [10]. Cell identity simply matches the target's location with the AP that it is connected to. The TOA, TDOA and AOA methods receptively measure the travel time from a transmitter to a receiver, the difference of travel time from several transmitters to a receiver and the angle from a transmitter to a receiver. The three above approaches are influenced greatly by multi-path effects of indoor environment. The TOA and TDOA require accurate time synchronization between transmitters and receivers.

The fingerprinting method is the most investigated WiFi-based localization method. It is based on the distance-to-signal-strength relationship. It measures the received signal strength (RSS) from APs in two phases: off-line phase and on-line phase. In the off-line phase the signal strength at various predefined locations (sample points) is rigorously measured and a fingerprint map is created. In the on-line phase, a location is estimated by comparing the signal strength measured at

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this location with the fingerprint map obtained in the off-line phase. Fingerprinting method is often used by WiFi-based indoor localization systems since it can provide an acceptable localization at meter level and is not too complicated to implement [20]. The fingerprinting approach has some shortcomings as well. For example, it requires a good coverage of WiFi APs and a large amount of off-line samplings to achieve the 1–2 m accuracy. Furthermore the precision could be low. Even high accuracy localization systems (e.g. *Quuppa* [21]) can generate measurements with low precision at some locations. This is to say that the measured locations drift significantly from the true location. In order to evaluate the performance of the positioning system, the cumulative probability functions (CDF) of the distance error (the distance between the estimated location and the true location) is used [22]. The CDF of the distance error describes the probability $P(E \leq e)$, where E is a random value and e is the variable of distance error in meter. $P(E \leq e)$ gives the probability of a positioning system within e meters of distance error. The range of the CDF is from 0 to 1.

Nowadays smart phones are mostly equipped with motion sensors. The most common motion sensors in a smart phone are accelerometer, gyroscope and magnetometer [23]. These motion sensors are valuable for indoor localization because they can provide information about the distance and bearing traveled by a user. The accelerometer sensor measures the acceleration with respect to the device's coordinate system (X, Y and Z). Gyroscope sensor measures the rotation rate also around the three axes of the device. The device's coordinate system used in this paper is defined by Android [24]. When the device is held in the upright position with the screen facing to the user, the X axis is horizontal and points to the right, the Y axis is vertical and points up and the Z axis points towards the outside of the screen. The magnetometer measures the orientation of the device with respect to the north-south pole of the earth. Accelerometer and gyroscope can detect the direction of a movement. However, the direction is a relative direction which obeys the coordinate system of the device. The magnetometer is able to get an absolute direction based the coordinate system of earth.

Constructing indoor map via crowdsourcing becomes popular in recent years [25,26], which leads to a quick increase of indoor maps. Building construction components such as walls, doors and furniture naturally restrict the pedestrian movement in indoor space. These constraints imposed by the indoor map are often used to correct the measurements of localization systems and thus to improve the accuracy of localization and tracking [9,27–30]. Such approach is independent from the hardware or the signal used and can be applied for different localization technologies. For example, the map matching presented in Spassov's research [29] aims to improve position estimation by snapping a measured position to the closest node of a navigation network. The map matching with particle filter presented in [8,27,28] requires floor plans, which indicates physical restrictions such as walls. Each measured position is represented by a set of particles. The algorithm estimates the false particles with the help of these physical restrictions. The ones passing through walls are not further considered.

Spatial models have been employed for various indoor applications. By far the most common application discussed in the literature is navigation, however there is also research on using spatial models for robotic exploration, indoor tracking and spatial analysis [31–33]. A suitable representation of environmental constraints is significant for indoor tracking. Spatial models can be categorized based on their representations, i.e. geometry, topology and semantics. Pure geometrical, topological or semantic model is rarely used, but hybrid models with various levels-of-abstraction are quite common [34]. In previous research, grid models (e.g. geometry-based models) are often employed for positioning and tracking. The grid model tessellates the indoor space into a finite number of regular cells. These cells can have properties such as occupancy value or semantic attributes. The grid model can also represent the topology of the indoor space. The grid model has some advantages compared to the topology (network) model: it allows all indoor spaces to be reached, it contains connectivity and adjacency information, and the storage can be very efficient [35]. Li, Claramunt, and Ray [36] proposed a node-edge grid graph to represent the indoor entities and their connections. The grid model was first employed for robot localization, also known as occupancy grid map [20,37]. Later this type of model is also used for pedestrian's localization [9].

The tracking methods proposed in the past mostly make limited use of spatial information. There are a few research have combined geometrical and semantic information to improve positioning results. For example, Leppäkoski, etc. [38] used map information about obstacles and walls to exclude the impossible locations. Guo, etc. [39] applied semantic landmarks (e.g. door, stair and turn) and the distance between landmarks to correct the locations estimated by pedestrian dead reckoning. In these studies, only simple geometrical information, such as obstacle location and distances between objects, is used. The semantics of indoor space are often not defined completely. Topological information (e.g. connection graph) is often used for the map matching based positioning method. It is hard to find any research on how to integrate geometrical, topological and semantic features of indoor environment for tracking. Thus this paper proposes a hybrid grid model containing all types of spatial information and develops a tracking algorithm based on the grid model. The tracking algorithm can be also applied to other localization approaches, such as Bluetooth based and RFID systems.

This paper is organized as follows. The next section presents shortly the WiFi localization approach and the spatial model used to improve the localization. Section 3 presents the algorithm. Section 4 elaborates on several experiments and the last section concludes on the status of the developments and future research.

2. Spatial model and localization technology

2.1. Spatial model

This paper employs a hybrid grid model (an example is shown in Fig. 2(b)) which contains geometrical, topological and sematic information of indoor space. The model is derived from the floor plan of the building by using GIS software (The detailed steps to build the grid model are described in the paper [40].). The floor plan in Fig. 2(a) shows the layout of indoor space (e.g. room, door, hallway and furniture) and the relationships between rooms, spaces and other physical features. When building the grid model, only stable features (e.g. table and cabinet) are considered since they have more influence on the walking path of a person than other moveable objects, such as chairs and whiteboard. The accuracy of the grid model depends on the grid size. The selection of the grid size is explained in the next section. The floor plan has been converted to GIS format. The extraction of geometrical, semantic and topological information from the floor plan can be done automatically by GIS software and scripts. By changing the grid size, the model can be updated to achieve a higher accuracy.

2.1.1. Geometry extraction

In the grid model, the indoor space is divided into small cells. To decide the grid size (it refers to the width or length of the grid cell), the following criteria are considered:

1 Importance of indoor objects, for instance door or obstacle, can be represented by the grid cell. Namely the grid size should be smaller than the objects' size.
2 The occupancy of a grid should be as less as possible, in an ideal situation that each grid is only occupied by a space or object. This enable a grid has unique attribute.
3 The human step length or average walking distance per second should be also taken into consideration.
4 The computational complexity should be considered. With increase of detail, the number of grid cells increases, which leads to grow of storage, computation load as well as redundancy.