A Fingerprinting Trilateration Method FTM for Indoor Positioning and Its Performance

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Abstract. This manuscript discusses a new indoor positioning method called a fingerprinting trilateration method or FTM using BLE beacons. The strength of BLE signals, referred to as received signal strength indicators or RSSI, decrease as they travel through space. FTM employs a list of fingerprints of RSSIs and performs trilateration between the three closest fingerprints to locate a receiver's current position. An experiment in positioning performance is conducted in comparison with a traditional method of fingerprinting and the result shows that FTM could locate the current position with a positioning error of 0.615 m while it is 1.162 m for fingerprinting using a Between-points condition.

Keywords: Trilateration · Centroid · Fingerprinting · 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 in population of elderly people aged 65 or older in Japan and it is believed to 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 no one is aware if their lives ever are in danger. Figure 3 shows the number of cases in which elderly people have died alone and it has been increasing constantly over the past 16 years. To keep elderly people safe while preventing their privacy from being invaded, an indirect and ambiguous way to protect them would be preferred. For example, a way of using cameras to visually capture them and recognize their activity accurately would obviously not be preferred. On the other hand, a way of using sounds like footsteps to ambiguously recognize their activity and learn they are not in danger would definitely be more preferred. This manuscript discusses an indirect way of locating elderly people in a room to make sure they are not in danger, utilizing a technique of fingerprinting.

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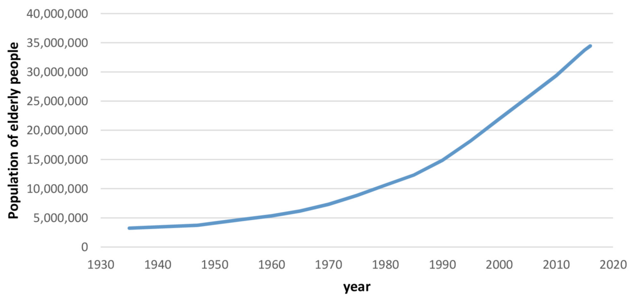

Fig. 1. Population of elderly people aged greater than or equal to 65 years old in Japan.

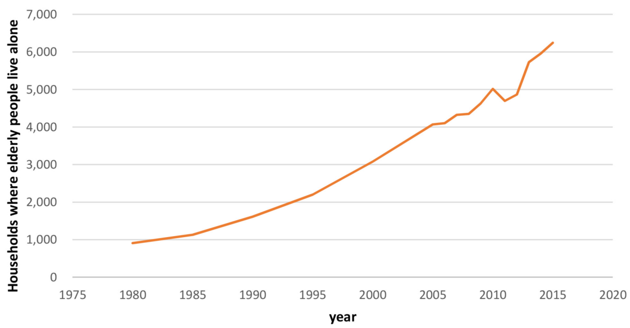

Fig. 2. Households where elderly people live alone in Japan.

Section 2 introduces traditional indoor positioning methods and Sect. 3 describes the related work to differentiate our approach. Section 4 explains our approach of a fingerprinting trilateration method or FTM. Section 5 conducts an experiment in positioning performance of FTM for a traditional method of fingerprinting and Sect. 6 gives a brief report of the results. Section 7 gives the concluding remarks.

2 Traditional Methods

Indoor positioning systems mainly rely on radio signals from multiple transmitters whose positions are already known. Centroid and fingerprinting [7] are common traditional 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 deal with this problem, fingerprinting is introduced. It works with the strength of radio signals, called a received signal strength indicator (RSSI).

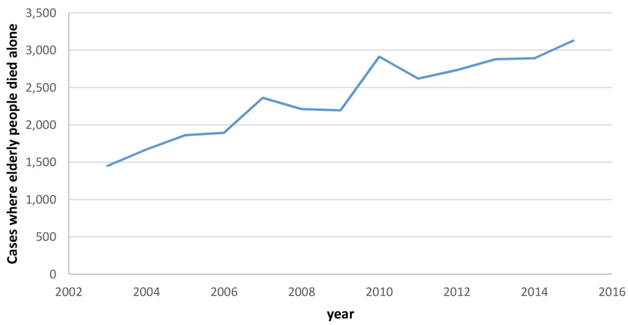

Fig. 3. Cases that elderly people died alone.

Theoretically, an RSSI decreases as the signal travels through space from the transmitter. The RSSI is expressed as the following propagation model of radio signals:

$$\mathrm{RSSI} = A - 20\log(r) \tag{1}$$

where r denotes the physical distance in meter from the transmitter and A denotes RSSI when $r = 1$. Equation (1) denotes that decrease of RSSI indicates a longer 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. Nakajima et al. [6] 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, obstructions by people, nearby obstacles, diffraction and other communication signals. Fu et al. [3] 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. Subhan et al. [9] and Bose et al. [1] investigated a gap between RSSIs and the propagation model RSSI expressed by Equation (1), and proposed a method to absorb the gap. The gap is caused by indoor environments such as interference between signals, obstruction by people, nearby objects and diffraction, especially in the case that the transmitters are placed in a small space. Fan et al. [2] utilized change of the magnetic field as fingerprints. Their method does not rely on infrastructure of the building. Tung et al. [10] 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 the building as well.

3 Related Work

This manuscript discusses a weighted 3-nearest neighbor (W3-NN) fingerprinting method using Bluetooth (Bluetooth low energy or BLE) signals for indoor positioning. A BLE beacon is a one-way transmitter running on 2.4 GHz, which sends signals or messages to nearby receivers such as smartphones and tablets.

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 weight should carefully be designed to reflect the physical distance between the reference point and the current position.

Gao et al. [4] built a system that employs a k-NN fingerprinting for radio signals of Wi-Fi that has commonly been installed throughout a building. Our method relies on BLE because it is a low-cost low-power lightweight transmitter and it is capable of working by solar power. In the long term, it has the advantage of low running-cost as compared to Wi-Fi devices.

Subedi et al. [8] built a hybrid system of a weighted centroid method and a Wk-NN fingerprinting method for radio signals of BLE 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. Our method is based on only a Wk-NN fingerprinting method by turning the weight carefully to the physical distance between the reference point and the current position.

Previously, the authors [5] proposed an indoor positioning method called a fingerprinting trilateration method or FTM, which is classified into a W3-NN fingerprinting, and conducted a pilot experiment on positioning performance of FTM. The result showed that their method is feasible. The objective of this manuscript is to conduct a further experiment for obtaining more data and report the latest result on positioning performance of FTM in comparison with a traditional indoor positioning method of fingerprinting.

4 Fingerprinting Trilateration Method [5]

An array of m BLE beacons is regularly attached on the ceiling and an array of n reference points are defined. A list of n fingerprints at the reference points is

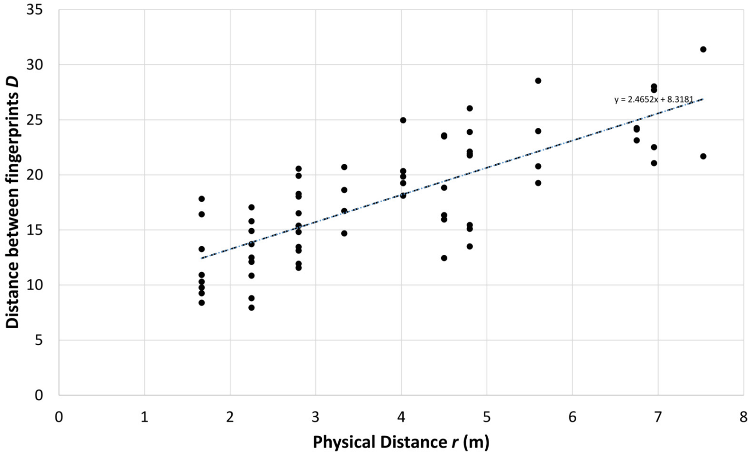

Fig. 4. Relation of distance between fingerprints with physical distance.

obtained. Each fingerprint comes from a different reference point it consists of m RSSIs obtained from all the m BLE beacons.

Locating the current position P_{crt} is performed as the following steps. Here let a symbol f_i be a i-th fingerprint, $RP(f_i)$ be the corresponding reference point, and D_{f_i,f_j} be the distance between fingerprints f_i and f_j.

Step 1. Measure the fingerprint f_{crt} at the current position P_{crt}.
Step 2. Calculate every distance between fingerprints $D_{f_{crt},f_i}, i \in \{1, 2, \ldots, n\}$.
Step 3. Find the top three closest fingerprints $f_i, i \in \{\text{top3}\}$.
Step 4. Convert the distance $D_{f_{crt},f_i}, i \in \{\text{top3}\}$ in physical distance. They are represented as $toPhy(D_{f_{crt},f_i}), i \in \{\text{top3}\}$.
Step 5. Determine the current position P_{crt} by performing trilateration among the three physical distances $toPhy(D_{f_{crt},f_i}), i \in \{\text{top3}\}$ and the reference points $RP(f_i), i \in \{\text{top3}\}$.

The distance between fingerprints D_{f_i,f_j} is defined as Euclidean distance as follows:

$$D_{f_i,f_j} = \sqrt{\sum_a (f_i[a] - f_j[a])^2}, \tag{2}$$

where $f_i[a]$ denotes the RSSI of the fingerprint f_i, which is observed from the a-th BLE beacon. The distance between fingerprints D_{f_i,f_j} is converted into the physical distance r by the following equation which is obtained experimentally in the previous work [5].

$$r = toPhy(D) = \frac{D - 8.32}{2.47} \tag{3}$$

Figure 4 shows a relation of the distance between fingerprints defined in Equation (2) with the physical distance between the corresponding reference points.

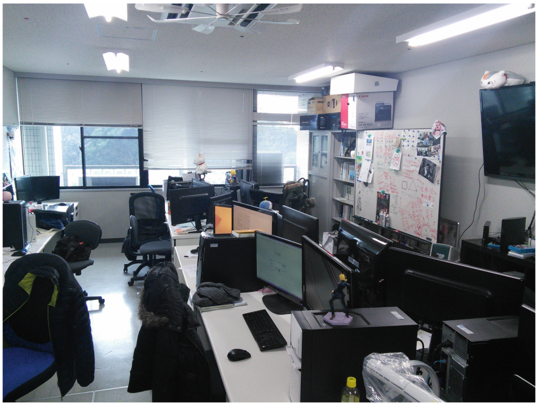

Fig. 5. A photo of our laboratory.

Regression Analysis confirms that the relation is significant [t(65) = 14.969 at p < .01]. The regression line is given in Eq. (3). When the physical distance r increases 1 m, it adds more 2.47 to the distance between fingerprints D.

5 Experiment on Positioning Performance

5.1 Settings and Preparation

Figure 5 shows a photo of our laboratory where an experiment is conducted in comparison with a traditional indoor positioning method of fingerprinting. There are a number of desktop computers and a television, a WiFi router etc. which create interference in radio signals of 2.4 GHz band.

In our experiment setting, a 3 by 4 array of 12 BLE beacons ($m = 12$) is attached on the ceiling of the laboratory whose dimension is 5 m wide by 9 m long as shown in Fig. 6. The grey boxes denote desks and the desktop computers and the dark gray boxes denote the television and the Wi-Fi router. An array of small circles denotes the array of 12 BLE beacons numbered from 1 to 12.

The reference points used in our experiment are placed at positions just under the 12 BLE beacons shown in Fig. 6, resulting in the 12 reference points ($n = 12$), and a list of 12 fingerprints at the corresponding reference points is obtained. While receiving each RSSI to build a fingerprint at each reference point, the receiver is held 1.7 m under the ceiling (1.0 m from the ground) and a temporal sequence of RSSIs for 4 min at 5-s intervals is stored and averaged for the fingerprint. Figure 7 shows all the 12 fingerprints. A value in a fingerprint shows the RSSI observed from the corresponding BLE beacon. For example, the RSSI of -63.52 in the top left corner in the fingerprint 1 comes from the BLE beacon 1 which is placed in the top left corner in Fig. 6.

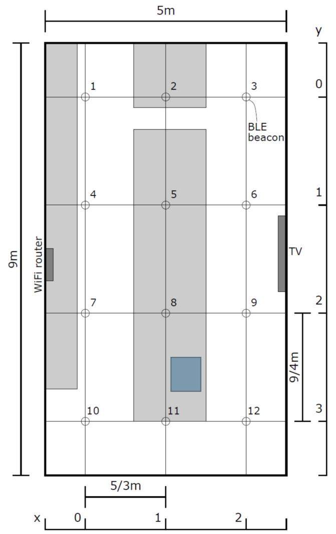

Fig. 6. Floor plan of our laboratory.

5.2 Procedure

An experiment on positioning performance of FTM in comparison with a traditional method of fingerprinting was conducted.

The experiment takes two layouts of evaluation positions into consideration, where indoor positioning methods are performed for evaluation. One is called a condition of Between-points and the other is a condition of On-points. For Between-points condition, evaluation positions are placed between neighboring four reference points. For example, the first evaluation position is in the center between reference points 1, 2, 4 and 5. There are six evaluation positions at all. For On-points condition, they are right under reference points. There are 12 evaluation positions at all. For each of those evaluation positions, fingerprinting and FTM are performed. The receiver is held 1.7 m under the ceiling (1.0 m 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 min at 5-s intervals, resulting in 49 pieces of positioning data P_{crt} at every single evaluation position:

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

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

6 Results

Figure 8 shows the positioning result performed by FTM and fingerprinting under Between-points condition and Fig. 9 is for On-points condition. The hori-

1		x		
		0	1	2
y	0	-63.52	-68.67	-81.09
	1	-67.02	-66.96	-72.79
	2	-66.79	-66.88	-72.90
	3	-72.94	-82.76	-74.18

2		x		
		0	1	2
y	0	-63.76	-66.48	-76.70
	1	-67.57	-64.75	-67.29
	2	-68.80	-71.25	-69.98
	3	-72.36	-82.27	-72.25

3		x		
		0	1	2
y	0	-65.47	-64.15	-74.81
	1	-71.78	-66.95	-63.67
	2	-71.96	-70.49	-71.21
	3	-74.36	-84.01	-74.19

4		x		
		0	1	2
y	0	-64.30	-69.46	-82.47
	1	-60.32	-66.26	-69.42
	2	-65.07	-68.78	-71.61
	3	-70.26	-81.23	-74.18

5		x		
		0	1	2
y	0	-64.17	-65.02	-79.04
	1	-65.93	-65.64	-68.41
	2	-65.42	-60.70	-66.48
	3	-72.62	-79.76	-70.74

6		x		
		0	1	2
y	0	-67.98	-71.23	-76.17
	1	-71.91	-64.86	-60.37
	2	-72.48	-69.64	-65.98
	3	-71.16	-80.90	-66.05

7		x		
		0	1	2
y	0	-67.20	-68.04	-83.17
	1	-66.08	-66.13	-72.67
	2	-65.75	-67.21	-73.84
	3	-65.53	-76.57	-67.87

8		x		
		0	1	2
y	0	-65.36	-68.76	-82.61
	1	-66.52	-68.02	-72.27
	2	-63.19	-64.05	-66.12
	3	-66.24	-77.21	-68.49

9		x		
		0	1	2
y	0	-68.59	-69.18	-80.48
	1	-71.45	-68.33	-62.89
	2	-72.53	-66.20	-63.30
	3	-70.88	-79.95	-64.84

10		x		
		0	1	2
y	0	-74.08	-76.59	-90.32
	1	-70.36	-72.57	-76.36
	2	-67.13	-65.22	-70.83
	3	-62.76	-72.84	-70.92

11		x		
		0	1	2
y	0	-74.56	-76.22	-85.04
	1	-70.07	-73.75	-75.63
	2	-65.89	-67.51	-69.57
	3	-65.13	-77.81	-64.82

12		x		
		0	1	2
y	0	-75.52	-74.71	-82.27
	1	-73.61	-74.17	-71.60
	2	-70.26	-67.14	-65.97
	3	-71.88	-76.53	-64.63

Fig. 7. The 12 fingerprints used in our experiment.

zontal and vertical axes correspond to those with the floor plan of Fig. 6. Each arrow represents accuracy of positioning at the corresponding evaluation position. The start point of the arrow denotes each evaluation position and the end does the predicted current position, and the length of the arrow denotes positioning error.

As shown in the positioning result under Between-points condition, FTM has a better positioning performance than fingerprinting. The average of positioning error for FTM is 0.615 in meter and it is 1.162 for fingerprinting, and the standard deviation is 0.375 and 0.305 for FTM and fingerprinting, respectively. Statistically, the unpaired t test confirmed that there is a significant impact over positioning error between FTM and fingerprinting [$t(10) = -2.772$ at $p < .05$].

For the positioning result under On-points condition, FTM has a worse positioning performance than fingerprinting. The average of positioning error for FTM is 1.246 in meter and it is 0.050 for fingerprinting, and the standard deviation is 0.574 and 0.087 for FTM and fingerprinting, respectively. Statistically, the unpaired t test confirmed that there is a significant impact over positioning error between FTM and fingerprinting [$t(12) = 7.128$ at $p < .01$ with Welch's correction]. The positioning error of FTM is 20 times or more worse than finger-

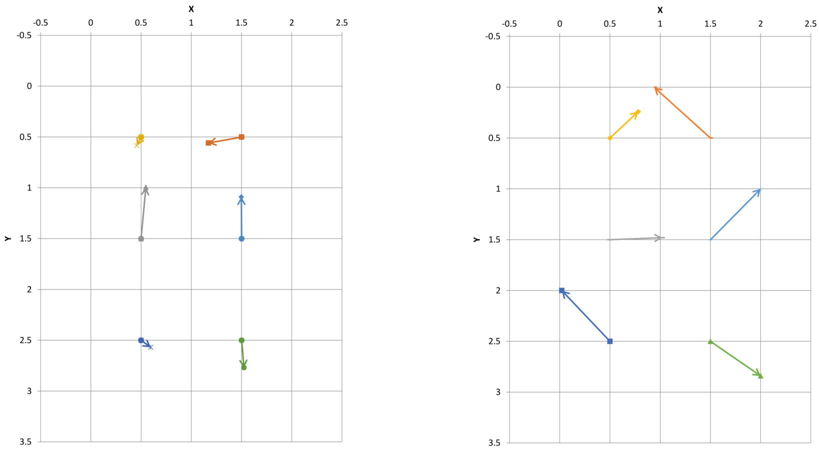

Fig. 8. Positioning performance performed by FTM (Left) and fingerprinting (Right) under Between-points condition.

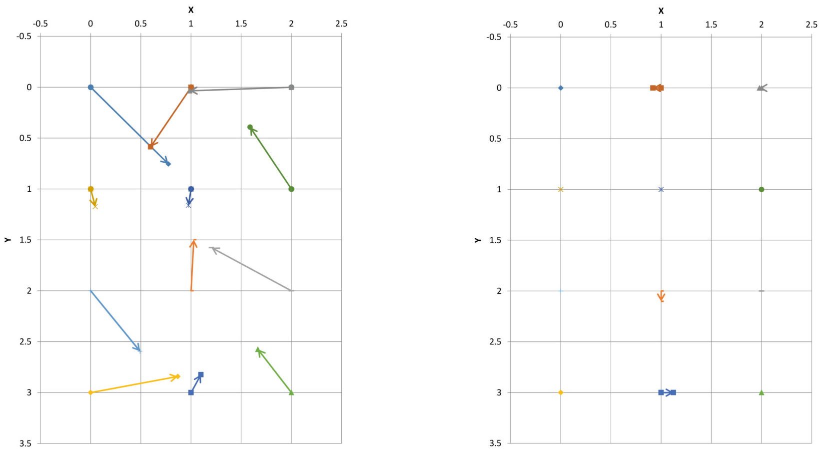

Fig. 9. Positioning performance performed by FTM (Left) and fingerprinting (Right) under On-points condition.

printing. This result could stem from difference of layouts of evaluation positions and lack of fidelity of Eq. (3) for conversion into physical distance from fingerprints distance, especially around physical distance of 0–2.

7 Conclusions

This manuscript proposed an indoor positioning method called a fingerprinting trilateration method or FTM using BLE beacons. FTM employs a list of fingerprints of RSSIs and performs trilateration between three closest fingerprints to locate a receiver's current position. The experiment result showed that FTM could locate the current position with positioning error of 0.615 m while it was 1.162 m for fingerprinting under Between-points condition.

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