Deep Learning-based Indoor Positioning System Using Multiple Fingerprints

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***Abstract*—Indoor positioning system (IPS) based on Wi-Fi signal has gained increasing attentions during the past few years due to the low cost of infrastructure deployment. In the Wi-Fi signal based IPS, the channel state information (CSI) has been widely used as the feature of locations because the CSI signal is more stable and contains richer location-related information compared to the received signal strength indicator (RSSI). However, the performance of the IPS depending on a single access point (AP) can be much limited due to the multipath fading effect especially in most indoor environments involved with multiple non-line-of-sight (NLOS) propagation paths. In order to resolve this problem, in this paper, we propose a hybrid neural network that employs multiple APs to receive the CSI from. Each AP provides unique fingerprints to all the locations. By fully utilizing all the fingerprints gathered from the multiple APs, which reduces the NLOS effect, the robustness of the IPS is significantly improved.**

Keywords—indoor positioning system, channel state information, non-line-of-sight, hybrid deep neural network, multiple fingerprints, robustness.

I. INTRODUCTION

In outdoor environment, global positioning system (GPS) can achieve a high accuracy due to the line-of-sight (LOS) signals; however, the performance of indoor positioning using GPS signal degrades significantly due to the blockage of buildings [1]. Compared to GPS signals, Wi-Fi signals are more stable and reliable in indoor environment due to its wide deployment and easy access. Thus, utilizing Wi-Fi signals to achieve accurate indoor localization has gained great popularity recently.

The methodology of utilizing Wi-Fi signals can be summarized into two groups. One is depending on received signal strength indicator (RSSI), and the other one is depending on channel state information (CSI). Since the RSSI changes over time even at the fixed location due to the multipath fading effect [2], the accuracy of the localization based on the RSSI is relatively low. In contrast to RSSI, CSI based indoor positioning system (IPS) has been researched extensively due to the ample information it carries with respect to subcarriers in an orthogonal frequency division multiplexing (OFDM) symbol.

Over the years, numerous localization technologies based on the CSI have been proposed, such as in [3], [4] for activity recognition and in [5], [6] for indoor localization. In those papers, machine learning algorithms such as K-nearest neighbor (KNN) [7], weighted K-nearest neighbor (WKNN) [8] and support vector machine (SVM) [9] are proved to be able to achieve excellent performance. Since those algorithms are primarily based on the features of data; therefore, how to select the features is vital in terms of getting a better performance. Conventionally, the feature recognition and selection require professional experience. However, when the amount of data needed for feature extraction is huge, the hand-engineering can become an intimidating work. In order to address this issue, in [2], deep neural network (DNN) solution has been proposed. The DNN has the ability to represent arbitrary mathematical functions by adjusting the weights of neurons through learning process during which features of the data can be automatically captured [10].

In the papers [5]-[10], the number of access point (AP) is limited to one, which means that all the locations only have one fingerprint as their identity feature. Although the claimed results in those papers seem reasonable, the environment where the experiments were conducted is mainly in the case of LOS. When NLOS is the dominant signal propagation path, which could be common when a number of walls, partitions, etc. exist, the problem is not properly emphasized and addressed in terms of the performance of the IPS in the related literature. In order to address the above issues, in this paper, we propose a new method which utilizes multiple APs and a hybrid neural network which combines multiple convolutional neural networks and a fusion network to increase the robustness of the. The main contributions of this paper are summarized as follows.

- Address the potential issues such as multipath effect and shadow fading that exist in the indoor environment where NLOS plays a dominant role in signal propagation.
- Address the limitation on the performance of the IPS when using a single AP as the source of constructing fingerprint map for locations.
- Propose a new method that utilizes the CSIs from multiple APs to create multiple fingerprints for all the locations to increase the robustness of the IPS.
- Propose a novel neural network to model the relations between the locations and multiple CSIs from multiple APs.

The rest of the paper is organized as follows. In section II, a brief introduction of the IPS structure, the CSI, and the process of data collection are presented. In section III, the detailed deep learning solution including the proposed deep neural network and data flow for training is explained. In section IV, the experimental results are shown and analyzed. In section V, the paper is summarized with the conclusion.

II. DATA PREPARATION

A. IPS

IPS can be divided into two phases. The first phase is offline phase, and the second phase is online phase.

During the offline phase, the training data set collected at reference points (RPs) from different APs are used to conduct deep learning process during which the weight of the neural network will be updated based on the loss function and optimization algorithms. As the calculated loss is lower than the threshold, the learning is complete, and the neural network model and the weights of neurons are stored in the fingerprint database. During the online phase, the testing data set collected at testing points (TPs) are fed into the fingerprint database as the input of the stored neural network model and the weights of neurons to estimate the locations.

B. CSI

CSI contains fine-grained information of the wireless channel over which signals propagate. Since the radio frequency (RF) front-end impairment that signals experience during the propagation from a transmitter to a receiver is different from location to location, CSI can be used to construct unique fingerprint map for indoor locations.

In this paper, we utilize universal software radio peripheral (USRP), which is software defined hardware with field programmable gate array (FPGA), to generate Wi-Fi signals in 2.4 GHz band. Let $\vec{T}$ and $\vec{R}$ denote the transmitted and received signals generated by USRPs. The received signal is represented as follows

$$\vec{R} = \vec{H} \cdot \vec{T} + \vec{N} \tag{1}$$

where $\vec{T}$ represents the transmitted signal, $\vec{R}$ represents the received signal, $\vec{N}$ represents the additive white Gaussian noise and $\vec{H}$ represents the CSI. Note that $\vec{H}$ can be acquired by conducting channel estimation using $\vec{R}$ and $\vec{T}$.

The ith subcarrier of the CSI H_i is a complex value, which is defined as

$$H_i = |H_i| e^{j\angle H_i} \tag{2}$$

where $|H_i|$ and $\angle H_i$ are the amplitude and the phase of the CSI for ith subcarrier, respectively.

Note that we only consider utilizing the amplitude of the CSI and ignore the phase information due to random jitters and noises caused by the imperfect hardware [11].

C. Data Collection

As shown in Figure 1, the receiving antenna receives Wi-Fi signals at RPs and TPs. Note that the principle of choosing the location of APs is to make all the points at least have one AP in LOS. Considering that APs in close proximity would occupy different channels to transmit and receive data to avoid interference, it would not make much difference whether to collect data from three APs at the same time or collect data separately at each AP location. Therefore, for the sake of simplicity, we placed the receiving antenna in three different places and conducted data collection process three times for each AP location.

The laboratory ($7.5m \times 6m$) shown in Figure 1 where the experiment is conducted has a number of walls and other blockage such as chairs and partitions, which are sufficient to create a rich NLOS environment. 21 RPs and 13 TPs are chosen with the spacing of 80 cm, which is approximately the length of one step of an adult. For each point, we collected 1000 CSI samples.

Given that there are 52 subcarrier values for each sample, the size of the training data set is $N_r \times N_s \times N_c \times N_a$, and the size of the testing data set is $N_t \times N_s \times N_c \times N_a$, where N_r and N_t denote the number of RPs and TPs respectively, N_s denotes the number of samples, N_c denotes the number of subcarriers, and N_a denotes the number of antennas.

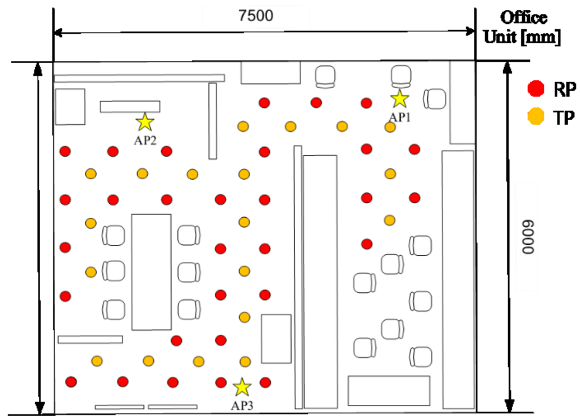

Fig. 1. The laboraroty with 30 RPs and 19 TPs.

III. DEEP LEARNING SOLUTIONS

A. Neural Network Architecture

As illustrated in Figure 2, the data from one AP with the size of 1000×52 is fed into the one dimensional convolution neural network (1dCNN), which consists of convolutional layer, batch normalization layer, activation layer, pooling layer, fully connected (FC) layer, and softmax output layer. Note that for the activation function in the activation layer, we used rectified linear unit (ReLU) function.

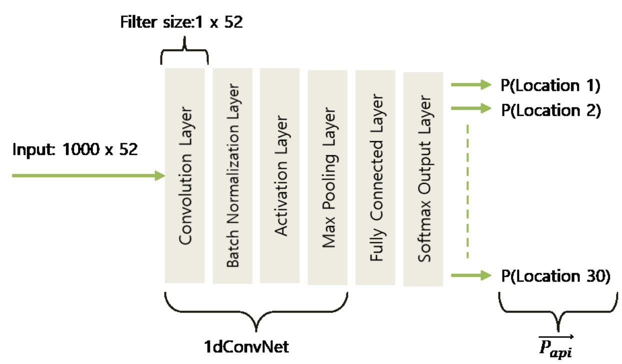

Fig. 2. The structure of 1Dcnn

The output of the 1dCNN is a probability vector $\overrightarrow{P_{api}}$, which consists of the probabilities of all the locations, where api indicates the index of AP. The location with the highest probability is considered to be the estimated location.

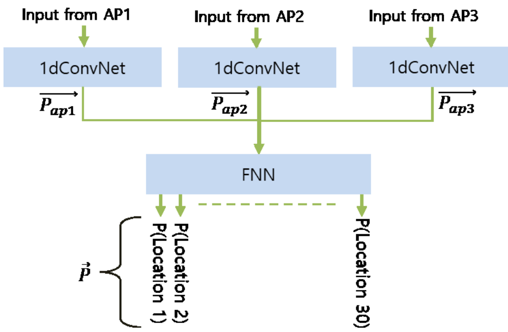

Fig. 3. The structure of hybrid neural newtork

TABLE I. NEURAL NETWORK ARCHITECTURE

Layers	FC (1dCNN)	FNN
Loss function	Cross Entropy	Mean Squared Error
Input Layer	1 x 50	90 x 1
Hidden Layer 1	Dense 150	Dense 256 x 1
Hidden Layer 2	Dense 64	Dense 128 x 1
Hidden Layer 3	Dense 48	Dense 64 x 1
Output Layer	1 x 30	1 x 30

As shown in Figure 3, the results of 1dCNN, $\overrightarrow{P_{api}}$ from three APs, are fed into fusion neural network (FNN) to be further combined to arrive at a final estimated location. In this way, when a fingerprint becomes unreliable due to the effect of NLOS, the other fingerprints based on other APs can shed more light on the accurate estimation. Therefore, the robustness can be improved significantly. More detailed information about the 1dCNN and FNN can be viewed in TABLE I.

IV. EXPERIMENTAL RESULTS

In this section, we provide the experimental results of utilizing three APs. As shown in Table II, we present the numerical results in terms of mean error and standard deviation for the case of using only a single AP and the case of using three APs together.

TABLE II. PERFORMANCE COMPARISON

Data Set	Mean Error	Standard Deviation
AP1	2.0431 m	1.1363 m
AP2	1.3217 m	0.6215 m
AP3	2.1279 m	1.1663 m
AP1, AP2, AP3	1.2669 m	0.6839 m

In the case of a single AP, different AP data set results in different mean error and standard deviation. This is because different AP data set suffers different degree of NLOS effect. We can see that the AP2 data set results in the best performance with 1.3217m mean error and 0.6215m standard deviation whereas AP3 data set results in the worst performance with 2.1279m mean error and 1.1663m standard deviation. However, when using the AP1, AP2, and AP3 data set together, we can see that the performance of the system is better than all the cases of using a single AP data set with 1.2669m mean error and 0.6839m standard deviation. This is because that the multiple fingerprint maps can bring more reliable data to be trained upon; therefore, a more robust performance that the IPS is able to achieve.

V. CONCLUSION

In this paper, we addressed the performance degeneration of the IPS due to the severe NLOS effect in an indoor environment. In order to increase the robustness of the IPS, we exploited the possibility of utilizing three APs located at three different places. By utilizing the CSI values received from the three APs, we are able to generate three unique fingerprint maps for all the locations. With more fingerprint maps, the accuracy of the IPS which used to rely on a single fingerprint map can rely on more fingerprint maps. Therefore, the IPS can perform more robustly in the indoor environment with the help of more reliable CSI values from less NLOS affected APs. We also proposed a hybrid neural network in this paper to extract features of the three different CSI data sets and combine them together in the FNN to get a more accurate result. By comparing the result of using a single AP data set and that of using three AP data sets, we find that the robustness of the IPS is increased significantly.

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