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Intelligent fusion of information derived from received signal strength and inertial measurements for indoor wireless localization

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ABSTRACT

In this paper, we focus on improving the accuracy of wireless localization in wireless sensor networks using information derived from the inertial measurement unit (IMU) in a smartphone and the received signal strength (RSS). We propose an algorithm to relate the RSSs and measurements obtained from the IMU to the coordinates of an indoor robot. To deal with the dynamic nature of fingerprint information in an indoor radio environment, we first use the hierarchical Bayesian hidden Markov model (HB-HMM) to process a time series of RSSs. Unlike other HMM-based methods, the HB-HMM depends only on a single initial hyper-parameter for global optimization. Next, we evaluate the measurements obtained from the IMU to identify the robot's state, which includes the rotating, moving, and bumping states. We used the IMU accelerometers to estimate the velocity. Lastly, a method based on the particle filter (PF) was used to fuse the results obtained from RSS and IMU. Experiments show that our algorithm can achieve better accuracy than related algorithms.

1. Introduction

Nowadays, users are demanding an increasing diversity of applications from wireless sensor networks (WSNs) [1]. Among these applications, indoor localization has emerged as a key function of wireless sensor networks for tasks including target tracking, robotics and navigation, smart space, intrusion detection, and inventory management [2]. Presently, most commercial WSNs are based on the IEEE 802.15.4 infrastructure, which can be incorporated into an Internet of Things (IoT) architecture with internet protocol version 6 over low power wireless personal area networks (6LoWPAN) [3]. It is widely believed that this will develop into one of the more pervasive wireless technologies of the future.

In particular, indoor wireless localization based on received signal strength (RSS) in an IEEE 802.15.4 infrastructure has long been a challenging problem [4,5]. On the one hand, RSS information can be acquired internally through the use of a WSN communication device, such that indoor localization based on RSS is an off-the-shelf commodity for WSNs. On the other hand, in an indoor wireless environment characterized by non-line of sight (NLOS) and multipath conditions, the distance-RSS conversion model becomes inaccurate.

Within an IoT environment, a smartphone can get data from the WSN [3]. Moreover, smartphones currently incorporate a number of inertial sensors, including accelerometers, gyroscopes, and magnetic compasses, within an inertial measurement unit (IMU). The fusion of data derived from RSS and IMU signals can then be employed to avoid the performance limitations associated with RSS alone, and represents a tangible solution for indoor localization in WSNs.

However, the performance of inertial sensors in smartphones is limited. Many studies have focused on using the peak-detection algorithm to analyze pedestrian gait in indoor environments [6]. Less attention has been paid to the more challenging problem of locating and tracking mobile robots or vehicles in an indoor environment using the IMU signals of a smartphone. In this paper, our goal is to enhance the value of WSNs in an IoT environment to provide accurate robot/vehicle location and tracking capabilities, which are of paramount importance for many applications such as smart space and inventory management.

In the field of indoor localization using WSNs, fingerprinting [7], trilateration [8], close-proximity [9], dead reckoning [10], and Bayesian filters [11] are commonly used techniques. Of these techniques, the close-proximity technique is the simplest, where a mobile target is assumed to be located in an area nearest the reference node transmitting the strongest signal. Systems employing this technique can provide only a coarse location and require a

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high density of reference nodes. In fact, RSS can provide a wider range of information based on logarithmic propagation models. According to theoretical and empirical models, the RSS can be used to establish the distance between the transmitter and the receiver [12]. Then, using trilateration or another range-based technique such as weighted least squares (WLS) [13], Semidefinite programming (SDP) [14] and Multidimensional scaling (MDS) [15], the locations of mobile devices within the WSN can be estimated.

However, the unpredictability of NLOS signal propagation and multipath propagation through indoor environments are major challenges in indoor localization. To mitigate the influence of NLOS and multipath errors, fingerprinting techniques have recently been examined. In these techniques, RSS values at specific locations are used as fingerprint information. This is also referred to as a range-free algorithm. Because RSS patterns are directly mapped out according to specific locations, the measurement errors caused by NLOS and the multipath environment are avoided. However, a significant investment of human labor is typically required to build a detailed map-database. Additionally, some authors have proposed Bayesian filter techniques to accumulate information from consecutive measurements. Among Bayesian filters, the extended Kalman filter (EKF) and the particle filter (PF) have been widely used in the field of indoor localization. However, the performance of Bayesian filter techniques depends on a priori knowledge of the statistical distribution of the measurement noise. The dead reckoning technique incorporates measurements derived from inertial sensors, and has also been used in indoor localization. This technique uses an accelerometer to perform distance detection, and then uses a compass for heading direction estimation. While the technique requires no infrastructure assistance, the location accuracy is limited by the performance of the inertial sensors.

In this paper, we propose an unsupervised learning algorithm, namely HPFRI (HB-HMM and Particle Filter for the Fusion of RSS and Inertial Measurements), which employs the hierarchical Bayesian hidden Markov model (HB-HMM) for the RSS time series analysis and the PF for fusion of the RSS and inertial measurements obtained from the IMU in a smartphone, for improved accuracy of wireless localization in WSNs. With respect to other localization methods employed in WSNs, the contributions of the present study are as follows:

- Because we generate the HB-HMM model of RSS values to estimate the location, and use the information obtained from the IMU which is completely irrelevant to signal propagation in the indoor environment, measurement errors caused by NLOS and multi-path is mitigated.
- Our algorithm is based on unsupervised learning that accumulates information through consecutive observation, and, thus, the RSS value is automatically collected.
- Novel methods are employed to identify the robot state based on IMU information.
- A PF method is employed for the fusion of RSS and IMU data.

The remainder of this paper is organized as follows. Section 2 provides an overview of related localization systems. The problem statement regarding indoor wireless localization is introduced in Section 3. Subsequently, Section 4 presents the HPFRI algorithm. Section 5 discusses the experiments run in indoor scenarios. The paper closes with conclusions in Section 6.

2. Related work

A number of localization techniques based on RSS and IMU data have been developed for WSNs. For instance, in response to an initiative for the development of a real-time indoor localization system for tracking people, D'Souza et al. designed the Indoor People Tracker, an approach that employed the proximity to static nodes in the WSN in conjunction with data obtained from onboard inertial sensors [16]. A multi-hypothesis estimation algorithm based on dead reckoning and Monte Carlo approaches was applied to the Indoor People Tracker, which attained an indoor resolution of 2.5 m. In the field of indoor localization based on inertial sensors, Bayesian filter techniques have been most commonly used. Correa et al. proposed an enhanced filtering method (Power Threshold Covariance Matrix Tuning, PT-CMT) for indoor localization using a WSN that employed the inertial measurements obtained from a nine-degrees of freedom IMU. The experimental results verified that the system correctly estimated the location of a mobile terminal indoors within an area of around 1 m $\times$ 1 m [17]. Hur et al. proposed a discrete-time H_∞ filter for indoor robot localization in WSNs based on IMU data and chirp spread spectrum (CSS) ranging [18]. This method improved the ranging precision accuracy to 1 m. Lee et al. proposed an indoor pedestrian localization system equipped both with inertial sensors and the IEEE 802.15.4a CSS radio [19]. Experimental results demonstrated a mean error of approximately 1.5 m with five position-unknown beacons. Aimed at monitoring groups of mobile nodes, Franco et al. proposed a data fusion method using information derived from an RSS indicator (RSSI) and an IMU [20]. The Kalman filter and multidimensional scaling were employed to estimate robot dynamics. The error distribution of the system was determined to demonstrate a mean error = 60.3 mm and a standard deviation = 56 mm. In another study, Tarro et al. proposed a framework based on RSS and IMU data for reducing energy consumption in localization systems [21]. For a given target accuracy, the proposed framework exhibited a lower energy consumption than conventional methods.

However, these approaches did not use unsupervised learning techniques. As such, their performance depended on prior information, which limited their applicability to their initial environments. Wang et al. proposed UnLoc, a self-learning method for indoor wireless localization [22]. By combining dead reckoning, urban sensing, and partitioning based on WiFi into a framework for unsupervised localization, they established landmarks from various sensors (e.g., accelerometer, magnetometer, sound, and ambient light) to substantiate the position estimate. However, the experiment did not employ time series data information, and this limited the validation because the transition probability is an important contribution for determining accuracy.

3. Problem statement

We consider a WSN deployed in an indoor environment with a robot equipped with a mobile node and a smartphone. Given this scenario, we seek to determine the robot's position based on RSS and IMU data. Specifically, a vector representative of the mobile node's signal strength received from M reference nodes, namely the fingerprint, is defined as (1).

$$S_i = \{s_{i,1}, s_{i,2}, \ldots, s_{i,M}\} \quad i = 1, 2, 3, \ldots N \tag{1}$$

Here, i denotes the ith signal strength sample in the time sequence, as received from the jth reference node, and N is the total number of samples. For convenience, we divide the indoor environment into grids. If an S_i is given, our goal is to locate the grid that matches the mobile node's position. In our unsupervised fingerprint method, a priori knowledge regarding the positions of the reference nodes is not essential. To save time and labor, in each of K grids we investigate only a single labeled fingerprint as an initial representative, which is defined as

$$F_k = \{f_{k,1}, f_{k,2}, \ldots, f_{k,j}, \ldots, f_{k,M}\} \quad k = 1, 2, 3, \ldots, K \ \ and \ \ j = 1, 2, \ldots, M \tag{2}$$