Wi-Fi-Aided Magnetic Field Positioning with Floor Estimation in Indoor Multi-Floor Navigation Services

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***Abstract*— Our paper addresses Indoor Navigation, i.e., the navigation in the three-dimensional space of buildings. Indoor navigation lifecycle is alike outdoor navigation, and it embraces Mapping, Positioning, Path Planning, and En-route Assistance. In such life cycle, positioning is, of course, a critical element. In indoor navigation, an ideal positioning should operate in the indoor three-dimensional space, and integrate sensors, magnetometer, accelerator, etc. In order to achieve this goal, we combine External Navigation System (ENS) and Inertial Navigation System (INS). In ENS, Wi-Fi signal strengths estimate the floor information, and magnetometer matches magnetic data in real time. In INS, pedestrian motion is measured by accelerator with heading, user steps and walking distance. An eXtended Particle Filtering (XPF) effectively combines both positioning measurements and user movements. The integration of Wi-Fi-aided magnetic field positioning and XPF with Dead Reckoning is the main novelty of our solution, which has been validated by experiments and shows a good performance.**

Keywords- Indoor Navigation Services; Magnetic Field Positioning; WiFi Signal Strength; Information Fusion; Dead Reckoning

I. INTRODUCTION

This paper addresses Indoor Positioning technology for indoor navigation services. Indoor Positioning technology is an element in the overall lifecycle of services [1] for indoor navigation as the input for Path Planning and En-Route Assistance. In Figure 1, we sketch the Indoor Navigation life-cycle. The upper row shows the service modules of the framework. The lower row lists techniques and technologies that may apply to each module.

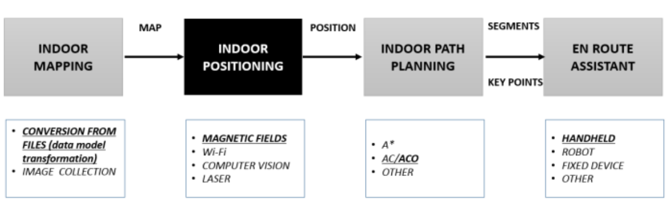


Figure 1 Service Modules of Indoor Navigation and Supporting Techniques/ Technologies

Let us focus on Indoor Positioning. It can be supported by various technologies with variable effectiveness. In most indoor contexts, the satellite coverage is not sufficient to provide an accurate result: in high buildings, multi-level highways, and tunnels, it is not possible to receive good satellite signals [2]. Therefore, it is necessary to find alternative indoor positioning. Radio frequency identification (RFID) [3] exchanges data in a non-contact and two-way communication by radio frequency mode; it is accurate, but it has short effective distance (generally up to tens of meters) and it requires certain hardware. In turn, Wi-Fi positioning [4] works in the range from 1 to 20 meters, but it is prone to be interfered by other signals. Bluetooth [5], which transfers data and locates positions from the signal strength, achieves accuracy from 2 m to 3 m with a delay of about 20 s. Inertial sensors that are independent with extra devices have become a primary element in navigation. Vision-based localization [6] approach for indoor positioning does not rely on infrastructure, and, therefore, it is scalable and cheap. Finally, geomagnetic positioning [7], provides a relatively high accuracy [8].

Let us consider geomagnetic field in detail. The geomagnetic field in buildings is influenced by disturbances, which are caused by steel shells, pipes, wires and electric equipment, etc. [9] However, those disturbances can be used as fingerprints, to describe the environment, and the uniqueness of fingerprints increases with the variability of local anomalies [10]. The three-axis magnetometer can sense not just navigation heading, but also variations in the magnetic field. Such variation and localized perturbations in magnetic field can be regarded as a positioning function.

Let us now consider PDR (Pedestrian Dead Reckoning). PDR models a user's pose by updating an ongoing pose estimation through internal measures of velocity, acceleration, time, pedestrian odometry, etc. [11]. It predicts the position by speed measurements with gravitation tracking and gyroscope-based orientation estimation, which is a probabilistic model for pedestrian movement. The reason of fusing magnetic measurement and PDR because: 1) PDR can reduce the computation time of pure magnetic data matching; 2) PDR itself get the relative positioning results with accumulated errors.

Additionally, indoor environments are always multi-floor buildings. In that case, a single tri-axis magnetometer is not enough, and it is necessary to combine it with other techniques to identify not only the horizontal but also the vertical position (in which floor you are). To achieve that result, we developed a Wi-Fi-aided positioning that estimates with received RF

(Reference Point) signal. Actually, the Wi-Fi localization relies on signal strength RSSI (Received Signal Strength Indication), and it is a relatively simple technique without any infrastructure. Experimental results perform a good floor estimation [12].

In our paper, we propose an integrated indoor positioning approach with two essential elements, namely feature-based positioning methods on reference map, and Dead Reckoning. Such approach includes External Navigation System (ENS) and Inertial Navigation System (INS). The overall integrated positioning technology is illustrated below (Figure 2):

- The collected magnetic fingerprints are matched against the observed terrain. Also, the Wi-Fi signal strengths need to be collected for floor estimation. The map is modeled by natural spline interpolation, which filters the abnormal information of a building's magnetic field.
- A person's movement being tracked is referred to as a Pedestrian Dead Reckoning. The accurate positioning result is calculated by data matching algorithm and is overseen by an extended particle filtering algorithm, which is a sequential Monte Carlo approach for proposing potential states and finding the observed one with matched ones.

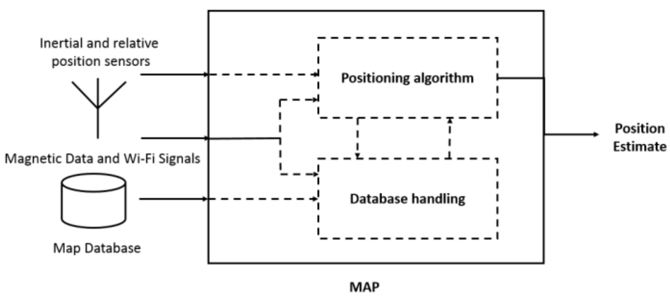


Figure 2 The architecture of proposed integrated indoor positioning technology.

Within such architecture, the positioning technology is based on an IoT approach. It is an information fusion strategy on multiple inertial sensors in our indoor navigation system. In ENS, the system estimates the floor information by Wi-Fi signals and positioning information by a single tri-axis magnetometer. In INS, pedestrian motion will be measured based on heading, user steps and walking distance. Thus, Dead Reckoning predicts the motion by accelerometer. The IoT framework of positioning technology is presented in Figure 3.

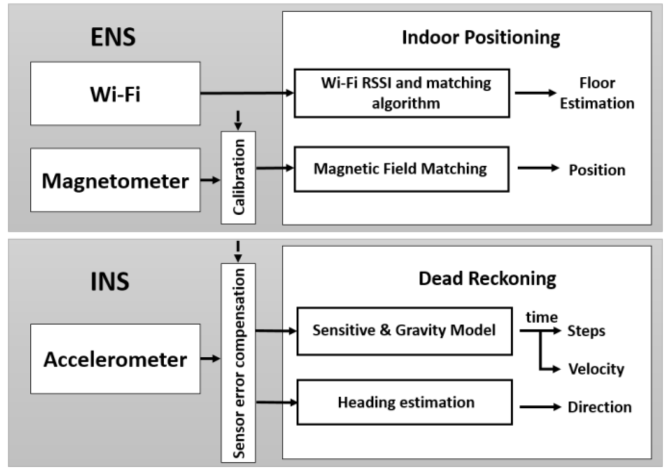


Figure 3 The IoT framework of Positioning Technology

The paper contains four more sections. Section 2 surveys the related work on magnetic field positioning technologies. Section 3 details the integrated magnetic field positioning approach. Section 4 evaluates the experimental results, and section 5 discusses the conclusion and future work.

II. Related Work

So far, some faculties and researchers have already done some research about magnetic field technologies. Here below, we survey some recent related works on journals and conferences.

Valter Pasku, et al. [13] proposes an approximated distance measurement model, which is characterized by a reduced complexity and the cost that is suitable for 3D localization system. The testing distance results depend on the height difference between coils. Another proposed approach [14] of magnetic field positioning is based on a tri-axial magnetometer and inertial measurement unit (IMU) that measure encoded magnetic field. Their extended Kalman Filtering algorithm integrates the encoded magnetic field with Dead Reckoning. Additionally, someone presents a multisource and multivariate dataset [15], which can collect and synchronize various data from different devices and environments. Such approach can easily fuse different data, e.g., WiFi signal, magnetic field data. R. Montoliu et al. [16] present a magnetic field positioning using Bag of Words paradigm [16], which allows user speed invariance. They classify the fingerprints and improve the localization accuracy from promising results. Currently, a camera-aided region-based magnetic field positioning technology [17] is proposed. It can distinguish positions with nearly same magnetic data, which performs a better positioning result. Also, a "MagSLAM" approach is proposed [18] for measurements of magnetic field strength and human odometry. Such extension of SLAM (Simultaneous Localization and Mapping) [19] algorithm obtains accurate localization results without an a priori map.

From the above surveyed magnetic field positioning technologies, we can see that they all would like to obtain more accurate results with low cost from different aspects. We propose a magnetic field positioning approach with extended particle filtering algorithm, which combines the real-time data matching and Dead Reckoning. Moreover, floor detection in multi-floor buildings by Wi-Fi signals is introduced in this paper. Users can be navigated with no infrastructure and floor restrictions. Table 1 lists the details of surveyed technologies and our technology.

Table 1 Comparison of surveyed magnetic field positioning technologies.

No.	**Technologies**	**Baseline**	**Optimized**	**Advantage**
1	3D localization system [13]	Outdoor Magnetic field positioning	Distance measurement model	Reduce complexity and cost
2	Magnetic field positioning [14]	Positioning with magnetic data and dead reckoning	Encoded magnetic data and extended Kalman Filtering	Improve accuracy
3	A special dataset [15]	Magnetic data storage	a multisource and multivariate dataset for other data as well	Data fusing more easily
4	Magnetic field positioning [16]	Magnetic field positioning	Bag of Words paradigm	Classify fingerprints and improve accuracy.
5	Magnetic field positioning [17]	Magnetic field positioning	Positioning with camera sensor and detect the region	Perform better positioning results
6	"MagSLAM" approach [18]	magnetic field strength measurement and human odometry	An extension of SLAM: "MagSLAM"	Accurate result without an a priori map.
7	Our approach	Magnetic field positioning	Extended particle filtering with heading measurement, WiFi signal for floor detection.	Accurate positioning in multi-floor buildings

III. INTEGRATED POSITIONING APPROACH WITH FLOOR ESTIMATION

Our integrated magnetic field positioning approach based on eXtended Particle Filtering (XPF) algorithm, which fuses magnetic fingerprints, Wi-Fi fingerprints, and PDR (Pedestrian Dead Reckoning).

A. Magnetic Fingerprint Measurement with PDR

This approach integrates absolute and relative positioning during the whole process. First, absolute positioning technology estimates the starting location by magnetic field data. Secondly, relative positioning results of Dead Reckoning are obtained when the users are moving. Absolute positioning result corrects the relative one, while, relative positioning assists the absolute one. We obtain the initial position of PDR location by magnetic fingerprints measurement. Then, the system observes the absolute positioning result continuously. The smaller the difference between the relative one and the matched one, the more reliable.

Since particle filtering is a non-linear method approximating the posterior probability of state by weighing the random sampled particles with the principal of minimum mean square errors. It resamples the particles combining Sequential Importance Sampling (SIS) [20] and additional resampling step [21]. Our XPF is evaluated with PDR displacement data as input, and measured by positioning algorithm. It is recursive in two phases: prediction and update. In prediction, we consider both PDR displacement and magnetic data matching measurement. Then, the state is updated by our non-linear motion model.

$$\begin{cases} x_{t+1} = f(x_t, u_t) + n_t \\ y_t = g(x_t) + e_t \end{cases}$$

In the formula, x is the random initial state, y is the update state, and f and g are non-linear functions. n_t and e_t are sense noises. In general, for each geomagnetic fingerprint, the more signals, the more precise the positioning result obtained. In g function model, we investigate and correct three kinds of signals, positioning, walking distance, and heading, as listed in the following table.

$$g_{t+1}^{(n)} = f(p_t^{(n)}, d_t^{(n)}, h_t^{(n)}) + \theta \cdot p_{bias}$$

Table 2 Investigated signals in positioning technology.

Object	**Position**	**Walking Distance**	**Heading**
User	$p^{(n)}, p_{bias}$	$d^{(n)}, d_{bias}$	$h^{(n)}, h_{bias}$

The walking distance and the heading always change in real pedestrian scenarios. The data accessed from sensors are always accompanied with deviations. Our approach measures all the numerical correlated biases, as Figure 4 presents.

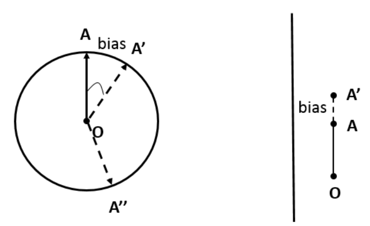


Figure 4 Two signals of which offsets occur

In other words, in Figure 4, we observe the current point A with surrounding potential points (e.g., A') to obtain the highest probability point and update the pedestrian location state.

1) Magnetic Data Matching Correction

We collect magnetic data along the path by walking. Therefore, the premise of the localization is the path matching. Matching the path based on heading information first can reduce the computational time on quite large dataset.

The matching algorithm is to calculate the distance between current point and candidate point in dataset. As the following formula presented, d is the distance between the current point

(x, y, z) and the collected point (x_1, y_1, z_1). Finally, the positioning result is corrected by matching biases.

$$d = \sqrt{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2}$$

$$p^{(n)} = d^{(n)} + \delta \cdot p_{bias}$$

2) Walking Distance Correction

Accelerometer senses linear acceleration along one or several directions. If the changes of magnitude of the acceleration vector is higher than sensitivity, the number of walking steps increases. At the same time, we assume walking distance based on step changes is calculated by the following formula:

$$d = \begin{cases} \left(\frac{Current_{step}}{2}\right) * 3 * Step_{length} * 0.01, Current_{step}\ is\ even. \\ [\left(\frac{Current_{step}}{2}\right) * 3 + 1] * Step_{length} * 0.01, Current_{step}\ is\ odd. \end{cases}$$

Among that, we define step length as 70.

3) Heading Direction Correction

The heading of a pedestrian in motion can be measured by a software-based sensor, orientation sensor. The value of azimuth φ is estimated from orientation sensor as:

$$h = (value[0] + 360)\ \%\ 360$$

$$h_t^{(n)} = h_t^{(n)'} + \delta \cdot h_{bias}$$

In the formula, the *value[0]* is the first data in the received sensor data array.

B. *Wi-Fi Fingerprint Measurement for Floor Estimation*

Each wireless AP (Access Point) has a global unique MAC address. A smart device can detect the surrounding AP signals and obtain their MAC addresses, regardless of whether the signal is encrypted or connected. Thus, the distance between the smart device and the AP can be calculated according to Wi-Fi signal strength [22]. The Wi-Fi RSSI can be accessed by Android SDK and is calculated as follows:

$$\mathrm{RSSI} = -(10\mathrm{n}\ \log_{10} d + \mathrm{R})$$

Where, d is the distance between smart device and the reference AP. R is the RSSI value when d is 1 m; n is the signal attenuation indicator (usually 2-4) [23].

Currently, Wi-Fi based positioning technology are mainly RF triangulation based and RF fingerprint based methods. We first test the triangular based algorithm, the accurate result of itself is not high enough. In the gird of 4*4 the average accurate result within 1m achieves 43%. That is because during propagation, Wi-Fi signals interfere and diffract [24]. In order to remedy the propagation drawbacks, we propose a new algorithm based on both two methods, which extends the triangular positioning approach.

1) Triangular Positioning algorithm

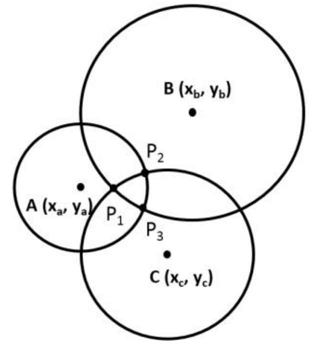


Figure 5 The figure of Triangular Positioning Theory

In triangular positioning algorithm (Figure 5), the RSSI signal strength corresponding to the anchor point {A, B, C} is $\{R_A, R_B, R_C\}$. The three circles are intersected with each other, as Figure 5 presented. Then, the distance between smart phone to AP is $\{d_A, d_B, d_C\}$. Thus, the formula is as follows:

$$\begin{cases} (x - x_A)^2 + (y - y_A)^2 = d_A^2 \\ (x - x_B)^2 + (y - y_B)^2 = d_B^2 \\ (x - x_C)^2 + (y - y_C)^2 = d_C^2 \end{cases}$$

The intersected point P_1 of circle B and circle C is calculated as follows, the same as intersected points P_2 and P_3:

$$F(x_1, y_1) = \begin{cases} (x_1 - x_B)^2 + (y_1 - y_B)^2 = d_B^2 \\ (x_1 - x_C)^2 + (y_1 - y_C)^2 = d_C^2 \\ (x_1 - x_A)^2 + (y_1 - y_A)^2 \le d_A^2 \end{cases}$$

Thus, the user location (location of smart device) (X, Y) is:

$$X = \frac{x_1 + x_2 + x_3}{3}, Y = \frac{y_1 + y_2 + y_3}{3}$$

2) Wi-Fi Fingerprint Matching algorithm

Triangular positioning approach runs on three non-collinear points on the same plane. But in multi-floor buildings, the positioning result, including the vertical data is essential to estimate floor information.

We propose a fingerprint based algorithm, which extends the triangular into 3D indoor space. Our algorithm using similarity ratio finds the potential points with minimum matching error between current RSSI and candidate RSSI dataset. Then, calculate the distance between current point (x, y, z) and potential points (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), (x_4, y_4, z_4) by fingerprint data. Finally, the current point (x, y, z) is obtained, and therefore so is the vertical data z. As the following formulas present:

$$\begin{cases} \frac{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2}{(x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2} = (\frac{{S_1}^{\lambda}}{{S_2}^{\lambda}})^2 \\ \frac{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2}{(x_3 - x)^2 + (y_3 - y)^2 + (z_3 - z)^2} = (\frac{{S_1}^{\lambda}}{{S_3}^{\lambda}})^2 \\ \frac{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2}{(x_4 - x)^2 + (y_4 - y)^2 + (z_4 - z)^2} = (\frac{{S_1}^{\lambda}}{{S_4}^{\lambda}})^2 \end{cases}$$

$$
\begin{cases}
S_1 = \sqrt{\sum [RSSI\ (x,y,z) - RSSI(x_1,y_1,z_1)]^2} \\
S_2 = \sqrt{\sum [RSSI\ (x,y,z) - RSSI(x_2,y_2,z_2)]^2} \\
S_3 = \sqrt{\sum [RSSI\ (x,y,z) - RSSI(x_3,y_3,z_3)]^2}
\end{cases}
$$

Our Wi-Fi fingerprint matching method extends the triangular positioning algorithm from 2D into 3D space, and it works well on small sparse dataset instead of building dense and complex one, which reduces large computational cost.

IV. Experiments and Evaluation

Among the various sensors of smart phone, motion sensors are accelerometer, gravity sensor, gyroscope, rotation-vector sensor, etc., and positioning sensors are magnetometer, GPS, etc.

Our testing device is the Samsung Galaxy S5 SM-G900F. The sensors that we use in such phone are listed in the below. Among them, the accelerator sensor counts the steps and walking distance, and geomagnetic field sensor collects and matches the geomagnetic fingerprints with orientation sensor for heading estimation, as Table 3 presented.

Table 3 The introduction of using sensors

Sensor	Description	Functions
MPU6500 Acceleration Sensor	Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity.	Motion detection.
Orientation	Measures degrees of rotation that a device makes around all three physical axes (x, y, z)	Heading estimation.
AK09911C Magnetic field Sensor	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in µT (micro-Tesla).	Position measurement.

A magnetometer works well in clean magnetic environments, however, in real scenarios, it should be tested to ensure the received data is well calibrated. The main error of a magnetometer is sensor offset bias (the response between axes is not centered at the origin or the response sensitivity is different along each axis or sensor non-orthogonality). Since the heading direction and the vertical direction are considered, a plane sensor calibration can be considered as a 3D calibration for a complete rotation of the device.

We test our sensor based on a compass swinging procedure, which rotates around three axes with a continuous series of angles. Figure 6 presents the testing results. In the figure, we can see that the origin located in the center of three planes, and the response sensitivity of each axis is equal. Thus, the testing sensor is well calibrated.

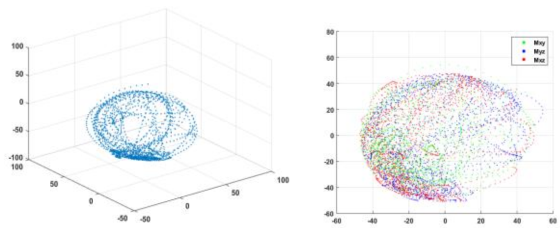


Figure 6 The calibrated testing result of magnetometer.

A. Magnetic Fingerprints Localization Testing:

Variations in the ambient magnetic field can be used as features in indoor positioning and navigation. Its characteristics changes with location. Our testing field is located in the engineering faculty of University of Pavia. We collect the magnetic fields of one testing area several times in different periods. As Figure 7 presents, we collected data six times on a corridor in three months, the magnetic field variations fluctuates steadily and the intensity is similar at the same location. Also, the changes of the geomagnetic field in a narrow area are significant. Thus, geomagnetic data of our testing field is feasible for accurate positioning.

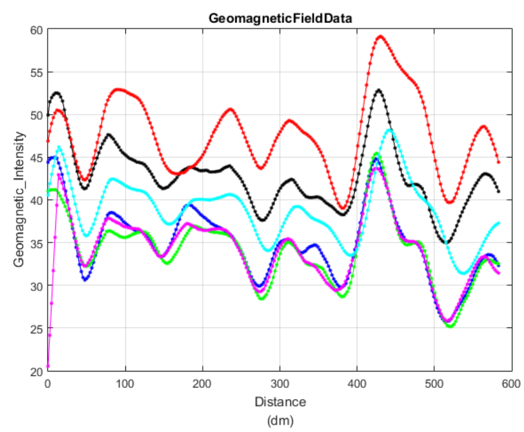


Figure 7 Different test of magnetic field intensity in one area.

Our artificially generated magnetic field is not affected by most obstacles on the path [2]. It is necessary to map the collecting magnetic field data primarily for matching. The magnetometer sensor produces a three dimensional vector $m = [m_x, m_y, m_z]$ consisting of the three components, in units of µT, of the magnetic flux density in x, y, and z directions, respectively. Figure 8 presents the mapping data of x, y, z components.

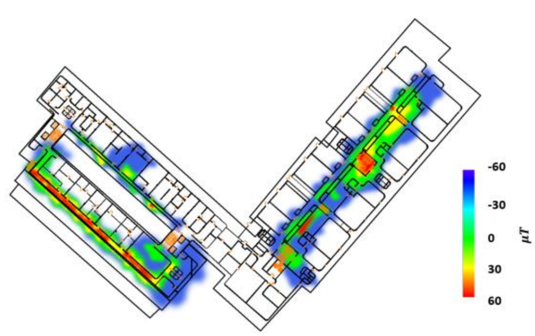


Figure 8(1) x-component of Indoor Magnetic Field Data

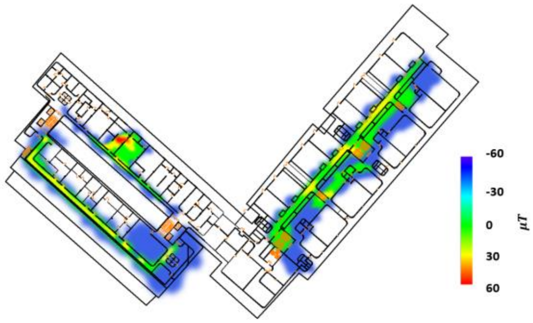


Figure 8(2) y-component of Indoor Magnetic Field Data

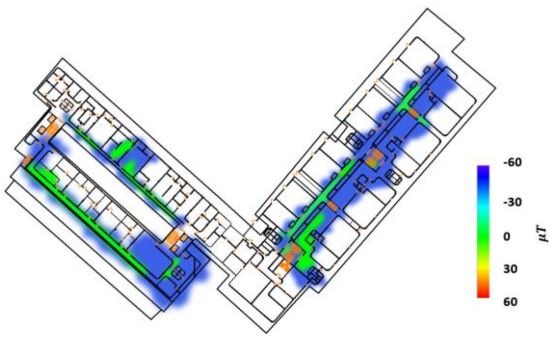


Figure 8(3) z-component of Indoor Magnetic Field Data

The nearly unique magnetic field fingerprints are collected on several overlapping corridors on floor CD of our engineering building. We compared three methods: only PDR for positioning; PDR positioning with distance correction and, PDR positioning with distance and heading correction. From our testing results, as the number of steps increases, the accumulative errors of PDR sharply increase. PDR with distance correction improves the accurate result, and it (red line in Figure 9) shows that the accumulative errors slowly increase. However, the method of PDR with distance and heading correction is best performed after comparing.

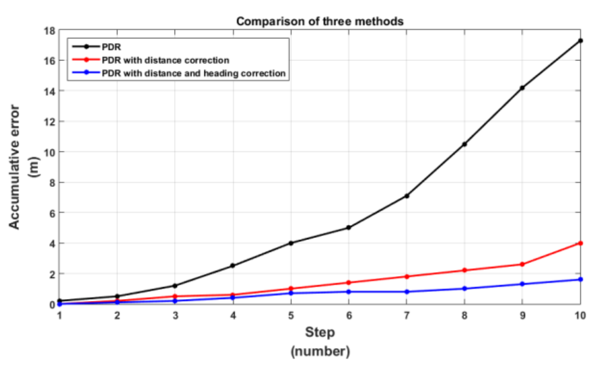


Figure 9 Different test of magnetic field intensity in one area.

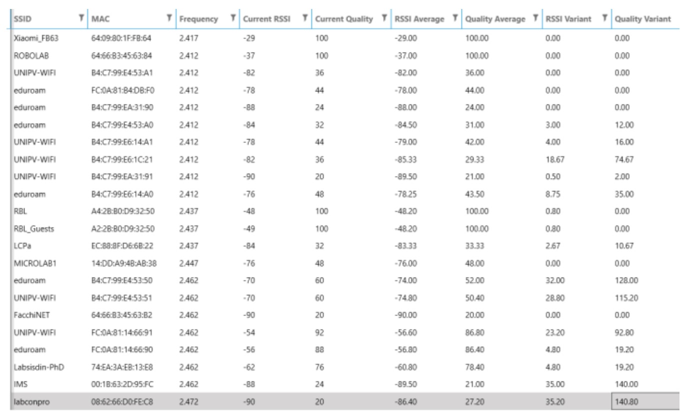
We update and resample 100 particles in XPF to test the following points on different planes in the building. In floor A to D, the average localization error of random 68 testing points achieves 1.975m, 120 points achieve 2.142m, 205 point achieve 1.621 m, and 55 points achieve 1.716 m (in Table 4) respectively. The average accurate positioning rate of all the points achieves 1.864 m. Such testing result proves our integrated positioning approach presenting a good performance.

Table 4 Evaluation of accurate positioning rate.

	Floor A	Floor B	Floor C	Floor D
#. of testing points	68	120	205	55
Average bias (m)	1.975	2.142	1.621	1.716

B. WiFi Signal Testing for Floor Estimation

We also tested our Wi-Fi floor estimation algorithm in engineering faculty of University of Pavia. Figure 10 presents an example of testing points' fingerprints.



SSID	MAC	Frequency	Current RSSI	Current Quality	RSSI Average	Quality Average	RSSI Variant	Quality Variant
Xiaomi_FB63	64:09:80:1F:FB:64	2.417	-29	100	-29.00	100.00	0.00	0.00
ROBOLAB	64:66:B3:45:63:B4	2.412	-37	100	-37.00	100.00	0.00	0.00
UNIPV-WIFI	B4:C7:99:E4:53:A1	2.412	-82	36	-82.00	36.00	0.00	0.00
eduroam	FC:0A:81:B4:DB:F0	2.412	-78	44	-78.00	44.00	0.00	0.00
eduroam	B4:C7:99:EA:31:90	2.412	-88	24	-88.00	24.00	0.00	0.00
eduroam	B4:C7:99:E4:53:A0	2.412	-84	32	-84.50	31.00	3.00	12.00
UNIPV-WIFI	B4:C7:99:E6:14:A1	2.412	-78	44	-79.00	42.00	4.00	16.00
UNIPV-WIFI	B4:C7:99:E6:1C:21	2.412	-82	36	-85.33	29.33	18.67	74.67
UNIPV-WIFI	B4:C7:99:EA:31:91	2.412	-90	20	-89.50	21.00	0.50	2.00
eduroam	B4:C7:99:E6:14:A0	2.412	-76	48	-78.25	43.50	8.75	35.00
RBL	A4:2B:B0:D9:32:50	2.437	-48	100	-48.20	100.00	0.80	0.00
RBL_Guests	A2:2B:B0:D9:32:50	2.437	-49	100	-48.20	100.00	0.80	0.00
LCPa	EC:88:8F:D6:6B:22	2.437	-84	32	-83.33	33.33	2.67	10.67
MICROLAB1	14:DD:A9:4B:AB:38	2.447	-76	48	-76.00	48.00	0.00	0.00
eduroam	B4:C7:99:E4:53:50	2.462	-70	60	-74.00	52.00	32.00	128.00
UNIPV-WIFI	B4:C7:99:E4:53:51	2.462	-70	60	-74.80	50.40	28.80	115.20
FacchiNET	64:66:B3:45:63:B2	2.462	-90	20	-90.00	20.00	0.00	0.00
UNIPV-WIFI	FC:0A:81:14:66:91	2.462	-54	92	-56.60	86.80	23.20	92.80
eduroam	FC:0A:81:14:66:90	2.462	-56	88	-56.80	86.40	4.80	19.20
Labsisdin-PhD	74:EA:3A:EB:13:E8	2.462	-62	76	-60.80	78.40	4.80	19.20
IMS	00:1B:63:2D:95:FC	2.462	-88	24	-89.50	21.00	35.00	140.00
labconpro	08:62:66:D0:FE:C8	2.472	-90	20	-86.40	27.20	35.20	140.80

Figure 10 Fingerprints of testing points.

We collect 70 fingerprints on each floor and randomly take 91 testing points on each of three floors. Figure 11 demonstrates that there are 70 collecting fingerprints on the CD floor of our engineering faculty. We can see in Figure 12, when λ is -1.7, the accuracy rate is the highest in our testing case. The ratio of 1 meter accuracy achieves 57.51%. After testing, our floor estimation result with -1.7 (λ) achieves 93% accuracy rate, which means there are 254 points among the 273 testing points for correct floor detection.

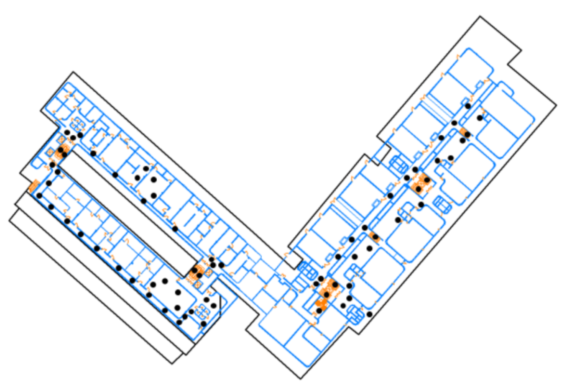


Figure 11 The 70 collected fingerprints on CD floor.

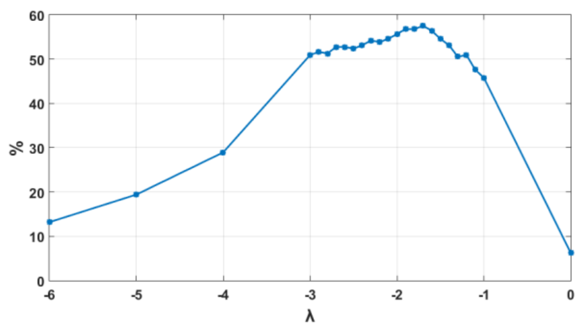


Figure 12 The accurate rate that within 1 meter with λ value.

V. CONCLUSION AND FUTURE WORK

The indoor positioning solution we have illustrated sits on a foundation of the complete framework, which covers the whole life-cycle of indoor navigation. Our paper proposes three novelties, namely, 1) an integrated indoor positioning approach with floor estimation based on multiple sensors, 2) a novel Wi-Fi fingerprint based matching algorithm for floor estimation, and 3) an eXtended Particle Filtering algorithm effectively combines both fingerprints matching and PDR. Our integrated indoor positioning approach consist of ENS and INS which are based on information fusion from multiple sensors: magnetometer, accelerator, etc.

The contribution of this paper has been tested, and encourages the indoor positioning results in our testing field. The proposed integrated positioning approach achieves a high accuracy (1.864m) and provides a solid foundation for further indoor positioning and navigation services.

The research on indoor positioning technology is complete. But for future work, in our opinion, three aspects can be further considered:

1) Matching magnetic fingerprints for collected data of various densities, e.g., take into account the velocity and sensitivity of the sensor, etc.;
2) Classifying various signals [25] by machine learning. The graphical signals can improve the efficiency of matching;
3) Unifying various sensor data [26]. Since the data from different sensors contains deviations. Effective data standardization is the primary premise of precise positioning.

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