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An improved inertial/wifi/magnetic fusion structure for indoor navigation

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ABSTRACT

This paper proposes a dead-reckoning (DR)/WiFi fingerprinting/magnetic matching (MM) integration structure that uses off-the-shelf sensors in consumer portable devices and existing WiFi infrastructures. One key improvement of this structure over previous DR/WiFi/MM fusion structures is the introduction of a three-level quality-control (QC) mechanism based on the interaction between different techniques. On QC Level #1, several criteria are applied to filter out blunders or unreliable measurements in each separate technology. Then, on Level #2, a threshold-based approach is used to set the weight of WiFi results automatically through the investigation of the EKF innovation sequence. Finally, on Level #3, DR/WiFi results are utilized to limit the MM search space and in turn reduce both mismatch rate and computational load. The proposed structure reduced the root mean square (RMS) of position errors in the range of 13.3 to 55.2% in walking experiments with two smartphones, under four motion conditions, and in two indoor environments. Furthermore, the proposed structure reduced the rate of mismatches (i.e., matching to an incorrect point that is geographically located over 15 m away from the true position) rate by over 75.0% when compared with previous DR/WiFi/MM integration structures.

1. Introduction

Indoor pedestrian navigation (i.e., determination of position, velocity, and attitude) is increasingly important due to their potential applications in a wide range of mobile location-based services (LBS) from emergency responders to commercial advertising and social networks [1,2]. Most LBS users spend 70 - 90% of their time in indoor or urban areas [3]. Thus, a trustworthy indoor navigation solution is highly demanding [4].

While Global Navigation Satellite Systems (GNSS) based outdoor navigation has greatly advanced over the past decades, positioning indoors is still an open issue [5]. The challenges include the unavailability or degradation of GNSS signals, the complexity of indoor environments, the necessity of using low-grade devices, etc. Various indoor positioning technologies based on Radio Frequency (RF) signals have been researched, such as IEEE 802.11 WLAN (WiFi), Radio Frequency identification (RFID) tags, ZigBee, Ultra Wideband Beacons (UWB), Bluetooth Low Energy (BLE), and pseudolites [6]. RF-based technologies can provide long-term absolute positions, but require the creation and maintenance of a network [7]. As WiFi chips become ubiquitous, positioning with existing WiFi infrastructures in public buildings becomes feasible [8]. WiFi fingerprinting approaches based on received signal strength (RSS) have gained a large amount of attention, as they can provide position without any knowledge of access point (AP) locations or radio propagation models [9]. Nevertheless, there are challenges for reaching high positioning accuracy by using WiFi RSS: a) the performance of a wireless positioning system depends on signal availability and geometry [10]. Weak geometry may lead to ambiguity problems [11]. b) The positioning performance is limited by RSS fluctuations caused by obstructions, reflections [12], and multipath effects [13]. Additionally, c) WiFi chips in smartphones are low-cost and have large signal diversity [14]. These issues have limited the promotion of WiFi and other wireless positioning techniques.

Advances in Micro-Electro-Mechanical Systems (MEMS) technology have made it possible to produce chip-based sensors, such as inertial sensors (i.e., accelerometers and gyros) and magnetometers. MEMS inertial sensors have been widely used in motion tracking and navigation applications because they are small size and light weight, and power saving [15]. For consumer portable devices, dead-reckoning (DR, by using either the inertial navigation system (INS) mechanism or pedestrian dead-reckoning (PDR)) is usually the algorithm used to navigate with inertial sensors; thus, inertial sensors are independent on the transmission or reception

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of signals from an external source [16]. The shortcoming is that inertial sensors provide only short-term accuracy and suffer from accuracy degradation over time due to the existence of sensor errors [17]. Calibration is useful to remove many deterministic sensor errors [18]; however, low-cost MEMS inertial sensors suffer from significant run-to-run biases and thermal drifts [19]. Residual sensor errors will accumulate and lead to navigation errors due to the integration process in the INS mechanization. Although the horizontal attitude errors can be controlled by accelerometer measurements, the heading error will grow when there is no aiding information [20]. Magnetometers can provide an absolute heading through leveling using accelerometers, magnetic heading calculation, and true heading computation [21]. However, this approach is developed based on the assumption that the local magnetic field (LMF) is mainly the geomagnetic field and thus the declination angle can be obtained from the International Geomagnetic Reference Field (IGRF) model [22]. Preliminary results indicated that the majority of outdoor tests met this assumption; however, the LMF was susceptible to magnetic interferences from man-made infrastructures in indoor areas. The existence of magnetic interferences is a critical issue when using magnetometers as a compass indoors [23].

The existence of indoor magnetic interferences can also be exploited as an advantage by leveraging the magnetic abnormalities as fingerprints or landmarks [24]. The magnetic matching (MM) approach has been proposed based on the hypothesis that the indoor magnetic field is stable over time and non-uniform (i.e., changes significantly) with location [25]. While MM utilizes a similar idea as WiFi fingerprinting, it has two advantages [25]: a) it is independent from any infrastructure as the magnetic field is omnipresent; and b) magnetometers have higher sampling rates. The challenge for MM is that magnetic data only consists of three components. Because heading is generally unknown, it is only feasible to extract two components (i.e., vertical and horizontal magnetic intensities, or total magnetic intensity and inclination). To increase magnetic fingerprint dimension without extra sensors, the profile-matching approach has been proposed [26]. A sequence of observations is saved in the memory and then compared with candidate profiles in a database. Profile-matching has been used in high-end self-contained terrain [27], gravity [28], and magnetic referenced navigation systems [29]; in addition, there are well-developed profile-matching methods such as terrain contour matching (TERCOM) [27] and iterative closest contour point (ICCP) [28]. However, the performance of MM is highly dependent on the LMF: MM solutions can be accurate but suffered from mismatches on some occasions, as there are hundreds of trajectories that have the similar magnetic features on the Earth.

Thus, all the existing indoor positioning technologies have advantages and disadvantages [30]. Considering their complementary characteristics, multi-sensor integration is a key factor of success for accurate and reliable navigation solutions. Because DR, WiFi, and MM are technologies that are available by using off-the-shelf sensors in consumer portable devices, their integration is investigated in this paper.

There is literature that focuses on enhancing navigation results through better fusion of inertial sensors and magnetometers. For example, the research [31] utilizes gyro-derived heading to detect severe magnetic disturbances, and the research [32] uses magnetometer measurements during quasi-static magnetic field (QSMF) periods to calibrate gyros. These approaches are effective on improving the robustness of DR, but still suffer from the issue inherent in DR – drifts of position. To provide long-term accuracy, a common approach is to integrate DR with absolute positioning techniques (e.g., WiFi). Different estimation techniques (e.g., Kalman filter [33] and particle filter [34]) have been used for information fusion. The majority of literature integrates DR with wireless technologies through a loosely-coupled way [33], while some apply a tightly-coupled approach [35]. Compared with DR and WiFi, the research of indoor MM started later and most of related works are on the independent use of MM [36] or the integration of MM and DR [37]. For WiFi and MM, the research [38] and [39] integrate these technologies for indoor pedestrian navigation. The former uses a region-point indoor localization approach, while the latter applies a two-pass particle filter to fuse magnetic and WiFi signals. The literature [40] compares the region-point indoor localization approach and the approach that regards the magnetic intensity and inclination as pseudo WiFi APs.

For the integration of DR, WiFi, and MM, the literature [41] uses a Kalman filter to fuse the information from different sensors, while the research [42] utilizes a bundle adjustment approach to implement simultaneous localization and mapping. The hybrid navigation structure (named as Structure #0 in this paper) behind these works is to feed all sensor data into a fusion module. DR is used to provide continuous position predictions and build the system model; meanwhile, WiFi and MM positioning results are utilized directly as position updates.

Furthermore, scholars have noticed that MM results have small fluctuations [38], but have a risk of mismatching due to low magnetic fingerprint dimension [36]; in contrast, WiFi results have a low mismatch rate but suffer from larger fluctuations [40] (The term “mismatch rate” means “the percentage of position results that have a position error of over 15 m”). Therefore, there is a potential to use WiFi for a rough positioning, and then use MM for a more precise localization [38]. Thus, an improved structure (named as Structure #1 in this paper) can be developed. WiFi results are used to limit the MM search space. Afterwards, both WiFi and MM (WiFi aided) results are utilized as updates to correct DR. Tests in this paper supported that WiFi-aided MM could provide better results than either the independent use of WiFi or MM. Consequently, Structure #1 provided more reliable solutions than Structure #0. However, there were still mismatches in MM (WiFi aided) results because fluctuations of WiFi results is the issue inherent in approaches based on RSS. Therefore, an improved structure is presented in this paper to further improve the reliability of the hybrid DR/WiFi/MM navigation. In this paper, the sign “/” represents the integration of different techniques.

By using the same data from sensors and WiFi, different information fusion structures may lead to various results in Engineering practice. This paper first investigates on the independent use of DR, WiFi, and MM to indicate their advantages and disadvantages, and then optimizes the DR/WiFi/MM integration structure. The proposed structure first uses DR to provide continuous position predictions and calculates WiFi and MM positioning results as potential updates, which is similar to traditional integration structures. Afterwards, it integrates DR with WiFi, and utilizes DR/WiFi results to determine the MM search space. Accordingly, a three-level quality-control (QC) mechanism is proposed to enhance the system robustness in the above steps. This paper enhances the use of DR and MM as follows:

- A two-filter algorithm is utilized to enhance DR. The algorithm is comprised of an INS-based attitude-determination Extend Kalman filter (EKF) and a PDR-based position-tracking EKF. Multiple constraints are used to assure the algorithm works under natural phone motions such as handheld, phoning (i.e., close to the ear), dangling (i.e., walking with phone in hand), and pocketed (i.e., in a pants pocket).
- Several approaches are used to improve MM. For example, (a) Dynamic Time Warping (DTW) is used to match time-series with inaccurate profile lengths. (b) k-nearest neighbor (k-NN) is introduced from WiFi fingerprinting into MM. Finally, (c) both magnetic-gradient and magnetic-intensity fingerprints are uti-