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Brief paper

Cellphone geolocation via magnetic mapping[☆]

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ABSTRACT

We develop novel algorithms based on interval analysis with theoretical guarantees, to augment the accuracy of cell phone geolocation by taking advantage of local variations of magnetic intensity. Thus, the sources of disturbances to magnetometer readings caused indoors are effectively used as beacons for localization. We construct a magnetic intensity map for an indoor environment by collecting magnetic field data over each floor tile. We then test the algorithms without position initialization and obtain indoor geolocation to within 2 m while slowly walking over a complex path of 80 m. The geolocation errors are smaller in the vicinity of large magnetic disturbances. Finally, we fuse the magnetometer measurement with inertial measurements on the cell phone to yield even smaller geolocation errors of under 50 cm for a moving user. Our theoretical results connect geolocation accuracy to combinations of sensor and map properties.

1. Introduction

Global Positioning System (GPS) receivers on cell phones offer accurate geolocation for customers, but these fail to be reliable in areas subject to multipath interference, shadowing and occlusion of a line of light to the satellites (Bajaj, Ranaweera, & Agrawal, 2002; Byun, Hajj, & Young, 2001). These GPS-denied areas include urban and natural canyons, forests, and indoor locations, or in the case that users are reluctant to drain battery power switching on GPS. The accuracy of cell phone geolocation in these areas with poor GPS performance is demanded by customers, especially for the indoors and urban canyon areas in which they work daily. Geolocation of any cell phone is *a priori* obtained to be within a range through the nearest cell tower (Weiss, 2003). To obtain a more accurate estimate, several approaches have been developed over the years. One main approach is to use the communication between the phone and the transceiver tower, including received signal strength (RSS) (Martin, Vinyals, Friedland, & Bajcsy, 2010; Rappaport, 1996), the time of arrival (TOA) (Bshara, Orguner, Gustafsson, & Van Biesen, 2010; Qi & Kobayashi, 2003) and the time difference of arrival (TDOA) (Sayed & Tarighat, 2005). Another approach using local landmarks includes utilizing indoor Wi-Fi transceivers and radio frequency identification (RFID) (Bekkali, Sanson, & Matsumoto, 2007), which performs better indoors. Moreover, by using the embedded sensors (Fang, Lin, & Lee, 2008) on cell phones, algorithms utilizing inertial measurement units (IMUs) and magnetometers have been introduced. Many previously developed algorithms and applications are recapitulated and compared in Gustafsson and Gunnarsson (2005).

Local fluctuations in magnetic field intensity make it possible to augment these methods for geolocation in some GPS-denied areas. With the measurement from magnetometers, a magnetic intensity map can be constructed by collecting measurements at each of the intersections on the meshed grid. In the case of indoor navigation using magnetometers (Bonnet & Héliot, 2007; Chung et al., 2011; Haverinen & Kemppainen, 2009), the mapping function can match each reading from a sensor to an area in a meshed grid from a floor plan. In our research, we use two types of magnetometers to build up the magnetic intensity map by collecting the steady-state value of the outputs at each point. We then develop algorithms based on interval analysis (Gning, Abdallah, & Bonnifait, 2007; Jaulin, Kieffer, Didrit, & Walter, 2001; Moore, Kearfott, & Cloud, 2009; Schweppe, 1973) to estimate each single measurement in quasi-static estimation and track the path of the cell phone user. For a single measurement, we develop an optimization algorithm based on concepts from Jaulin et al. (2001) to bound the local estimation into small 2-D intervals, and evaluate the performance by showing

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the relationship between sharpness of map, quality of sensor, and the geolocation error. To track the path of a walking user, we develop a dynamic algorithm to fuse each of the quasi-static interval estimates and generate a path of geolocation intervals with reduction of estimate size.

Moreover, with the help of embedded IMUs on smart phones, some auxiliary inertial navigation systems have been introduced (Bekkali et al., 2007; Cui & Ariyur, 2011; Fang et al., 2005, 2008; Jirawimut et al., 2003). The three-axis inertial measurements offer accelerations and angular rates at 16 Hz, with the advantage of introducing detailed information of the dynamic model, which can potentially improve the performance of the magnetic map navigation over short intervals of time. Hence, we develop an algorithm to fuse the IMU with the magnetometer, including an inertial update phase and a magnetometer update phase, in which estimated intervals being updated by inertial measurements are intersected with the next estimate at any sampling time. The result from dynamic estimation via magnetic map is improved significantly reducing the geolocation error. We then compare the result with the particle filter based on Monte-Carlo simulation (MCS) (Arulampalam et al., 2002; Doucet & Johansen, 2008), which is another algorithm for the grid-based tracking and sensor fusion. We apply the theory of particle filter into the tracking system to fuse the IMU with magnetometer and compare the performance of both algorithms, and the greatest precision is obtained from the interval analysis with estimate error less than 50 cm.

We organize this paper as follows, the system model and magnetic intensity map construction are introduced in Section 2. In Section 3, we introduce basic concepts from interval analysis as the tool to solve the problem. We present algorithms, theorems and results of both quasi-static estimation and dynamic estimation in Section 4. We then show the fusion process with IMU and comparison with particle filter in Section 5, and draw conclusions in Section 6.

2. Magnetic intensity map

The magnetic intensity map includes meshed grids and interaction nodes on it. Each node has the data collected from magnetometer and the position marked on the geometric map. Suppose we have a plane region $\mathbb{D} \subset \mathbb{R}^2$ considered as the *a priori* region, then any node in the region has a unique magnetic intensity. The value depends on the macro geolocation of this point obtained from the standard International Geomagnetic Reference Field (IGRF) (Finlay et al., 2010), and the impact from local extremely low frequency bias such as iron structure and devices (Burnett & Yaping, 2002). We define our mapping function as follows:

Definition 1 (*Mapping Function*)**.** The local magnetic intensity map is defined as the function from a point $(x, y) \in \mathbb{D} \subset \mathbb{R}^2$ to a magnetic intensity value m, $m : \mathbb{R}^2 \to \mathbb{R}^1$.

$$\forall (x, y) \in \mathbb{D}, m(x, y) = |(m_I(x, y) + m_B(x, y))|. \tag{1}$$

The $R_{3\times3}$ rotation matrix has the property of $|R_{3\times3}| = 1$ and eliminates the rotation effects when calculating the norm value. The map set including all of magnetic intensity values $m(x, y)$ is then defined as M. $M = \{m(x, y) \mid (x, y) \in \mathbb{D}\}$. In our case, we use a 3-axis magnetometer to measure $(m_x, m_y, m_z)^T$ and take its norm value $|m|$ to build up the map and hence we have:

$$m(x, y) = |(m_I + m_B)| = \sqrt{m_x^2 + m_y^2 + m_z^2}. \tag{2}$$

So far we have the model to construct the map. However, we need to consider the measurement with noise and we have:

$$z_m = \sqrt{m_x^2 + m_y^2 + m_z^2} + \nu_m \tag{3}$$

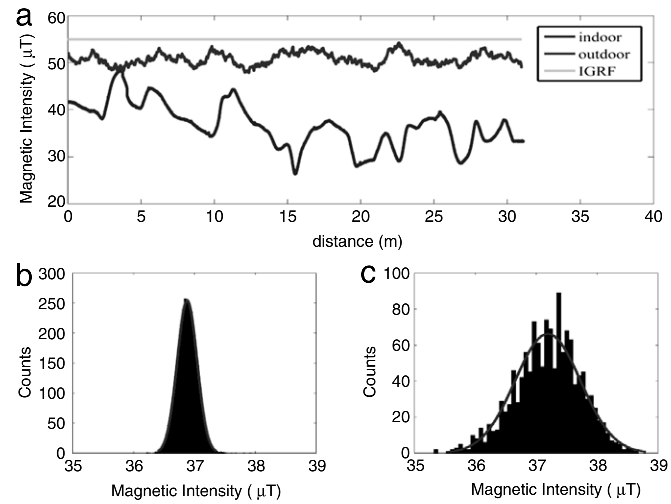

Fig. 1. Example of the magnetic intensity measurement. (a) The plot of local magnetic intensity from IGRF, outdoors, and indoors over 30 m. (b) The histogram of static measurement from 3DM-GX3 sensor, and $\mu_{3DM} = 35.9407$; $\sigma_{3DM}^2 = 0.0066$. (c) The histogram of static measurement from cell phone sensor, and $\mu_{phone} = 36.0952$; $\sigma_{phone}^2 = 0.0722$.

where z_m is the measurement and ν_m is the measurement noise. An example of the measurement of magnetic intensity is shown in Fig. 1, including local magnetic intensities from the IGRF model, an outdoor test around the ME building on Purdue campus, and an indoor test inside the ME building. From Fig. 1(a), the magnetic intensity fluctuates more indoors than outdoors, or the IGRF model, which permits us to use the larger fluctuations effectively as beacons. The noise in this case is non-central χ distributed with 3 degrees of freedom. This is because the magnetic vector measurement has Gaussian noise. In our calculations however, we only use an empirical standard deviation of this noise to construct intervals of uncertainty from our measurements.

We build up the map experimentally by collecting data on each node, and obtain the mean value after 2 s of measurement. The distance between two grid lines is 0.3 m. We place devices on a plastic cart which was tested to have no influence on the magnetic intensity measurement. The floor plan and the experimental region are shown in Fig. 2. An example of the magnetic intensity map is shown in Fig. 5(b). Having built up the map, we need to design algorithms to match the real measurement z_m to the map and estimate the geolocation. Here we define the cost function $c(x, y)$ as the error between a single measurement z_m at a random point (x, y), and the magnetic intensity $m(x, y)$ on the map.

$$c(x, y) = |z_m - m(x, y)|. \tag{4}$$

Hence, we need to find the local minimizers that minimize $c(x, y)$. Then we insert those local minimizers into an algorithm and approximately find the global minimizer which yields optimal geolocation. This is done with the mathematics of intervals which is introduced in the following section.

3. Interval analysis

Interval Analysis (IA) yields sets as estimates of optima or system states in sensor fusion (Horn et al., 2003; Jaulin et al., 2001; Jaulin & Walter, 1993; Kieffer, Jaulin, Walter, & Meizel, 2000; Moore et al., 2009). We use the initial magnetometer reading to determine all the possible spatial intervals that can contain the measurement, and then intersect them over subsequent readings to eliminate all local minimizers of $c(x, y)$. Interval analysis is better suited than the Kalman filter or the particle filter for this estimation task that exploits a random field, rather than being thrown off