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COLLONA: Design and Implementation of Corridor-Level Localization toward Indoor Pedestrian Navigation

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Abstract: Indoor positioning and navigation technology cannot depend on Global Navigation Satellite System (GNSS) due to the instability or unavailability of its signal. While conventional research activities about indoor pedestrian navigation is enhancing the accuracy of positioning, our approach simplifies a model for navigation and does not necessitate accurate positions. In this research, we have designed and implemented Corridor-Level Localization for Indoor Pedestrian Navigation (COLLONA), a system that performs positioning for indoor pedestrian navigation. Under the concept of indoor pedestrian navigation without needing accurate positioning, COLLONA represents indoor floor-plan as a graph composed of nodes and edges, aiming at estimating pedestrian's presence location at node and edge granularity levels.

Keywords: Indoor Localization, Indoor Navigation, Wi-Fi Beacons.

1. Introduction

Recently, with the spread of smartphones, tablets, and such mobile information devices, the implementation of indoor navigation services based on location information (LBS: Location Based Services) is underway [10]. Among technologies involved in LBS, technology for pedestrian navigation is especially important. However, positioning and navigation technology that does not depend on GNSS (Global Navigation Satellite System) is needed, since it is difficult to catch GNSS signals indoor.

So far, the mainstream in research activities about indoor pedestrian navigation consisted in accurate positioning. However, trying to obtain accurate positioning using smartphone or any other popular portable device, generates many issues such as the necessity to investigate in advance the electromagnetic environment, and regular calibration. Recently, positioning accuracy compensation technology such as PDR (Pedestrian Dead Reckoning) have increasingly used, though due to accumulated error and relative positioning issues it still requires to be combined with methods that can measure the absolute location such as radio signal strength.

Our research aims at facing above limitations. We have designed and implemented Corridor-Level Localization for Indoor Pedestrian Navigation (COLLONA), a system that performs positioning for indoor pedestrian navigation, using beacon emitters placed indoor. Under the concept of indoor pedestrian navigation without needing accurate positioning, COLLONA represents indoor floor-plan as a graph composed of nodes and edges, aiming at estimating pedestrian's presence location at node and edge granularity levels. The rest of the paper is organized as follows. In Section 2, we explain related works in localization technologies. Design and implementation methodology for this work are described in Section 3. In Section 4, we evaluate COLLONA system. Finally, we present our conclusions in Section 5.

2. Related Work

A. *Fingerprinting*

Indoor positioning technology using fingerprinting is known as a high-accuracy method [1, 5, 6]. Fingerprinting method requires investigating in advance the electromagnetic environment at multiple points in the targeted indoor area to make a reference database that is then used to realize high positioning accuracy by leveraging radio wave signal strength received by user

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device. For pedestrian navigation, a fingerprint-based indoor navigation system [2] is proposed. However, when the environment targeted by the positioning system becomes larger, the cost of building database increases. Figure 1 To solve this problem, LiFS [3] tried to decrease human cost, but it is unsuitable for long-term use because of regular calibrations. In addition, there is the issue that radio wave signal strength is highly affected by environmental and time changes, as well as people going in and out, such it is necessary to update the database frequently.

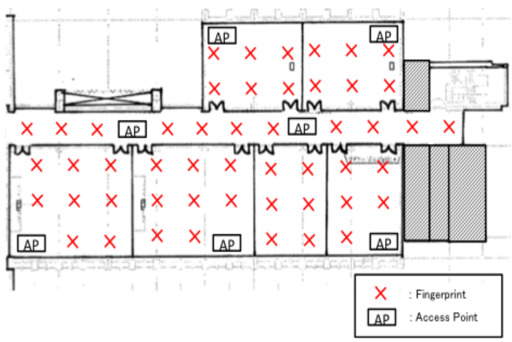

Figure 1. Points of fingerprinting

B. *Model-based technique*

Model-based localization based on the models such as the relationships between radio wave propagation and the actual geographical distance [8, 9]. Since these techniques can decrease the cost of creating databases like fingerprinting, the accuracy is not sufficient for pedestrian navigation. The other model-based techniques are time of arrival (ToA) [11], time difference of arrival (TDoA) [12], and angle of arrival (AoA) [13]. Although they can localize with accuracy, they compel pedestrians to hold some dedicated devices.

C. *Pedestrian Dead Reckoning*

Pedestrian Dead-Reckoning (PDR) for pedestrian navigation is a technology that aims at correcting user's location information using the values of sensors embedded in pedestrian's information terminal (smartphone, tablet, etc.), in cases it is not possible to catch the signal from the base stations used by the navigation or positioning system such those based on Wi-Fi access point or GNSS satellites. For example, it is possible to perform PDR using accelerometer, gyroscope, earth magnetic field sensor, and such smartphone embedded sensors [4, 7]. However, in PDR, a mechanism to compensate accumulated position drift error is necessary when walking for continuous periods. Moreover, since PDR is a technology to estimate relative position, to be able to provide navigation information to pedestrian, it has to be combined with a system that can estimate the absolute position.

3. Design And Implementation of COLLONA

Our system consists of a COLLONA server and a COLLONA Client that is held by a pedestrian. The client sends the obtained Received Signal Strength Indicator (RSSI) value to the server, and the server sends a localization result to the client.

In this study, the process to establish the COLLONA system is divided into two phases: pre-processing and navigation. In the pre-processing phase, the system administrator constructs Pathway maps, and subsequently installs beacon emitters. A Pathway map consists of nodes and edges of graph that reflects connectivity of corridors and rooms in the places of interests. In the localization phase, a pedestrian sends a set of RSSIs through the COLLONA client to the server at first, then the server estimates the pedestrian's location, and sends back the results for the client. The whole process of COLLONA is described in Figure 2.

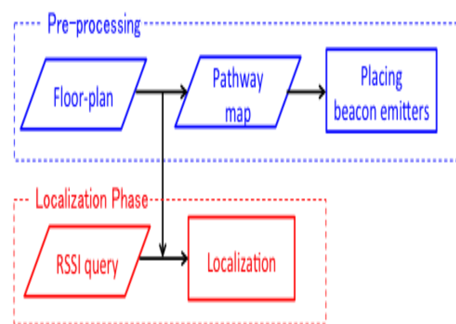

Figure 2. System architecture

A. *Pre-processing Phase*

The main purpose of Pre-processing phase is to create Pathway maps that have information about connectivity among the corridors and rooms in the place of interest. In addition, beacon emitters are installed according to the Pathway maps. Figure 3 shows an indoor floor-plan and Figure 4 describes the corresponding Pathway map. In addition, the symbols in Pathway map are explained in Table I.

Figure 3. An example of floor-plan

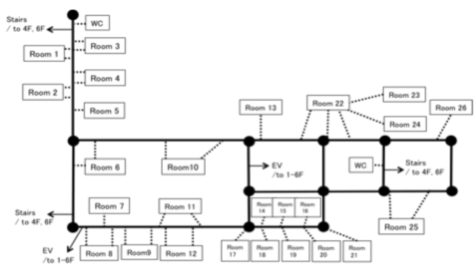

Figure 4. Pathway map for the floor-plan in Figure 3

TABLE I. SYMBOLS THAT CONTAINS A PATHWAY MAP

Symbol	Explain
—	This symbol indicates that there is an edge corresponding to a corridor to a corridor. An edge has the information about the length of the corridor.
●	This symbol indicates that there is a node. A Node is placed at a junction point or endpoint of edges. In the real environment, beacon emitters are placed at the node's location.
□	This symbol indicates that there is a room. Rooms can be connected to either a node or an edge.
…………	This symbol indicates the connection of a room and an edge.
→	This symbol indicates that there is an external Pathway map.

In this research, we locate beacon emitters at the places corresponding to nodes in the Pathway map. Figure 5 shows a Wi-Fi beacon emitter we implemented on Raspberry Pi [14].

Figure 5. Wi-Fi beacon emitter

1) *Places where a pedestrian can exist*

In this work, the place where a pedestrian can exists at a time is either a node or an edge of Pathway map. We address these two types of places "Existence Location" of a pedestrian.

A Node is defined as the junction point and the endpoint of a Pathway map. An Edge is described as a corresponding line to a corridor in the real world. It is defined by connecting two nodes of the both ends.

Whether a pedestrian exists on a specific Existence Location is expressed as probabilistic values. The probability that a pedestrian exists on a node is determined by the value of RSSI from the beacon emitter on the node.

B. *Localization Phase*

When a location query arrives, a set of RSSI values sent by a client, COLLONA calculates the probabilities that the pedestrian exists on each edge and each node, and then estimates the pedestrian's location. In this section, we explain how to calculate the probability that the pedestrian exists (1) on a node and (2) on an edge.

1) *Probability that a pedestrian exists on a node*

Our solution first determines the probabilities that a pedestrian exists on each node. To calculate them, we employ the following process. First, we calculate the probability $P(N,t)$ that a pedestrian exists on any nodes in the Pathway map at a time t. When a pedestrian exists on a node, we assume that the strongest RSSI will be received from the beacon emitter on the node. Therefore, $P(N,t)$ is determined by using the strongest value of RSSI r_{max} among all the beacon emitters. The equation is shown as (1).

$$\gamma_n = \frac{1}{e^{-\alpha(r_n-\beta)}+1} \qquad (1)$$

(1) Both α and β are pre-defined constants. α determines the gradient of the output function, and β is a threshold that the function outputs a probability value more than 50%. The form of the output function is shown in Figure 6.

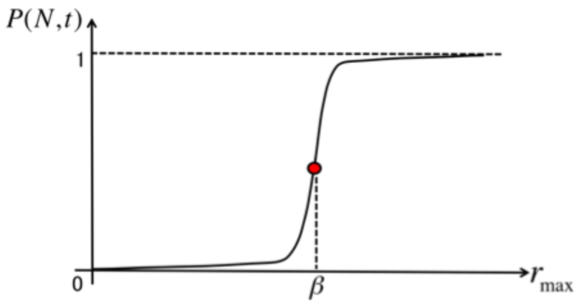

Figure 6. Form of the output function

Second, to distribute the probability among each node, we determine the weights for each node. To solve this, we define another output function to determine the ratios of probabilities that a pedestrian exists on each node. Equation (2) expresses the function that determines the weight γ_n for the node n.

$$P(N,t)=\frac{1}{e^{-\alpha(r_{\max}-\beta)}+1} \tag{2}$$

In the equation (2), r_n means the RSSI from beacon emitter installed on node n. The form of this function is the same as the equation (1). After determined γ for all the nodes, we calculate the ratio of probability for each node by using (3).

$$\Gamma_n=\frac{\gamma_n}{\sum_{k\in N}\gamma_k} \tag{3}$$

Finally, we determine the probabilities for each node. Using $P(N,t)$ in (1) and each weight Γ in (3), we can calculate each probability that a pedestrian exists on each node. For example, the probability $P(n,t)$ means that a pedestrian exists on a node n, can be expresses as follows.

$$\sum_{n\in N}P(n,t)+\sum_{e\in E}P(e,t)=1 \tag{4}$$

1) Probability that a pedestrian is on an edge

An edge can be defined by the two nodes that installed on the both sides of the edge. If the names of two nodes are n and m, there is an edge (n, m) between them. We describe this edge as $e(n,m)$. In addition, we assume that a client sends a set of RSSIs every time T to the server. In this context, $P(e(n,m),t)$ means the probability that pedestrian exists on an edge at a time t. To calculate $P(e(n,m),t)$, the requirements that we considered are shown as follows.

1. Probability that the pedestrian had existed on the node n at the time t-T, and moved to the edge (n, m) at the time t.
2. Probability that the pedestrian had existed on the node m at the time t-T, and moved to the edge (n, m) at the time t.
3. Probability that the pedestrian had existed on the edge (n, m) at the time t-T, and moved to the edge (n, m) at the time t. This means the pedestrian doesn't move on the edge (n, m) between time t-T and t.

Consequently, $P(e(n,m),t)$ is calculated as the following equation (5).

$$\begin{aligned}P(e(n,m),\,t)=\;&q_{(n,m),n}P(n,\,t-T)\\&+q_{(n,m),m}P(m,\,t-T)\\&+q_{(n,m),(n,m)}P(e(n,m),\,t-T)\end{aligned} \tag{5}$$

In the equation (5), $q_{(n,m),n}$ is the probability that the pedestrian had existed on the node n, and moved to the edge (n, m). Similarly to this, $q_{(n,m),m}$ is the probability that the pedestrian had existed on the node m, and moved to the edge (n, m). In addition, $q_{(n,m),(n,m)}$ is the probability that the pedestrian had existed on the edge (n, m), and moved to the edge (n, m).

We discuss how to calculate the probability that the pedestrian moves to an edge from a node. When considering moving to an edge from a node, we need to estimate which edge the pedestrian has moved to. Simply considering the increase and decrease of RSSI is difficult to accurate estimation, because the signals are unstable under the influence of multipath fading. Figure 7 shows a graph of RSSI with multipath fading, when a pedestrian walked toward a beacon emitter. Simply considering, the signal strength is monotonically increased, but in the real environment, it does not around 25m to 35m. Therefore, we consider the relative increasing and decreasing among the connected edges to the source node. If it assume a pedestrian had existed on the node n at the time t-T, the probability $q_{(n,m),n}$ is calculated as

$$q_{(n,m),n} = (1 - P(n,t)) \cdot \frac{\eta^{\Delta r_m(t-T;t)}}{\sum_{k \in C_n} \eta^{\Delta r_k(t-T;t)}} \qquad (6)$$

where C_n is a set of all the connected nodes of node n, $\Delta r_m(t-T;\, t)$ is amount of change of RSSI from beacon emitter m between the time t-T to t, and η is a pre-defined constants.

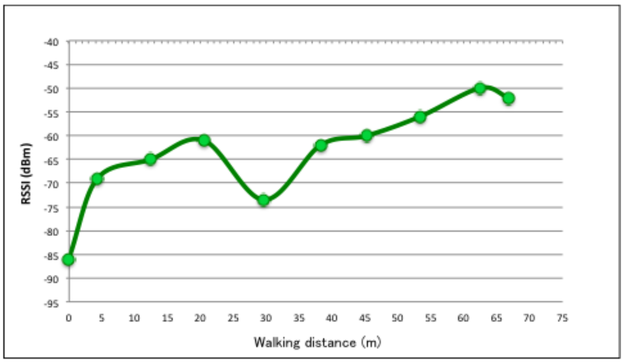

Figure 7. RSSI with multipath fading

Under the assumption that a pedestrian had existed on the edge (n, m), he moved to the edge (n, m), which means the pedestrian stayed on the edge (n, m). Therefore, $q_{(n,m),(n,m)}$ is expressed as equation (7).

$$q_{(n,m),(n,m)} = 1 - (P(n,t) + P(m,t)) \qquad (7)$$

Using (4), (5) for all nodes and edges at each time, the probabilities that a pedestrian exists on each Existence Location. Note that the probabilities satisfy the following equation (8).

$$P(n,t) = \Gamma_n P(N,t) \qquad (8)$$

In this equation, N is a set of all the nodes, and E is a set of all the edges in the Pathway map.

This algorithm estimates the pedestrian's location as a node or an edge with highest probability.

4. Evaluation

B. *Localization Accuracy*

We implemented a prototype of COLLONA and conducted the experiments on a building as shown in Figure 8. The building has a crossroad, and we set five beacon emitters at the nodes at the center and the endpoints of this crossroad. We walked along the path in Figure 8, and estimated the location by COLLONA. In the experiment, we set $\alpha = 2.0, \beta = 40.5$. In addition, the interval time T is 4s, which means the client measures a set of RSSI in every 4s and sends it to the server. The upper part of Figure 9 shows the places where the pedestrian actually existed, and the lower part shows the probabilities that COLLONA calculated.

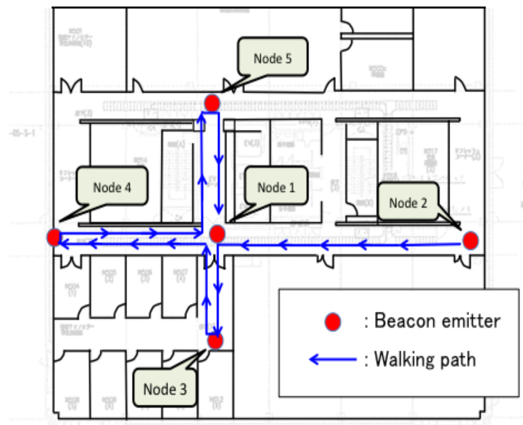

Figure 8. Experimental building with walking path

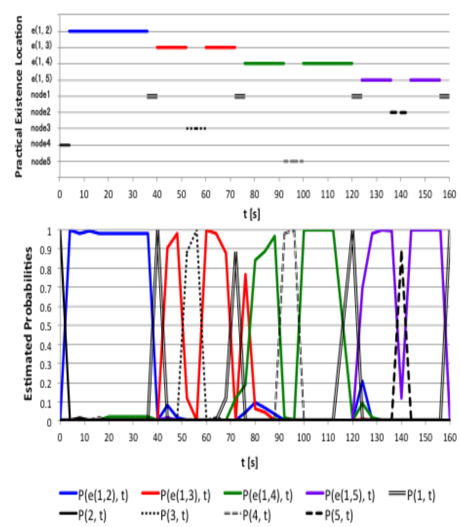

Figure 9. Result of localization

Considering that the highest probability at each time is the pedestrian's location, the experiment result shows that COLLONA can estimate the pedestrian's location in 92.5% accuracy.

C. *Comparing Accuracy over Time*

We conducted an experiment to compare the accuracy between COLLONA and the typical Fingerprinting method over time. First, we collected fingerprints in the building shown in Figure 10. Since fingerprinting method localizes the position as a point of absolute coordinates, we regarded the sets of fingerprints as corridors, namely, corridor A = {1, 2, 3, 4, 5, 6, 7}, corridor B ={8, 9, 10, 11, 12, 13, 14}, and corridor C = {15, 16, 17, 18}. For example, if fingerprinting method localizes that a pedestrian is at “fingerprint 3”, that means the location is “corridor A” in our experiment. Second, we localized a pedestrian’s location by COLLONA and fingerprinting at regular intervals. Finally, plot and compare the accuracy of the two methods. The result is shown in Figure 11.

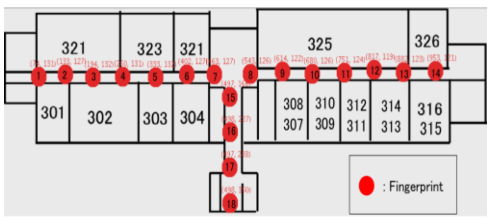

Figure 10. Experimental building with fingerprints

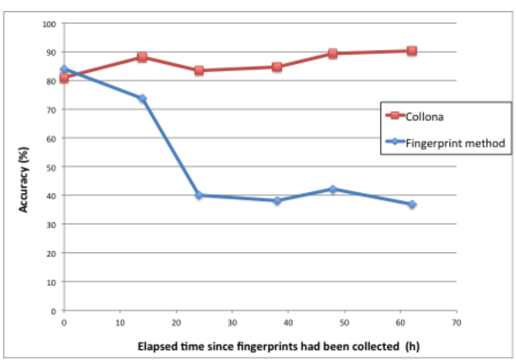

Figure 11. Accuracy of localization

By comparing the two methods, COLLONA and fingerprinting, we found that the localization accuracy of COLLONA does not be degraded. In fingerprinting method, it is assumed that the fingerprints become useless with changes of environment such as the changes of furniture’s position, weather, coming and going of people, and even the angle’s change of a chair.

5. Conclusion

In this paper we have proposed COLLONA, a system for Wi-Fi indoor navigation based on graph representation of building. COLLONA eliminated fine-grained Wi-Fi fingerprinting by expressing the locations inside a building in nodes and edges. Our implementation has shown that the pedestrian's location can be predicted correctly at 92.5%. Our future work includes flexible placement of Wi-Fi access points.

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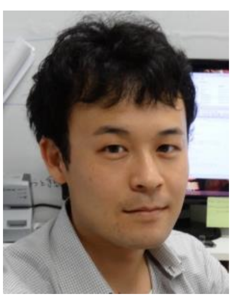

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