Chapter 7
Information Filter-Assisted Indoor Bluetooth Positioning

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ABSTRACT

This chapter studies wireless positioning using a network of Bluetooth signals. Fingerprints of Received Signal Strength Indicators (RSSI) are used for localization. Due to the relatively long interval between the available consecutive Bluetooth signal strength measurements, the authors applied an information filter method with speed detection, which combines the estimation information from the RSSI measurements with the prior information from the motion model. Speed detection is assisted to correct the outliers of position estimation. The field tests show the effectiveness of the information filter-assisted positioning method, which improves the horizontal positioning accuracy of indoor navigation by about 17% compared to the static fingerprinting positioning method, achieving a 4.2 m positioning accuracy on the average, and about 16% improvement compared to the point Kalman filter. In RSSI fingerprinting localization, building a fingerprint database is usually time-consuming and labour-intensive. In the final section, a self-designed autonomous SLAM robot platform is introduced to be able to carry out the Bluetooth RSS data collecting.

INTRODUCTION

Location and navigation technologies have been researched in a pervasive way in recent years. Diverse location based applications have been fast deployed in our daily life. GNSSs (Global Navigation Satellites Systems) have been widely accepted for positioning and navigation outdoors. The built-in GPS (Global Positioning System) on a handset is capable of providing location information in open signal environments. However, for
indoor positioning, GPS is unable to provide the desired level of accuracy or is even unavailable (Kaplan, 1996; Liu et al., 2012a). As an alternative, multiple sensors and signals of opportunity (SoOP) have been used for indoor positioning and navigation (Bahl & Padmanabhan, 2000; Pei et al., 2010a). Different with GNSS, SoOP are not originally intended for the purpose of navigation. With suitable methods, currently, research that utilize SoOP for navigation to achieve the positioning results includes WiFi, Bluetooth (Gomes & Sarmento, 2009; Chen et al., 2013), RFID (radio-frequency identification) (Ni et al., 2004), UWB (ultra wideband) (Pahlavan et al., 2006), long range signals of such as, GSM (global system for mobile communications) (Syrjärinne, 2001), and DTV (digital television) (Chen et al., 2012). In addition, multiple sensors can also be used to assist navigation indoors. Examples of such sensors include accelerometers, gyroscopes, compasses, cameras, proximity sensors (Pei et al., 2012).

In this work, we will focus on one of the SoOP, the Bluetooth, for the research of indoor positioning. Bluetooth is a technology for short-range wireless data and voice communication with low power consumption. It has been utilized in the communication and proximity market for a long time. As widely supported by mobile devices, Bluetooth is a potential technology to become an alternative for indoor positioning. However, indoor positioning using Bluetooth signals has not been widely studied so far. Bandara et al. (2004) developed a multi-antenna Bluetooth Access Point (AP) for location estimation based on received signal strength indicators (RSSI). The test obtained 2 meters of error in a 4.5 m × 5.5 m area with four antennas. Sheng & Pollard (2006) modified the Bluetooth standard to estimate the distance between a reference transmitter and a mobile receiver, using RSSI measurements and a line-of-sight radio propagation model within a single cell. A high-density Bluetooth infrastructure is necessary to achieve an accurate position in the above two approaches. In order to minimize the Bluetooth infrastructure, Kelly et al. (2008) used only one class 1 Bluetooth AP for a home localization system, which combined the measurements of the link quality, RSSI, and cellular signal quality to obtain room-level accuracy. Pei et al. (2010b) present a Bluetooth locating solution in a reduced Bluetooth infrastructure area by using RSSI probability distributions. Other topics related to Bluetooth positioning can be found in (Hay & Harle, 2009; Anastasi et al., 2003; Bargh & Groote, 2008; Jevring et al., 2008; Naya et al., 2005). New specifications and products have been developed for a relatively longer range of transmission. Compared with the class 2 device (e.g. the Bluetooth module in a smart phone), which has only the range of about 20-30 meters (Bluetooth, 2010), a class 1 Bluetooth device (e.g. the Bluegiga AP 3201) has an effective range up to 200 meters and the newly developed Bluegiga AP 3241 can even achieve an effective range of 800 m in an open area without obstructions (Bluegiga, 2010).

In this study, for the indoor positioning test, a Bluetooth network including 13 long range APs (Bluegiga 3201 and 3241) have been deployed in the area of interest. For a low cost receiver, RSSIs are the feasible observables that could be used for positioning. Generally, there are two basic approaches used for the estimation of locations with RSSI measurements. The trilateration-based approach first translates RSSI measurements into the distances between a mobile user and multiple access points (APs) based on a radio propagation model and then calculates the user’s location using the obtained distances and AP coordinates (Liu et al., 2012b). The major challenges in this approach include the large errors associated with estimated distances and difficulties in system deployment, e.g., the trouble associated with obtaining the AP coordinates indoors. In contrast, the fingerprint approach determines a user’s position by matching RSSI measurements with a fingerprint database in a deterministic or stochastic way. The k-nearest neighbors (KNN) method employs a determinis-
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