A CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE FOR MULTI-FLOOR INDOOR LOCALIZATION BASED ON WI-FI FINGERPRINTING

Xin Chen[1,2], Wan-Chi Siu[1], Yuk-Hee Chan[1], Chuen-Yu Chan[2] and Chun-Pong Chau[3]

[1]Department of Electronic and Information Engineering
The Hong Kong Polytechnic University, Hong Kong
[2]Maphive Technology Limited
[3]School of Professional Education and Executive Development
The Hong Kong Polytechnic University – HKCC, Hong Kong

***Abstract*—Nowadays Location Based Services applications are increasingly useful. However, problems like floor identification for multi-buildings and adverse effects of devices diversity are needed to be resolved. In this paper we propose a new approach using cosine similarity computed by Wi-Fi fingerprints and radio map and using Convolutional Neural Network (CNN) model to achieve multi-floor classification. We propose in this paper to use locations-based similarity as the feature vector instead of using conventional Access Point sets. We also use a timesaving walk-survey method to collect Wi-Fi fingerprint. Experimental results show that our proposed CNN floor classifier has 98.37% training accuracy and 99.51% test accuracy. Compared with recent deep neural networks, our proposed approach achieves state-of-the-art floor classification accuracy but only needs a training data set almost 5 times smaller than that of other approaches.**

Keywords—Cosine similarity, CNN, small data set, floor classification

I. INTRODUCTION

Positioning is to find out in real-time the location of a pedestrian, vehicle etc [1-3]. Particularly, indoor positioning has become increasingly popular and important because people spend around 70 percentage of time to stay indoors in modern society[1]. However, the trend in Location Based Services(LBS) applications becomes more complicated[4]. These applications are no longer just about indoor positioning on one floor. It has been found that it becomes very useful to know the floor positioning between different floors and between different buildings. Say, the Hong Kong Government has planned to have digital maps of major buildings in Hong Kong and city-wide pedestrian network data between indoor and outdoor by the end of 2024. In this paper we propose a system to solve the indoor positioning problem for multi-floor buildings.

It is well known that Global Positioning System(GPS) is a mature technology to find out where you are in the outdoor environment. GPS could provide very high accurate and real-time location in the outdoor. However, the GPS technique often fails to provide accurate locations in indoor environments[5]. Due to the obstruction of the building wall, the GPS signal is weakened or even cannot be obtained in the indoor environment[6]. Therefore, over the past few decades, scholars have proposed many different new methods or techniques to achieve or optimise indoor positioning, such as Wi-Fi finger printing[7], iBeacon[8], Ultra-Wide Band(UWB)[9], Round Trip Time(RTT)[10], Radio-Frequency Identification(RFID) [11], geomagnetic indoor positioning technology[12], Light-Emitting Diode (LED) based indoor positioning[13] and visual indoor positioning methods[14].

Wi-Fi finger printing is one of the most widely used technologies in indoor positioning. This method could provide relatively high precision positioning results with relatively low computational cost. One significant advantage of its wide usage is because it has high scalability and it can work together with other positioning technologies[15-16]. Another important advantage of Wi-Fi finger printing is that it has very low deployment cost. Most current indoor environments themselves have already deployed Wi-Fi, so this technology basically has no additional hardware deployment cost, and the data construction cost is also low[15].

In this paper, we aim to provide a higher accuracy solution for indoor floor detection based on Wi-Fi fingerprint. Researchers have already proposed some methods for indoor floor detection based on Wi-Fi fingerprint. The most common methods are Support Vector Machine(SVM) and Deep Neural Network(DNN) architecture. Zhang et al[17] proposed a classic two-class SVM classification to do floor recognition for three indoor floors. Chriki et al[18] presented two kinds of multi-class SVM classification in a building which consists of 21 rooms spread over three floors. These multi-class SVM methods got improvement making use of their proposed data. Swargam et al[19] compared various machine learning models including SVM and combined with K-Nearest Neighbors (KNN) classification algorithm to achieve floor localization. Alitaleshi et al[20] introduced a hierarchical structure of Extreme Learning Machine(ELM) to solve the problem of WiFi-fingerprint based floor estimation. Kim et al [21-22] described two DNN based

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architecture for indoor building and floor classification. Both of these two architectures mainly consisted of two parts: (i) an encoder to extract the features of input Wi-Fi data and (ii) a classifier for building and floor classification. The difference was that one classified with flattened building-floor together and the other classified the buildings and the floors separately. Quezada-Gaibor et al[23] proposed a new solution to combine Convolutional neural networks (CNNs) and ELM to achieve faster multi-building and multi-floor localization.

However, by using the above methods to achieve indoor building classification and/or floor classification, they all just made use of the real Received Signal Strength(RSS) data and did not consider the effect of device diversity. The effect of device diversity means the value of RSS signal varies when the survey uses different devices. The variations may come from different brands or system architectures of smartphones. At the same location this may have a small or even huge effect on the accuracy of classification result[24]. Also, the above methods all required a large training dataset for these models, which would take a long time to complete the Wi-Fi survey of all floors in a building and have high labour costs.

To address these drawbacks, we propose a multi-stage system using similarity and Convolutional Neural Network(CNN) model with small training dataset to solve the multi-floor classification problem. The remaining content of this paper is organised as follows. Section 2 describes the proposed approach. Section 3 introduces the experiments details and results. Finally, Section 4 give a conclusion and some potential directions for future works.

II. Proposed Approach

A. *Wi-Fi Fingerprints and Radio Map*

Wi-Fi fingerprint is a set of Wi-Fi Access Point (AP) signals collected by a WLAN antenna in one scan. It represents the signal features on the sampled location, that are transmitted from surrounding wireless routers, mobile hotspots, etc. Benefiting from the mobile communication technologies, it is simply to collect Wi-Fi fingerprints via any consumable smart phones. For instance, a Wi-Fi scan resulted from Android OS consists of several scanned AP with details. Each AP signal contains information of its SSID, BSSID, RSSI, and channel frequency (showed in Table 1).

BSSID (Basic Service Set Identifier), aka MAC (Media Access Control) address, which is a unique, 12-character alphanumeric attribute (e.g., 34:8f:27:e4:28:d8) that is used to identify individual electronic devices on a network, is used as the identity of an AP.

TABLE I.

Wi-Fi fingerprint sample

Wi-Fi Fingerprint	SSID	BSSID	RSSI	Freq.
AP1	CPCE_WiFi_Config	34:8f:27:e4:28:d8	-48	2437
AP2	CPCE_Student	34:8f:27:64:28:dc	-56	5560
…	…	…	…	…

RSSI (Received Signal Strength Indicator), which refers to the AP radio strength power received by the sampling device antenna, is used as the feature value in Wi-Fi fingerprints. This value is the log of radiation power which is usually a negative integer with unit of dBm, e.g. -75 dBm. The larger the RSSI value, the stronger the signal. The lowest strength for most smart phone is -95 dBm.

In our propose approach, we suggest to use only the BSSID and RSSI as the properties of a fingerprint. A Wi-Fi fingerprint is represented as a vector in AP dimensions, with contents like :

[$BSSID_1$: -47, $BSSID_2$: -94 , … …]

Sufficient amount of fingerprints have to be used collecting from the whole site to build a signal radio map. Typically, radio map is floor-based. The floor plan is divided into grid points (GPs) to integrate fingerprints that scattered around. Floor radio map consists of many GPs. Each GP has a representative fingerprint that gathers surrounding fingerprints, i.e. AP signals with their respective average signal strength (RSSI). A radio map is assembled in the following form:

{
GP1: [$BSSID_1$: -60.3, $BSSID_2$: -45.5, … …],
GP2: [$BSSID_1$: -75.0, $BSSID_4$: -90, … …],
GP3: [$BSSID_2$: -73.3, $BSSID_5$: -35, … …],
… …
}

B. *Feature Space*

Researchers had suggested various solutions to use Wi-Fi fingerprint features to achieve floor classification. For fingerprinting-based positioning, most of these approaches adopt vectors of AP strength directly as the raw input. To unify all samples in the same vector space, the whole AP set that appears on the same floor is used to construct the feature vector. This will form a very sparse matrix as the feature of the location. DNN could be used [21-22] to reduce the dimension of the feature space for robust and precise classification. Similarity measure is another important point in Wi-Fi fingerprinting. Cosine similarity has been used to solve the device diversity problem for indoor positioning based on Wi-Fi [25].

In this paper, we propose an approach to achieve floor classification by using the cosine similarities between the sampled fingerprints and the radio map, i.e., the grid representative fingerprints, as the feature vector. The dimension of this feature space will be determined by the number of grid points on corresponding floor radio map.

Cosine similarity is used to evaluate the similarity between two sequences independently from their length. One advantage of cosine similarity is its low complexity, especially for sparse vectors: only the non-zero coordinates need to be considered. That is suitable to act as a pre-treatment of the sparse AP signal vectors. The cosine similarity is calculated by:

$$cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \, \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2} \sqrt{\sum_{i=1}^{n} {B_i}^2}}$$

where **A** refers to a sample fingerprint vector, **B** refers to a grid representative fingerprint vector from the radio map, n is the total AP set number of **A** and **B**.

The novelty of our idea is to let this similarity vectors be features and fed to the training model instead of raw signal strength vectors. In our proposed approach, a training vector includes grid points from all floors. We have to sort the grid points in a fixed order, starting from 0,1, … N-1, where N is total number of grid points of the whole building.

C. Floor Classifier Model: AlexNet

Cosine similarity has been suggested as the feature vectors and CNN (AlexNet) model instead of DNN model is chosen, because this arrangement can exhibit the spatial relationship and lighten the effect of signal strength. Fig.1 shows the similarity distribution of a fingerprint sample. The small dots are the grid point locations of a floor radio map. The dot color indicates the cosine similarity between the Wi-Fi fingerprint sample and the representative fingerprint on that grid point. The lines are the survey paths, and the red cross symbol indicates the ground-truth location that this Wi-Fi fingerprint was collected.

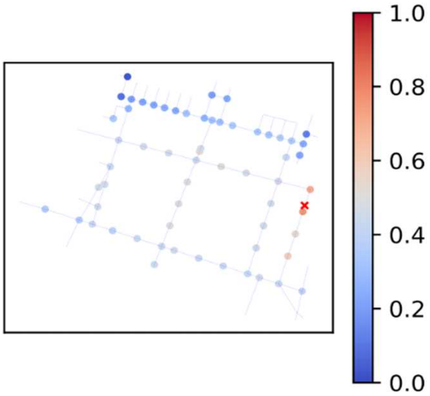

Fig. 1. Similarities distribution of a fingerprint.

D. Proposed Training Process

For the training process, we need to generate the radio map from the sampled Wi-Fi fingerprints collected for all floors. The radio map is a collection of grid points (GPs) with featured fingerprints. GPs from all floors are sorted as a sequence of similarities calculated with a sampled fingerprint in the sample pool to output an N-element feature vector. This vector is labeled with the right floor on which the fingerprint was sampled. All fingerprints in sample pool are used to generate the training set.

III. Experimental Work

A. Wi-Fi Survey

Point-to-Point(P2P) and walk-survey are the most useful survey methods in Wi-Fi fingerprinting. We used the walk-survey method which can reduce the time and labour costs [26] to collect Wi-Fi signals in all floors of The Hong Kong Polytechnic University (PolyU) Hung Hom Bay Campus for floor classification training and testing.

In this paper, we used android smart phone Google Pixel 5 to collect the training and testing Wi-Fi signals. The average scan interval was 2 seconds.

Fig. 2 shows a scheme of our walk-survey procedure. After finished the survey of all floors, we calculated the coordinates of each Wi-Fi fingerprinting.

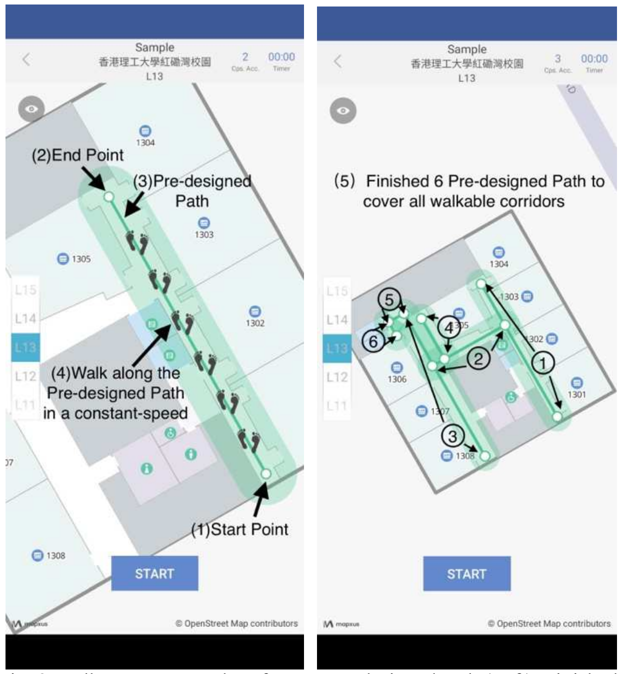

Fig. 2.Walk-survey procedure for one pre-designed path (Left). Finished walk-survey along walkable corridors in whole floor (Right).

In this paper, we used the constant-speed assumption and time interpolation to calculate the coordinates of each Wi-Fi fingerprinting. Therefore, the $pos_k = (x_k, y_k)$ is computed as below:

$$x_k = \frac{t_k - t_{start}}{t_{end} - t_{start}} (x_{end} - x_{start}) + x_{start}$$

$$y_k = \frac{t_k - t_{start}}{t_{end} - t_{start}} (y_{end} - y_{start}) + y_{start}$$

where (x_{start}, y_{start})refers the coordinate of start point and (x_{end}, y_{end}) refers the coordinate of the end point, t_{start} refers to the timestamp of start point and t_{end} refers the timestamp of the end point.

Then the Wi-Fi fingerprinting W_k was used to generate the radio map and to train and test the AlextNet Floor Classifier.

B. Training Data Set

When collecting the training data set, we used the walk-survey method which described in previous Wi-Fi Survey section to collect all 18 floors of the PolyU Hung Hom Bay Campus. On each floor, we did Wi-Fi survey of all walkable corridors.

Table 2 shows the details of training data set on each floor. The first row is the floor name of each floor. The Second row is the number of Grid Point, which means one location with coordinates. The Third row is the number of Wi-Fi fingerprints.

The number of all grid points is 1802 which is also the length of training vector. The number of Wi-Fi fingerprints is 6273 and it is also the size of training data set in this experiment.

C. *Testing Data Set*

When collecting the testing data set, we also used the walk-survey method to collect Wi-Fi data on all floors of the PolyU.

TABLE 2: TTHE DETAIL OF TRAINING DATA SET ON EACH FLOOR

Floor Name	UG	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16	L17
Number of Grid Point	203	146	123	168	76	80	82	79	88	140	62	100	63	64	59	106	107	56
Number of Wi-Fi fingerprint	845	644	429	501	278	168	174	184	211	361	146	277	176	160	195	332	1078	114

The length of pre-designed testing path could be different so the number of Wi-Fi fingerprints varies. The total number of Wi-Fi fingerprints is 408 and it is also the size of testing data set in this experiment.

IV. EXPERIMENTAL RESULTS

Figure 3 shows the training accuracy and loss of the AlexNet Floor Classifier. This figure shows that the model converges quickly and the training and testing accuracy have been 97.42% and 99.20% in fortieth epoches. After finishing 100 epoches in this work, the training and testing accuracies of this proposed approach have been 98.37% and 99.51%.

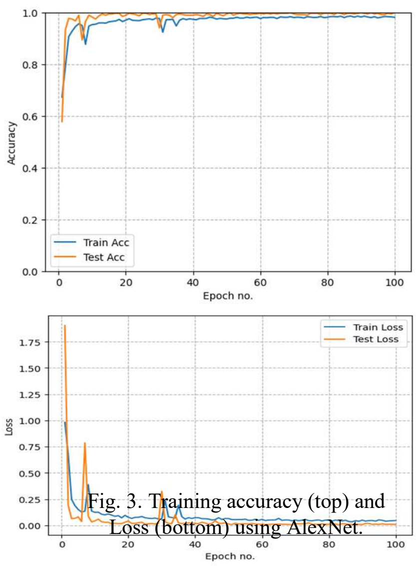

Fig. 3. Training accuracy (top) and Loss (bottom) using AlexNet.

Table 3 showed the accuracy comparison between others' work and the proposed approach in this paper. We got a competitive training accuracy among different methods and achieved the highest testing accuracy. Table 4 shows the size of different training datasets used in floor classification. The UJIIndoorLoc Data Set is the most popular Wi-Fi dataset used for indoor building and floor classification. The average numbers of samples of one floor both in UJIIndoorLoc Data Set and [5] are almost 5 times larger than ours.

Figure 4 shows (i) the training and testing accuracies with RSSI and (ii) cosine similarity as feature vectors. Both made use of the AlexNet as the classifier, and the dataset was obtained using the same walk-survey method to collect Wi-Fi fingerprints in a shopping mall in Hong Kong. This figure shows that our model converges more quickly when using cosine similarity as feature vectors and results of the training and testing accuracy are 95.63% and 98.73% in the 40th epoche, while using RSSI are 71.86% and 78.52%. After finishing 100 epoches, the training and testing accuracies of this proposed approach are 96.11% and 97.18% while the conventional approach using RSSI are only 75.80% and 75.41%.

V. CONCLUSIONS

In this paper, we propose a new strategic approach on using cosine similarity of Wi-Fi fingerprints, radio map and CNN deep learning with AlexNet to achieve multi-floor localization. The novelty of our approach includes the uses location-based cosine similarity and the data format for the input of the CNN model. Subsequently only a much smaller training dataset is required to achieve a competitive high accuracy in floor classification. This substantially reduce the training preparation for cities that is going to have indoor localization in all buildings, like Hong Kong. In the future, we will consider additional experiments to validate the improvements to device diversity problems of this proposed approach.

Table 3. The accuracy comparison with other methods.

Method	Train Accuracy(%)	Test Accuracy(%)
H-ELM[20]	99.71	98.13
UJI-KNN[27]	-	97.01
DNN based on SAE[21]	97.20	-
This paper	98.37	99.51

Table 4. The size of training dataset and time cost comparison with other methods.

Method	samples in training dataset	Average time for 1floor(min)	No. of Floor	Average samples of one floor
UJIIndoorLoc Data Set [20-21, 27]	19937	-	13	1533
Two-class SVM data set[17]	4999	30	3	1666
This paper	6273	12	18	349

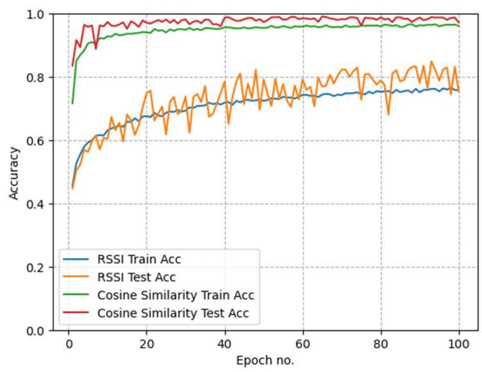

Fig. 4. Comparison between training and testing accuracies with RSSI as feature vectors and with cosine similarity as feature vectors; both making use of AlexNet in a shopping mall in Hong Kong.

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