EDGES: Improving WLAN SLAM with Logic Graph Construction and Mapping

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Abstract—In recent decade, the Received Signal Strength (RSS) based indoor localization has caught significant attention, but it always suffers from the time-consuming and labor intensive fingerprint calibration. At the same time, the Simultaneous Localization and Mapping (SLAM) technique is considered with the low time and laboring cost, whereas the dedicated hardware is often required. To solve these problems, a novel indoor WLAN SLAM approach by using the Edge Detection based Gene Sequencing (EDGES) is proposed. First of all, a batch of RSS sequences are sporadically collected in target area. Second, the spectral clustering is conducted on RSS sequences to construct the cluster graphs, and then the EDGES approach is applied to assemble the cluster graphs into a logic graph. Finally, the mapping from the logic graph into ground-truth graph is established to realize indoor WLAN SLAM. The extensive experimental results prove that the proposed approach can achieve satisfying localization accuracy without site survey of location fingerprinting or motion sensing.

Keywords—Indoor WLAN; SLAM; edge detection; gene sequencing; logic graph

I. INTRODUCTION

With the rapid development of pervasive computing and context-awareness services, the localization techniques become essential for the growing Location Based Services (LBSs). In most indoor scenarios, like the shopping malls, airports, and underground parking lots, it is difficult to conduct accurate localization by applying the existing localization systems which are generally used in outdoor, like the Global Positioning System (GPS), due to the serious fading of Received Signal Strength (RSS) caused by the complex indoor structures. With the wide deployment of Wireless Local Area Network (WLAN), the RSS based localization technique has been studied intensively [1], whereas the time and laboring cost involved in location fingerprinting is significantly high, and meanwhile the Simultaneous Localization and Mapping (SLAM) technique often has dedicated hardware requirement. In response to these problems, we propose a novel indoor WLAN SLAM approach by using the Edge Detection based Gene Sequencing (EDGES) which is independent of location fingerprinting, as well as requires no dedicated hardware. Compared to the existing motion sensing based SLAM approaches, two distinctions of the proposed approach are that: the i) motion sensors are not required; and ii) EDGES is used to assemble the cluster graphs into a logic graph which can be applied to characterize the topological structure of the target area. In general, the four contributions of this paper are summarized as follows: i) location fingerprinting is not involved; ii) no dedicated hardware, like the motion sensors, is considered; iii) EDGES is used to explore the correlation relations among different RSS sequences; and iv) indoor WLAN SLAM is realized based on the mapping from the logic graph into ground-truth graph.

The rest of this paper is organized as follows. In section II, we show some related works on the existed indoor WLAN SLAM approaches. The proposed approach is discussed in detail in Section III. Experimental results are shown in Section IV. Finally, Section V concludes the paper and presents some future work.

II. RELATED WORKS

As far as we know, the trilateration and location fingerprinting are recognized as two of the most representative approaches used in RSS based indoor WLAN localization. The trilateration approach [2] seriously depends on the estimated distance from each selected Access Point (AP) to the receiver, while the estimated distance is determined by the propagation model [3]. Hence, the efficiency of trilateration approach cannot be easily guaranteed due to the Non-line-of-sight (NLOS) propagation problem caused by the multi-path fading in indoor environment. On the contrary, the location fingerprinting approach is much preferred [4]. The location fingerprinting approach generally consists of two phases, namely the offline phase and online phase. In offline phase, at each calibrated Reference Point (RP), the RSSs from all the hearable APs are recorded to form a location fingerprint which is then used to construct the radio map corresponding to the target area. After that, in online phase, the newly recorded RSSs are matched against the location fingerprints in radio map to obtain the estimated locations of the target. One of the critical problems of location fingerprinting approach is the radio map construction which is time consuming and labor intensive.

To solve the previous problems involved in the most existed RSS based indoor WLAN localization technique [5], many works have suggested to utilize the motion sensors to conduct indoor SLAM. In [6] and [7], the authors proposed to use a logic graph to characterize the physical layout of the target area, and meanwhile rely on an accelerometer to explore the reachability among different subareas, as well as the motion state of the target. Using a smartphone, the authors in [8] invented an indoor pedestrian tracking system which simultaneously constructs the floor plan of the unknown target area, as well as the corresponding radio map. An indoor tracking system based on a labeled topological map which is constructed by SLAM technique is addressed in [9]. In [10], a foot-mounted Inertial Measurement Unit (IMU) is applied to
conduct the proprioceptive motion sensing, and then an action recognition system is designed to observe the landmarks of the location-related actions. The authors in [11] presented a pedestrian tracking system by integrating the odometry data collected by a foot-mounted IMU with the WLAN RSSs. The localization system developed in [12] is based on the fusion of the data from both the images and IMU with a smartphone. The GraphSLAM-like localization approach proposed in [13] was developed for the large-scale areas. The authors in [14] proposed a multi-model based signal map which is constructed by using the RSSs from all the available sources.

Different from the existed works in literature, there are four main steps involved in the proposed approach: i) spectral clustering is applied to construct the cluster graphs from the sporadically collected WLAN RSS sequences; ii) edge detection approach is conducted to roughly locate the segments of RSSs with high correlation; iii) gene sequencing is used to find the accurate locations of the highly correlated RSSs in each segment with the purpose of assembling the cluster graphs into a logic graph; and iv) mapping from the logic graph into ground-truth graph is established to realize indoor WLAN SLAM.

### III. System Description

#### A. Cluster Graphs Construction

We sporadically collect a batch of RSS sequences, notated as $\text{RSS}_1$, $\text{RSS}_2$, ..., $\text{RSS}_n$, where $\text{RSS}_i = \{\text{rss}_{i1}, \text{rss}_{i2}, \ldots, \text{rss}_{in}\}$ ($1 \leq i \leq n$); $\text{rss}_{ij} = \{\text{rss}_{ij1}, \text{rss}_{ij2}, \ldots, \text{rss}_{ijk}\}$ ($1 \leq j \leq m$); $\text{rss}_{ijl}$ ($1 \leq l \leq k$) is the RSS collected from the $l$-th AP, in the $j$-th RSS vector, and in the $i$-th RSS sequence; $i$ and $j$ are the number and length of RSS sequences; and $l$ is the AP number.

To preserve the transition relations of RSSs, we label the RSS vectors in each RSS sequence with timestamps in ascending order, as shown in Fig. 1. After that, we construct the new vectors from the time-stamped RSS vectors by distributing the weights, $w_{tx}$ and $w_{tss}$, to the timestamps and RSSs respectively, where $w_{tx} + w_{tss} = 1$. The new vector corresponding to the $j$-th RSS vector in the $i$-th RSS sequence is represented as $\varphi_{ij} = \{w_{tx}^j, w_{tss}^j \text{rss}_{ij1}, w_{tx}^j w_{tss}^j \text{rss}_{ij2}, \ldots, w_{tss}^j \text{rss}_{ijk}\}$.

After that, the spectral clustering [15] is applied to construct a cluster graph from each RSS sequence. Since each new vector belongs to a unique cluster, the transition relations of clusters can be used to characterize the environmental changes in target area. In cluster graphs, each vertex represents a cluster, while an edge between two vertices represents that the corresponding two clusters are with transition relations.

### B. Edge Detection

In image processing, the aim of edge detection approach is to find the edge pixels which separate the pixels with significant difference in pixel values. Based on this concept, for the image in which each pixel value represents the correlation of two RSS vectors, the edge detection approach can be conducted to roughly locate the segments of RSS vectors with high correlation. In concrete terms, we connect all the collected RSS sequences into one sequence, notated as $\text{RSS}_T = \{\text{RSS}_1, \text{RSS}_2, \ldots, \text{RSS}_n\}$, and then construct an image in which the value of pixel at $(x, y)$ ($1 \leq x, y \leq h$) is calculated as $p(x, y) = \|\text{rss}_{px} - \text{rss}_{py}\|_2$, where $\text{rss}_{px}$ and $\text{rss}_{py}$ are the $x$-th and $y$-th RSS vectors in $\text{RSS}_T$; $h$ is the number of RSS vectors; and $\| \bullet \|_2$ stands for the 2-norm operation. To convert the image into a binary one, we set a correlation threshold $S_{th}$. If $p(x, y) < S_{th}$, we set $p(x, y) = 1$, and otherwise, we set $p(x, y) = 0$. In Fig. 4, the white pixels (i.e., the pixels with $p(x, y) = 1$) indicate the pairs of RSS vectors which are correlated well, while the black pixels (i.e., the pixels with $p(x, y) = 0$) indicate the pairs of RSS vectors with low correlation.

However, due to the existence of environmental noise during the RSS sequences collection, the contours of the detected edge pixels are not regular, and thereby the segments of RSSs with high correlation cannot be easily located. To solve this problem, the median filtering and image erosion approaches are considered to conduct the image processing,

![Fig. 1. An RSS sequence labeled with timestamps.](image1)

![Fig. 2. An example of a cluster graph construction.](image2)

![Fig. 3. Results of all the constructed cluster graphs.](image3)
respectively. By using the Sobel factors in (1), pixels are named as the target pixel and neighboring pixels in image. In each window, the center pixel and the other 8 raw image in Fig. 4.

white pixels become more regular compared to the ones in the as shown in Fig. 5 and 6 respectively. As can be seen from Fig. 6, the contours of the edge pixels outlining the blocks of white pixels become more regular compared to the ones in the raw image in Fig. 4.

The steps of edge detection are described as follows.

Step 1: Select a $3 \times 3$ pixel window to traverse the pixels in image. In each window, the center pixel and the other 8 pixels are named as the target pixel and neighboring pixels respectively. By using the Sobel factors in (1), $G_x$ and $G_y$, we calculate the edge detection values, $G_{x,x}$ and $G_{y,y}$, with respect to each target pixel, $(x, y)$, by (2).

\[
G_x = \begin{bmatrix}
+1 & +2 & +1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{bmatrix},
G_y = \begin{bmatrix}
-1 & 0 & +1 \\
-2 & 0 & +2 \\
-1 & 0 & +1
\end{bmatrix}
\]

\[G_{x,x} = p(x+1, y+1) + 2p(x, y+1) + p(x-1, y+1) - [p(x+1, y-1) + 2p(x, y-1) + p(x-1, y-1)]
\]

\[G_{y,y} = p(x+1, y+1) + 2p(x+1, y) + p(x+1, y-1) - [p(x-1, y+1) + 2p(x-1, y) + p(x-1, y-1)]
\]

Step 2: Calculate the difference of pixel values with respect to each target pixel as $G_{xy} = |G_{x,x}| + |G_{y,y}|$.

Step 3: Set the threshold of the difference of pixel values as $G_{th}$. Then, if $G_{xy} \geq G_{th}$, we set $p(x, y) = 1$, otherwise, we set $p(x, y) = 0$. In this case, $p(x, y) = 1$ and $0$ indicate that $(x, y)$ is an edge pixel and non-edge pixel respectively. Based on the contours of edge pixels, we can roughly locate the segments of RSSs with high correlation.

Fig. 7 shows a part of image after edge detection in which the contour of edge pixels indicates that the segment of RSSs with IDs from 201 to 231.

C. Gene Sequencing

After the process of edge detection, we obtain the rough length and width of each segment of RSSs with high correlation. However, as can be seen from Fig. 6, since only a small number of white blocks (marked by red circles) are with the regular shape, the detected lengths and widths cannot be applied to accurately locate the white blocks. Fig. 8 gives an example of a white block with irregular shape. By using the edge detection approach, the detected length and width indicate that the segments of RSSs with IDs from 902 to 1026 and with IDs from 346 to 361 is highly correlated with the segment of RSSs with IDs from 201 to 231.

In gene sequencing, two gene fragments are matched by sequence correlation. Based on the concept of gene sequencing, we construct the scoring matrix, $H$, to characterize the correlation of every two segments of RSSs with high correlation, $a = \{a_i\}$ and $b = \{b_i\}$. The elements in $H$ satisfy the relations as follows.

1. $H(i, j) \geq H(i, j + 1)$ when $a_i = b_j$ and $a_i \neq b_{i+1}$;
2. $H(i, j) \geq H(i+1, j + 1)$ when $a_i = b_j$ and $a_{i+1} \neq b_{j+1}$;
3. $H(i, j) \leq H(i+1, j + 1)$ when $a_i = b_j$ and $a_{i+1} = b_{j+1}$;
Fig. 8. A white block with irregular shape.

Fig. 9. Flow chart of the proofs.

1. \( H(i, j) \geq H(i+1, j+1) \) when \( a_i \neq b_j \) and \( a_{i+1} \neq b_{j+1} \);
2. \( H(i, j) \leq H(i+1, j+1) \) when \( a_i \neq b_j \) and \( a_{i+1} = b_{j+1} \);

where \( a_i \) and \( b_j \) are the \( i \)-th and \( j \)-th RSS vectors in \( a \) and \( b \) respectively; and \( H(i, j) \) is the score between \( a_i \) and \( b_j \).

To satisfy the previous relations, we define \( H(i, j) \) in (3) and (4). The flow chart of the proofs is shown in Fig. 9.

\[
H(i, j) = \max \left\{ \begin{array}{ll}
0 & \\
H(i-1, j-1) + s(a_i, b_j) & \\
\max\{H(i-k, j) + W_k\} & \\
\max\{H(i, j-l) + W_l\} & \\
H(0, j) = 0, 1 \leq j \leq u & \\
H(i, 0) = 0, 1 \leq i \leq v & \\
H(0, 0) = 0 & 
\end{array} \right. 
\]

(3)

(4)

where

\[
s(a_i, b_j) = \left\{ \begin{array}{ll}
\alpha > 0 & (a_i = b_j) \\
\beta < 0 & (a_i \neq b_j) \\
\end{array} \right. , \\
W_k = -(\alpha - \beta)k,
\]

(5)

1 \leq i \leq u, 1 \leq j \leq v, and \( u \) and \( v \) are the number of RSS vectors in \( a \) and \( b \) respectively.

Therefore, we calculate the scoring matrix with respect to each detected white block in Fig. 10. In this figure, the higher scores are indicated with larger pixel values. After the scoring matrices are obtained, we continue to use the gene sequencing approach to find the accurate locations of the highly correlated RSSs in each segment. The steps of gene sequencing are described as follows.

Step 1: Find the highest score in \( H \), notated as \( H(i, j) \);

Step 2: Store the location \( (i, j) \) into the set \( L \);

Step 3: Set \( H(i, j) = \max\{H(i-1, j), H(i, j-1), H(i-1, j-1)\} \);

Step 4: Repeat Steps 2 and 3 until we obtain \( H(i, j) = 0 \). We assume that there are \( t \) locations included in set \( L = \{L(r)\}_{1 \leq r \leq t} \), where \( L(r) \) is the \( r \)-th location in \( L \);

Step 5: Set \( r = t \);

Step 6: Compare the locations of \( L(r) \) and \( L(r-1) \) in \( H \). If there is a diagonal jump from \( L(r) \) to \( L(r-1) \), the vertical and horizontal coordinates of \( L(r-1) \) in \( H \) are set as the IDs of the two RSS vectors with high correlation;

Step 7: Set \( r = r-1 \);

Step 8: Repeat Steps 6 and 7 until we obtain \( r = 2 \).

Fig. 11 shows an example of the process of gene sequencing. On this basis, we will obtain all the pairs of segments of RSSs with high correlation. After the IDs of all the highly correlated RSS vectors are obtained (e.g., in Fig. 11, the IDs of the highly correlated RSS vectors involves two parts with the first one from 12 to 13 and from 2 to 3, and the second one from 14 to 18 and from 3 to 7), we continue to assemble the cluster graphs into the logic graph. In concrete terms, the clusters containing the highly correlated RSS vectors are merged into a unique cluster, while the transition relations related to these clusters are preserved by the merged one.

D. Mapping Establishment

The purpose of establishing the mapping from the logic graph into ground-truth graph is to characterize the relations of the RSSs and physical layout, and thereby realize indoor WLAN SLAM. The ground-truth graph is constructed based on the physical segmentation of the target area in Fig. 12. The steps of mapping establishment are described as follows.

Step 1: Sequence the vertices in both the logic graph and ground-truth graph with the Adjacent Degrees (ADs) in
descending order. The AD of a vertex is calculated as the sum of its degree and the degrees of its one-hop neighbors.

Step 2: Notate the minimal and maximal ADs in logic graph and ground-truth graph as $A_{mil}$ and $A_{mal}$, and $A_{mig}$ and $A_{mag}$, respectively.

Step 3: Modify the AD of each vertex in logic graph, $A_{ADl}$, into

$$V_{ADg} = A_{mig} + \frac{A_{mag} - A_{mig}}{A_{mal} - A_{mil}} (V_{ADl} - A_{mil}) \quad (6)$$

Step 4: Map every vertex in logic graph into a vertex with the closest AD in ground-truth graph.

After the previous steps, we conduct the mapping modification by using the concept of the betweenness centrality of vertices in graph [16] with the purpose of guaranteeing the consistency of the center vertices in both the logic graph and ground-truth graph. The steps of mapping modification are described as follows.

Step 1: Construct the shortest path with respect to each pair of vertices in both the logic graph and ground-truth graph by using the Floyd algorithm [17].

Step 2: Define the vertices which are located on all the shortest paths as the center vertices. Then, we modify every center vertex in logic graph to be mapped into a center vertex with the closest AD in ground-truth graph.

Finally, to realize the target localization, we calculate the distances between the newly recorded RSSs and the average RSS in each vertex in logic graph. After that, the vertex in ground-truth graph which is mapped by the vertex corresponding to the smallest distance in logic graph is then selected as the estimated area where the target is located.

IV. EXPERIMENTAL RESULTS

Fig. 12 shows the ground-truth graph constructed from the physical segmentation of the target area in which 21 traces are selected for RSS sequences recording, as shown in Fig. 13. Fig. 14 shows the logic graph which is assembled by using the proposed EDGES, and meanwhile the mapping relations from the Logic Graph (LG) into Ground-truth Graph (GTG) is illustrated in Table 1.

Fig. 15 compares the localization probabilities in correct subareas by using the proposed EDGES and edge detection solely respectively for logic graph construction under different Timestamp Weights (TWs) used in spectral clustering. Fig. 16
EDGES compares the averaged localization probabilities in correct subareas by using different approaches of logic graph construction. From Fig. 16, we observe that the localization accuracy under most TW situations has been significantly improved by adopting the proposed EDGES. For instance, by using the EDGES for logic graph construction, the averaged localization probabilities in correct subareas with TW = 0.3, 0.5, and 0.6 are about 30, 20, and 40 percentages higher than the ones achieved by using the edge detection solely. Furthermore, as can be seen from Fig. 15, the EDGES reduces the dependency of localization accuracy on the TWs, and thereby enhances the adaptability of the proposed indoor WLAN SLAM approach.

V. CONCLUSION

In this paper, we proposed an improved indoor WLAN SLAM approach by using the proposed EDGES which is independent of the location fingerprinting and motion sensing. Based on the constructed image of RSS correlation, we rely on the edge detection approach to roughly locate the segments of RSSs with high correlation. After that, using the gene sequencing approach, we obtain the IDs of the highly correlated RSS vectors among different cluster graphs, and then assemble the cluster graphs into a logic graph. Finally, the indoor WLAN SLAM is realized based on the mapping from the logic graph into ground-truth graph. However, the logic graph construction without conducting the RSS clustering and timestamp labeling forms an interesting work in future.

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