Extracting valid indoor semantic trajectories using movement constraints

Hani Ramadhan
Big Data Department
Pusan National University
Busan, South Korea
hhani042@pusan.ac.kr

Yoga Yustiawan
Big Data Department
Pusan National University
Busan, South Korea
yoga017@pusan.ac.kr

Joonho Kwon
Computer Science and Engineering Department
Pusan National University
Busan, South Korea
jhkwon@pusan.ac.kr

***Abstract*—An indoor semantic trajectory is a sequence of timestamped semantic positions inside a building. However, its extraction depends on the erroneous indoor positioning. The error leads to an invalid trajectory that has distant consecutive positions. This invalid trajectory may lead to an issue of the non-sensical patterns when analyzing a big semantic trajectory data. To prevent extracting invalid trajectories, we apply the movement constraints to infer only close positions to the current position. We extend the constraints to several indoor positioning techniques, such as Hidden Markov Model, K-Nearest Neighbor, or Deep Neural Network. We show that our approach can effectively extract valid indoor semantic trajectories.**

***Index Terms*—Indoor Positioning, Indoor Semantic Trajectories, Big Trajectory Analysis, Machine Learning**

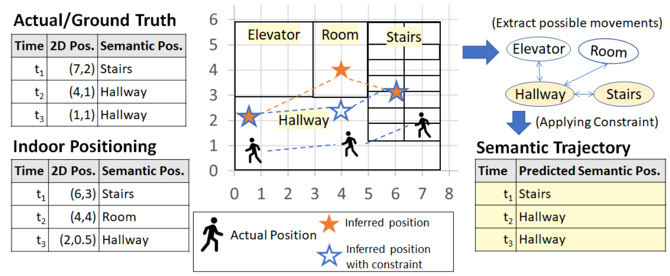
I. Introduction

In indoor positioning, the extraction of trajectories may be "jumpy" or invalid in 2D positions. Such a trajectory contains distant or impossible consecutive positions, which cannot happen in the real world. If we analyze a large indoor trajectory, this distant or impossible consecutive positions may lead to extracting non-sensical patterns, e.g., $Stairs \rightarrow Room$ although separated by a wall, as depicted in Figure 1. We assume that at timestamp t_1 The cause of the "jumpy" trajectory is the erroneous positioning [1], [2] from the noisy emitting devices, e.g., BLE (Bluetooth Low Energy) beacons.

The quality of the indoor positioning highly depends on the emitting device. The BLE beacons emit the RSSI (Received Signal Strength Indication) to the capturing device such as smartphones. However, the RSSI is often incomplete and noisy due to the interference of the furnitures or walls. Hence, the indoor positioning from those devices is always challenging. Thus, it also makes our indoor trajectory extraction difficult.

Our purpose is to extract the valid trajectories from the BLE RSSI data input with. We apply the movement constraints that restrict an inferred position to be accessible from the previous position. The constraints work on semantic positions [3] rather than 2D positions because they cover a wider area than 2D positions.

This work was partly supported by Capacity Enhancement Program for Scientific and Cultural Exhibition Services through the National Research Foundation of Korea (NRF) funded by Ministry of Science and ICT (NRF-2018X1A3A1069642) and by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2018R1A5A7059549).



Time	2D Pos.	Semantic Pos.
t_1	(7,2)	Stairs
t_2	(4,1)	Hallway
t_3	(1,1)	Hallway

Time	2D Pos.	Semantic Pos.
t_1	(6,3)	Stairs
t_2	(4,4)	Room
t_3	(2,0.5)	Hallway

Time	Predicted Semantic Pos.
t_1	Stairs
t_2	Hallway
t_3	Hallway

Fig. 1. Applying movement constraint to erroneous indoor positioning

Our key contributions in this paper are: (1) we apply movement constraints to several machine learning (ML)-based indoor positioning methods to extract valid semantic trajectories, and (2) we demonstrate that our approach can extract valid trajectories effectively in different indoor settings.

II. Movement Constraint

Our approach, the movement constraints, limits the movement from a semantic position to the accessible/close semantic position in a short time. Suppose a set S as the walkable semantic positions in the indoor plan and we predict a semantic position $\hat{s}^{(t)} \in S$ at time t. The next predicted semantic position $\hat{s}^{(t+1)}$ should be accessible from $\hat{s}^{(t)}$. However, we do not apply this constraint at the beginning ($t = 1$). Thus, we use the default prediction case from each machine learning model. Thus, we always produce a valid trajectory using those constraints.

Example 1. For example, in Figure 1, we represent the indoor floor plan as the graph on the upper-right. The node in semantic graph indicates a semantic position. If a semantic position is accessible to and close to another semantic position, their connection is represented by a bidirectional edge. Thus, if our predicted position is currently at the $Stairs$ area, we can only move to a $Hallway$ area or stay at $Stairs$ area (yellow-shaded in Figure 1). Also, we cannot move to semantic positions such as $Room$ or $Elevator$ because they are directly inaccessible or very far from each other.

We see semantic trajectory extraction as a continuous classification task. Then, we can enhance various ML-based indoor

TABLE I
DETAILED DATASET DESCRIPTION

Dataset	PNU	iBeacon
Deployed beacons	8	13
Semantic positions	14	48
Area	64.5 m × 17.4 m	80 m × 50 m
Reference set	72	143
Test set	28	16
Total length (points)	38,967	1,420

positioning techniques, such as HMM with constraints (HMM-C), K-Nearest Neighbor with constraints (KNN-C), and Deep Neural Network with constraints (DNN-C).

III. Experiment and Results

We experimented on two different datasets of BLE beacons indoor settings: the PNU and the modified iBeacon [4]. Table I describes the details of the dataset. We also depict the deployment details and the division of the semantic positions of both datasets' floor plan in 2. We modify the iBeacon to have 14 semantic positions with 8-neighbors. Thus, if the predicted semantic position is at the non-border positions, it can move to 8 surrounding positions or stays at the same position.

We compare our constrained approaches (HMM-C, KNN-C, and DNN-C), to the original HMM, KNN, and DNN. While the KNN-based methods use reference set to predict the semantic position, other methods use the set as the training data. We develop all our proposed methods from scratch except the base of DNN. We use Weka [5] to build our 3-layered DNN using hidden layers of 10, 20 and 15 neurons and maximum epoch of 200.

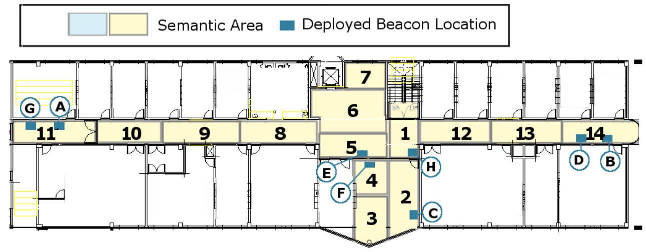
We measure the effectiveness of the methods by the classification error by comparing the predicted semantic position $\hat{s}^{(t)}$ to the ground truth $s^{(t)}$. The equation 1 describes the classification error formula of a predicted semantic trajectory $\hat{ST}$ to the ground truth ST. For the final result, we average the error of all trajectories in the test set.

$$Err(\hat{ST}, ST) = \frac{1}{|ST|} \sum_{t=1}^{|ST|} \begin{cases} 1, \hat{s}^{(t)} \neq s^{(t)} \\ 0, \hat{s}^{(t)} = s^{(t)} \end{cases} \quad (1)$$
$$\text{where} \quad \hat{s}^{(t)} \in \hat{ST}, s^{(t)} \in ST$$

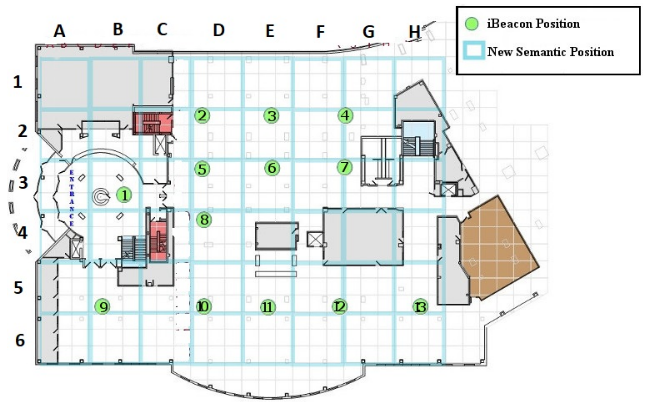
In Figure 3, our constrained approaches worked slightly better than the originals in both datasets with smaller errors. We also see that, given the datasets have a very small number of beacons, is effective to work in an unlikely environment. All approaches worked better in dataset iBeacon because it has more reference/training set than the PNU dataset.

IV. Conclusion

We have applied movement constraints to various indoor positioning techniques to extract valid indoor semantic trajectories effectively. We have demonstrate that our constrained ML-based approaches has improved the original approaches in terms of classification error in two different environments . Thus, in the future, we can avoid impossible patterns when we analyze big indoor semantic trajectories.



(a) PNU



(b) Modified iBeacon [4] dataset (iB)

Fig. 2. Deployment information of the collected datasets

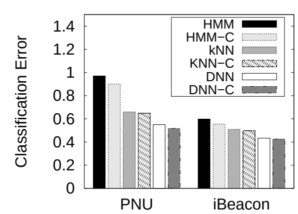


Fig. 3. The classification error of the extracted semantic trajectories

References

[1] Q. Wang, R. Sun, X. Zhang, Y. Sun, and X. Lu, "Bluetooth positioning based on weighted K-nearest neighbors and adaptive bandwidth mean shift," *International Journal of Distributed Sensor Networks*, vol. 13, no. 5, p. 155014771770668, may 2017.

[2] D. Yamamoto, R. Tanaka, S. Kajioka, H. Matsuo, and N. Takahashi, "Global map matching using ble beacons for indoor route and stay estimation," in *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, 2018, pp. 309–318.

[3] H. Li, H. Lu, G. Chen, K. Chen, Q. Chen, and L. Shou, "Towards translating raw indoor positioning data into mobility semantics," *Proceedings of the VLDB Endowment*, vol. 11, no. 3, 2017.

[4] M. Mohammadi, A. Al-Fuqaha, M. Guizani, and J. S. Oh, "Semi-supervised Deep Reinforcement Learning in Support of IoT and Smart City Services," *IEEE Internet of Things Journal*, pp. 1–12, 2017.

[5] "Weka 3: Machine learning software in java." [Online]. Available: http://www.cs.waikato.ac.nz/ml/weka/