A constrained k-nearest neighbor approach for semantic indoor trajectory extraction

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***Abstract*—One of the indoor location-based services use cases is giving real-time information to users while they are inside a building. For example, in a museum, they can check next-to-visit recommendations or emergency guidance in real-time. Thus, it is vital to extract their movement as indoor trajectories. However, most indoor positioning methods have some degrees of error due to noisy observations. Those errors may lead to distant consecutive positions, which is impossible in a real-world case. Thus, we propose the semantic space-based movement constraints to produce indoor semantic trajectory without distant consecutive positions. The proposed approach is designed to extract semantic trajectory effectively in a real-time manner.**

***Index Terms*—Location Based Service, Indoor Positioning, K-Nearest Neighbor, Semantic space, Indoor trajectory**

I. INTRODUCTION

The application of Internet-of-Things (IoT) devices has affected different aspects of human life, for example, the indoor location-based services (LBS). The indoor LBS may provide several use cases on people movements, for instance, in a museum: showing visitors' next-to-visit recommendation and emergency route guidance. However, Indoor LBS, where GPS is unusable [1], cannot estimate the user's position correctly without a reliable sensor. Some IoT RSSI-based device, such as RFID [2] and Bluetooth Low Energy (BLE) [3]–[8] can provide some measurements to calculate user's position. However, the RSSI-based devices are noisy, which causes an erroneous indoor positioning.

Erroneous indoor positioning, while produces inaccurate positions, has another implication for indoor trajectory extraction. Incorrect positioning may lead to distant consecutive positions. In real-world cases, a person cannot be at two far positions in a consecutive time step.

Several indoor positioning techniques attempted to reduce error from the noisy RSSI observations. Hidden Markov Model (HMM) [2], [6], [7], [9], [10] methods use Viterbi algorithm to produce the best indoor trajectory given the sequence of RSSI observations. Particle filter method [11] converts the RSSI observation to instantaneous velocity to update the positions. The K-Nearest Neighbor (KNN) [4], [5] methods estimate current indoor positions using a fingerprint dataset. However, most of them still worked on 2D spaces, yielded a considerable error, and produce distant consecutive positions.

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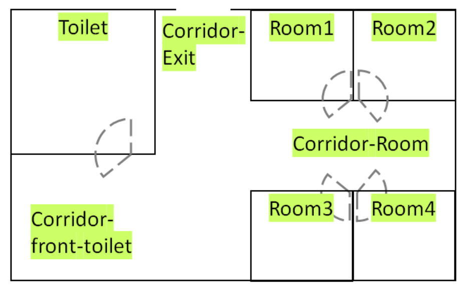

Fig. 1. Sample indoor floor plan

The current indoor positioning techniques often regard the indoor environment as grid or cartesian 2D space, given the floor map. However, giving the 2D positions to the user is not always beneficial. A less rigid representation, called semantic positions [1], [12], [13] can be better than 2D positions. Users will understand the inferred pattern Toilet $\rightarrow$ Hallway better rather than (1,5) $\rightarrow$ (4,3).

Meanwhile, even though the inferred 2D positions are not very accurate, we can still consider it correct in terms of semantic location (Toilet or Hallway1). In both pattern extraction and semantic correctness cases, the semantic location is more appropriate to use than the cartesian 2D-based position.

In this paper, we study the KNN implementation for semantic spaces to extract indoor trajectories. We set the previously collected dataset, called fingerprint dataset, with the semantic position rather than the 2D cartesian coordinates. The KNN estimates the current position by voting on k semantic positions rather than averaging k 2D cartesian coordinates. However, this method may still produce distant consecutive positions.

Thus, we propose movement constraint to ensure the KNN to not inferring the distant consecutive positions on semantic

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spaces. The constraint restricts a current semantic position only to be accessible from a previous position.

Example 1: Suppose a person's current position is at the Toilet area. Logically, this person cannot move far from the Toilet area in a short time. Due to erroneous indoor positioning, this person's inferred movement is Toilet $\rightarrow$ Room1. This movement is impossible because the consecutive positions are far apart and separated by another area and walls.

Given the movement constraints of the full indoor space, the KNN continuously estimate the user's position, thus extracts his/her indoor trajectory until leaving the building.

Besides, the movement constraints reduce the search space of KNN, thus making it more efficient than the naïve KNN and applicable to real-time setting. We use a real dataset of people's movements with sequences of BLE RSSI signals.

The key contributions of this paper is the application of movement constraints to KNN-based indoor positioning on semantic space to extract indoor trajectories in a real-time fashion. We present this paper as an initial study for extracting a semantic trajectory in an indoor environment.

II. Related Works

In this section, we briefly review some related works and provide the comparisons between our proposed method and existing research. We limit the discussion on the indoor spaces only for brevity.

Indoor Positioning: Inferring the users' indoor position in an indoor from RSSI signals, such as RFID [2] and BLE [3]–[8], is quite challenging. A particle filter indoor 2D positioning [11] yielded 2 meters positioning error. Another approach applied reinforcement learning [8] to grid space to extract indoor trajectories. However, all of them does not conform to indoor semantic space [1]. On semantic space, a beacon ST-matching method [6] applies global map matching from the beacon network and route network. Those network refers to the connectivity of the installed beacons and the semantic spaces. However, BST matching requires to see the whole observation, posing difficulties in real-time processing.

K-Nearest Neighbor-based Indoor Positioning: Several k-Nearest Neighbor (KNN) approaches give more accurate indoor positioning and immediately output the position, which is useful in real-time application. The Iterative Weighted kNN [4] uses a customized similarity formula to approximate current user position. Another approach, the weighted KNN with adaptive mean shift [5] performed indoor positioning with better performance. However, most of them still worked in 2D cartesian space instead of the more flexible semantic space and suffered from consecutive distant positions. Thus, we are interested in applying the movement constraints to prevent inferring successive distant positions and work directly on semantic space.

In this study, we apply semantic space-based movement constraints for KNN using the BLE observation. The constraints prevent inferring distant consecutive positions by removing the irrelevant search space of KNN.

III. Proposed Method

In this section, we describe our approach for applying movement constraints to extract semantic trajectories from BLE RSSI observations in details. Our approach consists of two phases: offline phase and online phase. The purpose of the offline phase is to build the fingerprint set for the online phase. Meanwhile, the online phase extracts the semantic trajectory in real time using the fingerprint set from the offline phase by the constrained KNN. Before explaining the offline and online phase, we describe the characteristic of our input, the BLE RSSI dataset, first.

A. BLE RSSI dataset

BLE RSSI is the signal strength observed by a bluetooth receiver device such as smartphone. The value of RSSI is negative, where larger values (closer to -1) indicates stronger signal reception. When the receiver device is close to an emitting BLE beacon, the receiver observes the RSSI from that beacon. Thus, it is possible to roughly determine a user's position because of this reason. However, the observed RSSI is noisy and incomplete. We define the RSSI value as zero to indicate that the RSSI of a beacon is missing at that time. Due to these characteristics, determining the user's position is not easy.

In our study, we collect the BLE RSSI from M installed beacons in an indoor environment. The collectors record their trajectory while they are walking from a certain semantic position and to another semantic position. Note that the collectors know the definition of the semantic positions in the indoor environment, therefore they label their semantic position as they walk. We develop an Android apps for the BLE RSSI collection. The collected data from one trajectory are formatted into a JSON file that contains the record ID, timestamp, semantic position at that timestamp, and captured M RSSI values of installed BLE beacons along with the MAC address of the beacons. We illustrate a part of the JSON file in Figure 2.


```
{
{"timestamp":        "2018-12-06 10:46:38.364",
"position_label":    "1",
"readings":          [{"mac-addresss":"xx:xx:xx:xx:xx:xx","rssi":0},
                     {"mac-addresss":"xx:xx:xx:xx:xx:xx","rssi":-50},
                     {"mac-addresss":"xx:xx:xx:xx:xx:xx","rssi":-90}]},
{"timestamp":        "2018-12-06 10:46:38.569",
"position_label":    "1",
"readings":          [{"mac-addresss":"xx:xx:xx:xx:xx:xx","rssi":-90},
...
                     {"mac-addresss":"xx:xx:xx:xx:xx:xx","rssi":-90}]}
}
```


Fig. 2. Collected BLE RSSI data in JSON format

Then, using the labeled trajectories, we can build the fingerprint dataset and execute the evaluation to measure the performance of our approach.

B. Offline phase

In the offline phase, we performed a smoothing operation and a transformation to the collected trajectory data. We perform the smoothing because the BLE RSSI data is noisy and incomplete, as mentioned before. Thus, the smoothing aims to acquire the statistical information and remove missing observation of BLE RSSI. In this study, we aggregate BLE RSSI observations of w seconds-length window using MAX function. We also aggregate the collected semantic positions alongside the BLE RSSI values in similar way but with the majority vote function.

Then, we transform the smoothed BLE RSSI data to a fingerprint set. The smoothed BLE RSSI data still holds the successive relationship of the trajectory data. However, in the online phase, the KNN does not require this relationship to acquire the semantic position. Thus, we drop this relationship by removing the timestamp and the trajectory notation. Then, we index the BLE RSSI observations with the semantic position.

Trajectory	**Semantic Position**	**BLE RSSI**
T_1	1	{-90, -80, -75}
	1	{-85, -70, -85}
	2	{-90, -70, -80}
	2	{-90, -75, -90}
T_2	1	{-95, -85, -90}
	1	{-98, -70, -95}
	3	{0, -65, -90}
T_3	4	{-95, 0, -50}
	5	{-90, 0, -75}
	5	{-90, -99, -60}

(a) Smoothed collected trajectory data

Semantic Position	**BLE RSSI**
1	{-90, -80, -75}
1	{-85, -70, -85}
1	{-95, -85, -90}
1	{-98, -70, -95}
2	{-90, -70, -80}
2	{-90, -75, -90}
3	{0, -65, -90}
4	{-95, 0, -50}
5	{-90, 0, -75}
5	{-90, -99, -60}

(b) Fingerprint set

Fig. 3. Transforming the smoothed RSSI trajectories data into the fingerprint set

Example 2: Suppose, in the data collection phase, we collect 3 trajectories from 3 beacons and 5 semantic positions for the offline phase. After the smoothing, the trajectories have lengths of $|T_1|, |T_2|, |T_3|$ observations, as depicted in Figure 3(a) respectively. The fingerprint set, as depicted in Figure 3(b), does not have the timestamp property. In contrast, the fingerprint set is not separated by the trajectory and like the original collected dataset; thus, its size becomes $|T_1| + |T_2| + |T_3|$.

C. Online Phase

In the online phase, we perform the trajectory extraction for a moving person inside a building. This person can see his/her past movements until he/she exits the building in real time. The input is the captured BLE RSSI at the time when he/she walks inside the building. Then, we smoothen the BLE RSSI using the aggregation window similar to the offline phase. After that, we execute the constrained KNN to infer the current semantic position as well as extracting the semantic trajectory.

There is an additional property called semantic graph that represents the movement constraints from the indoor floor plan. A semantic graph illustrates the semantic positions and the possibility to move among the semantic positions. The edges represents the movement constraints of a semantic position. When an edge that connects two semantic positions s_A and s_B in a semantic graph, a person at s_A can directly move to s_B in the real world. Thus, we can only infer the next semantic position to the previous position (staying) and the positions that are connected with the previous position (moving).

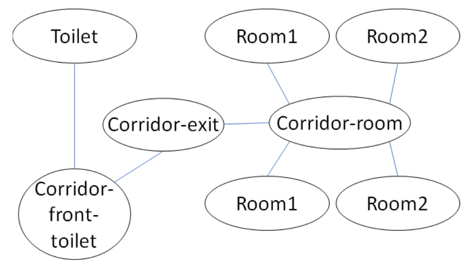

Fig. 4. Semantic graph from the Figure 1

Example 3: We depict the semantic graph from the floor plan of Figure 1 on Figure 4. The movement from the Room1 to Room2 is impossible because of the wall separation as well as from Corridor-front-toilet to Corridor-room because there is Corridor-exit between them. In contrast, movement from Room1 to Corridor-room is possible because they are directly accessible using the door.

D. Constrained KNN

A constrained K-Nearest Neighbor (C-KNN) is a modified K-Nearest Neighbor that uses movement constraints to infer only close semantic positions from the previous semantic position. Thus, it is useful for extracting indoor trajectories as it is impossible for consecutive distant positions to occur. On the other hand, the pruning also reduce the irrelevant KNN search space in the fingerprint set, thus improving efficiency.

The flowchart in Figure 5 represents the process to extract indoor semantic trajectory. At the beginning of the trajectory, we perform the original KNN using the whole fingerprint set. Otherwise, we subset the fingerprint set to contain only the accessible semantic position from the previously semantic position including the previous semantic position itself. We execute the KNN by comparing the distance between the current BLE RSSI and the collected RSSI in the fingerprint set. Then, we perform majority vote on k instances with the shortest distance in the fingerprint set to estimate the current semantic position rather than averaging the 2D positions. Finally, we continuously concat the semantic positions to extract the semantic trajectory.

IV. Dataset

We collect the dataset from the real movement of people moving in an indoor space of the 4th floor in our university building, as depicted in Figure 6. The semantic graph of the floor plan consists of 14 semantic positions and 16 edges. We

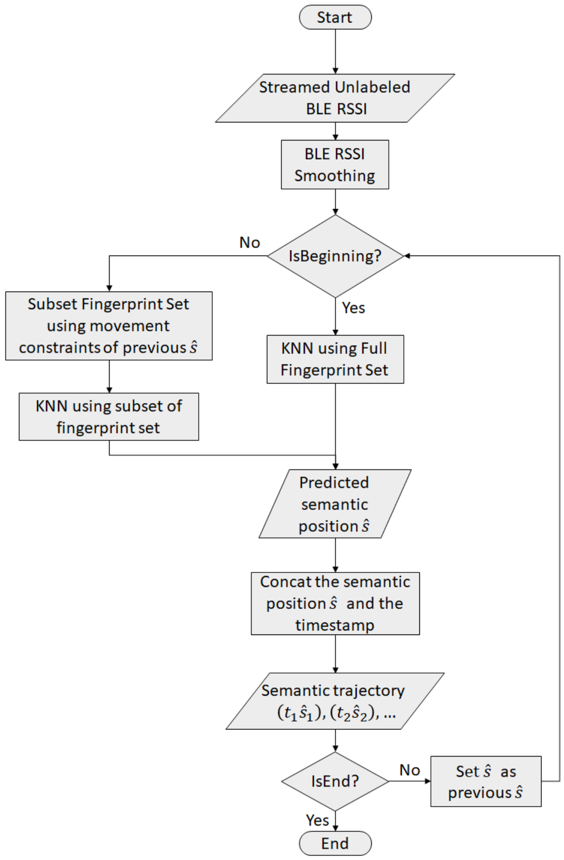

Fig. 5. Flowchart of C-KNN for extracting semantic trajectory

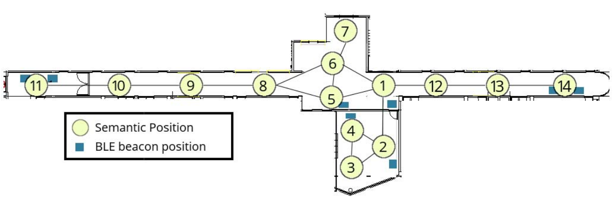

Fig. 6. The floor plan of the dataset

deployed eight BLE beacons at a certain configuration due to the limited electrical outlets. The sampling interval of BLE RSSI observation is 0.2 s.

We separate the collected dataset for the offline and the online phase. The offline dataset consists of 72 trajectories with 2 minutes length each, considering them as train data. The online dataset, also as test data, consists of 28 trajectories with lengths between 1 minute and 6 minutes.

V. Conclusion

In this paper, we presented the initial study of the constrained k-nearest neighbor for indoor positioning in semantic space representation. The constraints prevent inferring a distant consecutive position. This feature also reduces the computation time by removing irrelevant measurement points. Thus, we can apply this method for real-time applications.

In the future, we plan to investigate a more sophisticated approach for this indoor semantic space, such as deep learning methods. On the other hand, other preprocessing methods may improve the quality of BLE RSSI observations, which give more accurate indoor positioning.

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