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Article

Indoor Floor Localization Based on Multi-Intelligent Sensors

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Abstract: With the continuous expansion of the market of indoor localization, the requirements of indoor localization technology are becoming higher and higher. Existing indoor floor localization (IFL) systems based on Wi-Fi signal and barometer data are susceptible to external environment changes, resulting in large errors. A method for indoor floor localization using multiple intelligent sensors (MIS-IFL) is proposed to decrease the localization errors, which consists of a fingerprint database construction phase and a floor localization phase. In the fingerprint database construction phase, data acquisition is performed using magnetometer sensor, accelerator sensor and gyro sensor in the smartphone. In the floor localization phase, an active pattern recognition is performed through the collaborative work of multiple intelligent sensors and machine learning classifiers. Then floor localization is performed using magnetic data mapping, Euclidean closest approximation and majority principle. Finally, the inter-floor detection link based on machine learning is added to improve the overall localization accuracy of MIS-IFL. The experimental results show that the performance of the proposed method is superior to the existing IFL.

Keywords: indoor floor localization; sensors; geomagnetic field; machine learning

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1. Introduction

With the rapid development and widespread popularization of the mobile internet technology in smart city, the locating service industry has developed vigorously. Satellite positioning [1] and base station positioning [2] can only meet the requirements of individuals in the outdoor environment. However, more and more individuals in modern life are in crowded places such as indoor shopping malls, stations, airports and work units [3], which makes the demand for indoor positioning more urgent. Various indoor positioning technologies have begun to appear, drawing great attention from people. Taking photos and collecting pictures by smartphones for the construction of indoor maps is the most popular method [4–6], which has brought great help to individual's daily life and work and study. Unfortunately, there is not much difference in the layout of each floor of the buildings, and some LOGOs may appear multiple times on different floors, especially in large shopping malls or hospitals, resulting in large target locating errors only by using two-dimensional plane positioning method.

Therefore, obtaining the floor level of a mobile user is particularly useful for a variety of location-based applications. In addition, quickly and accurately locating a user's floor height is critical to saving lives in a fire emergency. Furthermore, navigation services such as Google Maps can prompt mobile users to use floor maps with the assistance of obtaining their current floor level in a shopping mall or an airport. The stereo floor localization method will be used to obtain the accurate floor to assist the planar localization technology to determine the user's position, so as to improve the localization accuracy and bring great convenience.

The existing IFL mainly relies on Wi-Fi signal and barometer data [7,8], which has the disadvantages of being susceptible to environmental changes, being cumbersome for data collection and relying heavily on infrastructure. The geomagnetic signals can be served as an indicator for indoor locating because of the uniqueness [9]. An IFL method based on geomagnetic signal and multiple intelligent sensors is proposed to solve the problems of cumbersome operation and low precision of the existing floor localization method, which uses machine learning classifiers to identify user activity patterns and combines the data from the accelerator sensor, magnetometer sensor and gyro sensor of the smartphone to locate the floors, providing technical support for future indoor localization.

The main contributions of the research are briefly summarized as follows:

(1) A collaborative approach is proposed based on geomagnetic signal and multiple sensors in a smartphone to achieve target floor localization.

(2) A machine learning classifier is designed for active pattern recognition and an inter-floor detection algorithm is put forward to improve the floor localization accuracy.

(3) The "global coordinates" and "gesture coordinates" are established for the mapping of magnetic samples, and the floor localization is performed according to the Euclidean closest approximation and majority principle. The proposed system is convenient to deploy and does not rely on any additional infrastructure, which will provide the possibility of fast, scalable stereo floor localization.

The rest of this paper is organized as follows: Section 2 presents related work considering different technologies and techniques for floors localization. Section 3 describes the architecture of IFL method based on the multiple intelligent sensors in smartphones. Section 4 gives the simulation results and analysis. Finally, Section 5 summarizes this paper.

2. Related Work

Currently, IFL technology can be divided into three categories: Wi-Fi-based technology, technology based on barometer technology and Wi-Fi–barometer hybrid technology. Wi-Fi-based technology without additional infrastructure only depends on the signals of deployed Wi-Fi access points (APs). Sun et al. [10] proposed an IFL framework based on floor recognition. They used training discriminant layer model to maximize the interlayer dispersion and triggered interlayer recognition through stair walking and elevator events. Liu et al. [11] proposed a Wi-Fi-based indoor localization system (WF-ILS), which combined the characteristics of three-side localization and the methods of scene analysis to determine the floor where the user is located. However, these techniques are susceptible to many factors such as multipath fading, shadows, the inconsistencies of AP and building materials. Furthermore, the uneven structure and open space of the floor will also result in bigger localization errors [12].

Barometer-based technology collects data by barometer sensors in smartphones. Ye et al. [13] proposed an IFL system based on barometers (B-Loc), which utilized a barometer sensor in a smartphone to construct a barometer fingerprint through crowdsourcing technology to locate the user's floor. Xia et al. [14] proposed a method considering multiple barometers as references to locate the floor (MB-ILS), which also used the barometer sensor of a smartphone. These techniques can work without the height of the building and the number of floors. However, barometric data are very sensitive to changes in weather conditions, window openings, air conditioning, heating and other external atmospheres and indoor conditions [15]. Therefore, locating floors requires the latest reference reading of the atmospheric pressure each time.

The hybrid method combines Wi-Fi and barometer for floor localization. Zhao et al. [16] proposed a hybrid floor localization algorithm that utilized the information of APs distribution and barometric pressure. The algorithm first extracted the distribution probability of APs scanned from different floors in offline training fingerprints, and used Bayesian classification to accurately identify well-formed floors without hollow areas. Then the floor information obtained from the APs distribution was used to initialize and calibrate the floor localization based on the barometer to compensate for the variable environmental impact. However, this approach relies heavily on infrastructure and communication networks.

In addition, geomagnetic anomalies caused by ferromagnetic construction materials (i.e., steel bars) on indoor paths are generally stable and unique [17]. Geomagnetic-based indoor navigation and map construction technologies have also been developed. Liu et al. [18] proposed an indoor navigation system based on the geomagnetic field. Ayanoglu et al. [19] proposed an automatic map construction algorithm based on geomagnetism, which combined the trajectories of many users into a fingerprint map of an indoor environment. Luo et al. [20] proposed an algorithm for constructing an indoor floor plan based on magnetic fields. The system used the dead reckoning technology, the observation model with geomagnetic signals and the trajectory fusion based on the affinity propagation algorithm to construct the planar map. Furthermore, we used the dynamic time warping similarity criteria to cluster the magnetic trajectory data to obtain an indoor path. The emergence of these methods provides technical support for the study of indoor floor localization technology based on geomagnetic field.

Based on the deficiencies of Wi-Fi signal and barometer data researches, an IFL method that utilizes magnetic field and multiple sensors is aimed to design. The sensors in smartphones that are integrated sensor terminals are used considering the popularity and practicability of the proposed method. The proposed method utilizes a stable geomagnetic signal, a magnetometer sensor, an accelerator sensor and the gyro sensor of the smartphone, through machine learning techniques to locate floors and detect inter-floors. The data collection phase is simple, and except in extreme cases, the complete database built is without updating and rebuilding. Furthermore, the floor localization requires only a smartphone.

3. The Algorithm of MIS-IFL

This paper proposes a method for realizing indoor floor localization using multi-intelligent sensors (MIS-IFL). The overall structure of the method is shown in Figure 1. The MIS-IFL includes a magnetic fingerprint database construction phase and a floor localization phase. Among them, during the magnetic fingerprint database construction phase, multiple acquisitions are required at each of the selected areas of chosen three buildings at a fixed separation distance to obtain multiple data values. Then the average data are stored as a fingerprint and a database is constructed. During the floor localization phase, the corresponding data need to be collected from the sensors in the smartphone, the collected magnetic data are mapped, and the mapped data are matched with the fingerprint database by the Euclidean closest approximation, and the localization result is obtained by the principle of the majority. This phase consists of three parts: the recognition of activity pattern, the localization of floor and the detection of inter-floor.

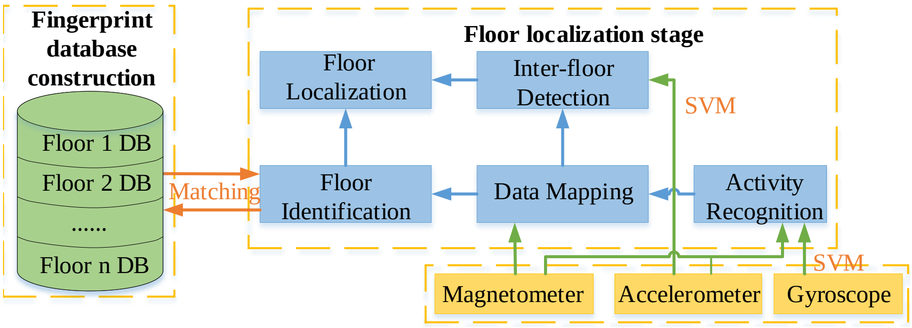

Figure 1. The overall structure of MIS-IFL.

3.1. The Construction Phase of Fingerprint Database

The first important task for MIS-IFL is to build a magnetic fingerprint database. Therefore, fingerprint databases needed to be constructed for each floor in the building where the experiments were conducted. The process of data collection on the 7th floor of the Physical and Electronics Laboratory Building is shown in Figure 2. Data collection was performed at a distance of 0.9 m from each selected area of each floor, and 100 magnetic samples were taken at each point with a sampling frequency of 10 Hz (a new sample is obtained every 100 ms). The collected samples should first be averaged after completing the data collection. Then the spline interpolation was performed to generate the interval value between the given points. Finally, the generated values, floor ID, longitude and latitude were stored in the magnetic fingerprint database. In addition, the sensors distributed in the photos were served for experiments of performance comparison in Section 4 and were used for calibration of Wi-Fi data. The distribution locations of the Wi-Fi sensors were the collection locations of the actual magnetic sample.

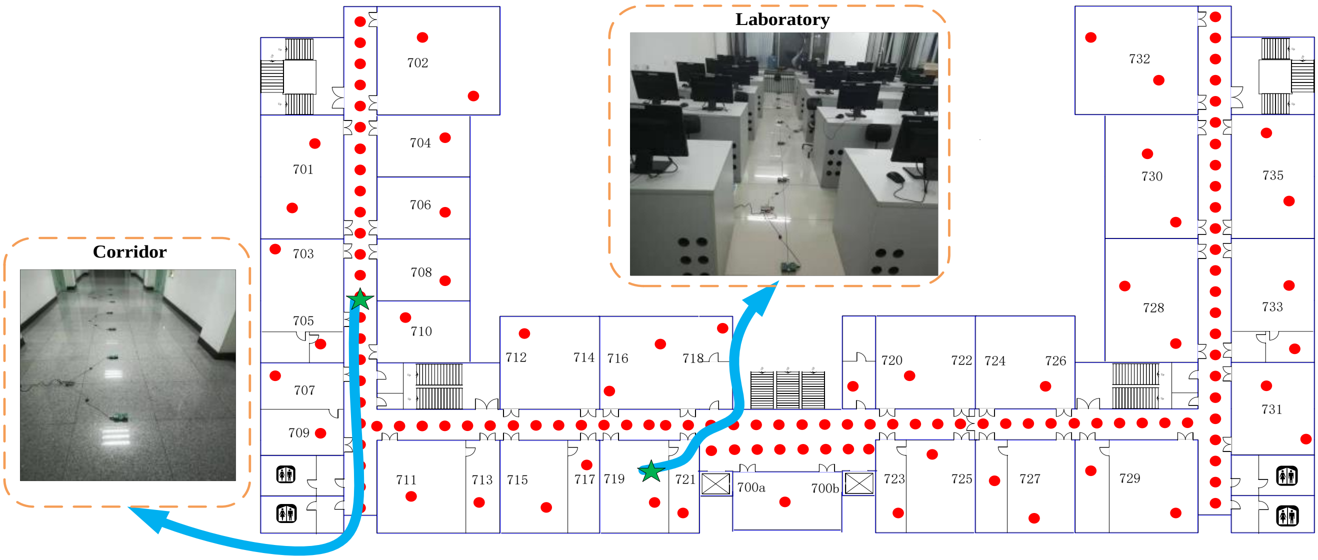

Figure 2. The collection process of magnetic fingerprint database.

3.2. *Floor Localization Phase*

3.2.1. The Recognition of Activity Pattern

The users' activity patterns must be correctly distinguished in order to increase the localization accuracy, because different users' activity patterns will produce different experimental results. The user activity patterns are divided into three categories: "normal walking", "phone calling" and "phone shaking" [21]. The three activity patterns are distinguished by obtaining acceleration data and orientation data of the smartphone from the accelerator sensor and gyroscope sensor. The process of the data acquisition is shown in Figure 3. The changes of the accelerator sensor data for three user activity patterns in x, y, and z directions are shown in Figure 4. It can be seen that the accelerator sensor data are greatly different along the x, y and z directions in different users' activity patterns. The user's smartphone states (orientation: yaw, pitch, rotation) show a significant difference in different users' activity patterns as shown in Figure 5. Therefore, a machine learning-based classification algorithm is used to process the user's smartphone states and acceleration data characteristics are used to distinguish users' activity patterns with the assist of magnetometers and gyroscopes.

The acceleration of the user's activity is calculated using the built-in accelerator of smartphone. The accelerator sensor shows the acceleration data in the x, y, and z directions. The total acceleration data are as Equation (1):

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

Unfortunately, the acceleration will have an error after the calibration, which is called "deviation". This "deviation" needs to be estimated and eliminated to obtain accurate information. The acceleration data in the x and y directions should be 0, and the acceleration data in the z direction should be 1 g (9.8 m/s^2) when the smartphone is stationary on a plane.

Furthermore, any other readings are deviations. So, the corrected acceleration value is as Equation (2):

$$a_x^c = a_x^m - S \cdot a_x^a \tag{2}$$

where a_x^c and a_x^m represent the acceleration value corrected and acceleration value measured in the x-axis direction, respectively. a_x^a is the actual acceleration value in the x-axis. S is the error coefficient.

The total corrected acceleration value for a given time t can be calculated as Equation (3):

$$a_t^c = \sqrt{{a_{xt}^c}^2 + {a_{yt}^c}^2 + {a_{zt}^c}^2} \tag{3}$$

The user's activity patterns can be categorized by the corrected accelerator data, gyroscope, and magnetometer after obtaining the correct acceleration.

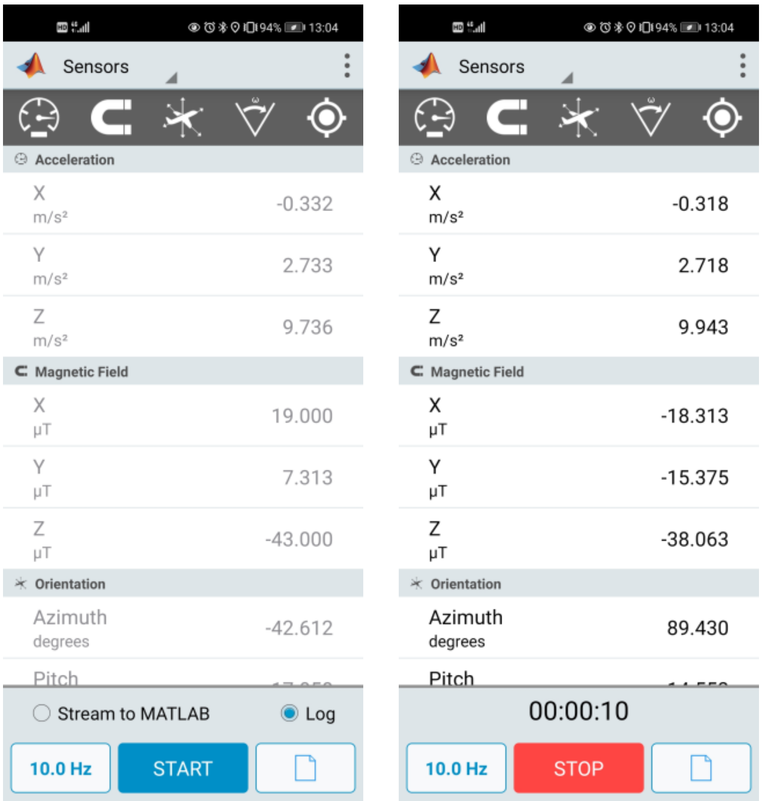

Figure 3. The process of getting data from sensors.

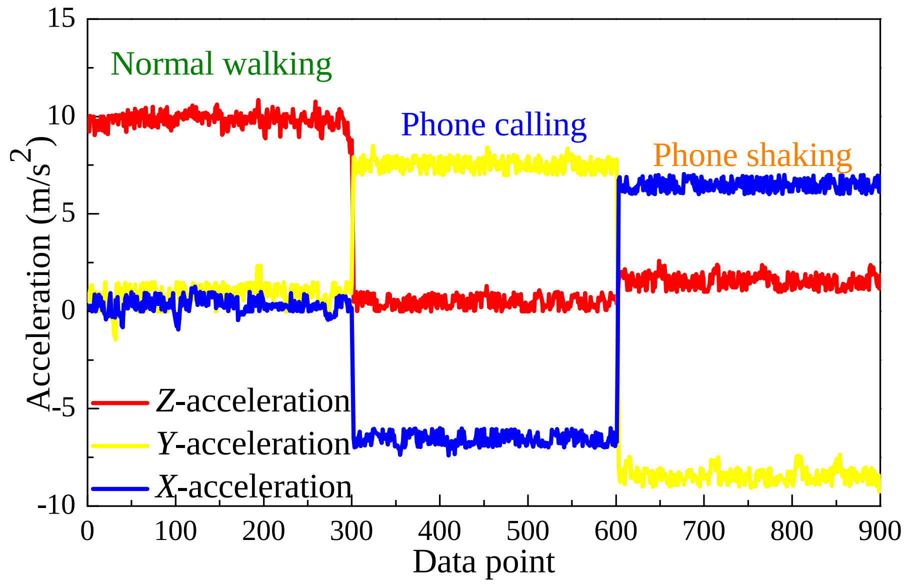

Figure 4. Acceleration of user's activity pattern in x, y, z directions.

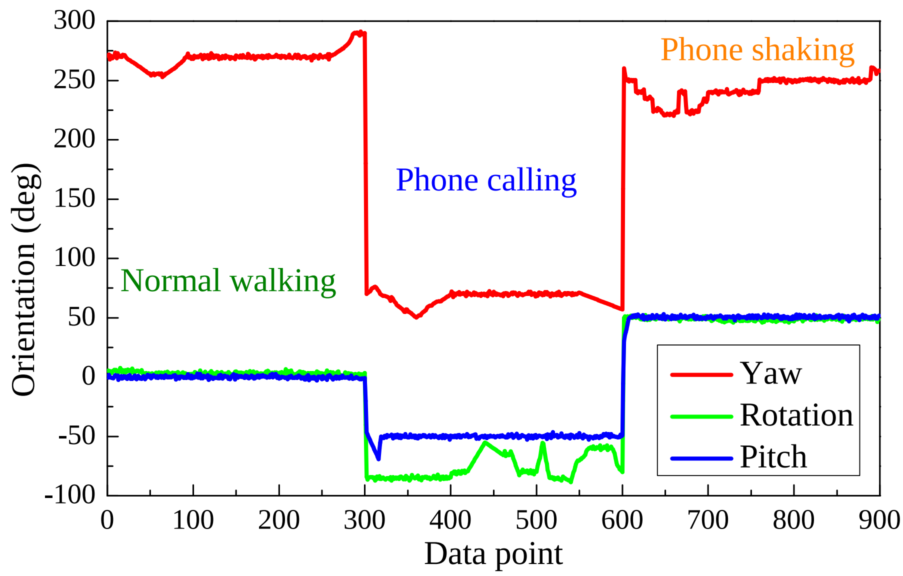

Figure 5. The smartphone states in different users' activity patterns.

3.2.2. The Localization of Floor

The magnetic fingerprint database of this paper is established according to global coordinates and is independent of the orientation of the smartphone. However, the magnetic sample obtained from the smartphone is related to the orientation of the smartphone, so it is necessary to determine the orientation of the user's smartphone before matching the floor. The smartphone orientation is obtained from the accelerator sensor and the magnetometer sensor. A machine learning-based classification algorithm is used to process the user's smartphone states. The performance of k nearest neighbor (K-NN), decision tree (DT) and support vector machine (SVM) are analyzed and compared to select the best classifier for classifying the user's activity patterns. Then the collected magnetic data are mapped according to the user's activity patterns. The recognition accuracy of the user's activity patterns largely affects the accuracy of the floor localization algorithm, because if there is a large error in the mapping of magnetic data, the erroneous floor localization will be led, which will ultimately affect the overall accuracy of the proposed method.

The DT-based classifier is one of the most widely used techniques among the three-machine learning-based classifiers. The advantages of DT are simple and low in computational cost. However, its problems are that it is prone to over-fitting, and it perform poor when dealing with data with strong feature correlation [22,23].

K-NN is another widely used classifier. The advantage of K-NN is that it is easy to understand. However, the problem is that the classification process may be slower if the training data are large [24].

The advantage of SVM is that the error rate of generalization is low and the speed of classification is fast. However, the problem is that it works poorly when dealing with large-scale training samples [25].

This paper selects SVM by analyzing and comparing the performance of classifiers to classify activity patterns. It collects k times of data as training samples in each sub-area in order to obtain the SVM classification model. The training samples belonging to the i-th sub-area are marked as 1, and not belonging to the i-th sub-area are marked as -1. The classification of the smartphone orientation belongs to the multi-classification problem of SVM, which needs to be decomposed into multiple two-class problems. There are two methods commonly used: a pair of remaining methods and one-to-one methods. Although the one-to-one method uses more decision functions than a pair of remaining method, the former performs faster. The one-to-one method selected can obtain $k(k-1)/2$ decision functions $f_{i,j}(x), (0 \leq i < j \leq k)$, where $f_{i,j}(x)$ represents the decision function obtained by comparing the i-th class and j-class. When predicting the sample x, we need to bring x into all $f_{i,j}(x)$ and count the number of wins for all classes. Furthermore, the class with the most votes is the class of x.

The floor localization link is performed after identifying the user's activity patterns. The magnetic data are mapped and the mapped magnetic data are compared with the data in the fingerprint database. Then the Euclidean closest approximation method and the principle of the majority are used for floor localization. The process of IFL based on magnetic data is shown in Algorithm 1.

In the Algorithm 1, N represents the total number of floors in the building, and O is the direction of the user's smartphone. M is magnetic data, and T_m is a magnetic sample for conversion that matches the database. P_j is a matching set between the mapped magnetic sample and each magnetic value in the database. E_d is a collection of Euclidean distances between a given magnetic sample and each magnetic value stored in the database, DB_a is a fingerprint database of one floor of building a, F_c is a set of calculated candidate floor sets, and F_d represents the determined floor of the building where the user is currently located.

Algorithm 1: The algorithm of floor localization.

Input: M,O
1: **For** $i = 1 \quad to \quad 5$
2: $T_m \leftarrow$ *mapMagData*(O_i, M_i);
3: **For** $j \leftarrow N_a$
4: $P_j \leftarrow match(T_m, DB_{aj}))$;
5: $E_d \leftarrow$ *EucDistance*(P_j);
6: **End for**
7: $F_c \leftarrow argmin(E_d)$;
8: **End for**
9: $F_d \leftarrow$ *Delete-Outliers* (F_c);
Output: F_d

Input magnetic sample data and the orientation data of the user's smartphone into the floor localization algorithm. The magnetic data are mapped according to the given smartphone states. In this paper, the magnetic sample collected online by the smartphone are needed to map because the magnetic fingerprint database was established according to the earth coordinates, regardless of the orientation of the smartphone. Two coordinate systems, including "global coordinates" and "gesture coordinates", are used. The global coordinates represent the fixed coordinate system of the Earth, and the gesture coordinates represent the coordinates of the smartphone. Map the magnetic data according to the orientation of the smartphone to match the database. Suppose F_G is the magnetic field value in the system of earth coordinates and F_S is the magnetic reading in the system of phone coordinates. Then the relationship between F_G and F_S can be defined as Equation (4) [26]:

$$F_S = R_x(\phi)R_y(\theta)R_z(\omega)F_G \tag{4}$$

where $R_x(\phi)$, $R_y(\theta)$ and $R_z(\omega)$ are the corresponding matrices of rotation, pitch and yaw. Furthermore, as shown in Figure 6, the rotation, pitch, and yaw indicate the rotation of the smartphone around the x, y, and z axes, respectively.

We need to identify the yaw, pitch and rotation to map the magnetic sample. The yaw is that the smartphone rotates around the z-axis of the smartphone frame and is expressed by ω. The rotation matrix $R_z(\omega)$ is represented as Equation (5):

$$R_z(\omega) = \begin{bmatrix} cos(\omega) & sin(\omega) & 0 \\ -sin(\omega) & cos(\omega) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

The pitch is when the smartphone rotates around the y-axis of the smartphone frame. It is expressed by θ and can be represented as Equation (6):

$$R_y(\theta) = \begin{bmatrix} cos(\theta) & 0 & -sin(\theta) \\ 0 & 1 & 0 \\ sin(\theta) & 0 & cos(\theta) \end{bmatrix} \tag{6}$$

The rotation is when the smartphone rotates around the x-axis of the smartphone frame. It is expressed by ϕ and can be represented as Equation (7):

$$R_x(\phi) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & cos(\phi) & sin(\phi) \\ 0 & -sin(\phi) & cos(\phi) \end{bmatrix} \tag{7}$$

The magnetic data are mapped by Equation (4), if the user's smartphone is yawed, pitched and rotated. Then the mapped magnetic sample T_m is matched to the fingerprint database of all floors in the building using the Euclidean closest approximation, as shown in Equation (8):

$$E_d = \sqrt{(T_{Maj} - DB_{aj})^2} \tag{8}$$

where T_{Maj} represents the converted magnetic data of the j-th floor in the a building. DB_{aj} represents the fingerprint database data of the j-th floor in the a building.

The floor with the smallest Euclidean distance calculated by Equation (8) is the result of Euclidean closest approximation (i.e., the floor candidate). Repeat this process for the given five frames of data, resulting in five possible candidates (one candidate per frame). Furthermore, each frame has the right to make a vote. Finally, the principle of the majority is used to determine the user's floor. In addition, the specific decision forms are as follows, each number represents a floor candidate for a given building: if F_c = {1,2,2,2,2} or F_c = {1,2,2,2,3}, then F_d is floor 2. If F_c = {1,1,2,2,3} or F_c = {1,2,2,3,3} or F_c = {1,2,3,4,5}, then F_d is determined by Equation (9):

$$F_d = argmin(E_d(F_c)) \tag{9}$$

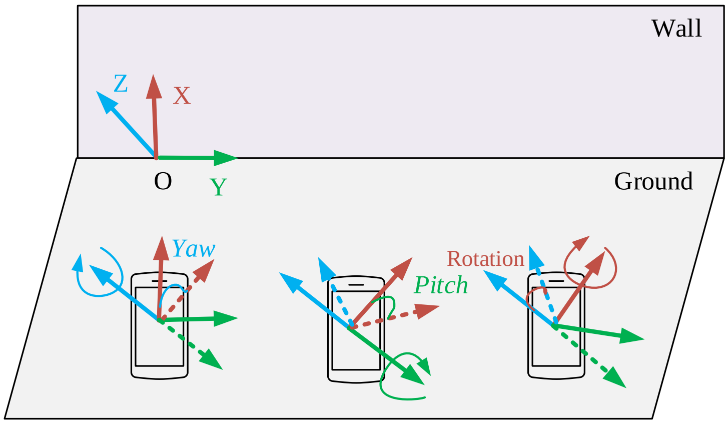

Figure 6. Three states of the smartphone.

3.2.3. Detection of Inter-Floor

Detecting inter-floor is necessary to improve the localization accuracy because when the user is between the floors (i.e., on the stairs), the accuracy of the IFL is affected. The characteristics of accelerator data and magnetometer data are combined to detect the case where user is between the floors. We only need to determine important characteristics that can be used to distinguish the state of walking on the floor or on the stair to detect whether the user is on the inter-floor, because the changes of acceleration amplitude are different when the user walks up the stairs. Therefore, we select five accelerator data characteristics and one magnetometer data characteristics that distinguishes between the two cases. The functions used to identify inter-floor are shown in Table 1.

Table 1. Characteristic needed to detect for inter-floor.

Symbol	Explanation
$\overline{a}_x$	Average acceleration in x direction per frame
$\overline{a}_y$	Average acceleration in y direction per frame
$\overline{a}$	Average total acceleration per frame
W_a	Peak of total acceleration per frame
$W_{\triangle a}$	Maximum change in total acceleration per frame
$W_{\triangle Mf}$	Maximum change in total magnetic density per frame

The above characteristics are the output based on the Recursive Feature Elimination (RFE) method. RFE is a well-known method for performing the important task of characteristic selection. It fits the model and removes the weakest characteristics and sorts the characteristics by recursively eliminating in each iteration. Furthermore, find the best number of characteristics by using cross-validation of RFE. The selected characteristics represent different values of the state of the user walking on the stair or the floor. For example, Figure 7 shows the characteristics of W_a when the user is walking on a floor and stair, respectively. Similarly, Figure 8 shows the characteristics of $W_{\triangle a}$ for two user activities, respectively (each value in Figures 7 and 8 is calculated by 1 frame (1 s) of data collected at 10 Hz). It can be seen that the above characteristics are quite different in two different cases. The calculated characteristics $\overline{a}_x$, $\overline{a}_y$, $\overline{a}$, W_a, $W_{\triangle a}$ and $W_{\triangle Mf}$ are fed into the training models of machine learning algorithm: K-NN, DT and SVM. Then the training model utilizes the data collected by the user to detect inter-floor. We increase the link of inter-floor detecting to increase the localization accuracy, because we do not keep tracking the user all the time during the floor locating, just mapping and matching the data sent by the user's smartphone and determining the user's current floor according to the principle of the majority, which may cause some errors due to special circumstances such as the user going up and down the stairs.

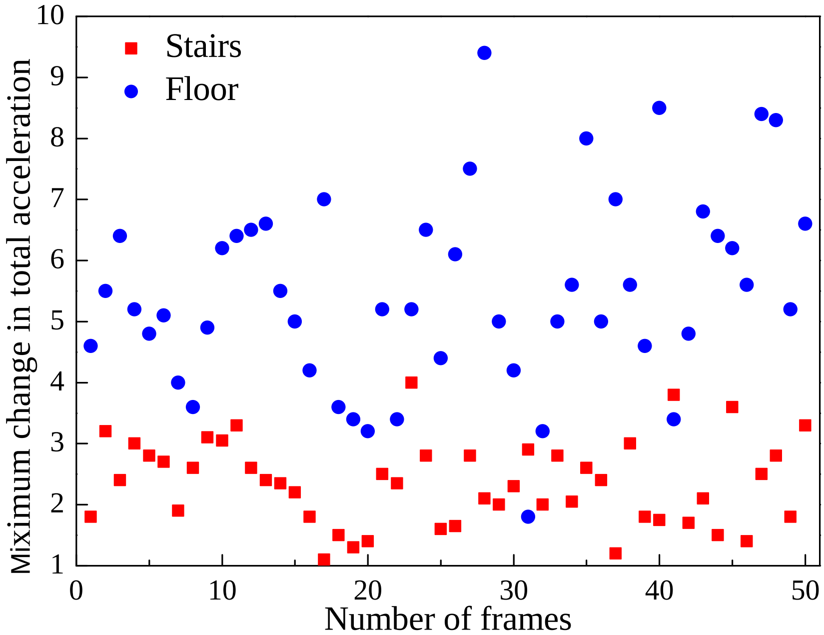

Figure 7. Maximum change in total acceleration.

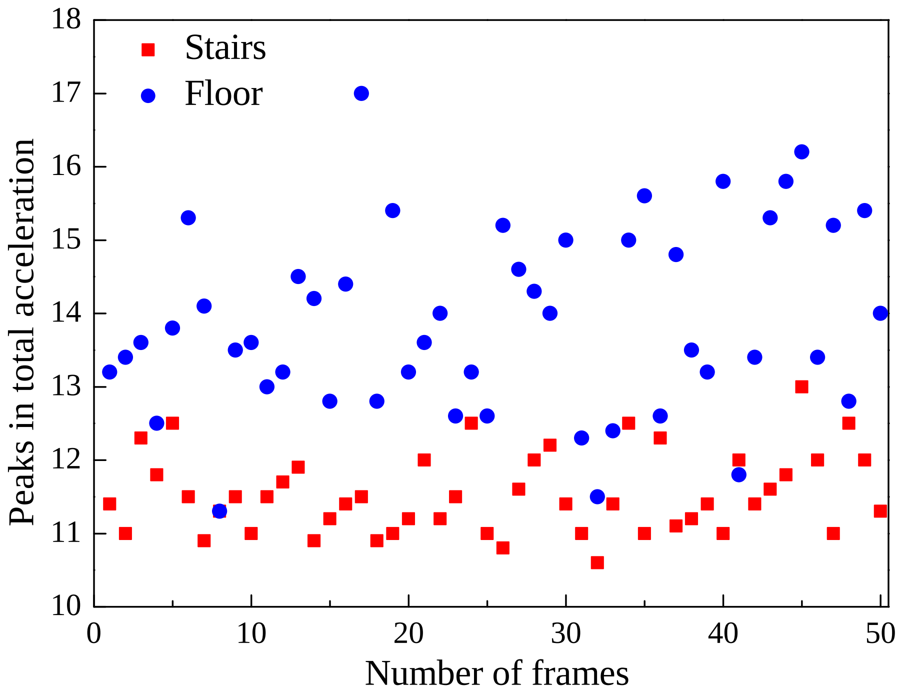

Figure 8. Peak of total acceleration.

In addition, as shown in Figures 9 and 10, the geomagnetism along the same path of the indoor floor is similar, and the geomagnetism of different paths along the indoor floor are quite different. Therefore, the magnetic fingerprint database is more convenient and simple in terms of maintenance and update than the barometer database and Wi-Fi database, and the accuracy of data collection is more reliable.

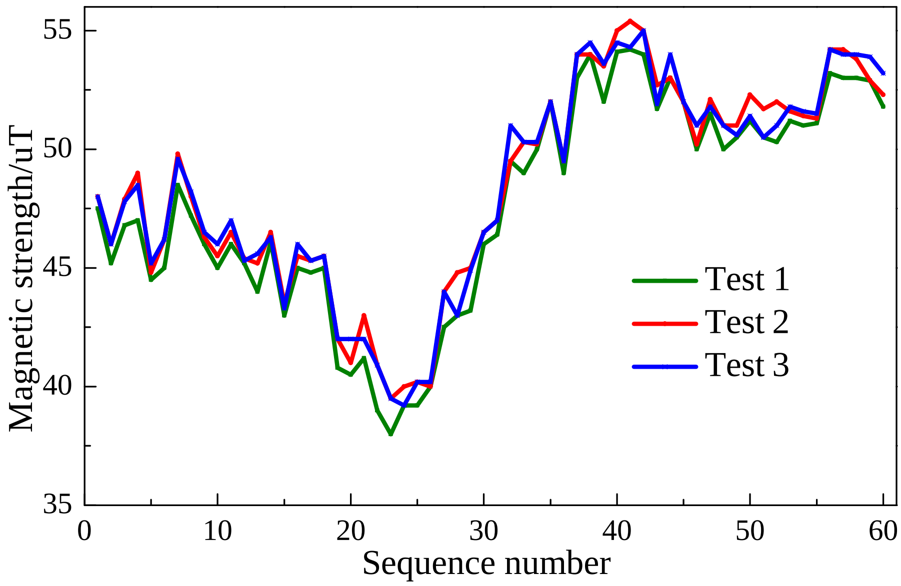

Figure 9. Comparison of indoor magnetic strength of the same path.

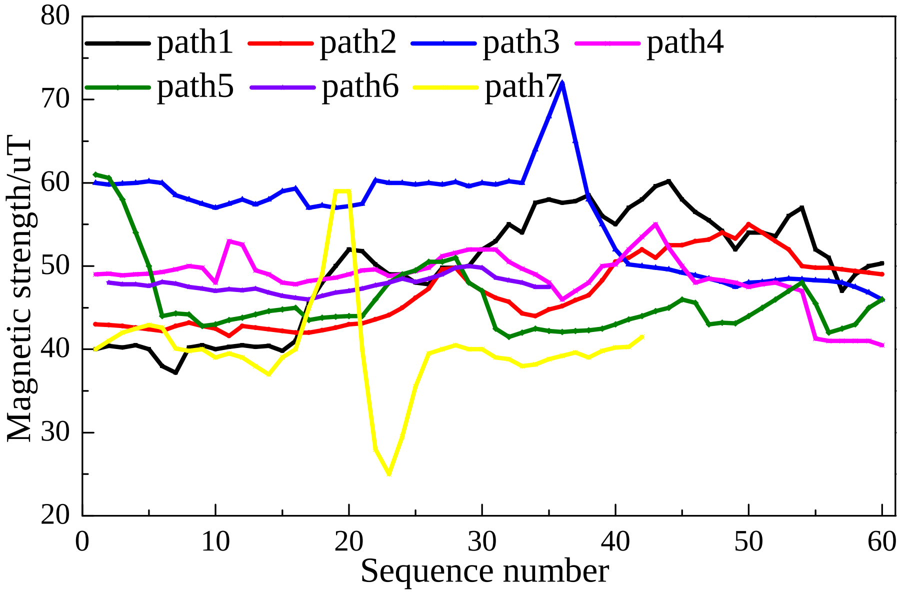

Figure 10. Comparison of indoor magnetic strength of different paths.

4. Simulation Results and Analysis

The selection of experimental site takes into account the concentration of people and the number of APs. The places where we conduct experiments are Harbin Clothing Market, Huiwen Building and Physical and Electronics Laboratory Building, respectively. Harbin Clothing Market is a constant crowded area with a large number of APs. Huiwen Building (teaching building) is an intermittent crowded area with less AP distribution. Physical and Electronics Laboratory Building has a lower population density and more AP distribution. The Huiwen Building has 10 floors, including one underground floor; the Physical and Electronic Experimental Building has eight floors; the Harbin Clothing Market has six floors, including one underground floor. The collection of magnetic samples in selected buildings is on different dates and at different time points within 4 months. Furthermore, data collection is performed by a smartphone model Huawei nova youth (WAS-AL00). In addition, data are collected from magnetometers, accelerators, gyroscopes, and barometers at a sampling rate of 10 Hz, and collected from Wi-Fi at a sampling rate of 1 Hz. The concentration of people and the number of APs in three buildings are shown in Figure 11. The black dots represent the distribution of Aps; grids of different sizes indicate each room; different colors indicate different population concentration levels, where blue indicates an average person flow of less than five persons (/h), green indicates an average person flow of between 5 and 20 persons (/h), and yellow indicates an average person flow of between 20 and 50 persons (/h), orange indicates an average person flow of between 50 and 100 persons (/h), and red indicates an average person flow of more than 100 persons (/h). Figure 11a is a planar structure of the 7th floor of the Physical and Electronics Laboratory Building. Figure 11b is a planar structure of the 3rd floor of the Huiwen building. Figure 11c is a planar structure of the 2nd floor of the Harbin Clothing Market. Among the three buildings, Harbin Clothing Market has the largest population concentration, and the Physical and Electronics Laboratory Building has the lowest population concentration; the Physical and Electronics Laboratory Building has the largest APs distribution, and Huiwen building has the lowest APs distribution.

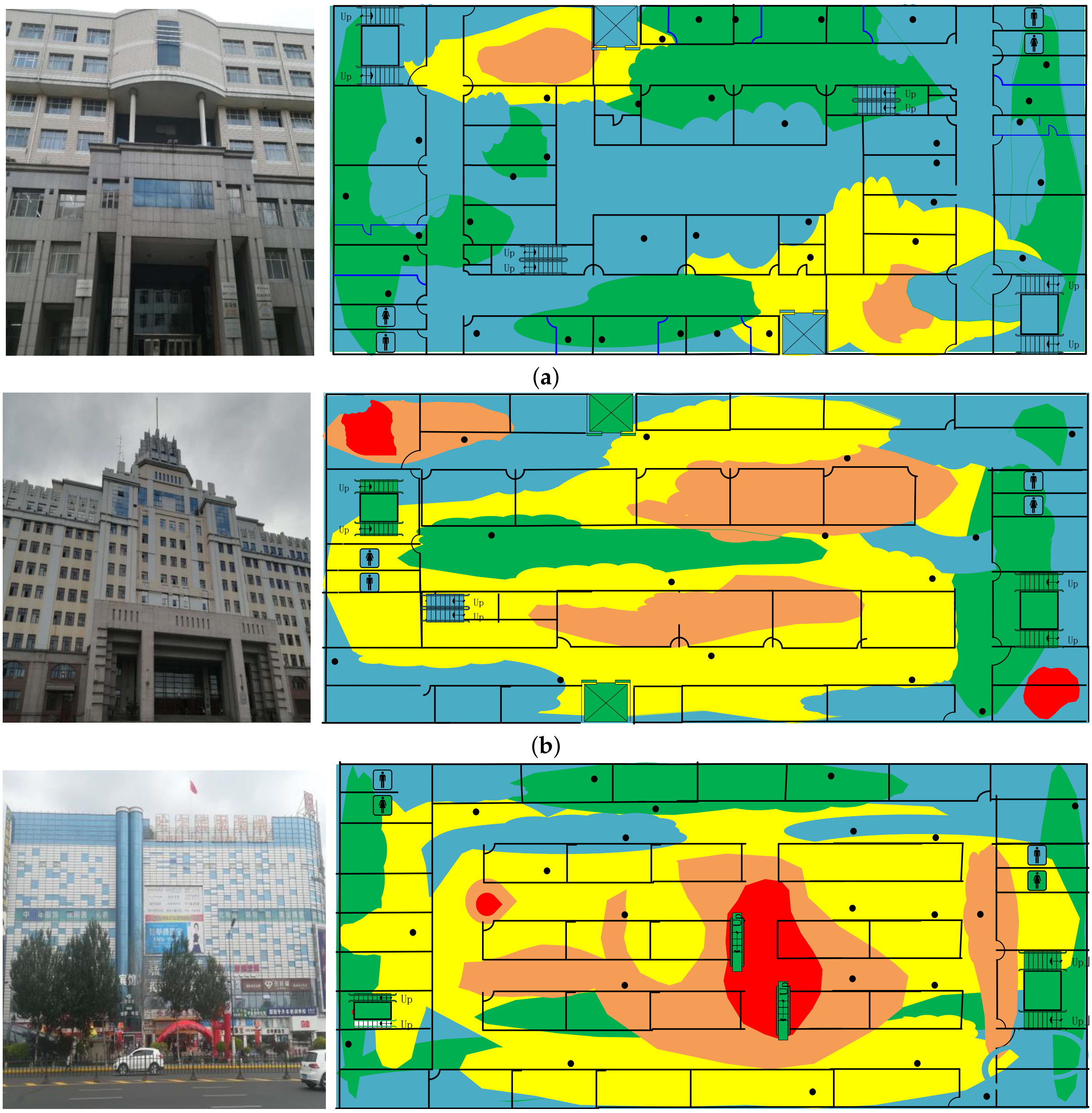

Figure 11. (**a**) Physical and Electronics Laboratory Building (**above**). (**b**) Huiwen Building (**middle**). (**c**) Harbin Clothing Market (**below**).

4.1. The Assessment of User's Activity Pattern

The performance of three machine learning-based classifiers for classifying the user's activity pattern is evaluated, in order to select the optimal classifier for MIS-IFL. The training data for the user's smartphone state contain 900 samples per orientation angle of smartphone and these samples are fed into the selected classifier. The labeled data are trained by supervisory training. The training vector contains yaw, pitch, rotation, and acceleration in the x, y, and z directions. Tests are conducted using data from the Physical and Electronics Laboratory Building, Huiwen Building, and Harbin Clothing Market, and 6000 samples of per smartphone state. The average result of the user's activity pattern is shown in Figure 12.

As can be seen from Figure 12, the three classifiers perform well when classifying the "normal walking", "phone calling" and "phone shaking", and the accuracy of the SVM classifier is higher than that of DT and K-NN. The classification accuracy using the acceleration data are slightly lower than the classification accuracy using the magnetic data because the noise of the acceleration data are larger than the magnetic data. However, the higher classification accuracy can be achieved when the acceleration data and the magnetic data are combined.

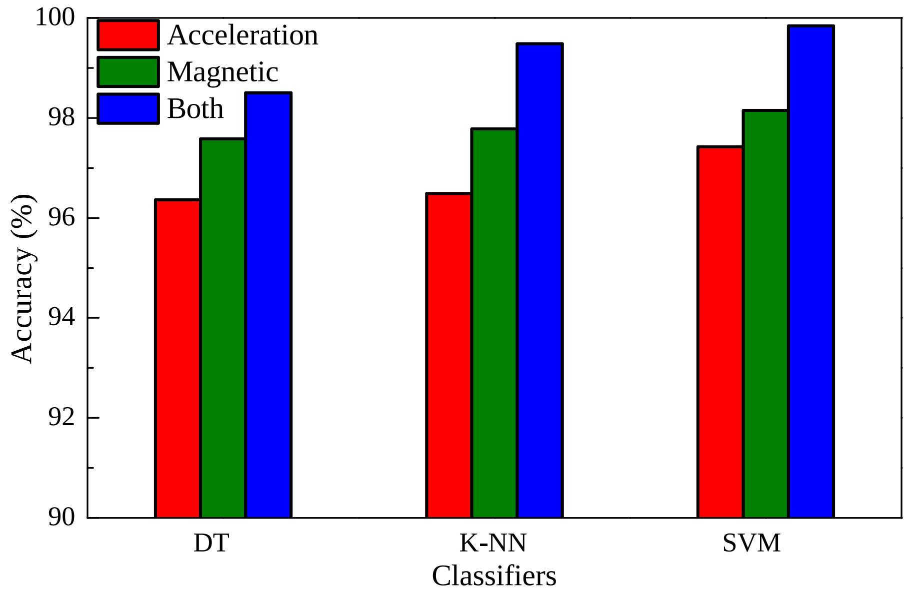

Figure 12. Accuracy of user's activity pattern.

4.2. The Assessment of Floor Localization

The proposed MIS-IFL is an IFL method based on geomagnetic signals. In order to verify the effectiveness of MIS-IFL, the proposed method is compared with the existing method MB-ILS (based on barometer data) and WF-ILS (based on Wi-Fi data) in three user activity patterns.

The data are collected for each floor of three building for 15 s to calculate the reference barometric pressure (RBP) of each experimental floor. The RBP is used to calculate the reference height (RH) of the relevant floor. Then the calculated RH is used for "normal walking" and the height limit (HL) is used for the patterns of "phone calling" and "phone shaking". In the pattern of "normal walking", we kept the smartphone at a height of 1 m from the floor. Therefore, we defined HL as RH $\pm$ 1 m for the patterns of "phone calling" and "phone shaking". In addition, the RBP value needs to be calculated each time when an experiment is performed because the atmospheric pressure changes at different times of the day. The calculated value is compared to the RH to determine the localization floor.

In IFL based on Wi-Fi, the method for Wi-Fi fingerprint database constructing is similar to a magnetic fingerprint database constructing. As shown in Figure 2, Wi-Fi data are collected at specified points separated by 0.9 m. Furthermore, we use some independent sensors for the calibration of Wi-Fi data to improve the accuracy of the collected data. The fingerprint database contains two elements: Basic Service Set Identifier (BSSI) and Received Signal Strength Indicator (RSSI) of the scanned AP.

During the test, the BSSI of the scanned AP and its associated RSSI value are compared to the fingerprint database of each layer. The fingerprint database of the floor with the smallest error is the floor where the user is most likely to be. The error is calculated in terms of two criteria: the number of matched APs and the lowest difference for each matched AP.

The localization accuracy of MIS-IFL and the other two methods is shown in Figure 13. The results show that the floor localization accuracy of MB-ILS is highest in the pattern of "normal walking" and lowest in the pattern of "phone calling". The overall accuracy can reach a good result of 86.4% because the reference value is used each time when the floor is located. Therefore, the main limitation of using a barometer for IFL is that it needs to retrieve the RBP or altitude when locating. It is common to place the barometer sensor on each floor at a specific height from the floor and then use the sensor's readings for locating floors.

The results also show that the localization accuracy of WF-ILS for locating floors is lower than MIS-IFL and MB-ILS, because the localization accuracy of Wi-Fi is highly dependent on the matching of a higher number of APs with the similarity of RSSI values. The overall accuracy of "normal walking" in the Huiwen Building and the Physical and Electronic Experiment Building are 90.76% and 78.53%, respectively. The reason for the large difference in accuracy is the small number of APs in Huiwen Building, only five to eight APs can be obtained in each location. However, the Physical and Electronic Experiment Building has an average of 20 APs per scanning location and the lowest concentration of people, making the localization accuracy is relatively high. Similarly, the number of APs in Harbin Clothing Market is also large, but the flow of people is relatively dense, causing the localization accuracy is 88.06%. In addition, Wi-Fi signals are susceptible to many dynamic factors. Moreover, Wi-Fi signals are exhausted over time, which also decreases the localization accuracy.

The data results of the proposed magnetic data-based MIS-IFL are superior to the other two methods. The average localization accuracy of the magnetic data is 89.34%, which is higher than the barometer data (86.4%) and Wi-Fi data (78.08%). Moreover, the average localization accuracy of proposed method can reach 89.34% using a small amount of data, which is better. Similarly, the localization accuracy of the patterns of "normal walking", "phone calling" and "phone shaking" are 96.54%, 79.83% and 66.05%, respectively. Differ from the barometer data and Wi-Fi, the established fingerprint database need not to be updated unless it involves changes in the main indoor infrastructure made of metallic materials. Magnetic fields are ubiquitous and the data collection requires only the built-in magnetic sensor of the smartphone. The fingerprint databases for floor locating were prepared in March 2019. Test data were collected at different times from March 2019 to June 2019.

In addition, we can find that the performance of MIS-IFL is seriously affected when the user is in the pattern of "phone shaking". The main reason is that the smartphone moves continuously in the front and rear direction, which affects the data and introduces noise. However, during the patterns of "normal walking" and "phone calling", the collected data are smooth, stable and exhibit good performance because the orientation angle of the smartphone changes but remains in a similar location with very little movement around the axis.

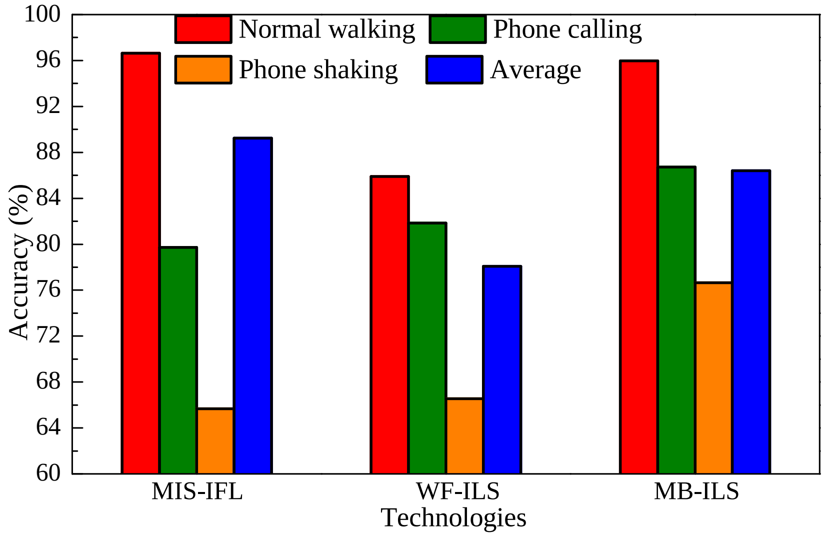

Figure 13. Accuracy of floor localization.

4.3. The Assessment of Inter-Floor Detection

The user is not tracked during the process of IFL, and the user's previous floor is not known when acquiring the data and performing floor localization. The whole process does not include inter-floor detection. Therefore, the link of inter-floor detection is added to improve the floor localization accuracy. The result of inter-floor detection by a machine learning-based classifier is shown in Figure 14. The three classifiers perform very well when utilizing the characteristics of the accelerator data and magnetometer data to detect up and down stairs. Furthermore, the performance of SVM is superior than K-NN and DT. Therefore, SVM is used in MIS-IFL for inter-floor detection.

The accuracy of proposed method can be slightly improved by adding the inter-floor detection. The reason for the slight improvement is that the user does not often walk on the stairs unless the floor needs to be changed. After adding the inter-floor detection, the average localization accuracy of the MB-ILS, WF-ILS and proposed method are 88.14%, 79.53% and 91.04%, respectively. The localization accuracy of the proposed method is still the highest.

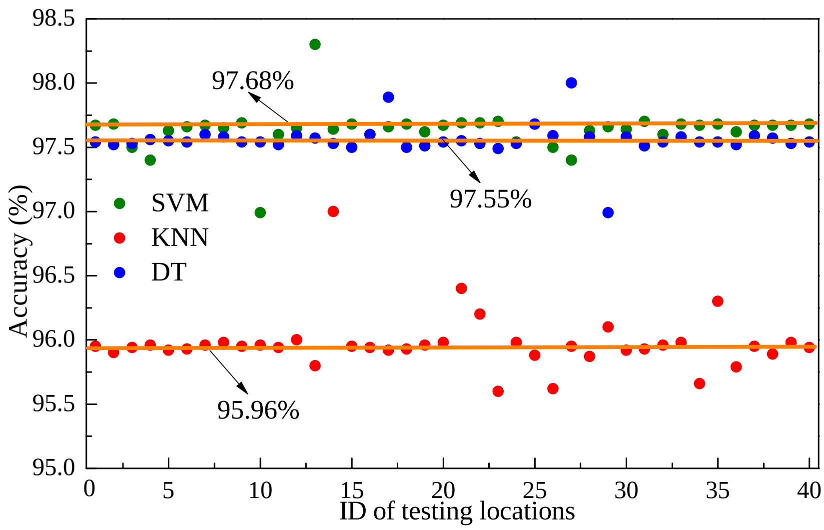

Figure 14. Accuracy of inter-floor detection.

5. Conclusions

The exciting IFL methods are not only susceptible to changes in the external environment, but are also cumbersome to collect and update data, bringing great limitations for practical application. This paper proposes a MIS-IFL method that relies on geomagnetic signal and uses multiple intelligent sensors synergy, which includes the fingerprint database constructing and the floor localization. Firstly, an accelerator and a magnetometer of the smartphones are used to obtain acceleration data and the machine learning classifier is used to identify the user's activity patterns. Then, the corresponding geomagnetic data mapping is performed according to the determined activity pattern, the mapped magnetic data are matched with the fingerprint database by Euclidean closest approximation, and the floor is located by the majority principle. Finally, the characteristics of the accelerator data and magnetometer data are combined to detect inter-floor to improve the overall localization accuracy. The data results show that the proposed method is feasible, providing a technical guarantee for future indoor multi-floor positioning based on geomagnetic signals

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Abbreviations

The following abbreviations are used in this manuscript:

IFL	Indoor floor localization
MIS-IFL	IFL based on magnetic signal using multiple intelligent sensors
AP	Access point
K-NN	K nearest neighbor
DT	Decision tree
SVM	Support vector machine
RFE	Recursive feature elimination
RBP	Reference barometric pressure

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