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반지도식 자기조직화지도를 이용한 wifi fingerprint 보정 방법

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Wifi Fingerprint Calibration Using Semi-Supervised Self Organizing Map

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요 약

무선 RSSI fingerprinting 방식은 기존 무선 인프라를 이용하면서 적정수준의 정확도를 얻을 수 있는 실내위치 인식 방법 중의 하나이다. 하지만 라디오 맵 구성(fingerprint calibration) 과정에서 목표 환경의 다양한 위치에서 정확한 물리적 좌표와 무선 신호를 측정해야 하므로 시간과 노력이 많이 소요된다. 이 논문은 이러한 방식으로 위치 정보를 수집하지 않고 반지도식 자기조직화지도 학습 알고리즘을 사용하여 labeled RSSI를 얻고 RSSI 조합으로부터 맵을 구성하는 방법을 제안한다. 모의 데이터에 대한 실험을 통해 제안 방법이 fingerprint 데이터베이스로부터 1%의 RSSI 샘플을 가지고 효과적인 전체 맵을 얻을 수 있다는 결론을 얻었다.

Key Words : Indoor positioning, fingerprint calibration, self organizing map, RSSI

ABSTRACT

Wireless RSSI (Received Signal Strength Indication) fingerprinting is one of the most popular methods for indoor positioning as it provides reasonable accuracy while being able to exploit existing wireless infrastructure. However, the process of radio map construction (aka fingerprint calibration) is laborious and time consuming as precise physical coordinates and wireless signals have to be measured at multiple locations of target environment. This paper proposes a method to build the map from a combination of RSSIs without location information collected in a crowdsourcing fashion, and a handful of labeled RSSIs using a semi-supervised self organizing map learning algorithm. Experiment on simulated data shows promising results as the method is able to recover the full map effectively with only 1% RSSI samples from the fingerprint database.

Ⅰ. Introduction

Nowadays, smartphone has become indispensable gadgets to everyone. Growing with their widespread use is the flourish of context awareness based services such as targeted advertisement, image geo-tagging, and proximity social networking. Their market value is estimated to worth US$10 billions by 2020[1]. For proper functioning of such services, user dynamic location is the crucial information that

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must be provided. Although Global Positioning System (GPS) units equiped in smartphone can obtain accurate location information in outdoor environment, they often perform poorly inside concrete buildings due to the fact that satellites' signal is none-exist or usually significantly week in indoor environments. New positioning techniques have been developed over the last decades[2] to overcome that hurdle by utilizing different hardware requirements. Among them, the wireless fingerprinting technique has recently become a research focus[3].

The approach is appealing as it can utilize existing wireless infrastructure while as the same time guarantees a reasonable level of localization accuracy. With the astonishing growth of public wireless networks, it is foreseeable that the approach has enormous potential. The main idea of fingerprinting method hinges on a reasonable assumption that similarity in geographic domain is transferable to signaling domain. In essence, wireless signal profiles measured at proximity locations should look noticeably similar. Therefore if we have a database of fingerprints , e.g. signal profiles measured at known locations, localizing an individual become straightforward by querying the database for location with the most similar signal profile.

However, fingerprinting-based method is without limitations. The need for manual calibration of the database is a key bottleneck since it is labour intensive. Further, the process has to be repeated for each new target area, or whenever there is a significant rearrangement of current environment, for example when a new wireless access point (AP) is added or existing one is repositioned. The cost of manual calibration thus hinders the widespread adoption of the method. Reducing the amount of calibration effort while retaining the localization accuracy is the main target of this research.

Early approaches[4,5] adopted the interpolation technique to recover signals at unknown locations. Basically, only a reduced number of locations are considered for wireless signal measures while the remaining locations' signal can be recover with mathematical computation. For that, knowledge of APs' locations must be available and a valid model of signal propagation has to be provided. Subsequently, some other works[6,7] have embraced the idea of utilizing crowdsourced data for inferring the full radio map. In these approaches, general users can participate in the data collection activity during normal operation of wireless devices. The collected data of this type is considered as unlabeled samples since the true locations of measurement are not known. By combining with some labeled samples, e.g. signal measurements at reference points (RP), full radio map can be inferred using semi-supervised learning techniques. Meanwhile, a large number of works[8-10] exploits additional data from inertial sensors embedded in smartphone. Although they can reduce the calibration efforts in some extent, the engagement of additional sensors raises new issues, such as availability, battery consumption and device heterogeneity.

In this research, we endorse the idea of combining labeled data and unlabeled data for learning the radio map. While solving the question of assigning location information for the unlabeled signal samples, previous methods formalize this into a projection problem where high dimensional RSSI data is projected onto the geographical space. Here, we view the problem as a matter of data cluster labeling. We first divided the indoor plan using grid lines into small cells of predefined size then consider cell centers as predefine locations. At the same time, the RSSI samples are grouped into clusters based on their similarity. Finally, the resulting clusters are mapped to the locations in a manner that preserving local topology. We apply a self organizing map learning (SOM) algorithm to integrate the two tasks into one framework. As the algorithm is known for regularly producing arbitrary results, we use labeled samples to guide the learning process to approach consistent solution.

The rest of the paper is organized as follows. In section II we briefly explain the basic concept of fingerprinitng method and relate works for fingerprinting map calibration. Section III explains the core concept of SOM learning and how we frame the problem into SOM learning framework. In Section IV, we describe the process of simulating data for experiment, followed by evaluation results of our method. We conclude with some remarks and discussions in the Section V.

Ⅱ. Related works

2.1 RSSI fingerprinting

Although various methods has been developed for indoor positioning systems, RSSI fingerprint matching is still one of the most popular approaches[2,3]. Its basic idea is based on the assumption that each spatial location can be identified by a unique measurable feature such as wireless signal, just like a human fingerprint. The method consists of two phases: an offline training phase (a.k.a fingerprint calibration) and an online localization phase. In the first phase, indoor plan of a building is usually represented as a set of discrete locations then wireless signals are measured at these points. Next, machine learning technique is utilized to build localization model that creates a mapping between locations and signals. The mapping is called fingerprint database. In the online localization phase, wireless signals measured by a user's smartphone is sent to system server to query the user's current location. A localization algorithm such as *k*-Nearest Neighbor (*k*-NN) at the server estimates the most likely location by matching the query signal with the fingerprints in the database.

The accuracy of a fingerprint based localization system is highly dependent on the quality of training data that is used for building the fingerprint database. The quality is defined solely by two factors: the accuracy of measured signals, and the density of RPs distribution. The strength of wireless signal is known to be temporally fluctuating and their measures also vary with many factors including device models, user's physical positions and user's movements, thus multiple measures at the same location has to be performed for better quality control of the signal. Beside, a fine-grained fingerprint database with a large number of RPs is a-must if high accuracy localization is required. As a result, collecting data for building the fingerprint database is usually a labor-intensive manual calibration. Furthermore, this process must be repeated if the training data are outdated due to changes in the environment such as addition, removal and relocation of APs. Reducing calibration efforts is therefore essentially important for practical implementation of fingerprint based indoor localization systems.

A recent favorable approach in reducing calibration efforts is utilizing a large amount of unlabeled data to learn the fingerprint database. Here, an unlabeled data sample is a wireless signal record from a smartphone without the location information of the device. Wireless signal profile with known location is called labeled sample. Collecting unlabeled samples is much easier than collecting the labeled samples as it can be done while a carrying-smarphone individual walking freely inside a target environment. It is especially suitable in a crowdsourcing system where wireless signals are collected from normal users while they are using localization service. Usually both unlabeled data and labeled data are provided as inputs to a semi-supervised learning machine so that it can learn to label the location information for the unlabeled samples.

2.2 Calibration with Multi-Dimensional Scaling

Multi-Dimensional Scaling (MDS) is a method widely used for visualizing high dimensional data. The algorithm aims to place samples in high dimensional space to d-dimensional space (usually $d=2$) such that the sample-between distances are preserved as much as possible. Each sample is then assigned coordinates in each of the d dimensions. The algorithm therefore can be adapted to learn the location coordinates of wireless signal in the fingerprint based localization systems[6]. The classical MDS can be described as follows.

Let $x_1, x_2, .., x_N$ be the wireless signal measurements where N is the number of measurements. Each x_i is a vector of M dimensions where M is the number of APs available in the indoor environment. The algorithm aims to map each sample x_i to a point $l_i = (l_i^x, l_i^y)$ in Euclidean space in a way that minimize the difference of distance between samples. Here l_i^x, l_i^y are physical coordinates of the location i^{th}. Let $d_{i,j}$ be the Euclidean distance between x_i and x_j then the problem can be turned in to a optimization problem with a loss function of the form:

$$f(x_1, x_2, .., x_N) = \sum_{i,j} (d_{i,j} - \| l_i - l_j \|^2)$$

The classical MDS has an analytical solution which can be found in popular advanced linear algebra textbooks.

The estimated coordinates from the classical MDS usually differ from the correct locations, thus adjustments need to follow. The authors in [6] proposed a re-calibration procedure using a small number of labeled samples as anchor points to correct absolute coordinates using linear transformation.

2.3 Calibration with Isomap

Another method considers the calibration problem as multidimensional reduction is Isomap[7]. While MDS tries to find a lower dimension representation of the data with smallest distortion of the between-samples distances, the Isomap aims to preserve the local structure of samples. The algorithm is identical to the MDS with one exception is that the distance metric is Geodesic instead of Euclidean.

In the Isomap, the geodesic distances $d_{i,j}$ are obtained by following procedure. First, a neighborhood graph is constructed from the high dimensional data (RSSIs). Each sample x_i is a vertex of the graph and it is connected to its K nearest neighbors in Euclidean distance estimated from the data. The weight of an edge connecting two vertexes is defined as their Euclidean distance. The distance $d_{i,j}$ then calculated as the sum of edge lengths along the shortest path connecting them. The shortest distance between two vertex can be found with the wellknown Floyd-Warshall algorithm.

Ⅲ. Method

3.1 Self Organizing Map

Self Organizing Map (SOM)[11] is a special type of artificial neural networks with a principal goal is transforming high dimensional input data into a much lower dimensional map, usually one or two dimensions. A typical structure of SOM is illustrated in Figure 1. Basically, it consists of a set of neurons, each is associated with two entities: a weight vector of the same dimension as the input data vectors; and a position in a map space. The arrangement of neurons is usually in the form a two dimensional regular spacing in a hexagon or rectangular grid. The structure of SOM describes a mapping from high dimensional input data space (input layer) into the map space. Mapping an input vector to a neuron is to search for the best neuron whose weight vector is the most similar to the given input. Therefore, similar input samples are grouped in the same neuron or its neighbors. Unlike other types of neural networks that base their learning on error-correction method, SOM learns their weigh vectors in a competitive process.

Let $X \subset R_M$ be the input data, L be the set of SOM's neurons, and W be the $M \times |L|$ weight matrix. Here, M is the dimension of the input and $|L|$ is the size of the output map, that is the number of neurons. Row w_j of the matrix W is the weight

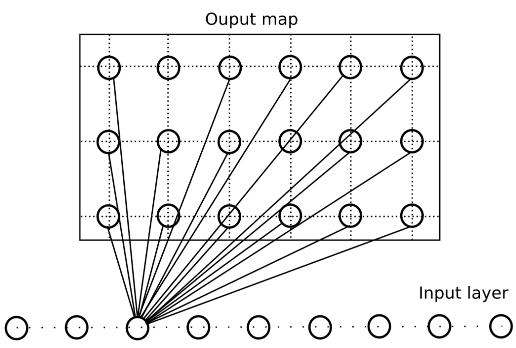

Fig. 1. A typical structure of a Self Organizing Map neural network

vector corresponding to the j^{th} neuron of the output map. The learning algorithm is based on this following pattern: given an input sample $x \in X$, find a neuron $i^* \in L$ whose weight vector is the most similar to x: $i^* = \arg max_{j \in L}(w_j x)$; that neuron is call best matching unit (BMU); adjust the weight vectors of all neurons follows:

$$w_j(t+1) = w_j(t) + \beta(t) H_{i^*,j}(t)(x - w_j)$$

where t is the current number of training iterations, $\beta(t)$ is learning rate that varies over time, $H_{i^*,j}$ is a neighborhood function centered around the BMU. Gaussian kernel is a common choice:

$$H_{i^*,j}(t) = e^{-\frac{d_{i^*,j}}{2\sigma(t)^2}}$$

where $d_{i^*,j}$ is the Euclidean distance between two neurons i^* and j in the output map space, and $\sigma(t)$ is a varying neighborhood size.

3.2 Fingerprint map calibration using SOM

SOM with a few neurons behaves somewhat similar to K-mean clustering. On the contrary, larger SOM rearrange input data in a way that fundamentally topological in character. We take advantage the later property to construct the full radio map for fingerprint-based localization. The indoor plan of the site is divided into small cells of identical size using grid lines. We then position the output neurons of the SOM at the centers of the cells. The set of RSSI samples, collected either by crowdsourcing system or design process, is considered as input data X for learning the weight vectors. It is common that the result of learning SOM is inconsistent, output map is arbitrary, depending on the initialization strategies. Therefore, we may expect that the result is a distorted image of the truth map. To overcome this drawback, we utilize the known locations of labeled samples to lock the output map to those anchors. It can be done in following fashion.

Let $X = X_L \cup X_U$ where X_L is the set of labeled samples and X_U is the set of unlabeled samples. Each labeled sample is coupled with its location to make a tuple (x_i, l_i) where $x_i \in X_L$, $i = 1, 2, .., |L|$ and $l_i \in L$ is its label, e.g. the index of neuron that corresponds to the location of measurement x_i. Each location l_i is implicitly mapped to a tuple (l_i^x, l_i^y) of known physical coordinates in a $1:1$ correspondence. For the sake of simplicity, when we mention the index l_i of a neuron, we also imply the presence of its physical coordinates. Our training algorithm has two modifications from the classical SOM learning. First, in the initialization of the weigh vectors, we use the whole labeled samples to learn their initial values. In the second step, all samples are drawn sequentially to train the weight vectors as in classical method. However, for each labeled sample input x_i, we do not search for BMU, instead, its BMU is immediately set to be the label l_i. That forces l_i consistently to be BMU of x_l and help anchoring the output map to known locations. The pseudocode of the algorithm is shown on Figure 2.

Algorithm 1 Learning SOM

Input: Labeled samples X_L, Unlabel samples (X_U, L), number of learning rounds r, learning rate bounds β_0, β_T, neighborhood size bounds δ_0, δ_T
Output: Weight matrix W
Set learning rate $\beta \leftarrow \beta_0$
Neighborhood size $\delta \leftarrow \delta_0$
//Step 1: Initialize the weigh matrix using anchors (the labeled samples)
$W \leftarrow 0$
for all $(x_i, l_i) \in (X_L, L)$ **do**
  Set x_i's BMU $bmu \leftarrow l_i$
  for all neuron l **do**
    Estimate $H_{l,bmu}$
    $w_l \leftarrow w_l + \beta H_{bmu,l}(x_i - w_l)$
  end for
end for
//Step 2: Learning weight matrix from all samples
for $i \leftarrow 1, r$ **do**
  for all x_i in $X = X_L \cup X_U$ **do**
    Adjust β and δ
    if $x_i \in X_L$ **then**
      $bmu \leftarrow l_i$
    else
      Find bmu
    end if
    for all neuron l **do**
      Estimate $H_{l,bmu}$
      $w_l \leftarrow w_l + \beta H_{bmu,l}(x_i - w_l)$
    end for
  end for
end for

Fig. 2. Pseudocode for the weight matrix learning algorithm from labeled and unlabeled samples.

Ⅳ. Experiment results

4.1 Data simulation

We evaluated the performance of the proposed method on simulated data. The data is generated with an indoor log-distance path-loss propagation model. In the model, received wireless signal power is defined as:

$$P_{rx}(d) = P_{rx}(d_0) - 10\gamma \log_{10}(\frac{d}{d_0}) + w$$

where the power $P_{rx}(\bullet)$ is given in logarithmic scale, d_0 is a reference distance, γ is a path exponent, and w is a normally distributed random noise which models the shadowing effect. The two parameter γ and $w$are dependent on the local propagation environment. In our simulation, we set $\gamma = 2.2$ and $w = 7dB$ to reflect an office environment. Typically, the reference distance d_0 is set to $1m$ and the signal power at the reference $P_{rx}(d_0)$ is known in advance. Here we assume that APs have different values of $P_{rx}(d_0)$ which follow a normal distribution of mean $-50dB$ and standard deviation $10dB$.

We assume that our experiment site is a single floor of a office building of size 20×100 meters. In that we assign 50 APs randomly using Latin hypercube sampling to guarantee their signal range cover the site map sufficiently. As for fingerprinting database construction, we divided the map into grid of $1m \times 1m$ cells. We using the aforementioned signal propagation model to generate RSSI for every point at center of the cells. That makes a database of $20 \times 100 = 2000$ fingerprints, each is a tuple of (x, i) where $x = x_1, x_2, .., x_{50}$ is a vector of wireless signal measurements and $i = 1, 2, .., 2000$ is the location index where measurement is taken. In our experiment, we picked only fraction of these samples to be labeled samples for the reconstructions the database. As for unlabeled data, we generate 10,000 signal samples from random location of the map. The location index of these samples is supposed to be unknown to the learning procedure, and later is used for evaluation of the localization performance.

4.2 Evaluation results

The SOM is learnt from the dataset combining of all unlabeled samples and a specific amount of labeled samples drawn randomly from the fingerprint database. Once the topological SOM map is built, the fingerprint database is available in form of its weight matrix W whose row w_j is the weight values of neuron j^{th}, and it can be considered as representative signal vectors at j^{th} locations. We then predict locations for unlabeled samples using 1 -nearest neighbor algorithm to report the localization errors. Note that in the learning procedure, coordinates of unlabeled samples are not known, thus it is normally feasible to reuse these samples for the localization accuracy evaluation. The error is estimated as average Euclidean distance from predicted location to the original location.

During the training process, the learning rate parameter $\beta(t)$ and the neighborhood size parameter $\sigma(t)$ are adapted to the number of training iterations following a exponential decay function:

$$f(t) = f(t_0) \frac{f(T)}{f(t_0)^t}$$

where T is the total number of training iterations, $f(0)$, $f(T)$ and $f(t)$ are the parameter value at the beginning, the end and at t^{th} learning iteration. We set $\beta(0) = 0.5$, $\beta(T) = 0.005$, $\sigma(0) = 50$ and $\sigma(T) = 1$. We trained the network for multiple rounds, in each round, all samples are presented sequentially. At the end of each round, overall training error is estimated as the average localization error of unlabeled samples. Figure 3 shows the convergence of the network as the training errors approach a constant small level after only 15 training rounds.

To investigate the effectiveness of full radio map recovery, we learned the networks using different

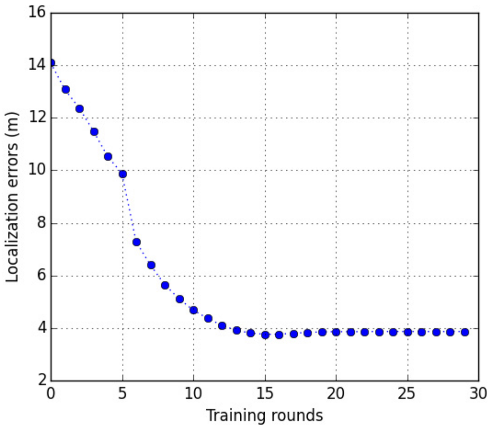

Fig. 3. Convergence of the learning algorithm

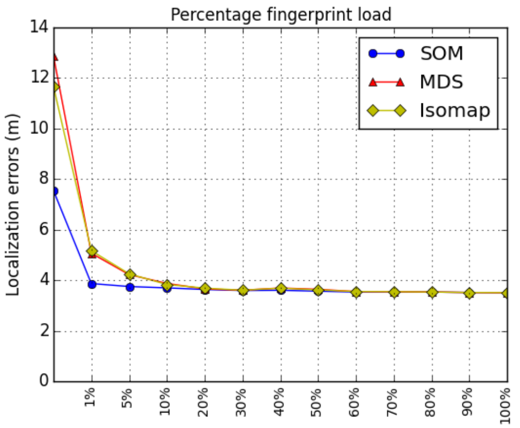

Fig. 4. Comparison of the effectiveness of radio map recovery from partial labeled data.

amount of labeled data, ranging from 1% to 100% number of samples, then evaluate the localization errors. The baseline error is $3.5m$ corresponding to 100% fingerprint load. In Figure 4, the blue solid line represents the localization errors of the proposed method versus the percentage of fingerprint data load. Without guidance of labeled samples, the localization errors is very large. However, the error is sharply decreased with the presence of labeled samples. With only 20% of fingerprint load, the achieved errors is mildly inferior to that of the baseline result. In extreme scenario where 1% fingerprint provided, we are only $0.4m$ off the baseline accuracy. The results clearly show the effectiveness of our proposed method

In the Figure 4, we also present the localization errors archived with the same settings of the other two methods: MDS and Isomap. Without the labeled data, these two methods also perform poorly. Their accuracies increase quickly once the labeled samples are introduced. However, they only keep up to the performance of the SOM method when the percentage load is at least 20%. After that, the three algorithm behave identically. The results show that our method is more effective as learning the radio map with a small percentage of labeled samples.

Additionally, our method has more practical usefulness compared to MDS and Isomap as training a SOM can be performed in an online fashion, that is data samples are presented sequentially. In MDS and Isomap, the whole data is used for training at the same time. Distances between every pair of samples have to be estimated which is computationally expensive, especially when a large crowdsourced data is used. On the contrary, our proposed method can utilize a previously built map to initialize the weigh vectors of the SOM then update their parameter values continually as new data samples are presented. No re-training with the whole data is necessary. This feature is extremely beneficial to the practical implementation of indoor positioning system as it is wellknown that radio map needs to be updated frequently due to the fluctuating nature of indoor environment.

V. Conclusion

In this paper, we proposed a method to learn radio map for indoor positioning. By utilizing a combination of crowdsourced RSSIs without location information and a handful of wireless signals measured at precise reference locations, we are able to construct the full map with acceptable level of accuracy degradation. Evaluation on simulation data show that the method can fully recover the radio map with only 20% fingerprint load. Event in the extreme case where only 1% fingerprint data is presented, the constructed map still manage to lost a 0.4m of localization accuracy. Our method has not utilized the dynamic of user movement which can be acquired with other type of sensors such as gyroscope or accelerometer. We believe that such information can be further improve the performance our method and we will follow that road in the future.

References

[1] H. Liu, S. Member, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," vol. 37, no. 6, pp. 1067-1080, 2007.

[2] G. Kim, I. Park, Y. I m, A. Hong, J. Kim, and Y. Shin, "Recent trends in location-based services," *J. KICS*, vol 28, no. 7, pp. 3-14, Jun. 2011.

[3] S. He, S. Member, S. G. Chan, and S. Member, "Wi-Fi fingerprint-based indoor positioning : Recent advances and comparisons," *IEEE Commun. Surveys & Tuts.*, vol. 18, no. 1, pp. 466-490, 2016.

[4] X. Chai and Q. Yang, "Reducing the calibration effort for probabilistic indoor location estimation," *IEEE Trans. Mob. Comput.*, vol. 6, no. 6, pp. 649-662, 2007.

[5] M. D. Redžić, C. Brennan, and N. E. O. Connor, "SEAMLOC : Seamless indoor localization based on reduced number of calibration points," *IEEE Trans. Mob. Comput.*, vol. 13, no. 6, pp. 1326-1337, 2014.

[6] T. Pulkkinen, T. Roos, and P. Myllymäki, "Semi-supervised learning for WLAN positioning," *Artif. Neural Netw. Mach. Learn.*, vol. 6791, pp. 355-362, 2011.

[7] J. Niu, et al., "WicLoc: an indoor localization system based on WiFi fingerprints and crowdsourcing," in *Proc. ICC '15*, pp. 3008-3013, Jun. 2015.

[8] M. Alzantot, "CrowdInside : Automatic construction of indoor floorplans," in *Proc. Sigspatial Gis*, pp. 99-108, Redondo Beach, California, Nov. 2012.

[9] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-Effort crowdsourcing for indoor localization," in *Proc. Mobicom '12*, p. 293, 2012.

[10] H. Abdelnasser, R. Mohamed, A. Elgohary, M. Farid, H. Wang, S. Sen, R. Choudhury, and M. Youssef, "SemanticSLAM: Using environment landmarks for unsupervised indoor localization," *IEEE Trans. Mob. Comput.*, vol. 15, no. 7, pp. 1770-1782, Sept. 2015.

[11] T. Kohonen, "Self-organized formation of topologically correct feature maps," *Biological Cybernetics*, vol. 43, no. 1, pp. 59-69, 1982.

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