Vector Calibration for Magnetic Field Based Indoor Localization

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Abstract. In fingerprinting techniques using a magnetic field signal, since the moving direction of the current user may be different from the moving direction of the person who creates the magnetic field map at the collection time, the sampled magnetic vector may have different values from the vector values recorded in the field map. This may substantially lower the positioning accuracy. In this paper we propose a vector calibration algorithm which can adjust the sampled magnetic vector values to the vector direction of the magnetic field map by using the parametric equation of a circle. This can minimize the inaccuracy caused by the direction mismatch. To implement this, we just need to compute the relative azimuth from the moving direction of the current user to the moving direction during the magnetic field map collection. To evaluate our vector calibration algorithm, we first collected a magnetic field map in our test-bed. Then, a user walked through a random path and we adjust the sampled vector values to match the recorded magnetic field direction in the map. As a result, we can decrease the difference between the sampled magnetic vector and the magnetic field map values from 17.34 μT to 2.98 μT in x dimension, and from 13.12 μT to 1.98 μT in y dimension on average. This translates to 85% reduction in the map mismatch compared to the numbers without calibration. In addition, we also demonstrate the effectiveness of the calibration by applying the algorithm to our LSTM-based indoor positioning system (IPS).

Keywords: Indoor Localization, Magnetic field, Vector Calibration.

1 Introduction

The magnetic field is the attractive signal for indoor localization. The magnetic signal has two distinct advantages over RF signals. First, it does not require extra signal generation infrastructure such as beacons or APs since they are everywhere by nature. Therefore, you do not have to worry about the maintenance of functionality or discharge. Second, the magnetic signals are quite stable over time unlike RF or acoustic signals in indoor environment [6]. Therefore, IPSs based on magnetic signals are inherently economical yet have a potential to deliver more accurate positioning performance than RF-based IPSs.

However, magnetic sensors have the disadvantage that their vector values differ depending on the direction. It causes a mismatch with the magnetic field map. To avoid this problem, many researches usually use only the magnitude of the vector, which remains constant for rotation. However, using only the magnitude reduces the uniqueness of the fingerprint. In the fingerprinting technique, the more values used as the fingerprint, the higher the uniqueness of the fingerprinting. The uniqueness of the fingerprint is an important factor affecting both the localization accuracy and the speed of initial positioning.

In this paper, we propose a magnetic vector calibration algorithm that can compensate the change of a user's moving direction and adjust the sampled vector sequence to the original direction recorded in the magnetic map. Since we calibrate the vector sequences dynamically all the time relative to the original direction in the magnetic map, the calibrated vector sequences can still match the numbers stored in the magnetic map, minimizing the difference between the sampled vector sequences and the original sequences in the map for the same path. Due to the uniqueness of vector fingerprint compared to the magnitude fingerprint, we can achieve higher positioning accuracy as well as faster initial positioning.

To do the calibration, we should be able to compute the relative azimuth from the moving direction of the current user to the moving direction during the magnetic field map collection. For this, we use a gyroscope in a smartphone. Since the gyroscope measures the angular velocity, we can calculate the rotation angle of the smartphone, that is, the walking direction of the user. And we measure the azimuth from the magnetic north with a compass sensor. Then by applying the parametric equation of a circle, we can adjust the sampled magnetic vector values to the moving direction of the field map collector. As a result, although the user walked in a random direction in real-time test, we could reduce the mismatch with the magnetic map to about 85%.

We also test the impact of our magnetic vector calibration, by applying it to our LSTM-based IPS [6, 8], where we use recurrent neural network models such as LSTM to learn all the potential moving paths of a user and their corresponding magnetic vector and position sequences. Without calibration, the actual real time test error for the test path rises-up to above 5 meters, more than an order of magnitude degradation in the localization performance. By applying the calibration algorithm, we could achieve the average positioning error of about 0.73 meters.

The remainder of this paper is organized as follows. Section II discusses the related works. Section III presents the detailed vector calibration algorithm. Section IV shows the experimentation results of a real-time test with and without our proposed calibration algorithm. Finally, Section V concludes the paper.

2 Related Work

In the magnetic signal-based fingerprinting, the three-dimensional magnetic vector signal is used as the fingerprint for each position. While the magnetic signal generally points to true north in outdoor environment, the magnetic field is further distorted in indoor environment by the structure of the building such as concrete walls, iron doors and elevators, which leads to a more unique signal value for each position.

In the magnetic field-based fingerprinting techniques, two types of magnetic signal values can be used: a magnetic vector or the magnitude of the magnetic vector.

Magnetic vector as a fingerprint: The 3-axis magnetic sensor reads a magnetic vector in the three-dimensional space relative to the smartphone orientation. The vector value differs depending on the orientation of the sensor, so it is quite difficult to use as a fingerprint. During the positioning phase, a user may sample magnetic vectors in a direction different from the field map. This can cause a mismatch for the mapping, which leads to inaccurate localization. To avoid this problem, Chung et al. [2] made the wearable device with four magnetic sensors to measure the magnetic field in four different directions simultaneously. Similarly, Xie et al. [1] collected magnetic field vectors for different directions each position. However, it takes a lot of time and manpower to construct a magnetic field map in a largescale indoor environment. For example, if it takes five hours to collect a magnetic field map in one direction, collecting four directions may take 20 hours. In addition, since a user may move in any of 360 degrees direction, other than those four directions, there could be other mismatches due to the sensor orientation difference.

Magnitude of a magnetic vector as a fingerprint: The magnitude of the magnetic vector is widely used in many magnetic field based IPSs [3, 4]. The magnitude remains constant regardless of the sensor orientation. So, using magnitude, you do not have to worry about the direction. However, using only magnitude reduces the uniqueness of the fingerprint since the number of values in the map matching the sampled fingerprint decreases as the three-dimensional vector becomes a scalar. In fingerprinting, the more values used as the fingerprint, the higher the uniqueness of the fingerprint. The uniqueness of the fingerprint is an important factor leading to the localization accuracy. For example in an IPS based on particle filter, as the uniqueness of the fingerprint is reduced, it may take a longer time to locate the position [1]. Therefore, particle filter based IPS usually use sensor fusion to increase the uniqueness of the fingerprint. Zeng et al. [4] used Wi-Fi and images as well as magnetic sensor as fingerprints. Akai and Ozaki [5] used Light Detection and Ranging (LIDAR) in addition to magnetic sensor for localization. However, this has extra cost and since the signal noise of these sensors may be larger than the magnetic sensor, the positioning accuracy may be lowered.

In our work we use a magnetic vector as a fingerprint, which can maintain the uniqueness of the fingerprint, while we collect the magnetic field map only in one direction to minimize the manpower and collection time. In addition, with the dynamic vector calibration algorithm proposed in this paper we can minimize the map matching mismatches even if a user may change his or her direction anytime.

3 Magnetic Vector Calibration to Compensate Sensor Orientation

If you hold a smartphone horizontally and rotate 360 degrees collecting the magnetic field vector in x and y dimension, the graph showing the magnetic vector draws a circle as illustrated in Figure 1.

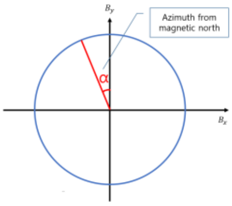

Fig. 1. If you rotate 360 degrees while measuring the magnetic vector at one position, the vector draws a circle. α is an angle rotated counterclockwise from the magnetic north.

In an indoor environment, the magnetic north may change depending on the location because of magnetic field distortion. For example, Figure 2 shows both the magnetic north direction and the moving direction of the administrator at each location. The red arrows point to the direction of the moving direction of the administrator during the field map collection while the black arrows point to magnetic north. Since the magnetic vector is sensitive to the moving direction, i.e. the sensor orientation, the measurement for the field map collection should be performed in one direction only.

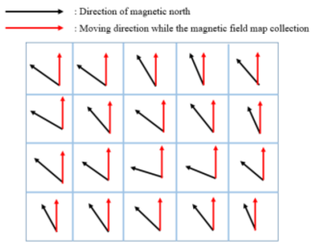

Fig. 2. The black arrow points to the direction of magnetic north. Due to magnetic field distortion, magnetic north varies depending on the location. The red arrows show the moving direction of the administrator during the field map collection.

Let us first define the notations used for the calibration algorithm. When creating a magnetic field map, we represent the magnetic vector collected from a certain position as a tuple $(B_{map_x}, B_{map_y}, B_{map_z})$. We also denote the angle between the direction of the map collector and the magnetic vector, i.e. magnetic north be α. Since we assume that a user holds a smartphone horizontally, we can express the magnetic vector as the Equation (1) and Equation (2) by using the parametric equation of a circle. Since we only consider holing a smartphone horizontally in this paper, B_{map_z}has the same value in any direction. So, in (1), r, the radius of the circle, can be expressed by Equation (2), where B_m is the magnitude of the magnetic vector.

$$B_{map_x} = r(-sin(\alpha)) \quad (1)$$
$$B_{map_y} = rcos(\alpha)$$

$$r = \sqrt{B_{map_x}^2 + B_{map_y}^2} \quad (2)$$
$$= \sqrt{B_m^2 - B_{map_z}^2}$$

When a user walks in some direction during positioning phase, let the value of the magnetic vector sampled by the user be $(B_{test_x}, B_{test_y}, B_{test_z})$ at the same position. Since we assume that the user holds the smartphone horizontally, the value of the magnetic vector in z dimension is invariant to rotation in the horizontal plane. So, B_{test_z} has the same value as B_{map_z}. Therefore, the radius r can also be obtained by Equation (3). Our goal is to calibrate (B_{test_x}, B_{test_y}) with respect to (B_{map_x}, B_{map_y}).

$$r = \sqrt{B_{test_x}^2 + {B_{test_y}}^2} \\ = \sqrt{B_m^2 - {B_{test_z}}^2} \tag{3}$$

During the positioning phase, if you know α, (B_{map_x}, B_{map_y}) can easily be obtained by (1) since we can compute radius r by using Equation (3). Since the radius r is invariant to rotation in the horizontal plane, they can be measured regardless of the user's moving direction. However, since α is changing depending on its position all the time, it cannot be computed by magnetic north.

To address this issue, we use a gyroscope and a compass sensor in a smartphone. The gyroscope can calculate the relative rotation angle, and the compass sensor can measure the azimuth from the magnetic north. When the map collection direction is zero degrees, the gyroscope calculates the current rotation angle, which we call the positioning relative angle. Also, whenever the user walks, the compass sensor calculate the azimuth from the magnetic north at each location, which we call the positioning azimuth. Then, the smartphone can calculate α by equation (4).

$$\alpha = positioning\ azimuth - positioning\ relative\ angle \tag{4}$$

Originally, for relative angle measurements, the user must know the direction of the magnetic field map collection. But if we use true north, the user do not need to. When collecting the magnetic field map, record the relative azimuth from the true north to the database. Then, by measuring the relative azimuth from the true north during positioning phase, the relative rotation angle from the direction of the magnetic field map collection can be calculated dynamically.

Now that we have obtained α by (3), we can calculate (B_{map_x}, B_{map_y}). In other words, we can compute the magnetic vector values of the map in any direction in real-time.

4 Evaluation

As we discuss in Section 2, we collect magnetic vectors only in one direction when collecting the field map. Figure 3 visualizes the magnetic field map for our test-bed by showing the vectors only in x dimension. When a user walks along the test path, the smartphone was kept horizontal as in the map collection, but the user may make any horizontal movement freely, i.e. random yaw rotation. The magnetic vector values may change with the yaw rotation, but our goal is to adjust these values as closely as the magnetic field values stored in the field map.

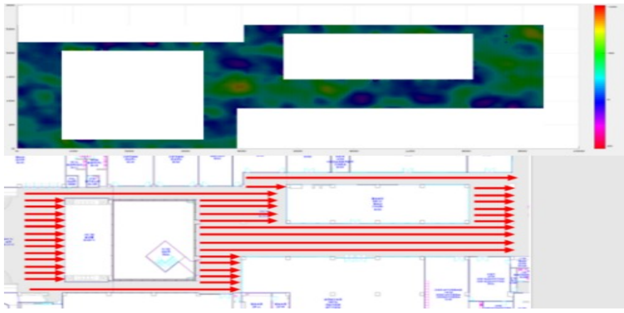

Fig. 3. The magnetic field map of our test-bed called Hana Square field map. When collecting the magnetic vectors during the field map construction, we moved in the red arrow direction

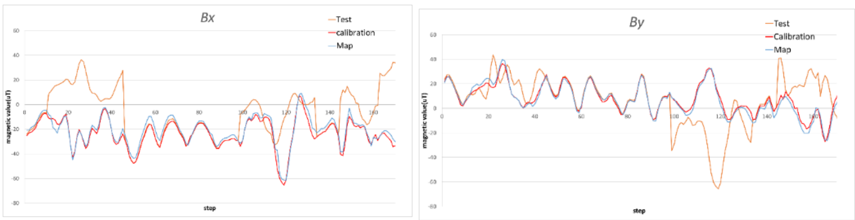

Fig. 4. The blue line shows the sequence of values extracted from the magnetic field map while the orange line shows the sequence of values measured by the user walking in a random direction. The red line shows the result of calibration. After calibration, the difference with the map is about 2.985µT in x dimension, 1.929µT in y dimension.

Figure 4 compares the same sequences for the same test path in dimensions x and y of the vector space. Unlike the case of magnitude, without calibration the mismatch between the map and the measured samples is quite large. The difference is as high as 65µT. Figure 5 compares only the differences between the map and measured samples in magnitude and vector space in dimensions x and y with and without calibration. The average difference in the magnitude is about 1.929µT while the average differences of the vector in dimensions x and y are 17.34 µT and 13.12 µT respectively. These huge differences will lead to inaccurate localization in a magnetic field based IPS. However, after applying our calibration, we could reduce these differences to 2.985µT on average in x dimension and to 1.981µT on average in y dimension. This suggests that we can effectively minimize sequence mismatches even with the magnetic vector with the proposed calibration algorithm.

Our LSTM-based IPS using the magnetic field has demonstrated outstanding localization performance in large scale indoor environment [8]. Recurrent neural network models allow continuous tracking since it can use not only the current fingerprint, but also the past sequence of fingerprints. However, since the artificial neural network models try to remember the map exactly, even a little noise can disturb the localization performance.

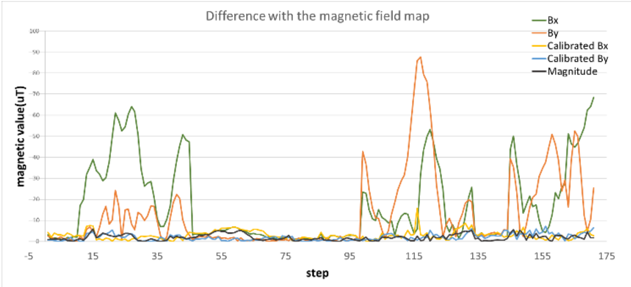

Fig. 5. Comparison of differences between the map and the measured samples in the magnitude and in the vector in dimensions x and y with and without calibration.

From the magnetic field map shown in Figure 3 we generate 300,000 data sets, each of which consists of 100 steps of a random pedestrian walk path assuming the random waypoint model [9] as mobility model. 60% of the data sets are used for training, 20% for validation, and the remaining 20% for the test.

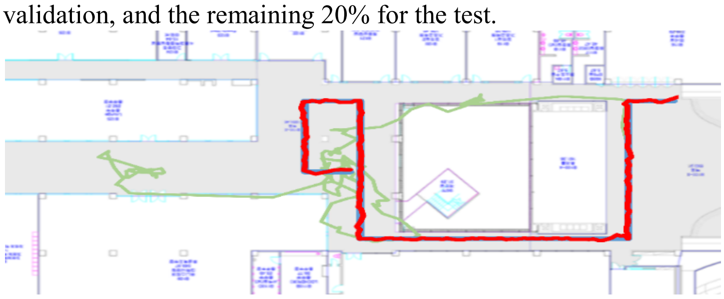

Fig. 6. The path predicted by LSTM based IPS compared to the actual test path. The blue line shows the actual path of the user. The green line shows the predicted path of LSTM based IPS using the magnetic vector without calibration while the red line shows the predicted path of LSTM based IPS with vector calibration.

After training, the LSTM model has an average positioning error of 0.43 meters for the test set. However, in a real time test with a smartphone, the average positioning error rises to 16.97 meters assuming that we use magnetic vectors without calibration as input to the LSTM model. Figure 6 shows the predicted path result of LSTM model with and without calibration compared to the actual test path. However, with calibration we could reduce this average positioning error back to 0.73 meters. The predicted path with vector calibration is illustrated by the red line in Figure 6.

5 Conclusion

In this paper we propose a magnetic vector calibration algorithm for indoor localization. Since the magnetic vector values change depending on the sensor direction, i.e. the moving direction of a user, it has been seldom used for indoor localization. To enable the magnetic vector based localization, we need to compute the relative angle of rotation from the direction of the user movement to the direction of the field map collector. This is because we can compute the magnetic vectors if we know only the azimuth from the magnetic north when the administrator collected the magnetic map.

To evaluate our vector calibration, we performed a random walk test to measure the differences in vector values between the map and the actual test. Without calibration, the average difference between the vector samples and the magnetic field map data was 17.34μT in the x dimension, and 13.12 μT in the y dimension. After we applied the calibration, we reduced these differences to 2.985μT in the x dimension, and 1.981μT in the y dimension. To demonstrate the effect of our calibration algorithm in a magnetic field based IPS, we applied the calibration algorithm to our LSTM-based IPS [8]. When we used the magnetic vector without calibration as an input to the trained deep learning model, the localization error was 16.97m. However, when using the magnetic vector with calibration as input, we could reduce the positioning error to 0.73m. This suggests that we can use magnetic vectors instead of their magnitudes for the magnetic field based IPS since vectors tend to provide more uniqueness for fingerprints than magnitudes and can achieve superior positioning performance compared to those traditional magnetic field based IPSs that rely on the vector magnitudes.

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