

Location-Based Services in Complex Indoor Environments via Modern Smartphone Multi-Sensor Integrated Navigation

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Abstract:

The problem of location-based services (LBS) in indoor environments, such as shopping malls, airports, and other large and complex buildings, has increasingly become more attractive. LBS are a type of service that utilizes the geographical location of a user or device to provide relevant information or functionality to that specific location or point of interest [Huang et al. (2018)]. These services typically rely on technologies such as Global Navigation Satellite Systems (GNSS), which are usually inefficient in indoor environments, Wi-Fi, Bluetooth, or Wireless Sensor Networks to determine the user's position in real-time. Nowadays, modern smartphones are equipped with many useful sensors, some of which are particularly important for mapping, positioning, and navigation in indoor environments [Zhuang et al. (2016), Al-Balasmeh et al. (2024)]. Recently, researchers have concentrated on enhancing the precision of positioning and navigation outputs through the integration of these sensors. The sensors used for integrated navigation are listed in the following, based on the type of measurement they provide. The first category is radio-based sensors that measure geometric quantities, such as distance or angle, either directly or indirectly. This includes GNSS, Wi-Fi, Bluetooth, including Bluetooth Low Energy (BLE), and, more recently, Ultra-Wideband (UWB). The second category is Inertial Measurement Units (IMUs), which measure physical quantities such as linear acceleration and angular velocity using Micro-Electro-Mechanical Systems (MEMS) accelerometers and gyroscopes, all within the smartphone's body frame. Finally, other sensors, such as the magnetometer (or magnetic compass), barometer, cameras, and pedometer, can also be used to determine location parameters through integrated navigation algorithms. For example, some useful Android and iOS applications collect this data simultaneously, allowing users to integrate it for LBS approaches. In this research, we introduce several of these applications based on the types of measurements, as shown in Table 1.

App	Android	iOS	Bluetooth	Wi-Fi	IMUs	Magnetometer	Barometer	Pedometer	Visual
Sensor Logger	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
phyphox	Yes	Yes	No	No	Yes	Yes	Yes	No	No
BLE Scanner	Yes	Yes	Yes	No	No	No	No	No	No
WiFi Meter	Yes	No	No	Yes	No	No	No	No	No

Table 1. Sensor Logger Applications for Integrated Navigation in Indoor Environments on Android and iOS Smartphones

To provide continuous LBS within complex indoor environments, it is crucial to integrate position-fixing sensors, such as Bluetooth, Wi-Fi, and cameras, alongside dead-reckoning sensors, including accelerometers, gyroscopes, and magnetometers. This integration is essential for the performance of integrated navigation systems. In this research, we propose a centralized, or tightly coupled, integration approach to address the challenges of combining diverse sensor data, offering improved indoor positioning accuracy compared to loosely coupled methods. This superiority arises from its ability to simultaneously incorporate all available sensor measurements to compute positioning parameters, thereby enhancing the accuracy and reliability of the system [Jekeli (2023)]. This method is particularly critical in complex indoor environments, where the dense and intricate structures may obstruct or reduce the availability of position-fixing sensor data. In such scenarios, the tightly coupled integration guarantees the system's continued effective operation by utilizing the continuous data provided by the dead-reckoning sensors, thus ensuring reliable and consistent positioning performance despite environmental challenges. The navigation Kalman filter typically consists of two primary phases: the first is the time update (TU), followed by the measurement update (MU), as outlined below [Teunissen (2024)]:

$$\hat{x}_{t|t-1} = \Phi_{t,t-1} \hat{x}_{t-1|t-1} \text{ (TU) and } \hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t (y_t - A_t \hat{x}_{t|t-1}) \text{ (MU).} \quad (1)$$

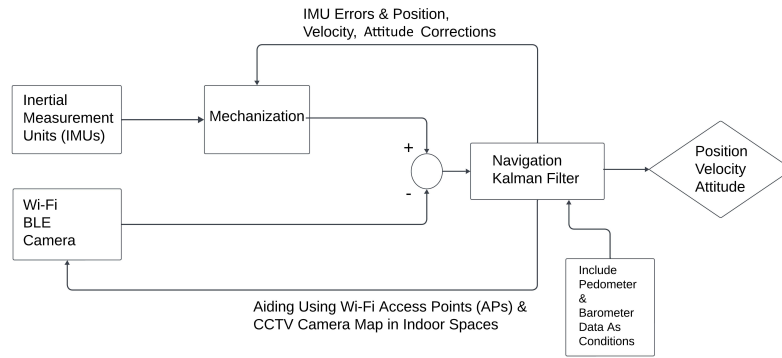


Figure 1. Centralized Integration (Tightly Coupled Integration) of Smartphone Sensor Data

In the above equation, the time update uses the filtered estimate $\hat{x}_{t-1|t-1}$ of epoch $t-1$ to predict the parameter vector of the next epoch, x_t , as $\hat{x}_{t|t-1}$. This predicted estimate, together with the new measurements y_t , is then combined in the measurement update to achieve the filtered estimate of x_t as $\hat{x}_{t|t}$. $\Phi_{t,t-1}$ is referred to as the transition matrix, K_t is the Kalman gain, and A_t is the design matrix of unknown parameters, respectively. Finally, the position, velocity, and attitude of the point of interest would be continuously estimated within a complex indoor environment for LBS applications.

For the implementation purpose, we have conducted a preliminary experiment on the campus of Université Laval in Quebec City, utilizing sensor data from a Samsung S22+ (logged via the Sensor Logger App). In this experiment, BLE beacons were deployed along a reference trajectory to transmit continuous 0.5 Hz signals to the receivers as position-fixing data, with the MEMS-IMUs and magnetometer inside the smartphone for dead-reckoning data. Sensor data integration was performed to determine the continuous position, velocity, and attitude along the reference trajectory at 1-second intervals, where the total duration of the experiment was 200 seconds. Figure 2 shows the locations of the start and end points of the reference trajectory obtained using the proposed method. In addition to the position, we have also estimated the velocity and attitude of the smartphone at the same points. The results demonstrate ± 1 -meter accuracy for LBS applications (e.g., indoor navigation).



Figure 2. Estimated Indoor Positions in Pavilion Louis-Jacques-Casault (Left), Deployed BLE Beacon and Reference Trajectory (Center), Estimated Position, Velocity, and Attitude of Start and Final Points of Interest (Right)

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