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A real-time robust indoor tracking system in smartphones

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ABSTRACT

Nowadays, a growing number of ubiquitous mobile applications has increased the interest in indoor location-based services. Some indoor localization solutions for smartphones exploit radio information or data from Inertial Measurement Units (IMUs), which are embedded in most modern smartphones. In this work, we propose to fuse WiFi Receiving Signal Strength Indicator (RSSI) readings, IMUs, and floor plan information into an enhanced particle filter to achieve high accuracy and stable performance in the tracking process. Compared to our previous work, the improved stochastic model for location estimation is formulated in a discretized graph-based representation of the indoor environment. Additionally, we propose an efficient filtering approach for improving the IMU measurements, which is able to mitigate errors caused by inaccurate off-the-shelf IMUs and magnetic field disturbances. Moreover, we also provide a simple and efficient solution for localization failures like the kidnapped robot problem. The tracking algorithms are designed in a terminal-based system, which consists of commercial smartphones and WiFi access points. We evaluate our system in a complex indoor environment. Results show that our tracking approach can automatically recover from localization failures, and it could achieve the average tracking error of 1.15 m and a 90% accuracy of 1.8 m.

1. Introduction

The rapid growth area of ubiquitous applications and location-based services has made indoor localization an interesting topic for research. In indoor environments, location-based services can be applied in many fields such as entertainment, logistic management, e-health, etc. However, to enable ubiquitous location-based services, a reliable localization and tracking approach for mobile devices must be implemented. In outdoor environments, Global Positioning System (GPS) is the most attractive and effective technology to perform object localization. However, in indoor scenarios, the performance of GPS is degraded because of the unavailability of the GPS signals to penetrate through solid building materials. In contrast to GPS for outdoor localization, currently there is not a simple and accurate solution for indoor localization. An additional challenge is the often limited computational and power resources of mobile devices. Thus, constraints on the algorithmic complexity of solutions must be regarded. Therefore, indoor localization is still considered an open challenging problem.

Radio-based localization is one of the most widely used approaches for indoor localization. Radio-based localization relies on the measured radio parameters, such as signal power, to estimate the absolute positions of targets. WiFi signals are often used because they are ubiquitously available indoors. RSSI is the most widely used radio parameter for indoor localization. However, RSSI is easily affected by the temporal and spatial variance due to multipath effects [1], which are severe in indoor environments due to the presence of diverse kinds of elements and obstacles e.g., ceiling, walls, floor and furniture.

Nowadays, smartphones are equipped with embedded IMUs, such as accelerometer, gyroscope and magnetic field sensors, etc. These sensors constantly measure users' behaviors, and can be used to estimate the relative movement of the target by detecting steps, estimating stride length and heading orientation. Pedestrian Dead Reckoning (PDR) systems exploit IMU readings to track the target devices by integrating the estimated relative movement at sequential time intervals. However, PDR-based tracking is prone to accumulated errors. Even small errors in each time interval can be magnified because of the integration in PDR [2].

Some approaches have been proposed to improve the positioning accuracy by combining radio-based positioning and PDR. For example, PDR can be used as a complementary method for localization. These two positioning methods (PDR and radio-based

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methods) are complementary because PDR can provide information about the relative movement between sequential intervals, e.g., velocity, heading orientation, which are missing in range-based methods. Additionally, the absolute location information provided by range-based methods can be used to mitigate accumulated errors in PDR. Moreover, the floor plan of the area of interest can be integrated to further improve tracking accuracy.

The vision of real-time indoor tracking on commodity smartphone devices, however, entails big challenges. For example, the noise in low-cost IMUs on commodity smartphones will introduce some errors in the process of numeric integration during tracking [2]. The sampling frequency of inertial sensors can achieve 100 Hz. However, the sampling rate of the WiFi sensor is much lower, i.e. approximately 4 Hz [2]. The limited computational resources (processor, memory, battery capacity, etc.) in commodity smartphones bring additional challenges to run complex algorithms.

There are some common problems to overcome in indoor localization systems. Two of them are the global localization problem and the kidnapped-robot problem. The former one happens when the localization system starts. Here, the initial position of the target is unknown. The target is located somewhere in the environment without any knowledge of its position.

In contrast to the global localization problem, the kidnapped-robot problem occurs during system operation. This problem is a variant of the global localization problem [3]. The kidnapped-robot problem appears when a well-localized target in operation moves to some arbitrary locations, while the target is not aware of this. Therefore, the target device might firmly believe to be somewhere else at the time of the kidnapping.

With the problems mentioned above, most of the state-of-the-art localization approaches cannot be guaranteed never to fail [3]. Therefore, the ability to recover from failures is essential for truly autonomous localization systems.

Despite the high localization and tracking accuracy, the tracking algorithm presented in our previous work [4] has some drawbacks, which can lead the system non-functional or non-efficient. Therefore, in this work we focus on addressing the problems by proposing three improvements:

- *An automatic localization failure recovery mechanism.* One of the most difficult problems in Monte-Carlo Localization (MCL) is the kidnapped-robot problem. This problem appears when the convergence process of the state hypothesis (particles) produces an absence of particles in some areas of the environment [5]. Therefore, if the target object moves into one of those areas, a localization failure will happen. In practice, real kidnapping is rare; however kidnapping is often used to test the ability of a localization algorithm to recover from global localization failures [6]. Our previous approach [4] does not consider any mechanism to recover the system from a localization failure. Therefore, this work proposes a mechanism to quickly recover the system from localization failures.
- *An improved PDR method by considering magnetic field and angular velocity measurements to further improve the heading orientation estimation.* The prediction phase of our previous approach relies on basic PDR methods. PDR methods provide information about the heading orientation of the smartphone, which is obtained by developing a digital compass based on magnetic field readings. However, a digital compass could behave erratically in indoor environments, where steel and concrete materials cause high distortions in the magnetic field [7]. Therefore, some mechanisms to deal with magnetic field distortions have to be implemented along PDR methods.
- *An efficient method to describe the physical environment*. In our previous approach, floor plan information is used to define the areas where the pedestrian is allowed to move. Although the system achieves good results, we noticed that in environments where walls have complex shapes (i.e., circles), the process to find a possible trajectory for the pedestrian could be computationally expensive. Therefore, in this work we implement an efficient method to describe the physical environment. This approach is able to further reduce the computation overhead on smartphones.

In this work, we propose an indoor tracking approach to support continuous positioning and tracking, which is able to provide high accuracy by fusing IMU, radio, and floor plan information in an enhanced particle filter. We introduce a double re-sampling method that is able to mitigate the errors caused by the low WiFi sampling rate on commodity smartphones. Moreover, we design a localization failure recovery mechanism, which makes our system more fault tolerant. Our additional improvements on magnetic field distortion and physical environment description further improve the PDR system performance significantly. We prototype our approach on commodity smartphones. Our approach can indicate the real-time location of a target without deploying an extra server, since all the tracking algorithms run on the smartphone itself. To validate our tracking system, we conduct extensive experiments in an indoor environment along complex moving paths. Evaluation results show that our infrastructure can achieve an average tracking error of 1.15 m with standard deviation of 0.8 m.

The main contributions of this work are summarized as follows.

- We incorporate a low pass and a Direction Cosine Matrix filter in the PDR methods. These filters smooth the heading orientation errors produced by magnetic field interference and noise in low-cost sensors on commodity smartphones.
- We implement a graph-based model to represent the physical environment. This approach is able to reduce the computational complexity in the prediction phase of our proposed particle filter approach.
- We propose a method to recover the tracking system from localization failures. Our method uses a machine learning approach to recognize rooms. We incorporate the room recognition in our enhanced particle filter to faster recover the system from a localization failure, such as the kidnapped-robot problem. Our approach is able to deal with these kinds of failures even when the accuracy of the room recognition is not high.
- We propose an enhanced particle filter to fuse range information estimated from RSSI, IMU data, as well floor plan information for indoor tracking.
- We implement and evaluate a real-time terminal-based positioning system, which runs our proposed tracking algorithms on commodity smartphones. Our solution does not require any interaction with an additional external server, and all computations are performed on smartphones.
- We conduct a set of extensive experiments to evaluate the system in a complex indoor environment with long tracking paths.

The rest of the paper is organized as follows. In Section 2 we present some previous work. The proposed localization system is presented in Section 3. The implementation of the terminal-based system is presented in Section 4. Section 5 presents the evaluation results of our approach. Section 6 concludes the paper.

2. Related work

The current social and commercial importance of indoor location-based applications have attracted significant attention in recent years. Indoor localization has been investigated lately and many solutions have been proposed. Radio frequency (RF) based approaches includes technologies such as wireless local area network(WLAN), Bluetooth, GPS and RFID localization, and non-RF-based solutions include technologies such as laser, audio, visual,