The performance of Wi-Fi fingerprinting indoor localization systems (ILS) in indoor environments depends on the channel state information (CSI) that is usually restricted because of the fading effect of the multipath. Commonly referred to as the next positioning generation (NPG), the Wi-Fi™, IEEE 802.11az standard offers physical layer characteristics that allow positioning and enhanced ranging using conventional methods. Therefore, it is essential to create an indoor environment dataset of fingerprints of CIR based on 802.11az signals, and label all these fingerprints by their location data estimate STA locations based on a portion of the dataset for fingerprints. This work develops a model for training a convolutional neural network (CNN) for positioning and localization through generating IEEE® 802.11data. The study includes the use of a trained CNN to predict the position or location of several stations according to fingerprint data. This includes evaluating the performance of the CNN for multiple channel impulses responses (CIRs). Deep learning and Fingerprinting algorithms are employed in Wi-Fi positioning models to create a dataset through sampling the fingerprints channel at recognized positions in an environment. The model predicts the locations of a user according to a signal acknowledged of an unidentified position via a reference database. The work also discusses the influence of antenna array size and channel bandwidth on performance. It is shown that the increased training epochs and number of STAs improve the network performance. The results have been proven by a confusion matrix that summarizes and visualizes the undertaking classification technique. We use a limited dataset for simplicity and last in a short simulation time but a higher performance is achieved by training a larger data

Keywords: 3D Localization, Wi-Fi, Deep Learning classification technique, confusion matrix, IEEE 802.11

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DEVELOPING THREE DIMENSIONAL LOCALIZATION SYSTEM USING DEEP LEARNING AND PRE-TRAINED ARCHITECTURES FOR IEEE 802.11 WI-FI

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1. Introduction

Positioning is a predictive issue in which the model's predicted position for a station (STA) is the task's output. Positioning may predict the user's precise location, however, compared to localization; it can have a greater error for positions throughout a region. In the classification job of localization, the model's estimated label for a given place of the map where an STA is situated is its output. The ability to accurately estimate a user's overall location is more crucial than being able to precisely place them for activities like locating a bedroom on an aisle in a shop or a floor of a building. The Wi-Fi™, IEEE 802.11az standard [1] is universally denoted as the next positioning generation (NPG) providing physical layer characteristics that can position and enhance ranging employing classical methods [2, 3]. Classical methods depend on the conditions of line-of-sight (LOS) to successfully obtain sequential information like the angle of arrival (AoA), spatial information, or time of arrival (ToA) from multi-path signals to calculate a range or distance between network nodes. At what time the range among three devices (minimum) is capable to measure, trilateration is possible to use to calculate position estimations.

Deep learning and fingerprinting systems are used for Wi-Fi localization techniques to obtain sub-meter accuracies including multipath environments non-line-of-sight [4]. A fingerprinting classically includes Channel State Information (CSI) like channel estimates or received signal strength indicators (RSSIs) from received signals measured at an environment or particular location [5]. Throughout the network training stage, the method generates a dataset via sampling the channel fingerprinting of an environment at numerous identified locations. The user location estimates of the network are based on received signals of unknown locations and rely on a reference database [6–8]. Directed Acyclic Graph residual network of Deep Learning was widely used for image classification [9] and for improving noisy images that are already filtered by the bilateral process via a multi-scale context aggregation network as discussed in [10].

It is important to create an indoor environment dataset of fingerprints of channel impulses responses (CIR) based on 802.11az waveforms and label all the fingerprints by their location data. These datasets are trained with deep learning convolutional neural network (CNN) to estimate STA position based on a portion of the dataset for fingerprints. The trained model performance is evaluated by creating estimations for the STA locations according to their remainder CIR fingerprints of the dataset.

2. Literature review and problem statement

Wi-Fi Round Trip Time (Wi-Fi RTT) is a new technology established by IEEE 802.11 that may be used for internal translation and range determination. With this in mind, the paper[11] proposed a combined internal localization approach for Wi-Fi RTT and PDR networks by integrating data based on the Kalman filter for Wi-Fi RTT and PDR, but the proposed approach didn't discuss the localization system for IEEE 802.11 Wi-Fi. The study [12] focused on Wi-Fi Fine Time Measurement as well as data analysis and processing for internal localization. Although an approach was proposed to decrease the error due to multipath propagation, the final positioning error was less than 2.2 m and the application of internal Wi-Fi localization was not accurate with a highly complex algorithm. The researchers in the study [13] modeled the received signal in a multipath channel based on the IEEE 802.11 standard and they seemed a statistical analysis of the received signal strength index based on IEEE 802.11 wireless LAN in indoor location sensor systems. However, this study also didn't discuss the issue of Wi-Fi localization. At the same pace, the study [14] sought internal zero-configuration localization across the IEEE 802.11 wireless infrastructure by developing a localization algorithm to build a zero-configuration system and create the theoretical base. Although the study discussed the indoor localization and tracking system to support and manage location-based network services, there are no details about the three-dimensional information for the proposed localization system. Ref [15] investigated Wi-Fi-based internal localization using CNNs by proposing several approaches to offer internal localization: magnetic field, Bluetooth, Wi-Fi, and so on. However, IEEE 802.11 didn't address 3D Wi-Fi localization. In terms of cost savings, the paper [16] dealt with a stand-alone sensory platform for monitoring excessive solar irradiation and sought to develop it for on-site monitoring of environmental parameters. The advantage of this paper is that it presented a sensory platform using the ESP8266 microcontroller, which is an open compact computer capable of communicating via Wi-Fi using the IEEE 802.11 standard, but the system was not discussed for 3D Wi-Fi fingerprints. The issue of fingerprints Wi-Fi modeling was discussed in the study [17], which involved the use of Wi-Fi fingerprints to identify joint activity and internal localization. However, the proposed system didn't cover the three-dimensional Wi-Fi environment.

Therefore, all this allows to argue that it is appropriate to conduct a study devoted to creating an indoor environment dataset of fingerprints of CIR based on 802.11az signals, and label all these fingerprints by their location data estimate STA locations based on a portion of the dataset for fingerprints. Furthermore, it may be essential to develop an IEEE 802.11n Wi-Fi protocol supported by one-dimensional convolutional layers for the common task of activity recognition.

3. The aim and objectives of the study

The aim of the study is to develop three-dimensional localization systems with STA and AP nodes using deep learning convolutional neural architecture for IEEE 802.11 Wi-Fi. This will make it possible to measure the performance of Wi-Fi fingerprinting indoor localization systems (ILS) in indoor environments.

To achieve this aim, the following objectives are accomplished:

– to visualize STA and AP objects in the indoor scenario;

– to analyze every STA-AP pair using ray-tracing techniques;

– to show the actual locations of STAs;

– to apply a Deep learning Convolutional Neural Network (CNN) and show the outcomes through a confusion matrix.

4. Materials and methods

4. 1. The object and hypothesis of the study

The object of research is deep learning convolutional neural systems nodes.

The research subject is to create deep learning convolutional neural architecture-based IEEE 802.11 Wi-Fi three-dimensional localization systems using STA and AP nodes. This will enable the evaluation of Wi-Fi fingerprinting indoor localization systems' (ILS) performance in enclosed spaces. The main hypothesis of the study is to consider a relatively small dataset for simplicity to execute the simulation in a short time. However, accurate results require a larger dataset. A MATLAB environment with both WLAN and Deep Learning toolboxes has been used to conduct the attempts. This work merges deep learning and Fingerprinting algorithms in a Wi-Fi positioning system to obtain an accuracy not exceeding one meter even with multipath environments of non-line-of-sight (NLOS). Therefore, two mathematical models including a single access point RSSI-based [4], and deep learning with CSI-based fingerprinting [5] for indoor localization models. Fingerprints usually have channel condition data like a channel estimation from an acquired signal or received signal strength indicator (RSSI), which can measure at an exact location in such environments.

4. 2. Environment creation of indoor propagation

In this stage, let's generate training data by specifying an indoor 3 Dimensional map of (STL) format, which is a common 3D map format. The office map includes studying and conference rooms with several tables and chairs, as shown in Fig. 1.

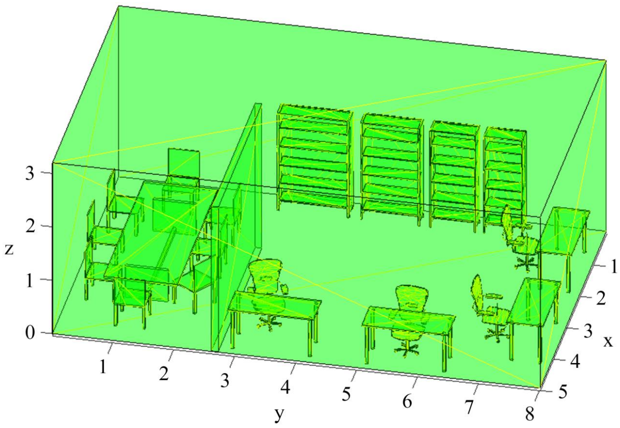


Fig. 1. Indoor 3 Dimensional office map of (STL) format

Let's assume that there are a number of STAs and four access points (AP) specifying the environment network, which defines the propagation channel to create fingerprints and its associated channel impulse response (CIR) with ray-tracing strategies [18].

4. 3. STA and AP Parameters

An increased number of channel realizations and CIRs per fingerprint are produced by larger antenna arrays. A greater bandwidth raises the CIR's sample rate, which sharpens its capture. Since the size of every fingerprint should match the geometry of the input layer model, altering these elements renders the dataset mismatched through the pre-trained architectures. Therefore, in this subsection, let's select the channel bandwidth and the transmitting and receiving sizes of each antenna array to control the resolution and data quantity for every fingerprint. Table 1 lists the parameters' values and the type of array for the developed model.

Table 1

Parameters values and array type for the developed model

Parameter	Values	Array type
rxArraySize	[4 1]	Linear receive array
txArraySize	[4 1]	Linear transmit array
chanBW	CBW40	Not applicable

Next, let's indicate the amount of STAs to 500, and their distribution as a uniform to map the environment. The distances between STAs have been specified at 0.5meters in all directions.

4. 4. Positioning and Localization

It is necessary to specify the simulation as positioning or localization. In this work, let's set the simulation to localization. Instead of identifying an STA's exact location, a localization operation identifies its overall location. The diagram of the small office's layout is depicted in Fig. 2, with distinct regions acting as categories for localization.

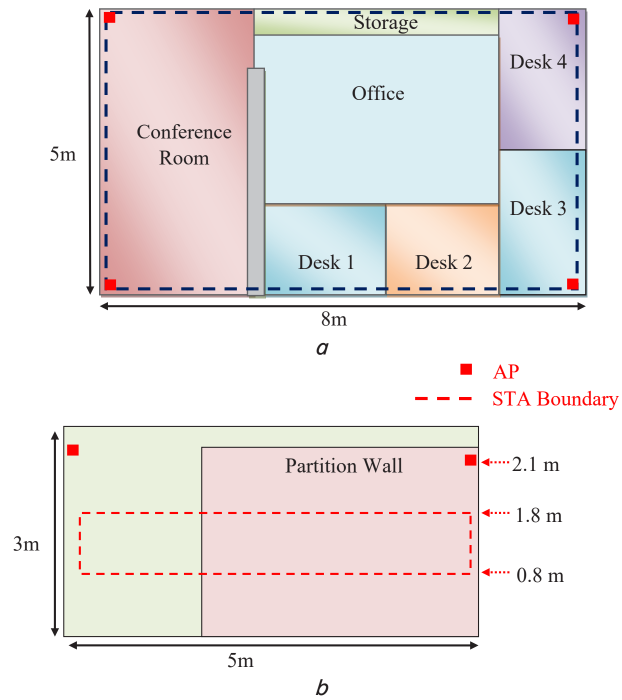


Fig. 2. The diagram of a small office's layout: *a* — overall top view; *b* — side view

The parameters are set in such that the APs' locations are indicated by the red square marks. The area where the STAs are distributed in the example during the training process is shown by the blue dashed box. In this study, let's limit the STAs' height to a range of (0.8–1.8) meters. For portable consumer electronics, this range provides a reasonable range of values. Additionally, this restriction reduces the possibility of STAs being positioned in inaccessible areas.

4. 5. Creating Labels and Features for 802.11az CIR Fingerprint.

This part demonstrates how to calculate the CIRs for all STA-AP pairs based on the computed ray-tracings. The processing chain to produce CIRs is shown in Fig. 3.

Every AP sends an 802.11az packet over a congested route, which every STA accepts. The case presupposes that every STA is able to distinguish among APs such that there are no AP interferences. If there is a pathway between an AP and a location or if synchronization was unsuccessful because of small SNR, packet receipt at that location fails. The produced CIR in this case is a zero vector. In this scenario, the training data is the magnitude of each multipath element in the CIR. As a result, the CIRs that are produced have genuine values.

The labels and features combination is used to train the Convolutional Neural Network (CNN) for the location names and STA positions [9]. Dataset is created initially for the deep learning CNN stage to estimate functions over varied domain ranges. In this work, four blocks make up the CNN, and each block has a ReLU, batch normalization, average pooling layer, and convolution. The utilized CNN includes seven major layers:

1. An input layer to identify the type and size of inputs.
2. A convolutional layer to perform the process of convolutions through several filters on the input layer.
3. A normalizing batch layer to prevent gradients instability using activation normalizing of layers.
4. A nonlinear ReLU activation function to threshold the prior functional layer output.

5. A pooling layer to pool and extract the features and the information.

6. A dropout layer to arbitrarily deactivate a fraction for the previous layer parameters throughout training to avoid over-fitting.

7. An output layer to define the data output type and size.

The workflow of the CNN application is shown in Fig. 4.

Before the final layers, the design here applies dropout regularization of (20 %).

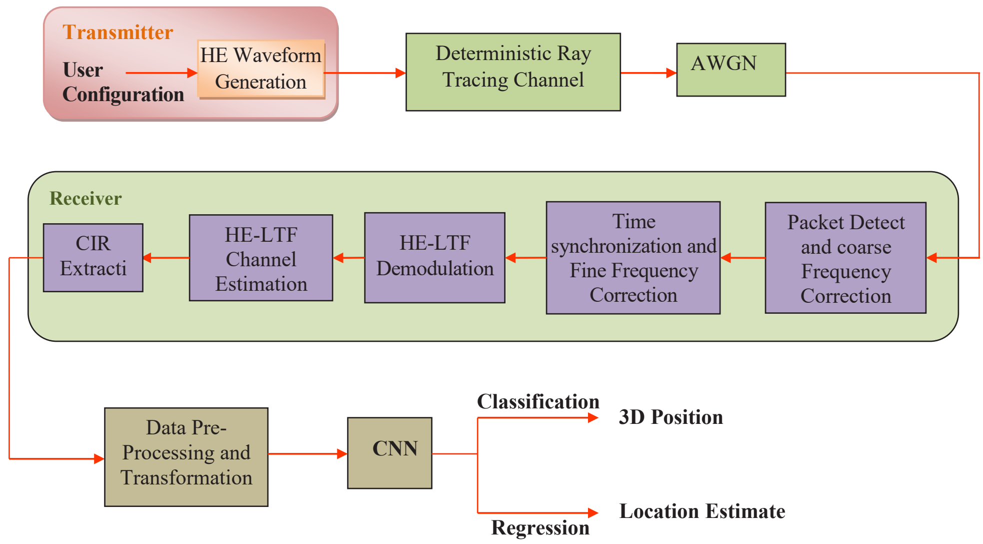
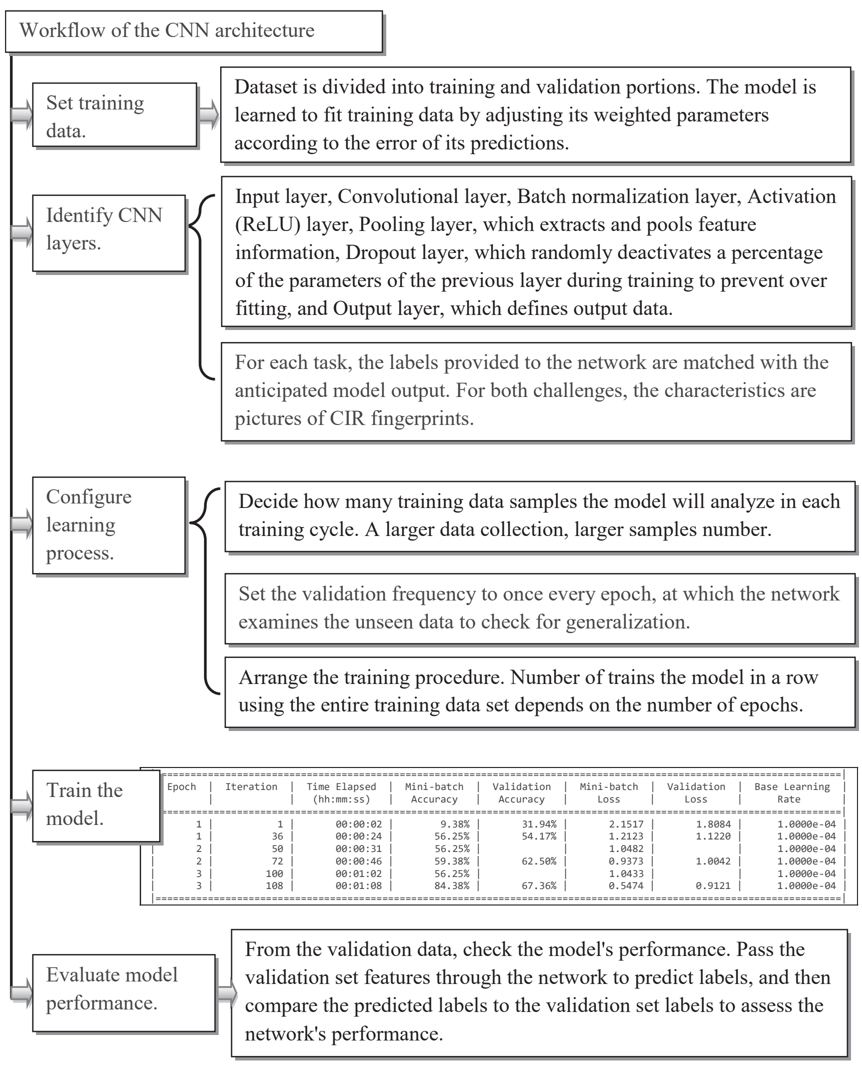


Fig. 3. The processing chain to produce CIRs



Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:02	9.38%	31.94%	2.1517	1.8084	1.0000e-04
1	36	00:00:24	56.25%	54.17%	1.2123	1.1220	1.0000e-04
2	50	00:00:31	56.25%		1.0482		1.0000e-04
2	72	00:00:46	59.38%	62.50%	0.9373	1.0042	1.0000e-04
3	100	00:01:02	56.25%		1.0433		1.0000e-04
3	108	00:01:08	84.38%	67.36%	0.5474	0.9121	1.0000e-04

Fig. 4. The workflow of the CNN application

5. Results of the developed network

5. 1. Create STA and AP Positions

Here, let's produce the STA and AP objects. A visualization of these objects in the indoor scenario is shown in Fig. 5.

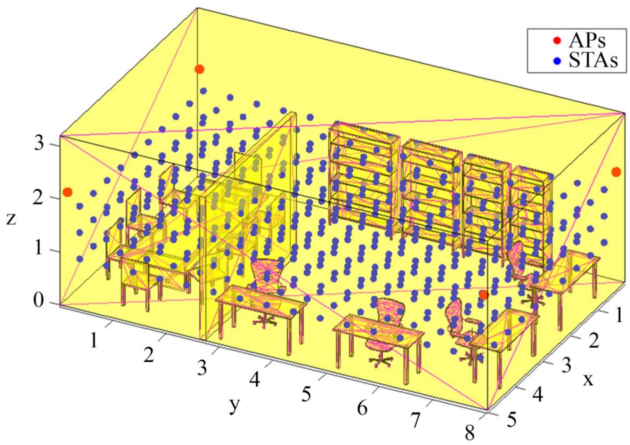


Fig. 5. A visualization of STA and AP objects in the indoor scenario

The waveform parameters are set. Let's set the number of STSs that represent space-time streams to the size of the transmit antenna array in order to guarantee that the signal from each send antenna participates in the fingerprinting of an STA during channel estimation. Where the APs are represented by red circles while the STAs with blue ones.

5. 2. Creating Channels' Characteristics based on Ray-Tracing Strategies

Here, let's only consider the first-order reflections and LOS to adjust the ray-propagation parameters because the simulation time is increased as the reflections max number increases. Ray-tracing techniques in parallel for all receivers and transmitters are considered. The visualization of the computed ray-tracings among a single STA and all the APs is shown in Fig. 6.

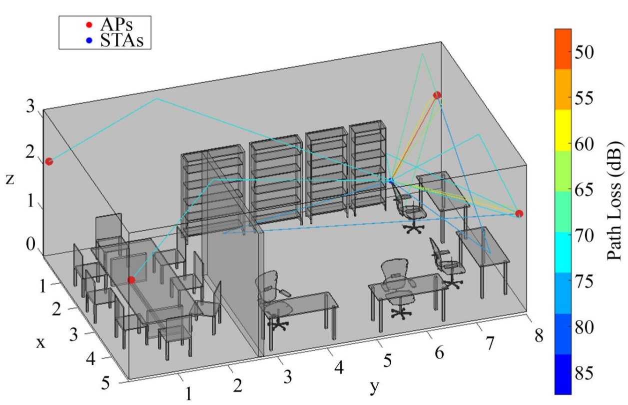


Fig. 6. The analysis of every STA-AP pair using ray-tracing techniques

The colored lines represent the related path losses in dB.

5. 3. The actual locations of STAs

Fig. 7 shows a three-dimensional map that shows the actual positions of STAs.

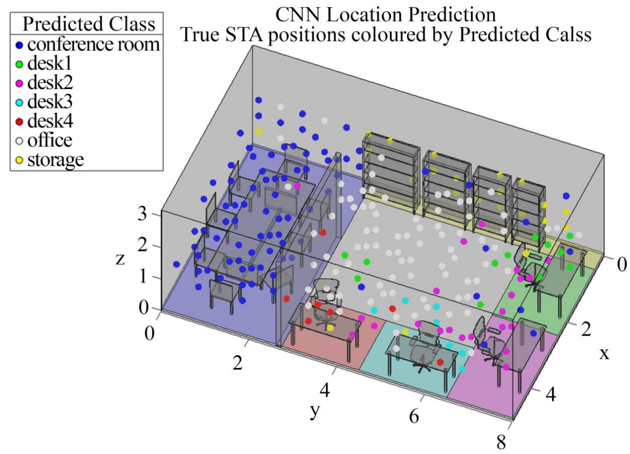


Fig. 7. A three-dimensional map shows the actual locations of STAs

The three-dimensional map shows the actual positions of STAs according to the predicted class that are represented here the conference room, the desks (1–4), the office, and storage classes.

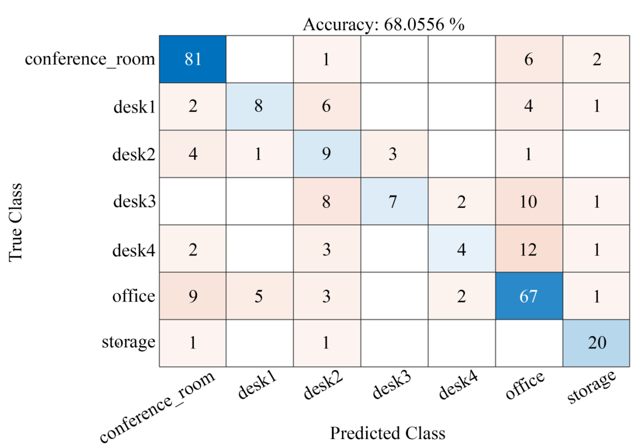
5. 4. Applying Deep learning CNN

This subsection includes applying a statistical and visual view of CNN architecture.

Fig. 8 displays a confusion matrix where the rows represent the expected class and the columns represent the actual class.

The diagonal cells relate to accurately categorized observations. The off-diagonal cells are associated with observations that were misclassified.

The major diagonal's elements will be noticeably larger than the other matrix elements if the network functions correctly.



True Class \ Predicted Class	conference_room	desk1	desk2	desk3	desk4	office	storage
conference_room	81		1			6	2
desk1	2	8	6			4	1
desk2	4	1	9	3		1	
desk3			8	7	2	10	1
desk4	2		3		4	12	1
office	9	5	3		2	67	1
storage	1		1				20

Fig. 8. A confusion matrix where the columns represent the actual class and rows represent the expected class

A screenshot of the model training, when executed on a 1.3GHz CPU/8GB memory computer, is shown in Fig. 9.

Because of the short data set and brief training period used in this section of the work, the results are modest.

A CNN that has been pre-trained on a huge amount of data can produce more accurate findings.

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:06	25.00%	20.83%	2.0571	1.8696	1.0000e-04
1	36	00:01:10	56.25%	58.33%	1.3624	1.0933	1.0000e-04
2	50	00:01:35	56.25%		1.1143		1.0000e-04
2	72	00:02:14	56.25%	61.81%	0.9554	1.0125	1.0000e-04
3	100	00:02:58	84.38%		0.5363		1.0000e-04
3	108	00:03:23	65.62%	68.40%	0.9750	0.8674	1.0000e-04

Fig. 9. Model training iterations when executed on 1.3GHz CPU/8GB memory computer

6. Discussion of the results of simulating a three-dimensional localization system

The STA and AP objects were produced initially and visualization of these objects in the indoor scenario was shown in Fig. 5. The fingerprinting procedure is repeated under various noise settings [10, 15, 20] by defining a range of SNR values in order to imitate environmental fluctuations. Ray-tracing techniques were carried out in parallel for all receivers and transmitters, where the results between STA signals and all the APs are shown in Fig. 6. Each STA's allocated color indicates where it is expected to be. Each STA's allocated color for positioning indicates the expected position's distance error as indicated in Fig. 7. A cumulative distribution function is also produced by the function (CDF). The percentage of the data for which the measured distance error is less than or equal to the corresponding value on the x-axis is represented by the y-axis.

The results have been proven by a confusion matrix that summarizes and visualizes the undertaking classification technique as depicted in Fig. 8, where the rows represent the expected class and the columns represent the actual class. The diagonal cells relate to accurately categorized observations. The off-diagonal cells are associated with observations that were misclassified. The major diagonal's elements will be noticeably larger than the other matrix elements if the network functions correctly.

The presented example was with a limited performance level, where the accuracy is about 68 %. Therefore, it is possible to exploit pre-trained models with more training data, which can achieve higher performance levels.

7. Conclusions

1. This work visualized STA and AP objects in three-dimensional indoor scenarios by defining a range of SNR values. The fingerprinting process is repeated under varied noise conditions to simulate environmental changes, where the results demonstrated the connection between STA signals and all of the APs.

2. The Ray-tracing techniques were carried out in parallel for all receivers and transmitters, where every STA-AP data pair has been analyzed and visualized using ray-tracing techniques.

3. The presented approach succeeded to show the actual locations of STAs. Each STA's allocated color indicates where it is expected to be. Each STA's allocated color for positioning indicates the expected position's distance error.

4. The application of Deep learning CNN achieved 68 % accuracy with this limited information through a confusion matrix that summarizes and visualizes the undertaking classification technique.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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