Indoor Map Construction Method Based on Geomagnetic Signals and Smartphones

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Abstract. Indoor map construction techniques based on geomagnetic signals can achieve better effects for constructing indoor maps, because indoor geomagnetic signals are uniquely representative. An Indoor Map Construction Method based on Geomagnetic Signals and Smartphones (IMC-GSS) is proposed. The magnetic trajectory data are collected through smartphones and crowdsourcing technology, the Dynamic Time Warping (DTW) is utilized to cluster the obtained magnetic trajectory data, and the trajectory fusion technology based on the affinity propagation algorithm is applied to fuse the trajectories belonging to the same cluster in the magnetic trajectory domain to obtain a relatively accurate indoor path. The experimental results show that constructed indoor fingerprint map is reliable as well as effective.

Keywords: Indoor map construction · Geomagnetic signals · Smartphones · Affinity propagation algorithm · Hierarchical clustering

1 Introduction

With the rapid development and widespread popularization of the mobile internet technology, the locating service industry has continued to expand. 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 location-based services more urgent. However, the traditional method of hiring professionals to make indoor maps layer by layer is expensive and time-consuming, and cannot be applied to large-scale indoor coverage. In addition, occasional changes of indoor floor plans pose challenges to updating indoor maps within a reasonable time. The use of stable geomagnetic signals and smartphones for map construction can bring great convenience to people.

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An indoor map construction method based on geomagnetic signals and smartphones is proposed, aiming at the problems that the existing indoor maps constructing technologies are expensive as well as time-consuming. The geomagnetic signals can be served as an indicator for indoor locating because of the uniqueness [4]. Based on geomagnetic signals, this paper uses data from the compass, accelerometer and gyroscope sensors of smartphones, combines dead reckoning methods, geomagnetic signals observation models and trajectory fusion techniques based on affinity propagation algorithms to realize indoor maps construction.

2 Related Work

In recent years, with the increasing demand for indoor locating, methods for location research are constantly emerging. There are several methods for constructing indoor maps that use different technologies. Li et al. [5] proposed an automatic radio map construction system based on crowdsourcing Pedestrian Dead Reckoning (PDR). The system processed some opportunistic PDR traces (such as a user walking through a building), and generated partial road paths by panning, rotating, and zooming the traces based on opportunistic GPS locations and doorways as landmarks. Then, turn errors were processed and PDR trajectories were merged based on the similarity of Wi-Fi fingerprints. Finally, road coverage was further expanded based on the merged PDR trajectory. Sun et al. [6] proposed an RSS-based indoor map construction algorithm using only Wi-Fi fingerprint information, which converted the indoor map construction problem into the classification problem of reference points in the fingerprint database. The algorithm used a hierarchical classification system consisting of a single AP-based basic classifier and a multi-AP-based combined classifier to ensure the accuracy of the classification results. An accurate line segment feature map was obtained by identifying the dividing line between two categories from a hierarchical classification system. Chen et al. [7] proposed a dynamic method for constructing indoor floor plans using existing motion sensing functions. This method abstracted the unknown indoor map into a matrix and combined three mobile sensing technologies (Accelerometer supporting dead reckoning, Bluetooth RSSI detection and Wi-Fi RSSI detection) using curve-fitting fusion technology. The floor plan reconstruction was extended from one room to the entire building by using shadow rate and anchor point analysis. The techniques and ideas used in these methods provide inspiration for the research in this paper.

Based on the above research, this paper aims to design an indoor map localization method based on geomagnetic signals and smartphones. This method is based on stable geomagnetic field data, and performs indoor map constructing using the built-in accelerator sensor, gyroscope sensor, and compass in the smartphone.

3 IMC-GSS Algorithm

Aiming at the problems of the expensive and time-consuming of making indoor maps, this paper proposes an indoor map construction method based on geomagnetic signals and smartphones (IMC-GSS). The overall structure of proposed method is shown in

Fig. 1, which can be divided into four parts: pedestrian trajectory atomization, hierarchical clustering, trajectory fusion, map construction.

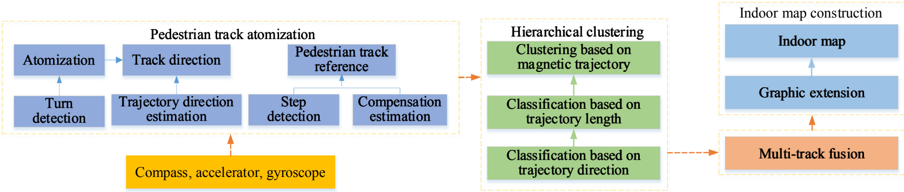

Fig. 1. Architecture of the map building system

3.1 Pedestrian Track Atomization

The complex indoor environment is characterized by a combination of large long trajectories generated by various pedestrian walking paths These trajectories only partially overlap, it is difficult to cluster them as a whole and fuse them into precise indoor paths. So, a turn detection method (i.e., trajectory segmentation) is used to solve this problem, dividing the long trajectory into short straight-line segments.

The turning point of the indoor path is taken as the natural segmentation point for dividing the long indoor trajectory into regular short trajectories, which will make all short trajectories be straight lines with no inflection points in the middle. A turn detection method is used to accurately detect the turning points on the trajectory, which uses both an accelerator and a gyroscope, as shown in Eq. (1):

$$\begin{cases} \theta = \sum_{i=1}^{m} w_v^i \Delta t \\ w_v^i = \left(w_x^i, w_y^i, w_z^i\right) \cdot \left(\overline{a}_x, \overline{a}_y, \overline{a}_z\right) \Big/ \sqrt{\overline{a}_x^2 + \overline{a}_y^2 + \overline{a}_z^2} \\ \overline{a}_x = \frac{1}{n}\sum_{j=1}^{n} a_x^j, \overline{a}_y = \frac{1}{n}\sum_{j=1}^{n} a_y^j, \overline{a}_z = \frac{1}{n}\sum_{j=1}^{n} a_z^j \end{cases} \tag{1}$$

where n is the sliding window size corresponding to the even steps. w_v^i represents the vertical speed. $\left(w_x^i, w_y^i, w_z^i\right)$ represents the gyroscope observation vector. $\left(a_x^i, a_y^i, a_z^i\right)$ represents the accelerator observation vector. w_v^i is the dot product of $\left(w_x^i, w_y^i, w_z^i\right)$ and $\left(\overline{a}_x, \overline{a}_y, \overline{a}_z\right) \Big/ \sqrt{\overline{a}_x^2 + \overline{a}_y^2 + \overline{a}_z^2}$ (unit vector of gravitational acceleration). A moving average method of acceleration data is used to offset acceleration fluctuations caused by pedestrians walking to obtain the unit vector of gravitational acceleration (The average vector of the accelerator $\left(\overline{a}_x, \overline{a}_y, \overline{a}_z\right)$ approximates the gravity acceleration vector, which points directly at the center of gravity of the earth.). In a pre-defined sliding window, the cumulative rotation angle θ is used to determine whether a turning event occurs when a pedestrian walk on a certain path. m represents the corresponding window size for the time period.

The turn detection algorithm recognizes the turning activity of pedestrians as shown in Fig. 2. There are 5 pedestrian tracks in Fig. 2.

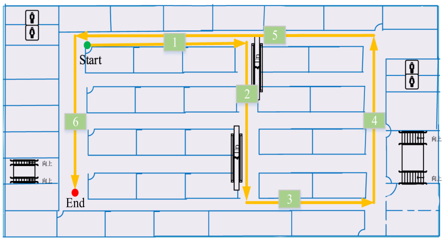

Fig. 2. Trajectory path diagram

3.2 Hierarchical Clustering

Due to the influence of the inertial sensor and compass sensor noise, the indoor trajectory obtained by walking by only one pedestrian will produce step and heading errors. The accuracy of indoor trajectory and indoor plane planning can be improved by identifying and merging multiple atomic trajectories corresponding to the same indoor path. Reliably identifying and correctly correlating multiple inferred trajectories on the same indoor path is the core of the indoor map construction algorithm used in this paper. A hierarchical clustering algorithm is used to improve the clustering accuracy and speed of the algorithm, which mainly includes three classifiers: Classifier based on trajectory direction, classifier based on trajectory length, and classifier based on magnetic sequence (as shown in Fig. 1).

Classification Based on Trajectory Direction. The atomic trajectory direction is defined as the average compass direction of all detected steps on the atomic trajectory. The direction of atomic trajectory will fluctuate in the direction of the indoor compass and deviate from the actual direction, because affected by the geomagnetic anomaly caused by ferromagnetic building materials and the shaking during walking [8]. The average direction of the compass along this atomic trajectory is took to increase the accuracy of the atomic trajectory direction. Figure 3 shows a comparison of step orientations and average orientation each time when walking on the same straight path. In the figure, the step orientation 1 indicates the step orientation of the first round of walking on the same straight path, and the average orientation 1 indicates the average step orientation of the first round of walking on the same straight path. It can be found that the average orientation remains stable when repeatedly walking on the same indoor atomic trajectory, but the orientation of each step fluctuates greatly due to the non-uniform magnetic anomaly in the indoor environment.

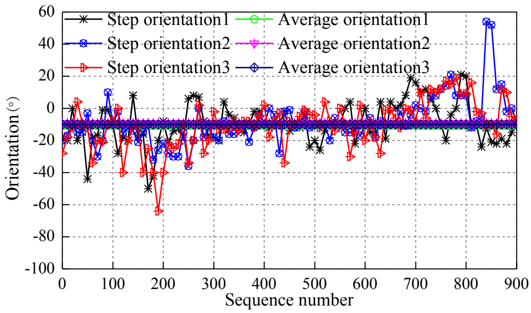

Fig. 3. Comparison of step orientations and average orientation along same atomic trajectory

The classifier based on the trajectory direction is characterized by the average direction of each atomic trajectory, and clusters all atomic trajectories into several clusters. The clustering results are basically consistent with the actual directions of indoor trajectories. Multiple walking experiments along a square path are conducted to further evaluate the effectiveness of proposed method. The estimated trajectories of different direction estimation methods are shown in Fig. 4.

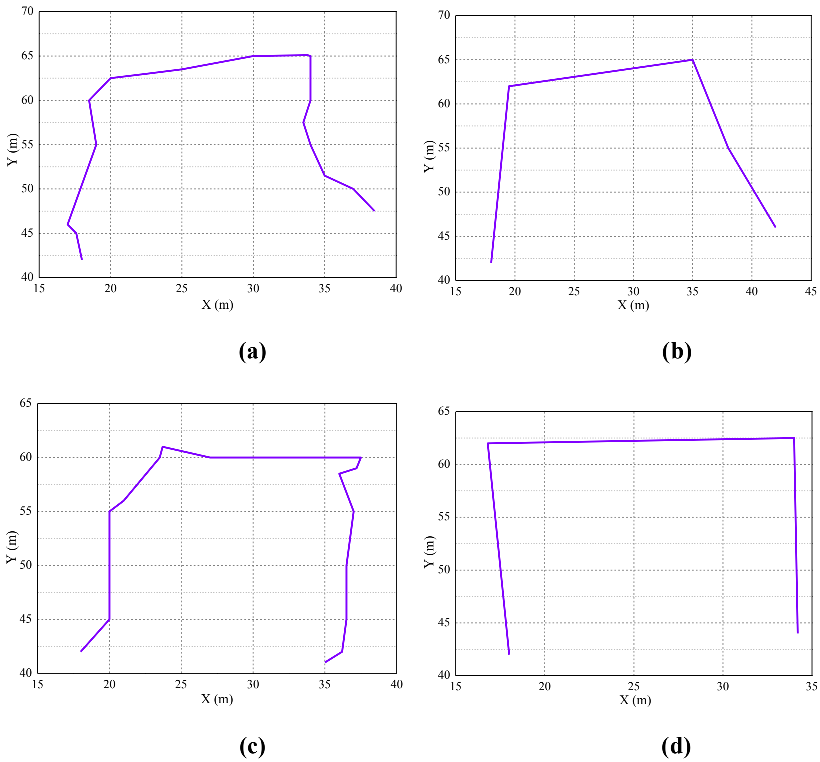

Fig. 4. Trajectory inference using (a) Gyroscope, (b) Atomic trajectory based on gyroscope, (c) Compass and (d) Atomic trajectory based on compass

First, a step is defined as a unit, and the calculated average direction of each step measured by the gyroscope is regarded as the trajectory direction, the trajectory inference results are shown in Fig. 4 a). Different from taking steps as units, the trajectory direction in Fig. 4 b) is calculated according to the unit of atomic trajectory. The average direction of atomic trajectory obtained from the gyroscope is regarded as the direction of atomic trajectory. The trajectory direction in Fig. 4 c) is inferred based on the step unit of the compass. The trajectory direction in Fig. 4 d) is inferred in units of atomic trajectories using a compass. The accurate trajectory direction estimates are obtained using atomic trajectory direction averaging method, and combining with the compass, gyroscope, and accelerator. It can be seen that the classifier based on the trajectory direction can effectively identify the corridor direction that is parallel or perpendicular to the building direction.

Classification Based on Trajectory Length. After completing the clustering based on the trajectory direction and implementing the classification for all atomic trajectories in different directions, the atomic trajectory is further grouped using a classifier based on the trajectory length (trajectory length is an estimate of the distance for a user walking on an atomic trajectory).

There are many different indoor paths in an indoor environment, and many different indoor paths in these paths have the same direction and different path lengths. The classifier based on trajectory length is mainly used to distinguish indoor atomic paths of different lengths. For paths of different lengths in the same direction, classification based on trajectory length can be performed. Affinity propagation clustering algorithm is also used in the classification based on trajectory length.

Classification Based on Magnetic Sequence. All the atomic trajectories are grouped according to different directions and lengths after completing the classification based on the trajectory direction and the trajectory length, then the final classification corresponding to the same physical path is obtained using magnetic sequence classification. The classification based on the magnetic sequence is based on the stability and uniqueness of the magnetic measurement sequence for each indoor path. The atomic magnetic sequence is associated with the atomic measurement trajectory based on the same time base. Affinity propagation and dtw algorithms have also been adopted for classification based on magnetic sequences.

The DTW algorithm can effectively measure the similarity between two time sequences (the two time sequences may be different in time or speed). The similarity between two atomic magnetic sequences was calculated using the DTW to eliminate the influence of different walking speeds and different sampling frequencies on different amounts of geomagnetic data collected on the same path. For the atomic geomagnetic data sequences $M_1 = \{m_1^i | i = 1, 2, \ldots, n\}$ and $M_2 = \{m_2^j | j = 1, 2, \ldots, k\}$ (n and k are not necessarily equal), the similarity $d_{i,j}$ (shortest accumulation distance) between sequence M_1 and sequence M_2 is calculated using the DTW algorithm, as shown in Eq. (2).

$$d_{i,j} = \min\left(d_{i-1}, d_{i,j-1}, d_{i-1,j-1}\right) + dist_{i,j} \tag{2}$$

where $dist_{i,j}$ is the Euclidean distance between sequence m_1^i and sequence m_2^j, and $i \in (1, n), j \in (1, k)$. $d_{n,k}$ represents the similarity of two atomic geomagnetic data sequences. In addition, a fast DTW algorithm with a time complexity of $O(n)$ is used in this paper [9].

3.3 Multi-track Fusion

Hierarchical clustering operation divides all crowdsourcing trajectories into different groups, which respectively correspond to indoor linear trajectory segments. A multi-track fusion scheme is adopted to address the problem that a single motion trajectory has a lot of noise due to sensor error accumulation. Multi-track fusion scheme fuses all atomic trajectories belonging to the same group to get the final trajectory.

All points in the non-clustered representative magnetic sequence in the same cluster are mapped to the cluster representative members after the DTW-based magnetic sequence clustering is completed. All mapping positions of the non-clustered representative magnetic sequence are averaged with the corresponding positions of the cluster centers to obtain the path position estimates.

Indoor path estimation is obtained by fusing all positions in the cluster center as shown in Fig. 5. Two different types of smartphones (OPPO R9s and Huawei Nova Youth) are used by different users to collect six atomic trajectories with different trajectory lengths and trajectory directions. The results show that the six original atomic trajectories deviate from the actual path. But the fusion trajectory after DTW-based multi-track fusion is similar to the actual observed trajectory.

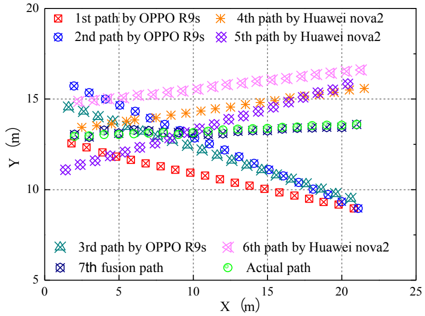

Fig. 5. Comparison of atomic trajectories

3.4 Map Construction Based on Graphic Extension Algorithm

The following expansion process is performed to systematically generate a path graph with path width information. First each fusion trajectory is drawn on the canvas, then the fusion trajectory is expanded to 0.5 m wide according to the distribution of related atomic trajectories (that is, from lines to shapes). The pixel occupied by the atomic trajectory is proportionally weighted according to its distance from the fusion trajectory (that is, the closer the pixel is, the weight will be the higher).

Because the multiplicity of atomic trajectories, the extended atomic trajectories will overlap, the weights of the overlapping pixels will be added. The path expansion process continues until all atomic trajectories are traversed, and finally a complete path graph is formed. A shrinking process is used to delete those external pixels whose weight is less than a certain threshold to eliminate the large error effect of some atomic trajectories. In view of the fact that some atomic trajectories may experience more frequently than other atomic trajectories, a dynamic weight threshold is adopted, and the dynamic weight threshold of each pixel is set to a certain proportion of the maximum weight of the pixel neighborhood. The threshold proportion is set to 20%. Finally, the isolated pixels are removed and the edges of the reduced path map are smoothed to obtain the final path map.

4 Simulation and Results Analysis

4.1 Experimental Setup

The verification experiment about the map construction is performed on the second floor of Harbin Clothing Market. The experiment area and the indoor layout are shown in Fig. 6.

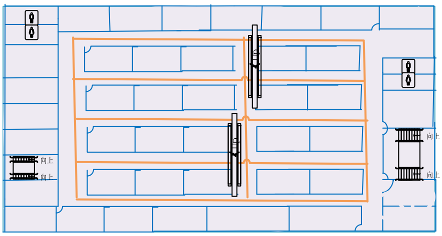

Fig. 6. Partial floor plan of Harbin Clothing Market

During the experiment, the tester holds a smartphone in his hand, places it on his chest, and walks along the corridor. Data are collected using two Android smartphones (OPPO R9s and Huawei nova youth). The smartphones collect data generated by the magnetometer, gyroscope, and accelerometer at a sampling frequency of 2Hz. During the experiment, testers walk at a constant speed and collect data on 8 different paths. The 10 test points on each path are uniformly selected and their actual positions are recorded. When the testers pass these test points, they trigger the relevant application to obtain the position data of the corresponding test points. Finally, according to the cumulative distribution function, map construction accuracy analysis is performed on the selected test points.

4.2 Evaluation of Performance

The comparison of map construction results is shown in Fig. 7. The two figures are the result of constructing the orange path of Fig. 2. Figure 7 (a) shows the trajectory constructed using the step trajectory fusion algorithm (that is, the original direction of each step is used as the path direction). Figure 7 (b) shows a plan view constructed by the proposed algorithm. Due to the direction fluctuation caused by environmental factors, the direction trajectory derived by the step trajectory fusion algorithm has a large deviation from the actual trajectory, but the proposed algorithm shows very good performance.

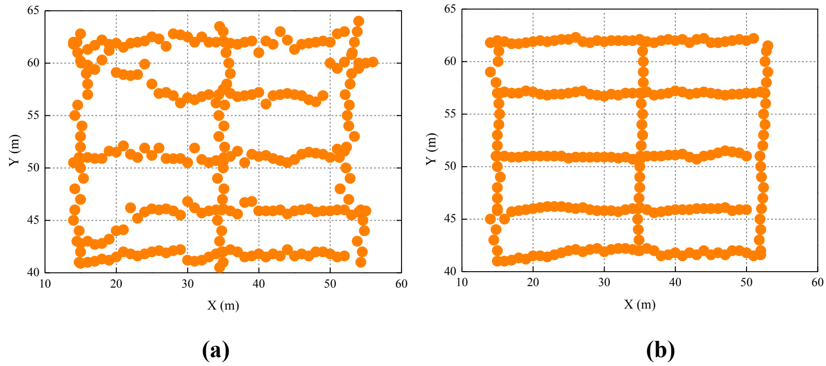

Fig. 7. Comparison of map constructing results of (a) Step trajectory fusion algorithm and (b) Proposed algorithm

In addition, a comparative analysis of the CDF of map construction errors is also performed. Figure 8 shows the CDF comparison results of the proposed algorithm and the step trajectory fusion algorithm. It can be seen from the figure that when the step trajectory fusion algorithm achieves a 1m map construction error, the confidence is only 40%. However, the confidence is about 90% when the proposed algorithm achieves a 1 m map construction error, which shows good performance.

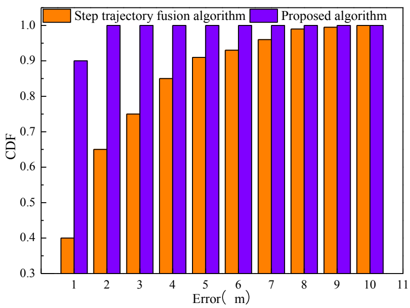

Fig. 8. CDF of map construction error

5 Conclusion

This paper proposes an indoor map construction method that relies on the geomagnetic signals and uses the synergy of multiple sensors in a smartphone. The method uses the turn detection algorithm to atomize the pedestrian trajectory, uses affinity propagation algorithm and DTW to cluster crowdsourcing trajectories, merges atomic trajectories that belong to the same cluster, and expands the linear trajectory into a trajectory with a certain width by graphic expansion algorithm to complete the construction of the indoor map. The experimental results show that the proposed algorithm successfully constructs a high-precision indoor map, which provided guarantee for subsequent map database matching and locating navigation.

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