PAPER

Multi-Distance Function Trilateration over k-NN Fingerprinting for Indoor Positioning and Its Evaluation

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SUMMARY This manuscript discusses a new indoor positioning method and proposes a multi-distance function trilateration over k-NN fingerprinting method using radio signals. Generally, the strength of radio signals, referred to received signal strength indicator or RSSI, decreases as they travel in space. Our method employs a list of fingerprints comprised of RSSIs to absorb interference between radio signals, which happens around the transmitters and it also employs multiple distance functions for conversion from distance between fingerprints to the physical distance in order to absorb the interference that happens around the receiver then it performs trilateration between the top three closest fingerprints to locate the receiver's current position. An experiment in positioning performance is conducted in our laboratory and the result shows that our method is viable for a position-level indoor positioning method and it could improve positioning performance by 12.7% of positioning error to 0.406 in meter in comparison with traditional methods.

key words: trilateration, multiple distance function, fingerprinting, centroid, indoor positioning

1. Introduction

Nowadays the population of elderly people in Japan is increasing and the percentage of those who live alone at home is arising as well. Figure 1 shows the increase of population of elderly people aged greater than or equal to 65 years old in Japan and it will reach 35 million in 2020. Figure 2 shows the number of households where elderly people live alone in Japan and it will reach 7,000 in 2020. In this circumstance, one of the ongoing and urgent problems is that nobody could be aware of them even if their life was in danger.

To keep an eye on elderly people for safety reasons while preventing their privacy from being invaded, an indirect and ambiguous way to watch out them is discussed. T. Sugihara et al. [1] built a camera-based care support system for elderly people in a group home and discussed the prospective problems. The results showed that the use of cameras to capture them would be a considerable impact on their feelings of invading their privacy and it should only be used in the public space such as an entrance hall, and it should also not be used while they take a break; even so they desire for the power being plugged off in the dressing room in use. L. Melanie et al. [2] shows that for in-home monitor-

ing systems, a non-camera-based way is preferred because it is unobtrusive and makes the residents' privacy kept intact.

As regards non-camera-based ways, indoor positioning has been commonly studied so far. S. Masanari [3] built a prototype that localizes people in a room by sounds of their footsteps. In the prototype, a 2 by 2 array of microphones attached on the ceiling is used for a location detection technique of time-difference of arrive (ToA) and the result shows that the positioning error is about 20cm within a radius of 4m from the center of the array of microphones in a quiet environment with concrete floor. It however shows that the sounds of footsteps vary in the material of the floor, their shoes, style of walking and temperature. It has the potential for localizing people accurately when the number of the underlying factors mentioned are carefully taken into consideration. This manuscript employs characteristics of propagation of radio signals, which are more likely to go with daily environments.

As regards required positioning accuracy, it depends on physical condition of elderly people. For example, room-level indoor positioning [4], [5] is preferred for those whose condition is fine while position-level indoor positioning is required for those who had a stroke, suffering from lame and a paralyzed leg(s), and those who have poor eyesight such as cataract and glaucoma due to aging. For those with lame and a paralyzed leg(s), if they stayed at the unexpected position for minutes, they might have been toppled down and injured. For those with poor eyesight, the system should warn them that there was an obstacle within the next single step of their movement and it requires more reliable positioning. There has not been a successful positing method yet for those with poor eyesight.

This manuscript proposes a position-level indoor positioning method using radio signal with two techniques of fingerprinting and multiple distance functions for conversion from fingerprinting data space into physical one. The target positioning accuracy is a single step length of 40cm as referring to [6] which says that the step length of people with poor eyesight is 40 to 90cm. This manuscript demonstrates that our proposed method achieves positioning error of 40.6cm on average with 80% of cumulative distribution function.

Section 2 introduces traditional indoor positioning methods and Sect. 3 describes the related work to differentiate our method. Section 4 explains our approach of a multiple distance function trilateration over k-NN fingerprinting method. Section 5 conducts an experiment in positioning

Manuscript received September 8, 2019.

Manuscript revised December 13, 2019.

Manuscript publicized February 3, 2020.

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DOI: 10.1587/transinf.2019EDP7241

Fig. 1 Population of elderly people aged greater than or equal to 65 years old in Japan [reported by Ministry of Health, Labor and Welfare in 2016–'17].

Fig. 2 Households where elderly people live alone in Japan [reported by Ministry of Health, Labor and Welfare in 2016–'17].

performance and Sect. 6 evaluates our method in comparison with traditional ones. Section 7 discusses properties of positioning performance of our method and Sect. 8 gives the concluding remarks.

2. Traditional Methods

Indoor positioning methods mainly rely on radio signals from multiple transmitters whose positions are already known. Centroid and fingerprinting [7] are common traditional indoor positioning methods.

Centroid is a way of locating a receiver's current position by averaging all the positions of transmitters whose signals can be observed by the receiver. The process of positioning is simple and the accuracy is comparatively high but it is affected easily by interference between multiple signals that bounce off the walls, ceilings and floor, especially in the case that transmitters are placed in a small space.

To absorb the interference between multiple signals, fingerprinting is introduced. It works with the strength of radio signals, called received signal strength indicator (RSSI). Theoretically, a RSSI decreases as the signal travels through space from the transmitter. The RSSI is expressed as the following propagation model of radio signals:

$$\text{RSSI} = A - 20\log(r), \quad (1)$$

where r denotes the physical distance in meter from the transmitter and A denotes a RSSI when $r = 1$. Equation (1) denotes that decrease of RSSI indicates long physical distance from the transmitter. For fingerprinting, a fingerprint is defined as an array of RSSIs from all the transmitters, which are observed at a given reference point. A fingerprint works as a signature of the reference point and multiple fingerprints are stored in a DB. The receiver's current position is located by calculating Euclidean distance between the measured fingerprint at the current position and the stored fingerprint in the DB. Once the closest fingerprint to the measured one is found, its reference point is returned as the current position.

Based on centroid and fingerprinting, various indoor positioning methods and the related topics have been studied so far. N. Nakajima et al. [8] proposed a directional fingerprint that consists of multiple child-fingerprints. A child-fingerprint is an array of the RSSIs measured by a receiver facing in a given direction at the same reference point with the parent one. The child-fingerprint can express angular changes of radio waves due to interference between signals, obstruction by nearby objects, diffraction and other communication signals. N. Fu et al. [9] proposed a method of updating fingerprints automatically by numerous users because building a bunch of fingerprints is a time-consuming task. In their method, accelerometer and gyroscope built in a smartphone are used to track the user's position and the fingerprint at the position is updated by measuring the RSSIs there. F. Subhan et al. [10] and A. Bose et al. [11] investigated a gap between RSSIs and the propagation model RSSI expressed by Eq. (1), and proposed a method to absorb the gap. The gap is caused by indoor environments such as interference between signals, obstruction by nearby objects and diffraction, especially in the case that the transmitters are placed in a small space. X. Fan et al. [12] utilized change of the magnetic field as fingerprints. Their method does not rely on infrastructure of buildings. Y. Tung et al. [13] employed acoustic signature to locate the current position. A receiver emits a sound actively and records its reflection, and analyzes features of the spectrum. Their method does not rely on infrastructure of buildings as well.

3. Related Work

A k-nearest neighbor (k-NN) fingerprinting method is an extended version of fingerprinting. It locates a receiver's current position by averaging reference points of the nearest k fingerprints. Furthermore, a weighted k-NN (Wk-NN) fingerprinting method is an extended version of k-NN fingerprinting. It locates the current position by weighting the reference points of the nearest k fingerprints and averaging them. The commonly used weight is the inverse of Euclidean distance between the measured fingerprint at the current position and the stored fingerprint for the reference point for which the weight is applied [14]–[17].

A trilateration over k-NN (Tk-NN) fingerprinting method is another extended version of k-NN fingerprinting as well. It locates the current position by performing trilateration among the reference points of the nearest k fingerprints and the physical distances from the reference points to the current position. The physical distance should be obtained correctly from the Euclidean distance between the measured fingerprint at the current position and the stored fingerprint for the reference point to which the physical distance is measured. The difference of a Tk-NN fingerprinting method from a Wk-NN one is that the Wk-NN one outputs an approximation of the current position, which still depends on the density of reference points while the Tk-NN does theoretically the exact current position.

Gao et al. [18] built a system that employs a k-NN fingerprinting method for radio signals of Wi-Fi that has commonly been installed throughout a building. For Wk-NN fingerprinting methods, G. Amin and S. Stavros [19] discussed the number of k for improving position accuracy and found that the number of 5 demonstrates the best performance for their system. The weight could be the inverse of physical distance from the current position to the reference point for which the weight is applied but it still outputs an approximation of the current position. As regards the weight to be the inverse of the physical distance, L. Wen et al. [20] discussed a Wk-NN method (note that it is not fingerprinting). It locates the current position by weighting positions of the nearest k transmitters and averaging them. The weight is the inverse of physical distance from the transmitters to the current position, which is obtained by Eq. (1). However, the weight is easily fluctuated by the interference between radio signals, obstruction by nearby objects and diffraction in indoor environments. S. Subedi et al. [21] built a hybrid system of a weighted centroid method and a Wk-NN fingerprinting method for BLE signals to reduce the number of transmitters. Here a weighted centroid method (WCM) locates a receiver's current position by weighting positions of the transmitters whose signals can be observed by the receiver and averaging them. A provisional current position is obtained by WCM and its position is used to perform Wk-NN fingerprinting for refining it.

Generally, fingerprinting-based methods mentioned above absorb an influence of the interference between radio signals etc. that happens around mainly the transmitters not the receiver. This manuscript proposes a modified version of a Tk-NN fingerprinting method called a multi-distance function Tk-NN (hereafter, it is called Multi-DF Tk-NN) fingerprinting method to absorb the influence that happens around the receiver as well as the transmitters. It employs multiple distance functions for conversion from the Euclidean distance between fingerprints to the corresponding physical distance in an adaptable manner to the influence.

Previously, the authors [22] proposed their indoor positioning method called a fingerprinting trilateration method, which is classified into a Tk-NN fingerprinting with a single distance function, and conducted a pilot experiment on performance. The result showed that their method is feasible.

The objective of this manuscript is to evaluate positioning performance of its modified version: Multi-DF Tk-NN one and make sure that our method is viable for position-level indoor positioning.

4. Multi-DF Tk-NN Fingerprinting

This section introduces an indoor positioning method of Multi-DF Tk-NN fingerprinting using Bluetooth (Bluetooth low energy or BLE) signals. A BLE beacon is a one-way transmitter running on 2.4GHz, which sends signals or messages to nearby receivers such as smartphones and tablets. The Multi-DF Tk-NN fingerprinting method is also applicable to Wi-Fi signals. Without loss of generality, the latter part of this manuscript discusses the method for BLE signals because of portability and easiness of their deployment for experiment.

4.1 Preparation

The first is to attach an array of BLE transmitters, called beacons, on the ceiling of a room in a grid pattern. In our setting, a 3 by 4 array of 12 BLE beacons is attached on the ceiling of our laboratory whose dimension is 5m wide by 9m long as shown in Fig. 3. The light grey boxes denote PC desks and the dark grey boxes denote a bookshelf, a TV, a Wi-Fi router running on 2.4GHz, a cupboard and a frig & microwave. An array of small circles represented from B1 to B12 denotes the array of 12 BLE beacons.

The next is to obtain a list of fingerprints at given reference points. In our setting, the reference points are placed

Fig. 3 Dimension of our laboratory and layouts of BLE beacons, reference points and evaluation positions.

Table 1 A list of 12 fingerprints under the layout of BLE beacons and reference points shown in Fig. 3

Reference point	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
R1	-63.5	-68.7	-81.1	-67.0	-67.0	-72.8	-66.8	-66.9	-72.9	-72.9	-82.8	-74.2
R2	-63.8	-66.5	-76.7	-67.6	-64.8	-67.3	-68.8	-71.2	-70.0	-72.4	-82.3	-72.2
R3	-65.5	-64.2	-74.8	-71.8	-66.9	-63.7	-72.0	-70.5	-71.2	-74.4	-84.0	-74.2
R4	-64.3	-69.5	-82.5	-60.3	-66.3	-69.4	-65.1	-68.8	-71.6	-70.3	-81.2	-74.2
R5	-64.2	-65.0	-79.0	-65.9	-65.6	-68.4	-65.4	-60.7	-66.5	-72.6	-79.8	-70.7
R6	-68.0	-71.2	-76.2	-71.9	-64.9	-60.4	-72.5	-69.6	-66.0	-71.2	-80.9	-66.0
R7	-67.2	-68.0	-83.2	-66.1	-66.1	-72.7	-65.7	-67.2	-73.8	-65.5	-76.6	-67.9
R8	-65.4	-68.8	-82.6	-66.5	-68.0	-72.3	-63.2	-64.0	-66.1	-66.2	-77.2	-68.5
R9	-68.6	-69.2	-80.5	-71.4	-68.3	-62.9	-72.5	-66.2	-63.3	-70.9	-79.9	-64.8
R10	-74.1	-76.6	-90.3	-70.4	-72.6	-76.4	-67.1	-65.2	-70.8	-62.8	-72.8	-70.9
R11	-74.6	-76.2	-85.0	-70.1	-73.7	-75.6	-65.9	-67.5	-69.6	-65.1	-77.8	-64.8
R12	-75.5	-74.7	-82.3	-73.6	-74.2	-71.6	-70.3	-67.1	-66.0	-71.9	-76.5	-64.6

at positions of 1.7m just under the BLE beacons and there are 12 reference points in total. The reference point under B1 is referred to as R1 and the one under B2 is done as R2 and so on. A list of 12 fingerprints for reference points is obtained and Table 1 shows it. Each line represents a fingerprint and each value of the fingerprint shows the RSSI observed from the corresponding BLE beacon. While receiving each RSSI to build a fingerprint, the receiver is held at the reference point and a temporal sequence of RSSIs for 4 minutes at 5-second intervals is stored and averaged for the fingerprint. The fingerprint obtained at R1 is referred to as f_1 and the one obtained at R2 is done as f_2 and so on. As shown in the table, the RSSIs are not perfectly proportion to the physical distance due to interference between radio signals, obstruction by nearby objects and diffraction. For example, the RSSI of the fingerprint f_1 , which is observed from B3, is a quite small in comparison to the nearby RSSIs.

The last is to define distance between fingerprints. In our setting, Euclidean distance is employed as follows:

$$D_{f_i, f_j} = \sqrt{\sum_k (f_i[k] - f_j[k])^2}, \quad (2)$$

where D_{f_i, f_j} denotes the distance between fingerprint f_i and fingerprint f_j . The fingerprint f_i denotes a fingerprint obtained at the reference point R_i ($1 \leq i \leq 12$) and $f_i[k]$ denotes the RSSI of the fingerprint f_i , which is observed from the BLE beacon B_k ($1 \leq k \leq 12$). The distance between fingerprints is used for converting the distance to the closest fingerprint into the physical distance to its reference point. The next subsection discusses properties of fingerprints and their distance.

4.2 Properties of Fingerprints and Their Distance

Generally, RSSIs of fingerprints are influenced by interference between radio signals, their obstruction by nearby objects and diffraction that happens around BLE beacons and the receivers, the travelling path between them. To see the influence that happens around BLE beacons, Fig. 4 shows the average of RSSIs of BLE signals coming from each BLE beacon. The horizontal axis shows BLE beacons and the vertical does the average of RSSIs. From the figure, there

Fig. 4 Average of RSSIs that came from each BLE beacon.

are two significant drops at BLE beacons B3 and B11. These two drops could stem from existence of a steel bookshelf placed near B3 and a cupboard near B11, causing an influence on the signals. The influence like these two drops appears in all the fingerprints so that they absorb it in terms of less impact on their distance. To see the influence that happens around the receiver (in this case, reference points), Fig. 5 shows the average of RSSIs observed at each reference point. The horizontal axis shows reference points and the vertical one is the same with Fig. 4. From the figure, it remains almost constant with small ups and downs over reference points but there is a drop at reference points R10, R11 and R12. This drop affects all the RSSIs of the fingerprints for R10, R11 and R12 so that it will impact on distance from the fingerprint to other fingerprints.

Thus the interference that happens around reference points shown in Fig. 5 could have a considerable impact on calculating the distance because the interference could make all the RSSIs in that fingerprint overestimated or underestimated. Figure 6 shows an average of distances from the fingerprint obtained at each reference point to the other fingerprints. The horizontal axis shows reference points and the vertical one shows the average of distances. From the figure, there seems to be an increase around reference points R10, R11 and R12 (R4, R5 and R6) in comparison with the same relative reference points of R1, R2 and R3 (R7, R8 and R9), and there is also a strong peak at the reference point R10.

Fig. 5 Average of RSSIs that were observed at each reference point.

Fig. 6 Average of distances from the fingerprint for each reference point to the other fingerprints.

Fig. 7 The 12 relation graphs of physical distance between reference points with distance between their fingerprints.

For performing Tk-NN fingerprinting, the interference that happens around reference points must be taken into consideration carefully in order to convert the distance between fingerprints into the corresponding physical distance.

Figure 7 shows the 12 relation graphs of the physical distance between reference points with the distance between their fingerprints. All the plots were obtained from all the pairs of a given reference point to any other ones. The horizontal axis is the physical distance and the vertical one is the distance between fingerprints. As shown in each relation graph, there seems to be a certain linear relation between them. The influence of the interference that happens around reference points mentioned above appears on the relation graphs of R10, R11 and R12 (R4, R5 and R6) in comparison with the same relative reference points of R1, R2 and R3 (R7, R8 and R9), and the former graphs have sharper gradients. The regression analysis confirms that most of the relation graphs have a significant relation as shown in the bottom right corner of each relation graph as well as the obtained regression line in the top right corner. The regression line obtained at the reference point R_i ($1 \leq i \leq 12$) which converts the physical distance r into the distance between fingerprints D is hereafter represented as follows:

$$D = toFin_i(r) \quad (3)$$

4.3 Procedure of Multi-DF T3-NN Fingerprinting

In the later part of the manuscript, the Multi-DF Tk-NN fingerprinting where k is 3 (hereafter, it is called Multi-DF T3-NN fingerprinting) is discussed.

Locating the current position P_{crt} is performed as the following steps. Here let a symbol f_i be a fingerprint at the reference point R_i ($1 \leq i \leq m$, m is the number of reference points). In this experiment, m is 12.

Step 1 Measure the fingerprint f_{crt} at the current position P_{crt} .

Step 2 Calculate every distance between fingerprints D_{f_{crt}, f_i} , $i \in \{1, 2, \dots, m\}$.

Step 3 Find the top three closest fingerprints $f_i, t \in \{i | \min_{top3} D_{f_{crt}, f_i}\}$.

Step 4 Convert the distance D_{f_{crt}, f_i} , $t \in \{i | \min_{top3} D_{f_{crt}, f_i}\}$ in physical distance by $toFin_i^{-1}(D_{f_{crt}, f_i})$.

Step 5 Determine the current position P_{crt} by performing trilateration among the three physical distances $toFin_i^{-1}(D_{f_{crt}, f_i})$, $t \in \{i | \min_{top3} D_{f_{crt}, f_i}\}$ and the three reference points R_t .

In this procedure, the gradient of regression lines given by Eq. (3) is multiplied by a constant of 1.325 and the intercept is added by the standard deviation of their own plots in order to prevent the trilateration process from diverging.

5. Experiment

An experiment on positioning performance of Multi-DF T3-NN fingerprinting in comparison to traditional methods of

fingerprinting and trilateration: NN fingerprinting, 3-NN fingerprinting, W3-NN fingerprinting, W5-NN fingerprinting and 3-NN trilateration, was conducted in our laboratory. The k -NN trilateration method [23], [24] is a trilateration among positions of the transmitters and the physical distance from them to the current position, which is obtained by Eq. (1). Note that it does not rely on fingerprinting. The layouts of BLE beacons and reference points shown in Fig. 3 and the list of fingerprints shown in Table 1 are used.

The experiment takes two layouts of evaluation positions into consideration in order to validate the experiment by comparing results from those two layouts. Theoretically, a NN fingerprinting method locates the current position accurately and precisely if the current position is right on a reference point while it does not if the current position is between reference points. The former is called a layout of On-points and the latter is a layout of Between-points. For On-points layout, evaluation positions are right on reference points. There are 12 evaluation positions E1~E12 at all. For Between-points layout, they are placed between neighboring four reference points. For example, the evaluation position E13 is in the center between reference points R1, R2, R4 and R5. There are six evaluation positions E13~E18 at all.

All the 18 evaluation positions are shown in Fig. 3. For each of those evaluation positions, the traditional methods and our method are performed. The receiver is held 1.7m under the ceiling (1.0m from the ground) and a temporal fingerprint f_{crt} is obtained and the current position P_{crt} is calculated by the given method for 4 minutes at 5-second intervals, resulting in 49 pieces of positioning data P_{crt} at every single evaluation position:

$$\begin{aligned} &49 \text{ pieces of positioning data} \\ &\times (12 + 6) \text{ evaluation positions} = 882 \text{ in total} \end{aligned} \quad (4)$$

The receiver used in this experiment is Nexus7 (2013) for both the preparation and evaluation.

For the 3-NN trilateration method, note that there is a vertical gap of 1.7m between the transmitters and the receiver in the experiment setting, and it must be taken into consideration to make the method work properly because it originally works on a 2-dimensional plane. In the experiment, the method employs a single distance function of Eq. (1) where variable A is -59.157 . The variable is calculated from all the pairs of diagonal travelling distances between the transmitters and the receiver, and the observed strength of radio signals which is shown in Table 1. Once the diagonal travelling distances are obtained by the equation, their horizontal physical distances between the receiver and the transmitters are calculated by the 3-square theorem then the 3-NN trilateration method is performed to locate the receiver's position on a 2-dimensional plane.

6. Results and Evaluation

6.1 Overall Results

Figure 8 shows the cumulative distribution function or CDF of positioning error across two layouts of evaluation positions at each method. The horizontal axis is the positioning error in meter and the vertical one is the rate of CDF. Each line represents a CDF obtained from the given method. Note that the number of pieces of positioning data is not equal between On-points layout and Between-points one as shown in Eq. (4), so that they are weighted and averaged for overall results. From the figure, all the lines increase sharply as the positioning error becomes 1.5 in meter and after that they gradually come close to 1, and our method seems to do more sharply and more gradually. It is noteworthy that the line obtained from a NN fingerprinting method takes a S-curve between the positioning errors of 0.0 to 1.5 in meter.

Figure 9 shows the rate of CDF across two layouts of evaluation positions at the given positioning error of 0.4 or 0.9 in meter at each method. The horizontal axis is the methods and the vertical one is the rate of CDF. From the figure, the highest rate of CDF at the positioning error of 0.4 in me-

Fig. 8 The cumulative distribution function of positioning error across layouts of evaluation positions.

Fig. 9 The rate of cumulative distribution function at the given positioning error of 0.4 or 0.9 in meter across layouts of evaluation positions.

ter came from the NN fingerprinting method due to an effect of the S-curve of CDF observed in Fig. 8 and it was the rate of 0.41. At the positioning error of 0.9 in meter the highest one came from our method and it was the rate of 0.82.

Figure 10 shows the average of positioning error across two layouts of evaluation positions where the rate of CDF is less than and equal to 0.8. The horizontal axis is the methods and the vertical one is positioning error. From the figure, our method demonstrated the best performance and the positioning error was 0.406 in meter and the standard deviation was 0.197 in meter. The unpaired t test with Welch's correction confirms that there is a significant difference in positioning errors between our method and the others [$t(1088) = -6.80$ at $p < .01$, $t(1622) = -13.56$ at $p < .01$, $t(1702) = -22.27$ at $p < .01$, $t(1858) = -6.14$ at $p < .01$, $t(1441) = -23.85$ at $p < .01$ in the same order with the horizontal axis of Fig. 10].

6.2 Between-Points and On-Points Layouts

Figure 11 shows CDFs of positioning errors for On-points layout (left) and Between-points one (right) of evaluation positions. The horizontal axis is the positioning error in meter and the vertical one is the rate of CDF. From the figures, all the lines have a dramatic increase at the beginning of positioning error both for On-points layout and Between-points layout. As regards the S-curve shown in Fig. 8, it comes from the fact that the lines obtained from a NN fingerprinting method take different paths and the rate of CDF increases quickly around the position error of 0.1 in meter for On-points layout and it does around 1.4 in meter.

Figure 12 shows the average of positioning error for each layout of On-points or Between-points where the rate of CDF is less than and equal to 0.8. The horizontal axis is the methods and the vertical one is positioning error. From the figure, there seems to be a gap between positioning errors for those two layouts. Especially, for the NN fingerprinting method, there is surely a considerable gap between the positioning errors. The average of positioning error is 0.03 in meter for On-points layout and it is 1.18 in meter for

Fig. 10 The overall positioning error across layouts of evaluation positions where the cumulative distribution function is less than or equal to 0.8.

Fig. 11 The cumulative distribution function of positioning errors for each layout of evaluation positions.

Fig. 12 The positioning error for each layout of On-points and Between-points where the cumulative distribution function is less than or equal to 0.8.

Between-points one. The standard deviation is 0.06 and 0.27 in meter for On-points and Between-points layouts, respectively. The unpaired t test with Welch's correction confirms that there is a significant difference in positioning errors between the two layouts for all the methods [$t(413) = -7.87$ at $p < .01$, $t(183) = 56.03$ at $p < .01$, $t(621) = -9.50$ at $p < .01$, $t(562) = -7.25$ at $p < .01$, $t(667) = 7.81$ at $p < .01$, $t(649) = -10.54$ at $p < .01$ in the same order with the horizontal axis of Fig. 12].

7. Discussion

7.1 Validating the Experiment

This subsection validates the experiment by looking into the underlying positioning properties of the NN fingerprinting method: 1) it theoretically locates the current position without any positioning error if the current position is right on a reference point (On-points layout), and 2) it also locates the current position with positioning error of $1.40 (\approx \sqrt{(5/3)^2 + (9/4)^2}/2)$ in meter if the current position is between reference points (Between-points layout).

To see the positioning properties, appropriateness of selection of the closest fingerprints for performing

fingerprinting-based methods is firstly confirmed and secondly the positioning properties are discussed. Figure 13 shows a temporal progress of the top 3 closest distance from the obtained fingerprint at each evaluation position to the stored fingerprints for reference points (left) and it also shows a temporal progress of the top 3 closest reference points based on the obtained distance (right) for On-points layout. The horizontal axis is the elapsed time for 4 minutes at 5-second intervals, which is separated by evaluation positions and the vertical one is the distance between fingerprints (left) or the chosen reference points (right). From the left graph, the distance is observed comparatively large in the beginning at every evaluation position due to instability of radio signals from BLE beacons and it is moving on the path to be stable. The closest distance is correctly going to be almost zero finally and the closest reference points are almost chosen properly as shown in the right graph.

Figure 14 is for Between-points layout. Looking at the evaluation positions of E16, E17 and E18 in the left graph, the stable distance is still larger than those for E13, E14 and E15, and this could be caused by overestimating the distance due to influence of the interference between radio signals, etc. that happens around the reference points of R10, R11 and R12 shown in Fig. 5 and Fig. 6. Even if the distance from those evaluation positions was overestimated, it happens equally to affect all the distance from those evaluation positions, so the closest reference points are chosen properly as shown in the right graph. In the graph, some ups and downs are observed due to existence of multiple reference points in the same distance. The same tendency to overestimate the distance can be seen at evaluation positions from E10 to E12 in Fig. 13.

Coming back to the positioning properties 1) 2) of the NN fingerprinting method, referring to Fig. 11, the CDF climbs up steeply around the position error of less than 0.1 in meter for On-points layout and it means that the method locates the current position almost correctly. It also climbs up steeply from the position error of 1.0 to 1.5 in meter for Between-points layout and it means that the method locates the current position with the expected positioning error of

Fig. 13 The temporal progress of top 3 closest distances from the stored fingerprints for reference points to the obtained fingerprint at each evaluation position (left), and the top 3 closest reference points (right) for On-points layout.

Fig. 14 The temporal progress of top 3 closest distances from the stored fingerprints for reference points to the obtained fingerprint at each evaluation position (left), and the top 3 closest reference points (right) for Between-points layout.

1.4 in meter.

Figure 12 shows the average of positioning error for both the layouts. As mentioned in the previous section, it is 0.03 in meter for On-points layout and it is 1.18 in meter for Between-points one, and there is a significant difference between positioning errors at those two layouts for the NN fingerprinting method.

Above all, it is confirmed that the experiment is validated.

7.2 Influence of Layouts of Evaluation Positions on Positioning Performance

Two layouts of evaluation positions of On-points and Between-points were employed in this experiment. On-points layout represents the case that the current position is placed on a reference point and Between-points one does the case that it is between reference points. Theoretically, positioning performance of a NN fingerprinting method is heavily affected by those cases as explained in the previous subsection while its extended versions or later ones are strongly desired to work properly under those two cases.

However, Fig. 12 shows the difference in positioning

performance between the two layouts of evaluation positions and confirms that there is a significant difference for all the methods. The difference is 0.121, 1.145, 0.186, 0.134, 0.119 and 0.258 in meter in the same order with the horizontal axis of the figure. The smallest one came from the W3-NN fingerprinting method and our method took the second smallest place.

To see how two layouts of evaluation positions affect positioning performance, Fig. 15 shows the difference in CDF between the two layouts at each method. The horizontal axis is positioning error and the vertical one is CFD. Each graph comes from each method. If the trajectory of the graph is smaller towards the origin, it means the method works more independently of different cases of the current position. From the figure, our method seems to have less impact on positioning performance in comparison with the other methods including the W3-NN fingerprinting method.

7.3 Effectiveness of Use of Multiple Distance Functions

Our method employs multiple distance functions to absorb influence of interference between radio signals, etc. that happens around the receiver, and to convert the distance be-

tween fingerprints into the corresponding physical distance. As regards use of distance functions, the 3-NN trilateration method employs a single distance function which converts strength of radio signals to the travelling distance as defined by Eq. (1). Note that our method works for fingerprinting and the 3-NN trilateration one does not, so our method is just compared with the 3-NN trilateration method in terms of tendency of positioning performance over evaluation positions in order to see effectiveness of use of multiple distance functions.

Figure 16 shows positioning performance for every evaluation position at either positioning method on On-points layout (left) and Between-points one (right). The horizontal axis is evaluation positions and the vertical one is positioning error in meter. From the left two bar graphs, our method works somewhat with a constant amount of positioning error over evaluation positions in comparison with the 3-NN trilateration one whose positioning error is quite bumpy over evaluation positions, which could lead to drops of RSSIs at almost the same positions of reference points shown in Fig. 5. It implies that multiple distance functions are going to absorb the influence. From the right two bar graphs, our method works somewhat with a constant amount of positioning error over evaluation positions as well in com-

parison with the 3-NN trilateration one whose positioning error increases at almost the same positions that certain drops of RSSIs can be seen in Fig. 5. It implies that multiple distance functions are going to absorb the influence as well.

Above all, multiple distance functions are viable for absorbing influence of the interference between radio signals, etc. that happens around the receiver.

7.4 Positioning Performance

Throughout a series of discussions about properties of our method mentioned in the previous subsections, it was shown that our method could have the potential for working well independently of positions at which the current fingerprint is measured even though there was a certain difference in positioning performance between layouts of evaluation positions. It was also shown that the use of multiple distance functions could have the potential for absorbing influence of interference between radio signals, obstruction by nearby objects and diffraction that happens around the receiver, which cannot be absorbed by a single distance function. These properties of our method are expected to have an impact to increase positioning performance.

As mentioned in Sect. 6.1, Fig. 10 showed positioning performance at each method across layouts of evaluation positions. An unpaired t test with Welch's correction confirms that there is a significant difference between any pair of two methods except NN fingerprinting and 3-NN fingerprinting methods. The first place was our method and the positioning error was 0.406 in meter, and the second one was the W3-NN fingerprinting method and it was 0.465 in meter.

Consequently, our method demonstrated the best performance of indoor positioning and improves the positioning performance by 12.7% from positioning error of the W3-NN fingerprint method.

7.5 Density of BLE Beacons and Reference Points

The positioning performance of indoor positioning methods using fingerprinting is considered to be dependent of the

Fig. 15 Gap between positioning performance for On-points layout and Between-points one.

Fig. 16 Effectiveness of multiple distance functions for positioning error.

density of placement of BLE beacons because higher density of BLE beacons is going to include more neighboring RSSIs in fingerprints, leading to adding more dimensions into data space where fingerprints are expressed. It results in making the fingerprints more reliable as well as redundant. However, the higher density of BLE beacons would yield more influence of interference between radio signals, etc. The positioning performance is also considered to be dependent of the density of placement of reference points because higher density of reference points is going to include more neighboring reference points in the DB, leading to adding more hints of positions in the given data space. It results in making the given data space accurately catch the current position. However, the higher density of reference points requires extra tedious work to store and update more fingerprints in the DB.

The experiment did not cover discussions about an impact of density of placement of BLE beacons and/or reference points on the positioning performance while it was conducted under 12 BLE beacons and 12 reference points placed in our laboratory whose area is 45 in square meter (the dimension is 9 by 5 in meter) and our method achieved the positioning accuracy of 0.406 in meter. A further experiment is required to discuss the impact of density of placement of BLE beacons and reference points.

7.6 Possession of Smartphones

Our method requires users, especially elder people, to carry a receiver such as smartwatches, smartphones and other wearable devices. The ministry of Internal Affairs and Communications in Japan investigates into possession of smartphones for elderly people aged greater than or equal to 65 years old in Japan. The report says that the percentage is 3.1%, 6.8% and 27.6% in 2011, 2013 and 2017, respectively, for elderly people who live alone. It is 12.2%, 32.8% and 46.5% in 2011, 2013 and 2017, respectively, for households where elderly people live together. The percentage has been increasing gradually past a few years and it will keep increasing for several years from now. At the time of writing this manuscript, it is not circumstance that indoor positioning methods which work with radio signals and ask elderly people to carry a smartphone, are accepted for those people without any burden. Instead of using smartphones, when deploying these methods, use of some IoT products where sensors, circuits and processing units are embedded into everyday clothes and accessories, for example shirts, trousers, belts and glasses, in an unobtrusive way, is hopefully taken into consideration.

8. Conclusion

This manuscript discussed a new indoor positioning technique of Multi-DF T3-NN fingerprinting. Multi-DF T3-NN fingerprinting employs a list of fingerprints comprised of RSSIs to absorb an influence of interference between radio signals, etc. that happens around the transmitters and it also

employs multiple distance functions for conversion from distance between fingerprints to the physical distance in order to absorb the influence that happens around the receiver then it performs trilateration between the top three closest reference points to locate the receiver's current position. An experiment in positioning performance was conducted in our laboratory and the result showed that our method is viable for a position-level indoor positioning method and it improves positioning performance by 12.7% of positioning error to 0.406 in meter.

In future work, the authors are going to take further experiments in relationship of non-regular layouts and/or density of BLE beacons and reference points to positioning performance. The authors are also going to take improvement of speed of positioning into consideration.

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