Using Wi-Fi/Magnetometers for Indoor Location and Personal Navigation

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Abstract—New location algorithms using Wi-Fi or/and magnetometer sensors are proposed considering the orientation impact on the measurements. The feasibility of magnetometer alone fingerprint positioning and orientation inference is also assessed with real indoor data. Android smart devices with low cost sensors are used to build up database along with a Gaussian Processes Regression (GPR) model and to collect independent track test to validate results. The corresponding performance of various solutions such as Wi-Fi alone, magnetometer alone and the magnetometer-aided Wi-Fi are compared. The effects of user’s orientation on Wi-Fi signal strength, sensed magnetic fields and overall positioning results in real indoor office-like scenarios are also assessed and investigated.

Keywords—Wi-Fi; magnetometer; orientation; fingerprint; Gaussian processes regression

I. INTRODUCTION

With the ever-growing demand of Location-Based Services (LBS) in smart devices, indoor positioning has attracted significant attention. The common solutions include pedestrian dead-reckoning using accelerometer, gyroscope sensors, fingerprinting using Wi-Fi \cite{1}, \cite{2}, \cite{3}, \cite{4}, \cite{5} or magnetometers \cite{6}, \cite{7}, triilateration with beacon signals, or integration with high sensitivity Global Navigation Satellite System (GNSS) receivers \cite{8}, \cite{9}, to name a few.

Generally speaking, Wi-Fi techniques based on Received Signal Strength (RSS) fall into two categories: trilateration with a path loss model and fingerprinting with database. The first one heavily relies on the signal propagation model and requires locations of Access Points (APs) \cite{10}. Fingerprinting, to the contrary, has no such stringent assumptions and determines the likelihood of user location directly using a training database. To compute a user location, various metrics can be used to pattern-match the online measurements with the database \cite{1}. In some indoor environments such as office buildings and shopping malls, the abundant number of APs gives rise to good performance of the fingerprinting methodology. As a consequence, Wi-Fi RSS-based fingerprinting positioning has become a popular technique, at the cost of laborious training pre-survey or complex crowdsourcing.

However, there are some factors that will degrade RSS fingerprinting performance. One such inevitable challenge is due to blockage caused by the user’s body with certain orientations referenced to a local level frame. \cite{2} assumes that mobile devices are in front of the body and considers the body blockage and ‘heading’ when building up the database. However, the ‘heading’ of the direct reading from the magnetometer is not reliable for use due to the presence of magnetic field anomalies and no assessment/inference of the actual heading is attempted. In this paper, the heading is treated as an additional state and will be jointly estimated with user location. Investigations will be conducted to evaluate the potential of this method for the accuracy and robustness of the location estimate.

The indoor magnetic field anomalies caused by structural steel elements affect the orientation estimation as mentioned above, but in the meantime it is a signature for location purposes \cite{6}. \cite{11} showed that the indoor magnetic vector field disturbance is spatial fine-grained and long temporal persistence in terms of direction and intensity, which is a promising candidate for accurate positioning with fingerprinting, but it is only evaluated in a small area. Common approaches are evaluating the magnetic field norm \cite{6}, \cite{7}, Euclidean distance with magnetic field vector \cite{11}, or magnetic field vector directly \cite{6}. It is commonly assumed that the magnetic norm is a rotation invariant scalar; however, the magnetometer cannot be calibrated perfectly in practice. In \cite{6}, magnetic data was collected back and forth in corridors to remove the rotation dependency, which is not a practical solution. The magnetic vector is a sensor orientation dependent measurement, and in the indoor environment it is also somehow location dependent. This paper will assess the feasibility of using such dependence to improve location performance.

Fingerprinting relies on an accurate likelihood model, meaning that sufficient data are needed to train the statistical model for a specific location, which may be not practical such as for maps that are too large or some areas that are not accessible for pre-survey. To overcome this problem, Gaussian Processes Regression (GPR) has been widely used to estimate RSS Gaussian distributions at arbitrary locations based on training data collected at other locations \cite{10}. In this paper, the
extension of GPR for indoor magnetic anomaly ‘heat maps’ is conducted for the purpose of positioning/navigation.

The main contributions of the paper are:
- assessment of Wi-Fi alone fingerprinting performance with/without considering orientation and body blockage effects in real environments;
- feasibility evaluation of magnetometers alone location using indoor anomaly map in relatively large area;
- assessment of the improvement when combining magnetometer and Wi-Fi for positioning with considering orientation and blockage effects;
- Real field test verification with extensive RSS and magnetic field data collected in real office-like environments using an Android device.

The methodologies are first described in Section II and III. Second, the experiments with Android devices are discussed. A data analysis is then conducted in Section V and followed by the conclusions in Section VI.

II. FINGERPRITING METHODOLOGY

In this paper, the user location and user heading are explicitly modeled as states, which is not commonly considered with RSS-based fingerprinting. In general, location should be 3D. For practical reason, this paper considers 2D location and azimuth heading estimation, an approach still valid for large single storey buildings. Correspondingly, in both database training and track test stages, the experimental device is held flat on the same floor of a building. The state vector \( \theta \) can then be defined as \([p \varphi]^{T}\), where \( p \) is a 1x2 vector representing the location and \( \varphi \) is a scalar representing the azimuth.

Given measurements \( x \) which could be RSS or magnetic field measurement readings, the objective is to compute the probability density of the states conditioned on \( x \), that is the a posteriori probability distribution of \( \theta \), which can be expressed using Bayes’ rule as:

\[
p(\theta | x) = \frac{p(x | \theta) p(\theta)}{p(x)}
\]

where \( p(\cdot) \) represents the Probability Density Function (PDF), \( p(x | \theta) \) is the likelihood, \( p(\theta) \) is the prior and \( p(x) \) is a normalizing factor since it is not a function of \( \theta \) [1]. The modeling of the likelihood \( p(x | \theta) \) plays an important role and model parameters are trained by the measurements obtained in the training phase and stored in a database for online state estimation. In this paper, since the user heading \( \varphi \) is a component of the state vector \( \theta \), the database must be built as a function of the azimuth. The likelihood models for RSS and magnetic field are discussed below.

A. Likelihood for RSS Fingerprinting

In this case, the measurement vector is defined as

\[
r = [r_1 \cdots r_m \cdots r_w]^{T}
\]

where \( r_m \) is the RSS of the \( m \)th AP and there are \( M \) APs observed, each of which is associated with a unique Basic Service Set Identifier (BSSID). It is assumed that the PDF of RSS of each AP, \( p(r_m | \theta) \), is Gaussian distributed with mean \( \mu_{r,m} \) and variance \( \sigma_{r,m}^2 \) [3]. Further assume the RSS components are independent. The likelihood model of RSS-based fingerprinting then is

\[
p(r | \theta) = p(r_1, \cdots r_w | \theta) = \prod_{m=1}^{M} p(r_m | \theta)
\]

In the training stage, the mean and variance values of the RSS likelihood model at each Reference Point (RP) for four orientations are computed using a certain number of training measurements. Only the APs with the number of occurrences greater than a certain threshold are chosen to build the database. GPR are then used to spatially interpolate the database. With the measurements in the online stage, the likelihood is obtained using (3). Only the APs with RSS greater than a certain threshold are chosen to compute the likelihood.

B. Likelihood for Magnetic Field Fingerprinting

The magnetic field vector measurement \( b \) is composed of three components denoted by

\[
b = [b_x b_y b_z]^{T}
\]

Each of them is measured in units of \( \mu T \). The likelihood in this case can be modeled by a multivariate Gaussian model with mean \( \mu_{b} \) and covariance matrix \( Q_{b} \) [7]:

\[
p(b | \theta) = \frac{1}{(2\pi)^{3/2}|Q_{b}|^{1/2}} \exp \left\{ -\frac{1}{2} [b - \mu_{b}(\theta)]^{T} Q_{b}^{-1}(\theta) [b - \mu_{b}(\theta)] \right\}
\]

Similar to the RSS case, the mean and covariance matrix values are first computed and then spatially interpolated using GPR in the training stage. Measurements collected in the online stage are then used to compute the likelihood using (5).

C. State Estimation

In this paper, unless explicitly specified, \( \theta \) is assumed uniformly distributed. The states can be estimate using the Maximum Likelihood Estimator (MLE) as

\[
\hat{\theta}_{MLE} = \arg \max_{\theta} \left\{ p(\theta | x) \right\}
\]

to jointly estimate location as well as heading.

D. Combination of RSS and magnetic field fingerprinting

As will be shown next, Wi-Fi location is virtually ubiquitous for an entire area, whereas magnetometer location is only possible when anomalies are sufficient. The combination of RSS and magnetic field in this paper consists in applying magnetic field fingerprinting conditioned on the location estimate given by RSS fingerprinting when significant anomalies are present. In other words, a location prior distribution provided by RSS fingerprinting is used to weight the likelihood of the magnetic field measurements. Thus the
state estimator in (6) becomes a Maximum A Posteriori (MAP) estimator.

III. GPR LIKELIHOOD MODEL SPATIAL INTERPOLATION

A spatially fine-grained database has the potential to improve location performance. To do this, spatial interpolation techniques can be used to predict the likelihood in locations where no training measurements are available [10]. GPs are able to predict the likelihoods at arbitrary locations and give the corresponding uncertainty of the prediction. Express n noisy measurements by an n×1 vector:

\[ x = f(P) + w \]  

(7)

\( P \) is an n×2 matrix that includes n 2D locations associated with the n measurements. \( w \) is a white Gaussian noise n×1 vector and \( f(\cdot) \) emphasizes the dependence of the measurement on location. For the application in this paper, \( x \) represents n training RSS or magnetic field measurements collected at n locations represented by \( P \).

Basically, the GPs technique assumes that measurements are spatially correlated with a spatial correlation matrix:

\[ \text{cov}(x) = K + \sigma^2_{\nu} I \]  

(8)

Here, \( \sigma^2_{\nu} \) is the variance of noise, \( K \) is the covariance matrix of \( f(P) \) and entries of \( K \) can be specified using some kernel functions, from which the Gaussian kernel is typically used [10]:

\[ k(p_i, p_j) = \sigma^2_{\nu} \exp \left( \frac{1}{2l^2} \| p_i - p_j \|^2 \right) \]  

(9)

\( p_i \) and \( p_j \) represent two locations. \( \sigma^2_{\nu} \) is the variance of \( f(p) \) and \( l \) is a length scale quantifying the spatial decorrelation rate of the measurements [10]. The mean function of the measurements, on the other hand, needs to be considered differently for RSS and magnetic field measurements because it reflects physical properties of a specific type of measurement. [10] assumes a mean function for the RSS measurements where the mean decreases linearly with the distance from an AP:

\[ \mu = s_r \| p - p_{\text{AP}} \| + c_r \]  

(10)

where \( \| p - p_{\text{AP}} \| \) is the distance from the AP to the position where the measurement is obtained. \( s_r \) is the propagation slope and \( c_r \) is the RSS at the AP. For the magnetic field measurements, the mean function is assumed to be constant:

\[ \mu = c_B \]  

(11)

which represents the earth magnetic field. To summarize, the measurements \( x \) are jointly Gaussian with covariance matrix given by (8) and the mean functions are given by (10) and (11) for RSS and magnetic field measurements, respectively.

It is desired to estimate \( f(p^*) \), where \( p^* \) denotes an arbitrary location, given the training measurements \( x \) and \( P \), the positions of RPs. From (9), the a posteriori distribution of \( f(p^*) \) is also Gaussian with mean [12]

\[ \mu_{p^*} = \left( k^* \right)^\top \left( K + \sigma^2_{\nu} I \right)^{-1} x + \mu \]  

(12)

and variance [12]

\[ \sigma^2_{p^*} = \sigma^2_{\nu} - \left( k^* \right)^\top \left( K + \sigma^2_{\nu} I \right)^{-1} k^* \]  

(13)

where \( k^* \) is the vector of covariances between \( f(p^*) \) and the measurements in RPs. The mean and variance values are then stored in the database as fine-grain maps.

Another key part of the likelihood model interpolation with GPs is the estimation of hyperparameters, namely \( s_r, p_{\text{AP}}, c_r \) in (10), \( c_B \) in (11), \( l, \sigma^2_{\nu} \) and \( \sigma^2_{\nu} \) in (8) and (9). Given the log likelihood of the training measurements as

\[ \log p(x) = -\frac{1}{2} \left( x - \mu \right)^\top \left( K + \sigma^2_{\nu} I \right)^{-1} \left( x - \mu \right) - \frac{1}{2} \log |K + \sigma^2_{\nu} I| - \frac{n}{2} \log 2\pi \]  

(14)

this can be done by maximizing (14) with respect to the hyperparameters for RSS or magnetic field [10] [12].

IV. SYSTEM SETUP AND DATA COLLECTION

To analyze the methods discussed above, experiments were conducted in the hallway of the second floor of the EEEL building on the campus of the University of Calgary. The operation area is approximately 40 m by 56 m, with Wi-Fi RSS and magnetic field training measurements covering the area of 620 m². Fig. 1 shows the experimental environment and Fig. 2 is the floor plan.

A Google Nexus tablet was used to collect RSS and magnetic field measurements. The RSS data sampling rate was set to 1.4 Hz and the magnetic field data sampling rate at 100 Hz. Android applications were developed for both training and track test stage to collect and stream the measurements to a file on the tablet.

![Fig. 1 Experimental environment](image)

There are in total 155 RPs with spacing of 2 m in the testing area, marked by blue circles in the floor plan shown in Fig. 2. In the training phase, the tablet was held in front of the body, and RSS and magnetic field measurements were collected in the center of each RP for 4 orientations, namely north (0°), east (90°), south (180°) and west (270°). 50 RSS measurements and 4000 magnetic field measurements were collected at each RP for every orientation. Analysis of training data shows that there are 220 APs in the experimental environment.

To validate the algorithm performance, independent track test is conducted with the same device and App on different days. To collect independent trail test measurements, the tablet was held by the user walking at a speed of approximately 1.16 m/s in the reference trajectory shown in Fig. 2. As can be seen, the reference trajectory is designed to cover all the four orientations. In both the training and track test phases, the
orientation of the tablet was fixed with respect to the user. Also, the trajectory does not coincide with the RPs, aiming to test the performance of the proposed positioning algorithm with interpolated RSS and magnetic field maps. To compute the reference solution, markers are placed along the test route and the distances between them are first measured by a subcentimeter laser range sensor. During the data collection, a stopwatch is used to record the time when arriving a marker.

V. EXPERIMENTAL RESULTS

A. RSS and Magnetic Field Maps Interpolation

Prior to the RSS map interpolation, hyperparameters of the GP need to be estimated. For each AP, 50 RSS training measurements at each RP for each orientation are used to learn the hyperparameters. Once these are learned, they are used to interpolate the maps according to (12) and (13). RSS maps of APs are built with a spatial resolution of 0.2 m by 0.2 m for the 4 orientations. A RSS mean value heat map of an AP is shown in Fig. 3(top). The overall path loss effects can be seen and the corresponding AP is more likely located at the point marked with a white cross in Fig. 3(top). Also shown is the complicated propagating condition of wireless signals in some local areas, which poses a challenge to trilateration positioning using a path loss model. The variance value heat map of the same AP is shown in Fig. 3(bottom). The area with high variance corresponds to the area not covered by the training data or the unavailability of this AP in the area.

Similarly, for each of the three magnetic field components, 50 magnetic field training measurements at each RP for each orientation are used to learn the hyperparameters that are then used to interpolate the magnetic field maps with a spatial resolution of 0.2 m by 0.2 m for 4 orientations. The maps of the three components with user heading to the west are shown in Fig. 4. It can be seen that the anomalies happen quite often near steel doors and pillars that contain steel. Good location performance is expected at these locations.

B. Fingerprinting with RSS alone

This section demonstrates the location performance of the RSS fingerprinting that jointly estimate location and heading with four-orientation database, as compared to the single orientation database without considering heading. Specifically, the trail test RSS measurements are processed under five cases. In the first scenario, the measurements are used to compute the likelihood with the four orientation databases separately; the location and heading estimates are then chosen to be the values that maximize the likelihood. For each of the other four cases, the measurements are used with the single orientation database to compute the likelihood; the location estimate is produced by maximizing the likelihood without attempt to estimate the heading.

180 RSS trail test measurements collected along the route as shown in Fig. 2 are used to produce location estimates for each scenario and percentiles of the error distance are shown in Fig. 5. It can be seen that the four-orientation database curve is more convex than all the other four. Specifically, the 95% error percentiles drops from 6.2 m, 6.2 m, 7.9 m, 6.3 m for west, north, east and south cases, respectively, down to 5.7 m by using the proposed algorithm. The Root Mean Square Errors (RMSE) of location and heading are summarized in Table I. The results above indicate an obvious location performance improvement of the proposed algorithm. The major contribution is due to the more accurate database used for location when heading is considered as a state.
TABLE I. RMSE of location and heading estimates with RSS alone fingerprinting for the entire test route

<table>
<thead>
<tr>
<th>Databases</th>
<th>East</th>
<th>West</th>
<th>South</th>
<th>North</th>
<th>Four orientations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE [m]</td>
<td>4.5</td>
<td>3.5</td>
<td>3.8</td>
<td>3.8</td>
<td>3.1</td>
</tr>
<tr>
<td>Heading</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE [º]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>50</td>
</tr>
</tbody>
</table>

Fig. 4 Mean of magnetic map of x (top), y (middle) and z (bottom) components with west heading

Fig. 5 Location performance using database with different orientations

C. Fingerprinting with Magnetic Field Measurements Alone

Experimental results and analysis for location with magnetometers alone are demonstrated in this section. Global and local fingerprinting, which refer to fingerprinting in a large area and in a local area conditioned on location prior information, respectively, are discussed. Their performances are compared in terms of estimation availability and the location and heading estimation performance.

720 magnetic field track test measurements were collected along the same test route as in RSS fingerprinting case. As can be seen, some tracks of the test route are close to pillars in some places to verify that significant anomalies are able to provide reliable location results or not. Similar to the RSS fingerprinting case, the magnetic field trail test measurements are then used for joint estimation of location and heading using MLE as shown in (6).

Global fingerprinting is first applied. Specifically, the likelihood is computed in all the possible location with uniform weighting. The availability of fingerprinting with magnetic field for location is investigated. The maximum likelihood values for the 720 measurements versus the distance of the test route are shown in Fig. 6. The large values in the plot correspond to the places where significant anomalies show up. State estimates should be less ambiguous in these places. In practice, a threshold is needed to determine the valid estimates, which is defined as the estimates that maximize the likelihood with less ambiguous estimates. The second row of Table II shows the number of valid estimates versus the threshold applied. As can be seen, of all 720 estimates, the number of valid estimates is very small. For example, only 6% availability is obtained even if a low threshold is set, as compared to the likelihood values shown in Fig. 6. To sum up, the availability of using the magnetic field for global fingerprinting is not very effective due to the ambiguity problem.
Fig. 6 Maximum likelihood values along test route for global fingerprinting with magnetic field

<table>
<thead>
<tr>
<th>Threshold</th>
<th>0.01</th>
<th>0.03</th>
<th>0.05</th>
<th>0.07</th>
<th>0.09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability (global) (%)</td>
<td>6.0</td>
<td>4.4</td>
<td>3.3</td>
<td>2.5</td>
<td>2.0</td>
</tr>
<tr>
<td>Availability (local) (%)</td>
<td>33.1</td>
<td>8.3</td>
<td>4.5</td>
<td>2.6</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Table II Availability of magnetic field alone fingerprinting

The performance of the valid estimates is shown next. Fig. 7 and Fig. 8 plot the RMSE of location and heading estimates, respectively, versus the threshold for the global fingerprinting. It can be seen that as the threshold increases, the location performance improves very slightly. This is because ambiguous estimates still affect location performance.

It would be useful to use some prior location information, if applicable, to equivalently narrow the fingerprinting range, which is referred to as local fingerprinting. This is equivalent to applying a prior distribution to $p(r)$ in (1) so (6) becomes a MAP estimator. To study this, assume the location prior distribution is Gaussian with mean as the true value of the location and a standard deviation. Then, for each of the magnetic field measurement, the likelihood is computed then weighted by the prior distribution of location.

With 3 m used as the standard deviation of the Gaussian prior distribution of location, the performance of local fingerprinting is evaluated. The estimation availability is shown in the second row of Table II, and the location and heading estimation performance are given in Fig. 7 and Fig. 8, respectively. It can be seen that the availability increases significantly for the threshold less than 0.03. The location RMSE reduces greatly as compared to that of the global fingerprinting case, dropping to less than 2 m for the threshold less than 0.09. This is partly due to the location prior information applied to the estimator. For the heading estimation, the performance is improved as well and correct estimate can be produced with the threshold greater than 0.09, at the price of low availability.

D. Magnetic Field–aided RSS fingerprinting

As discussed in the last section, a local fingerprinting with magnetic field measurements can greatly improve the location and heading estimation performance as compared to the global fingerprinting. For this reason, the combination of RSS and magnetic field in this paper consists of applying a local fingerprinting with magnetic field conditioned on the location estimates given by RSS fingerprinting.

The same RSS and magnetic field measurements as in the previous processing are used. Since the data rate of magnetic field measurements is four times higher than the RSS measurements, four consecutive magnetic field measurements are used to compute the individual likelihood conditioned on the same prior location distribution provided by the RSS fingerprinting.
The distribution of location estimates given by RSS fingerprinting is critical for the combination. However, the discussion of its PDF is outside the scope of this paper. To continue the investigation of the combination solution, it is assumed that the 2D location estimates are distributed according to an uncorrelated bivariate Gaussian distribution. The mean vector of this PDF is given by the MLE, whereas the variances are computed as the mean square of the position errors across the two dimensions (3.6 m in south-north direction and 5.5 m in west-east direction). The prior distribution of location is multiplied by the likelihood of magnetic field measurements and then a MAP estimator is used to estimate the location and heading. Again, a threshold is needed to detect the anomalies. When an anomaly is detected, the estimate given by magnetic field fingerprinting will be used as the final estimate. Therefore, the combination is equivalent to magnetic field fingerprinting making correction to the RSS fingerprinting when anomalies are present, and the following analysis will evaluate the estimation performance before and after the correction in the anomaly area.

The anomaly areas that have been used are highlighted by black arrows in Fig. 4. Table III summarizes the location and heading estimation performance in the anomaly area. As can be seen, by using the magnetic field–aided fingerprinting, the heading estimation performance improves significantly while location performance is improved slightly.

Table III Performance of RSS and magnetic field–aided RSS fingerprinting in anomaly area

<table>
<thead>
<tr>
<th>Methods</th>
<th>RSS</th>
<th>Magnetic field–aided RSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location RMSE [m]</td>
<td>3.0</td>
<td>2.3</td>
</tr>
<tr>
<td>Heading RMSE [°]</td>
<td>52</td>
<td>22</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

A new algorithm for RSS and magnetic field fingerprinting was proposed for joint estimation of location and heading. It has been shown that the proposed algorithm improves location performance as well as provides heading estimates with RSS alone. Fingerprinting with the magnetic field alone in a large area does not show good estimation performance due to an ambiguity issue. However, conditioned on location prior information, local fingerprinting with magnetic field exhibits the potential to greatly improve the location as well as heading estimation. Based on this, a magnetic field–aided RSS fingerprinting solution is proposed. Experimental results show that the combination improves the location as well as heading estimation performance in anomaly area.

REFERENCES