1. INTRODUCTION

In recent years, the opportunity to use location information on mobile terminals such as smartphones and tablets has increased for a wide range of application such as navigation, entertainment and health support. A global positioning system (GPS) is mainly used for acquiring location information on the earth. In research, cooperative GPS localization methods [1-3] have been actively discussed to improve accuracy of location information by employing multiple GPS receivers to locate a single position. As regards indoor positioning, GPS cannot work indoors because GPS signals cannot penetrate through buildings, so other approaches to indoor positioning are strongly desired especially for welfare purposes.

At present, radio waves are mainly used for indoor positioning. The radio waves have a property that their intensity attenuates according to their traveling distance in space. The relation between intensity (received signal strength indicator (RSSI)) of radio waves and their traveling distance is given by the following equation:

\[ \text{RSSI} = A - 20 \log(r) \]  

(1)

, where RSSI denotes the RSSI of radio waves and \( r \) denotes their traveling distance, and \( A \) is the RSSI when \( r \) is 1. Utilizing this equation, trilateration among positions of three stationary transmitters and traveling distances of radio waves sent from those transmitters to a receiver is performed to locate the receiver’s position. But the RSSI is easily influenced by interference between radio waves especially in small rooms.

To solve this problem, the use of fingerprinting is a main trend for indoor positioning. A fingerprint is an array of RSSIs of the obtained radio waves from stationary transmitters by a receiver at a predefined position so that it absorbs the influence of interference between radio waves, resulting in working for a signature of the predefined position. An array of fingerprints for a number of predefined positions is stored in a database prior to execution of indoor positioning. At the time of positioning, radio waves sent from the stationary transmitters are read by the receiver and a (current) fingerprint is made from the obtained radio waves. The similarity of the current fingerprint to the one stored in the database is calculated and the corresponding predefined position of the fingerprint in the database with the highest similarity is outputted as the estimated current position. A variety of radio waves includes Wi-Fi [4, 5], Bluetooth [6, 7], and FM [8]. Thus, fingerprinting works well and it is capable of absorbing the interference between radio waves indoors. It however has an underlying drawback with setup costs and maintenance costs of transmitters and fingerprints.

The use of geomagnetic field for indoor positioning has the potential for dealing with the underlying drawback. Geomagnetic field is a vector field represented by a set of three-dimensional arrows in space. Each arrow has intensity and direction of the field at the corresponding position. For indoor environments, geomagnetic field varies from place to place due to existence of steel frames,
electric wiring, and other things inside buildings and it is expected to work as signatures of positions in the building. There are two categories of research activities on geomagnetic field. One is to improve positioning accuracy by combining geomagnetic field with radio waves such as Wi-Fi [9, 10] and the other is to use only geomagnetic field so that setup costs and maintenance costs of transmitters are not required. For commercial products, NariNAVI is an indoor positioning service provided by NTT DATA corporation. NariNAVI has been installed in the Narita Airport and it employs a hybrid way which relies on both geomagnetic field and BLE signals for indoor positioning. IndoorAtlas and MazeMap companies provide an indoor positioning service as well with use of multiple sources of data like geomagnetic field, Wi-Fi, BLE signals etc. They all come from the former category. This paper focuses on the latter one to leverage its advantage.

As regards indoor positing that relies on only geomagnetic field, the traditional work [11–13] uses a geomagnetic sensor to grasp a sequence of change in intensity and direction of the geomagnetic field along a predefined path and stores it in a database for later reference. In this way, the sensor is required somewhat to go through the geomagnetic field, resulting in having the user walk some distance along the predefined path. At the time of positioning, the change in intensity and direction of the geomagnetic field along a path is collected and it is compared with those in the database then the predefined path in the database with the highest similarity is considered roughly as the current position. The resolution of positioning depends on the length of the predefined path where geomagnetic field is collected, and it is comparatively low.

To deal with this problem, the authors conducted a pilot experiment on a way of positioning without walking [14]. The five positions (hereinafter they are referred to as reference points) on the floor of the authors’ laboratory were predefined and geomagnetic field at those reference points was collected by an action of turning around shown in Figure 1. In the figure, a user stands still and holds a geomagnetic sensor with his/her arms stretched. The upper part is the top view of the user and the lower one is the side view. The red arrow shows the movement of the user turning around 360 degrees with the arms been kept stretched. As a result, it was found that even the sequence of collected geomagnetic field in such a nearby space has features and could work as a signature of that reference point. Figure 2 shows the change of intensity of collected geomagnetic field at two reference points R1 and R2 among the five ones. The line indicated by the symbol “A” was taken first, and the one indicated by the symbol “B” was taken 30 minutes later at the same reference point. Figure 3 shows the change of direction of the collected geomagnetic field. Comparing the lines from R1 with those from R2, the tendency for them to go up/down uniquely to each reference point is observed. In other words, it shows that the tendency can distinguish reference points. Comparing the line from A

![Figure 1: Action of collecting geomagnetic information](image1)

![Figure 2: Change of geomagnetic field (Intensity)](image2)

![Figure 3: Change of geomagnetic field (Direction)](image3)
with the one from B at the same reference point, they look almost the same over a period of time and then it could work as a signature of the reference point. The authors built a prototype of an indoor positioning system with the proposed method and demonstrated the performance at a glance in the paper [15].

The aim of this paper is to propose an indoor positioning method using geomagnetic field which is collected by an action of turning around without walking, and conduct experiments on positioning accuracy and then make an evaluation of the proposed method with some traditional ones in positioning performance.

Section 2 categorizes indoor positioning for welfare purposes and summarizes some related work, and it also refers to a desired positioning accuracy. Section 3 describes features of geomagnetic field, and Section 4 introduces the proposed method. Section 5 conducts experiments on positioning accuracy of the method, and Section 6 describes the experiment results. Section 7 gives discussion and evaluates feasibility of the method, and Section 8 gives the concluding remarks.

2. INDOOR POSITIONING FOR WELFARE PURPOSES

Indoor positioning for welfare purposes has been studied so far for two levels in positioning accuracy. One is a room-level indoor positioning. The positioning is performed to locate the room in which the elderly people exist. For the room-level indoor positioning, Tam et al. [16] proposed the system called Online Behavioral Change Detection (OBCD) using online streaming data from binary sensors. The binary sensors are attached on walls around the house and detect motions of elderly people every 10 minutes. The system records a temporal sequence of IDs of the sensor that detects their motion and watches out for their unexpected behavior. Marie et al. [17] evaluated the daily lifestyle of elderly people using a multi-infrared sensor monitoring system for the purpose of improving the smart home. In their system, each infrared sensor is attached on the ceiling of each room and detects if they exist in the corresponding room. The room-level positioning mainly works well without any incidents for healthy people.

The other is a position-level indoor positioning. The positioning is performed to locate the exact position of elderly people. For those with special needs such as those who suffer from lame and a paralyzed leg(s), and those who have poor eyesight, Ishihara et al. [18] introduced a position-level indoor positioning system using fingerprinting technique with radio waves of BLE signals. In the system, they target the positioning accuracy at the step length of people with poor eyesight which is 0.4 to 0.9 m and the system achieves a positioning error of 0.406 m on average. It still requires setup costs and maintenance costs of transmitters and fingerprints. Wang et al. [19] proposed a method for tracking and discovering people indoors by robots using geomagnetism. The positioning error of their method achieves less than 1m at the maximum, but it still requires some spatial movement like the mentioned ones [11-13] in Section 1 even for those with special needs.

Our method is a position-level indoor positioning one which relies on geomagnetic field and does not require users to walk for positioning.

3. FEATURE OF GEOMAGNETIC FIELD

Geomagnetic field is a vector field that starts from the north to the south. However, the geomagnetic field is altered indoors depending on positions by influence of building’s steel frames et al., so that it works as signatures for those positions, making indoor positioning possible. A common geomagnetic sensor mounted on most smartphones can acquire vector information of the magnetic field at the position, which is represented by a three-dimensional vector in the smartphone’s relative coordinates system shown in Figure 4. This smartphone’s relative coordinates system is also shown in Figure 1. Referring to the method introduced by Fan et al. [11], the three-dimensional vector is converted into the form of the intensity $M$ and the direction $\theta$ as follows:

$$M = \sqrt{x^2 + y^2 + z^2}$$  \hspace{1cm} (2)

$$\theta = \tan^{-1}(z/\sqrt{x^2 + y^2})$$  \hspace{1cm} (3)

, where $x$, $y$ and $z$ denote values on X, Y and Z axes of the smartphone’s relative coordinates system, respectively. These two pieces of data are used for positioning in our method.

![Figure 4: Smartphone’s relative coordinates system](image-url)
4. GEOMAGNETIC FIELD-BASED INDOOR POSITIONING WITH TURNING AROUND ACTION

The proposed method in this paper consists of two phases. One is a phase of Data Collection and the other is a phase of Perform Positioning. The following subsections explain them in detail.

4.1 Data Collection

This phase is to collect pieces of information on intensity and direction of geomagnetic field, which are given by Equations (2) (3), and store them in a database.

First, an array of positions (hereinafter, referred to as reference points) at which intensity and direction of geomagnetic field are collected, is determined. Next, a temporal sequence of intensity and direction of geomagnetic field is collected for each reference point by asking the user to turn around holding a geomagnetic sensor horizontally by a certain angle shown in Figure 1. Finally, a database is created and the obtained sequences of intensity and direction of geomagnetic field and their corresponding reference points are stored in the database.

4.2 Perform Positioning

This phase is to locate the current position in a building by comparing the obtained information on intensity and direction of geomagnetic field at the current position with the ones stored in the database.

First, the user is asked to stand in the position (called the current position) which he/she wants to figure out. This position may be right on a reference point or a different position from the reference point. Then, the user performs the action of turning around a certain amount of angle to collect a sequence of intensity and direction of magnetic field in the same manner as Data Collection phase. Next, the similarity between the obtained sequence at the current position and all the stored ones in the database is calculated using dynamic time warping (DTW) algorithm. Finally, the reference point with the highest similarity in the database is outputted as the estimated current position.

5. EXPERIMENT IN POSITIONING ACCURACY

This section conducts two experiments on impact of density of reference points and amount of turning around angle upon positioning accuracy, and discusses feasibility of the proposed method.

5.1 Experimental system

The proposed system works on Nexus 7 (2013) running an Android OS (version 6.0.1). The system performs two phases of Data Collection and Perform Positioning mentioned in the previous section. The flow chart that the system executes is shown in Figure 5.

The system initializes all the variables at the beginning and it selects either phase of Data Collection or Perform Positioning then it goes into an acquisition process of geomagnetic field. The variables of $mx$, $my$, and $mz$ are the elements of the three-dimensional vector of geomagnetic field at a position, which is acquired by the geomagnetic sensor and the array of $\text{Int}[l]$ stores a temporal sequence of vector intensity represented by Equation (2), and the array of $\text{Ang}[l]$ stores a temporal sequence of vector direction represented by Equation (3). The variable of $n$ denotes the index of those two arrays. The system executes the acquisition process of geomagnetic field iteratively at 60 ms interval.

![Figure 5: Flow chart for Data Collection and Perform Positioning](image-url)
After the system finishes the acquisition process, it goes into the selected process of Data Collection or Perform Positioning. For the phase of Data Collection, the variable of $Ref$ denotes a data structure that consists of the corresponding reference point $Pos$, its signature of $Int[]$ and $Ang[]$, and then $Ref$ is stored in a database. For the phase of Perform Positioning, the variable of $Cur$ denotes a data structure that consists of the signature of $Int[]$ and $Ang[]$ at the current position, and $Cur$ is compared to every $Ref$ stored in the database to find the most similar one. The variable of $Prox$ holds the proximity.

5.2 Experiment1: Density of reference points and positioning accuracy
In general, as the density of reference points increases, positioning accuracy increases while neighboring reference points will have similar geomagnetic field, resulting in miss-positioning. The aim of this experiment is to confirm how much positioning accuracy alters depending on the density of reference points.

In this experiment, reference points are arranged in a straight line with nine different intervals on the sixth floor of Building C in Fukuoka Institute of Technology. The length of the straight line in this experiment is 47.43 m and Table 1 shows nine different intervals. For example, reference points are placed in a line at interval of 1.24 m for Layout 1. To evaluate positioning accuracy, 77 evaluation points where the proposed method is performed are set and their interval is 0.62 m which is half the distance of neighboring reference points for Layout 1. Figure 6 shows a sketch of the experimental site and illustrates all the 77 evaluation points. For Layout 1, the reference points equal the evaluation points with one-skip interval and they do those with three-skip interval for Layout 2. The skip interval increases by 2 as the layout no. increases such as five, seven, nine and so on. The theoretical positioning errors are shown in Table 1 as well.

Data Collection is performed 3 times for each reference point and the average of those pieces of data is stored in a database as a signature for the reference point. The start direction of turning around is the upper direction of the floor plan. The amount of turning around angle is 360 degrees. After that, Perform Positioning is performed 10 times for each evaluation point. That is, a total of 770 times are performed for each layout. The start direction of turning around and the amount of turning around angle are the same with those of Data Collection.

| Layout No | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|-----------|----|----|----|----|----|----|----|----|----|
| Number of reference points | 39 | 26 | 20 | 16 | 13 | 11 | 10 | 9  | 8  |
| Distance between neighboring reference points[m] | 1.24 | 1.86 | 2.48 | 3.1 | 3.72 | 4.34 | 4.96 | 5.58 | 6.2 |
| Number of evaluation points | 77 | 77 | 77 | 77 | 77 | 77 | 77 | 77 | 77 |
| Positioning error (theoretical value)[m] | 0.31 | 0.465 | 0.62 | 0.775 | 0.93 | 1.085 | 1.24 | 1.395 | 1.55 |

5.3 Experiment2: Angle of turning around and positioning accuracy
In general, as the amount of information on geomagnetic field increases by turning around the geomagnetic sensor for much more angle, positioning accuracy increases while it is going to be a burden on the user. The aim of this experiment is to confirm how much positioning accuracy alters depending on the amount of turning around angle for collecting geomagnetic field.

In this experiment, the layout with the highest positioning accuracy from Experiment 1 is employed, and the amount of turning around angle has four ways: 360, 180, 90 and 45 degrees. The obtained sequence of intensity and direction of geomagnetic field by turning around 360 degrees for Data Collection and Perform Positioning in the previous experiment is cut out to half, quarter, and eighth, respectively, and they are used for positioning.

6. RESULT
Figure 7 is the result obtained from Experiment1 and it shows positioning accuracy at each layout. The horizontal axis shows layout numbers and the vertical one does the average of positioning errors and their standard deviation in meter. From the figure, there seems to be a constant increase in both positioning error and standard deviation over layouts. There is also a certain drop in positioning error only for Layout 7 among Layout 6 to 9. This could
be because when the density of reference points is sparse, the influence of measurement noise in geomagnetic field stored in the database for those reference points could be large so that, for most of evaluation points, the influence would let the estimated current position vary. The lowest positioning error is 3.4 m for Layout 1. The t-test shows that there is a significant difference between every neighboring two layouts between 3 to 8.

Figure 8 is the result obtained from Experiment2 and it shows positioning accuracy at each amount of turning around angle. In Experiment2, Layout 1 was used. The horizontal axis shows the amount of turning around angle in degree and the vertical one does the average of positioning errors and their standard deviation in meter. From the figure, there seems to be a constant increase in both positioning error and standard deviation over turning around angles. The lowest positioning error is 3.4 m for the turning around angle of 360 degrees. The t-test shows that there is a significant difference between all the neighboring pairs.

7. DISCUSSION AND EVALUATION

As regards the relation between the density of reference points and positioning accuracy, the positioning accuracy becomes high as the density increases shown in Figure 7. As the density of reference points increase, the neighboring reference points are however expected to have similar geomagnetic field, resulting in positioning errors. Table 2 shows how many times the measured positioning errors is larger than the theoretical ones shown in Table 1 for each layout. From the table, as the density of reference points increases, the proportion of the measured positioning error to the theoretical one increases. This shows that the neighboring reference points with high density will lead to lower positing accuracy comparatively to the ones with low density.

Figure 9 shows an approximation curve of positioning accuracy over density of reference points. The horizontal axis is the rate of the number of reference points per a single meter and the vertical one is the average of positioning errors in meter. Each dot in the figure comes from the result of Experiment1 and the line is the approximation curve to those dots. The model formula of an exponential function $y = ae^{mx}$ was used and the parameters were obtained by the least squares method. The approximation curve of $y = 7.1168e^{-1.073x}$ was obtained. From this curve, the positioning error $y$ of the proposed method decreases by about 11% every time the density $x$ of reference points increases by 0.1.

As regards welfare purposes, aiming for the target of positioning error of 0.4m for those with special needs especially with poor eyesight, it is currently necessary to have 2.7 reference points per 1m from the approximate curve, and it is necessary to place reference points at 0.37 m interval. To make it sure, a further experiment is required.

As regards the relation between the amount of turning around angle and positioning accuracy, the positioning accuracy becomes high as the amount of turning around angle increases shown in Figure 8.

Figure 10 shows an approximation curve of positioning accuracy over amount of turning around angle. The horizontal axis is the amount of turning around angle in degree and the vertical one is the average of positioning errors in meter. Each dot in the figure comes from the result of Experiment2 and the line is the approximation curve to those dots. Using the same approximation function, the approximation curve of $y = 6.9177e^{-0.002x}$ was obtained. From this curve, the positioning error $y$ of the proposed method decreases by about 0.2% every time the turning around angle $x$ increases by a single degree.

| Table 2: Proportion of measured positioning errors to theoretical ones |
|-------------------------|---------|--------|--------|--------|--------|--------|--------|--------|
| Layout No.              | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      |
| Ratio                   | 11.1   | 7.8    | 6.0    | 5.7    | 5.4    | 6.0    | 4.2    | 4.7    | 4.4    |

![Figure 7: Relationship between Layout No. (density of reference points) and positioning error](image)

![Figure 8: Relationship between the amount of turning around angle and positioning error](image)
Looking into positioning errors in terms of cumulative distribution function (CDF), Figure 11 shows the CDF obtained from the result of Experiment1. The horizontal axis is positioning error and the vertical one is the ratio of positioning errors less than the given one. From the nature of CDF, a curved line which goes nearer the top left corner represents a positioning method with a better performance in positioning accuracy. From the figure, as the density of reference points increases more, the corresponding curved line goes nearer the top left corner and the CDF from Layout 1 which demonstrates the best performance among them is around 0.8 when the positioning error is less than 5 m. Next, Figure 12 shows the CDF obtained from the result of Experiment2 with use of Layout 1. From the figure, as the amount of turning around angle increases more, the correspond curved line goes nearer the top left corner and the CDF from the angle of 360 in degree which demonstrates the best performance among them is around 0.8 when the positioning error is less than 5 m.

Figure 13 shows a comparison of the proposed method with the traditional ones in positioning accuracy. For the proposed method, the result from Layout 1 with the turning around angle of 360 degrees is used. The traditional methods come from Fan et al. [11], Wu et al. [12], and Vandermeulen et al. [13]. From the figure, the CDF for the proposed method is higher than those for the other methods if the positioning error is less than about 1.3 m. After that the CDF for Fan et al. holds the highest place.
The reason why these CDFs are obtained, is discussed from a point of view of point-based positioning and line-based one. The point-based positioning is a way of positioning where reference targets are points (called reference points) and each reference point has its own signature made of nearby geomagnetic field while the line-based positioning is a way of positioning where reference targets are lines (called reference lines) and each reference line has its own signature made of geomagnetic field along the line. The proposed method belongs to point-based positioning and the method from Fan et al. [11] does line-based one.

For line-based positioning, the correct reference line is more properly selected when the line along which geomagnetic field is read, is longer enough to be its own unique signature. If the line is long enough, the positioning error will be the length of half the line at most, meaning that the CDF reaches 1.0 at the positioning error which equals the length of half the line. Figure 13 shows that the CDF for Fan et al. reaches 1.0 at the positioning error of about 2.5 m, so the length of the line is around 5 m, which is confirmed in [11]. For point-based positioning, the positioning error decreases when the density of reference points increase. This is confirmed in Section 6. For high density of reference points, the positioning accuracy is high while the neighboring reference points will have similar geomagnetic field, resulting in a certain positioning error. It means that the tale of CDF increases gradually to 1.0 while the head does sharply.

One of ways to improve the proposed method, is to introduce a window on reference points, in which the estimated current position is selected, preventing the method from selecting a reference point far from the previously selected one, so that the tale of CDF lifts up.

8. CONCLUSION

This paper proposed an indoor positioning method using geomagnetic field with less spatial movement, and discussed its positioning accuracy. The result showed that the proposed method works with a positioning error of 3.4 m on average and it also demonstrates the best CDF with the positioning error less than about 1.3 m.

In the future, the authors plan to work on improving positioning accuracy by introducing a hybrid model between the proposed method and the method from Fan et al.

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