# Indoor Positioning System Using Geomagnetic Anomalies for Smartphones 

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#### Abstract

In this paper, we propose an indoor positioning system using smartphones. To localize the position of target that is pedestrian in usual indoors, we make use of perturbations of the geomagnetic field caused by structural steel elements in a building. The system based on magnetic field does not need any physical infrastructure, so it is possible to be realized with low cost. To estimate the target's position using the geomagnetic anomaly, the proposed system measures the magnetic field on its own position using a magnetometer embedded in smartphones and compares the sensor measurement with the magnetic map that has been created for the building in advance. The estimated position is calculated by a stochastic system based on the particle filter. To calculate control inputs for the particle filter, such as moving distance and direction, we exploit the inertial measurement unit (IMU) that is composed of 3 -axis accelerometer and gyroscope built in the smartphone. The experimental results show that accuracy is within 3 meter. These results imply the potential to track people in the buildings that have geomagnetic map in advance at the meter scale using only smartphone with embedded sensors.


Keywords-indoor positioning; earth magnetic field; magnetic fingerprinting; particle filter; inertial measurement

## I. Introduction

There are many strategies for outdoor navigation using the Global Positioning System (GPS) which provides reliable positioning information. However, the GPS is not useful for indoor navigation because satellite signals are attenuated thorough building structures and degraded due to multipath propagation [1]. Therefore, alternative methods are required to establish an accurate and reliable indoor positioning system. To solve this problem, wireless access point or Bluetooth beacon based approaches have been proposed [2], [3]. Although the approaches achieve high accuracy solution, they often require installation of expensive infrastructure. A demand for novel indoor systems without the need of additional infrastructure has led researchers to have interest in magnetic field in buildings. Researchers have focused on the fact that some animals use Earth's magnetic field for navigation and orientation detection [4]-[8]. Some animals, such as spiny lobsters and green seaturtle, are not only able to detect the direction of Earth's magnetic field, but also able to even sense their true position relative to their destination, which means these particular
animals are able to derive positional information from local cues that arise from the local anomalies of Earth's magnetic field.

It is reported that steels and reinforced concrete structures of buildings cause distortion of the geomagnetic field and make anomalies [9], [10]. In general, magnetic distortions have been considered as undesired property for detecting the heading using an electric compass. However, since the distortions vary depending on the locations, the localization is possible by using these distortions as map features. Some work has been done for indoor robot localization using magnetic fields and these techniques have been exploited in the design of an indoor navigation system for humans [11]-[14]. Samrtphones equipped with accelerometers, gyro scope, and magnetometers are feasible. In this paper, we present a novel smartphonebased positioning and navigation method. The only infrastructure in this paper is a smartphone, the availability and convenience factor of which overwhelms that of utilizing external sensors.

In this paper, Monte Carlo Localization (MCL) based on a particle filter method [15], [16] is used to estimate the position of the user. In general, it is assumed that the observations of the magnetic field and user's motion are known roughly. This work focuses on estimation of the position of user moving on corridors in the buildings. It is very useful to consider the corridors since many rooms in the building are connected along long corridors usually. In addition, this approach is analogous to terrain navigation techniques used for underwater vehicles.

This paper is organized as follows. In section II, we reviews related work. Section III describes the experimental setup and the proposed indoor magnetic navigation system is presented in section IV. Section V provides experimental results from real data, and conclusion and future work are given in Section VI

## II. Related Work

WLAN (802.11)-based positioning has been the most popular approach. This approach includes two main methods for localization: triangulation by measuring signal strength, or times of arrival from known access points (APs), and a fingerprint method to measure relative signal strength from nearby APs when the positions of the APs are unknown [2]. The fingerprint methods rely on a map of fingerprints including
received signal strength indication (RSSI) at each location [2]. However, the technology requires many APs installed in the environment.

Instead of using the RSSI distribution, the indoor magnetic field can be used to create a reference map for localization. The study on magnetic field based localization is beginning to appear in recent literature, since this technique does not need additional infrastructure.

In [11], Suksakulchai et al. developed a localization system using the heading of a mobile robot equipped with a single electronic compass. They first collected changing headings and stored them. At each location, the mobile robot measured a heading using the electric compass and compared it with the pre-stored data. They used the heading error from the current data and nine previous data points to create a distinctive signature. Using a sequential least squares approximation approach for matching the signature, the mobile robot localized the current position. This approach limits their work to localization only in corridors as the robot had to first pass through the same nine points in order to accurately recognize a location's signature.

Haverinen and Kemppainen [12] proposed a global selflocalization method using the local properties of the magnetic filed in one dimension i.e., only the position of the target within the corridors. The robot ran through a corridor and collected data to create a map of the hallway. They used Monte Carlo Localization (MCL) (a particle filter) to determine its location from any starting position. They showed that estimation error for person localization was larger than in robot localization due to discrepancies between map and observation data. This difference results from lack of proper odometric information for pedestrian motion.

Chung et al. [13] tried to investigate a self-localization approach that does not use odometry or any other model relying on data that are difficult to obtain from pedestrian motion using a wearable badge device that consists of four magnetic sensors. They used a root mean square (RMS) based nearest neighbor searching algorithm for localization. They collected data every 60 cm along the corridor 1 m above the floor around a 5 cm diameter circle every 3 degrees (120 magnetic fingerprint sample at each measured location). This work provides an insight of the self-localization system without constraints on direction and speed.

In our work, we proposed a novel magnetic field based approach for localization considering a pedestrian motion using only accelerometers, gyro scope, and magnetometer embedded in smartphones. When step is detected by step detection method [17], a current position is estimated by using a particle filter in a predefined search area.

## III. Experimental Setup

## A. System

The navigation system is implemented based on the Galaxy Note smartphones from Samsung Electronics with a built-in AK8975 orientation sensor. The three-axis sensor from Asahi Kasei consists of a Si monolithic Hall geomagnetic sensor


Figure 1. A measuring device (left) and a floor plan (right)
detecting geomagnetism in the $x, y$, and $z$-axes. For faster geomagnetic map generation for the buildings, we developed a measurement system. The measurement system consists of four laser distance meters, a server and WiFi AP to measure the distances from four walls and send the distances to smarthphones using WiFi as shown in the left picture of Fig. 1. An application written in Java and C++ runs on the phone to activate the sensors and record their readings. The magnetic field was measured in the $x, y$, and $z$-directions, and the magnitude was calculated. We use the inertial sensor including an acceleration sensor and a gyroscope to detect step. The step detection library for $\mathrm{C}++$ is offered from the Sensing and Interaction Lab at Samsung Electronics.

## B. Map Building

The measurement was conducted in 3rd floor of the Samsung Advanced Institute of Technology (SAIT) building whose framework consists of steel and concrete. The right picture in Fig. 1 shows the brief floor plan having corridors of 156 meters total length. On the corridors, we collected fingerprints in the middle of the corridor along the 3 lines which are 60 cm apart from each other. For fingerprint mapping, we pushed the measurement system (Fig. 1) along the 3 lines at 1.2 m high from the floor at roughly constant speed to collect magnetic data with distances from four walls. In this measurement, the collected data was represented as a seven-dimensional vector $\left\{m_{x}, m_{y}, m_{z}, d_{1}, d_{2}, d_{3}, d_{4}\right\}$, where $m$ is three components, in units of $\mu \mathrm{T}$, of the magnetic flux density in $x, y$, and $z$ directions, respectively, and $d$ is the four distances from four walls in corridors. The final map is created by applying a linear interpolation to the seven-dimensional vector, i.e., the map consists of spatially 2-D magnetic vector $\left\{a, b, m_{x}, m_{y}, m_{z}\right\}$ with a 0.6 m space where a and b are coordinates in a Cartesian coordinate plane.

To perform localization, we use the norm of the magnetic field $\boldsymbol{m}=\left\{m_{x}, m_{y}, m_{z}\right\}$ as the observation because $\|\boldsymbol{m}\|$ is a rotation invariant scalar quantity. However, since the magnetic sensor embedded in the smartphone cannot be perfectly calibrated, i.e., $\|\boldsymbol{m}\|$ can differ according to the angular motion.


Figure 2. Graph theory interpretation of a floor plan
Hence, we collected two-way magnetic data back and forth in the corridors.

## IV. Indoor Magnetic Positioning System

## A. Graph Theory Interpretation of a Floor Plan

To simplify the floor plan, the corridors and corners are represented as edges and nodes respectively as used in the graph theory (see Fig. 2). After estimating the current position, the system automatically chooses the edge and its two nodes where the current position belongs to. By comparing magnetic azimuth with the predetermined azimuth of each edge, the moving direction is determined. Thus, the moving direction is always one of two predetermined azimuths in the edge.

## B. System Model based on the Particle Filter

The magnetic field based navigation is similar to the terrain navigation approach proposed by Nygren in [18] that describes a method for combining multiple depth measurements to figure out how far the submarine has traveled by counting propeller turns and determining a submarine's position using a maximum likelihood estimate (MLE).

However, odometric data, such as counting propeller turns, was not available for human, so the person localization can be simply conducted by assuming that the person was walking at the approximately constant speed. Deviations in walking speed, however, caused large bias to the estimation error due to discrepancies between map and observation data. To solve this problem, we exploit a step detection technique by using inertial sensors in order to estimate person's state. When a step is detected, the localization algorithm is conducted using MCL algorithm [15] which was utilized in order to estimate the position of the localization target starting from an unknown position. MCL method is usually implemented by a particle filter to approximate the a posteriori distribution when it is too complicated to sample directly.

The particle filter is sequential Monte Carlo (SMC) methods based on point mass presentations of probability densities [16]. It follows a generic framework of the sequential importance sampling (SIS) algorithm, which proceeds by generating a set of $N$ samples from a priori probability density as $x_{t}^{i} \sim \mathrm{p}\left(x_{t} \mid x_{t-1}^{i}\right)$ and then assigning a weight $w_{t}^{i} \sim \mathrm{p}\left(z_{t} \mid x_{t}^{i}\right)$ to each sample corresponding to the measurement density. The weights are normalized to sum 1 before the resampling. The

## Algorithm 1

## Initialization:

Draw particles $x_{0}^{i}$ uniformly with $w_{0}^{i}=1 / N$

For time steps $t=1,2, \ldots$
For particle numbers $i=1: N$
Measurement:
Obtain magnetic magnitude $z_{t}$

## Prediction

Draw particles $x_{t}^{i} \sim p\left(x_{t} \mid x_{t-1}^{i}\right)$
Weight update
Calculate $w_{t}^{i}=\mathrm{p}\left(z_{t} \mid x_{t}^{i}\right)$
End For

## Re-sampling

Make CDF of $w_{t}^{i}$ and
For particle numbers $i=1: N$
Draw $u_{i} \sim \cup(0,1)$
Resample $x_{t}^{i^{*}}=\operatorname{CDF}\left(u_{i}\right)$
End For
Approximation
$\hat{x}_{t}=\sum_{\mathrm{i}=1}^{\mathrm{N}} x_{t}^{i^{*}} w_{t}^{i}$
End For
basic idea of resampling is to eliminate particles that have small weights and to concentrate on particles having large weights. We use the systematic resampling [19] since it is simple to implement. The motion model for 2-D localization is given by

$$
\begin{equation*}
x_{t}^{i}=x_{t-1}^{i}+H v_{k-1}, \tag{1}
\end{equation*}
$$

where $v_{k-1} \sim \mathcal{U}(0, L)$ when $\mathbb{U}(a, b)$ is the uniform distribution on the interval $[a, b], L$ is a moving distance, and

$$
H=\left[\begin{array}{cc}
\sin \theta & 0  \tag{2}\\
0 & \cos \theta
\end{array}\right]
$$

In (2), $\theta$ is the moving direction. We choose an appropriate $L$ according to person's stride. The measurement model for $z$ is based on the single variable Gaussian probability density function with mean $f(x)$, which is given by

$$
\begin{equation*}
\mathrm{p}\left(z_{t} \mid x_{t}\right)=\frac{1}{\sigma_{r} \sqrt{2 \pi}} \exp \left(-\frac{\left(z_{t}-\left\|f\left(x_{t}\right)\right\|\right)^{2}}{2 \sigma_{r}^{2}}\right) \tag{3}
\end{equation*}
$$



Figure 3. The simulation tool for localization performance test


Figure 4. The averaged error as a function of distance
where the function $f$ returns an magnetic field of position $x_{t}$ on the magnetic map. Algorithm 1 describes the procedure of particle filter in detail.

## C. Corner Detection

In corridors, the corners are important landmarks. The localization error accumulated during the pedestrian walks on the edge can be compensated at its nodes once it is sure that the pedestrian is passing through the corner. Using gyro scope built in the smartphone, we could approximate the angular motion and calculate the angle of rotation. Based on the comparison the rotated angle and the magnetic heading, the corner detection is performed. If a corner is detected, the predicted position is moved to the corner position.


Figure 5. A sample image for the developed navigation App (Galaxy Note)

## V. Positioning Results

## A. Simulation Tests using a Simulator

First, we conducted off-line experiments using a simulator written in $\mathrm{C}++$ language as shown in Fig. 3. The floor plan of the $3^{\text {rd }}$ floor, where the experiments were conducted, is presented in Fig. 1. We set four paths with 78 m through the main corridors which are displayed with arrows in Fig. 3. The magnetic map for the paths was created by using the map building device under manual control. This map was used as the ground truth. In addition, observation data for the four paths were collected while walking the paths carrying a smartphone in a hand.

We carried out 100 experiments to evaluate the prediction error. We suppose that the initial starting point is unknown. In simulations, the particle number and the standard deviation of the measurement model $\sigma_{r}$ are set to 5,000 and 2, respectively. Fig. 4 shows the averaged error as a function of distance for four paths. The average distance to be localized is 2.75 meters using the entire search space. In addition, the average predicted error after localization is 2.32 meters.

## B. Real Tests using the Smartphone

We conducted the same experiments with the simulation using a smartphone (Galaxy Note). To set up the test environment in the smartphone, we developed a navigation App for the android system. When the App begins, a floor plan and a current position are displayed in the screen as shown in Fig. 5. The floor plan and magnetic map are given prior to experiments. In this app, the initial starting point is unknown, but the initial position can be set by touching a position on the screen, and the initial search area is limited to a circle with 5 m radius centered at the initial position. The particle filter for estimating the current position is running even time when a step of person is detected. The procedure of the proposed navigation app is described in Fig. 6. We obtained prediction


Figure 6. A block diagram of the developed navigation App


Figure 7. Prediction errors for 20 experiments
errors by taking a round in a clockwise and a counterclockwise direction along the corridors ( 156 m ) in Fig. 1. As varying the starting point, the experiments are repeated 20 times for each direction. The results of experiments are plotted in Fig. 7. Except one, all errors are less than 2 meters. The overall performance of localization is listed in Table I.

TABLE I. Localization Performance (20 EXPERIMENTS)

| Path | Error mean <br> $\mathbf{( m )}$ | Error SD <br> $(\mathbf{m})$ | Error max <br> $(\mathbf{m})$ | Failure rate <br> $(\%)$ |
| :---: | :---: | :---: | :---: | :---: |
| CW | 1.12 | 0.87 | 4.4 | 0 |
| CCW | 1.07 | 1.02 | 5.2 | 0 |

CW: clockwise, CCW: counterclockwise

## VI. Conclusion and Future Work

Compared to other positioning technologies listed in Table 3 in [13], the proposed system looks better performance and has possibility of realization in practice. In addition, magnetic based navigation system does not need any infrastructure and just requires the magnetic fingerprint map. We demonstrated performance of the proposed method that is good enough for localization, but we assumed that an initial position was given by users. To effectively localize the initial position within 10 meters, we will combine a WLAN RSSI method with our system as future work.

## Acknowledgment

We would like to thank Jeong-Gwan Kang for the provision of the step detection library and the help in using it.

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