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A tutorial on Federated Learning methodology for indoor localization with non-IID fingerprint databases

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Abstract

This paper presents a tutorial on Deep Learning (DL) with Federated Learning (FL)-based indoor localization method for non-Independently and Identically Distributed (non-IID) fingerprinting databases. To this end, this paper explains systematic approaches for addressing privacy concerns and performance degradation issues in non-IID fingerprinting databases. The method presented in this tutorial entails the application of a personalized layer, model reliability, and Layer-wise local model's Weight Change (LWC) information to FL. This tutorial provides intuitions to be considered by future researchers to improve the performance of FL-based fingerprinting localization by summarizing the above-mentioned methods into three FL-based techniques: high-complexity training for performance improvement of local training models, exact characteristics of the local model for global model aggregation, and Bayesian data fusion for probabilistic clustering, to improve FL-based indoor localization performance.

Keywords: Federated Learning; Fingerprinting; Indoor localization; Layer-wise local model Weight Change; Non-IID database

Contents

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1. Introduction

In recent years, the increasing use of various Internet of things (IoT) sensors and high-performance mobile devices has generated a large number of data [1]. As the number of devices generating data increases, various services and applications, such as Location-Based Service (LBS), is being developed [2]. It is essential to develop localization technologies that accurately estimates the device's current location for LBS application scenarios and requirements. Broadly, localization technologies are categorized as outdoor or indoor-based localization techniques depending on the application scenarios and requirements.

Specifically, the indoor localization techniques are further classified into triangulation and fingerprinting methods. The triangulation method directly uses Radio-Frequency (RF) signals such as Time of Arrival (ToA), Time Difference Arrival (TDoA), and Angle of Arrival (AoA) measurements. Pre-work, such as creating a radio map, is not required, but it is sensitive to time synchronization between Access Point (AP)s and radio propagation according to the environment. The fingerprinting method makes a radio map of collected RF signals and utilizes them. If there is no significant change in the RF collection environment, localization performance does not highly depend on the RF signal propagation model.

In traditional fingerprinting localization studies, interpolating/extrapolating methods are usually used for constructing RF radio map. An indoor localization algorithm has been proposed using the k-Nearest Neighbors (kNN) [3]. kNN employs the highest similarity method by comparing the information in the existing database for new information estimates. In the kNN, the smaller the difference calculated by the distance metric, the higher the similarity. A Gaussian Process (GP) based Bluetooth-Low-Energy (BLE) Received Signal Strength (RSS) fingerprint database reconstruction algorithm for indoor localization has been presented in [4].

Several studies have proposed using Machine Learning (ML) and fingerprinting for indoor localization applications. The performance of the fingerprinting-based localization can be enhanced by leveraging Deep Learning (DL) [5]. DL models help improve performance by effectively learning the features of large amounts of data. Specifically, the performance of the localization accuracy is generally improved as the fingerprinting radio map (database) size increases. Hence, research on the application of DL models in fingerprinting is growing in fields such as indoor localization, image classification, Natural Language Processing (NLP), and voice recognition [6–8].

DeepFiTM, a Deep Neural Network (DNN) based indoor fingerprinting localization method with Wi-Fi Fine Time Measurements (FTM) that leverages the Wi-Fi FTM measurement and the variance as environment features to provide accurate indoor location estimation, was presented [5]. A DL-based Wi-Fi fingerprint localization method called CNNLoc has been studied in [9]. The CNNLoc effectively extracts and analyzes features of Wi-Fi RSS radio maps by combining two different DL models, a Convolutional Neural Network (CNN) and a Stacked-AutoEncoder (SAE). An indoor localization method referred to as Weighted Indoor Positioning (WIP) has been studied in [10]. The WIP analyzes fingerprints created using five features of UWB signals by combining Long Short-Term Memory (LSTM) and DNN models. In fingerprinting-based localization, since we can treat radio maps as 2D images, it is an excellent direction to apply ML that shows robust performance in terms of image recognition.

There are still open research challenges regarding the various ML-based fingerprinting. These challenges include; the time/resource consumption trade-offs associated with the traditional ML algorithms [11]. Secondly, the user privacy-preserving concerns sending all data to a central server. While many studies were proposed on privacy-preserving data management and data mining [12–14] in a centralized setting, they cannot handle the cases of distributed databases. One key and common data challenge in such distributed databases is that data distributions in different clusters are usually non-Independently and Identically Distributed (non-IID). Hence, to address these problems, consideration is given to distributed processing on the device without sending data to the server. This work adopts the Federated Learning (FL) approach from the ML community, which has recently been studied as an attractive distributed learning algorithm [15–17].

Regarding the development of practical FL-based algorithms for indoor localization with non-IID database, there a few studies on a systematic understanding of the limitations. The fingerprint database is non-IID due to different characteristics of the indoor environment. The performance of the FL-based algorithms are degraded due to these different indoor environment characteristics. Different from existing algorithms, this paper presents an FL-based approach for indoor localization with a non-IID fingerprint database using dynamic data clustering. The contribution of this research is to develop an FL-based technique for compensating for the performance degradation due to the non-IID characteristics of the fingerprint database. This research analyzes the existing FL-based localization techniques. The effect of DL with FL on the convergence of performance have also been analyzed. The remainder of this paper is organized as follows: Section 2 describes the preliminaries on FL for indoor localization, and Section 3 describes various FL techniques. Section 4 describes the performance comparison of FL-based localization techniques. Finally, Section 5 concludes the paper.

2. Preliminaries on federated learning for indoor localization

In this section, we present preliminaries on FL for indoor localization. FL is a promising technique that enables joint training of an ML model while keeping their local data decentralized. There have been some studies trying to develop effective FL algorithms under non-IID data including FedProx [18], SCAFFOLD [19], and FedNova [20]. Federated Averaging (FedAvg) has been established as the most representative FL algorithm that uses database size information collected from local devices [15]. The FL algorithm generally works well with IID databases; nevertheless, there are inherently non-trivial limitations associated with the FL algorithm

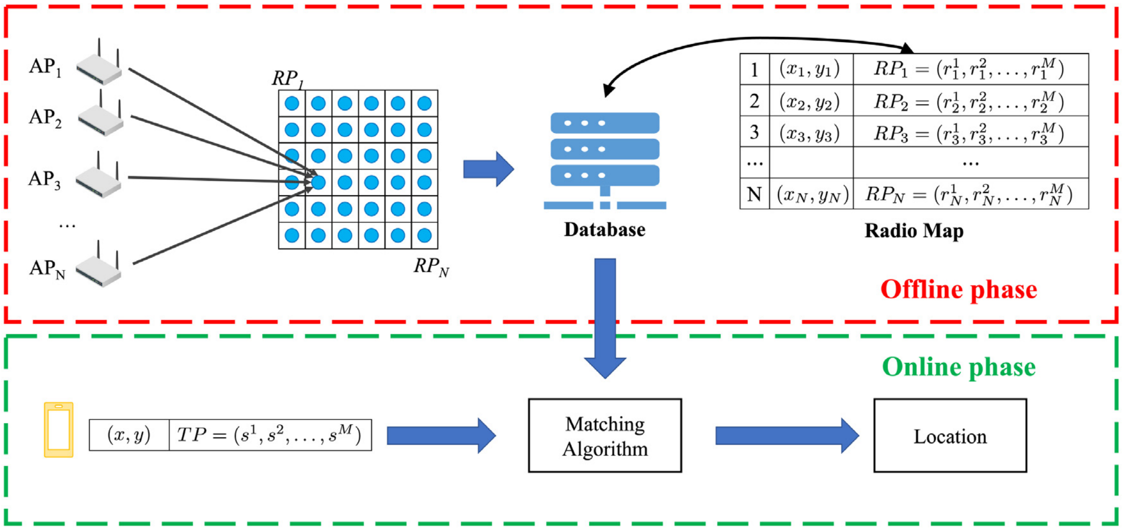

Fig. 1. An illustration of fingerprinting-based localization.

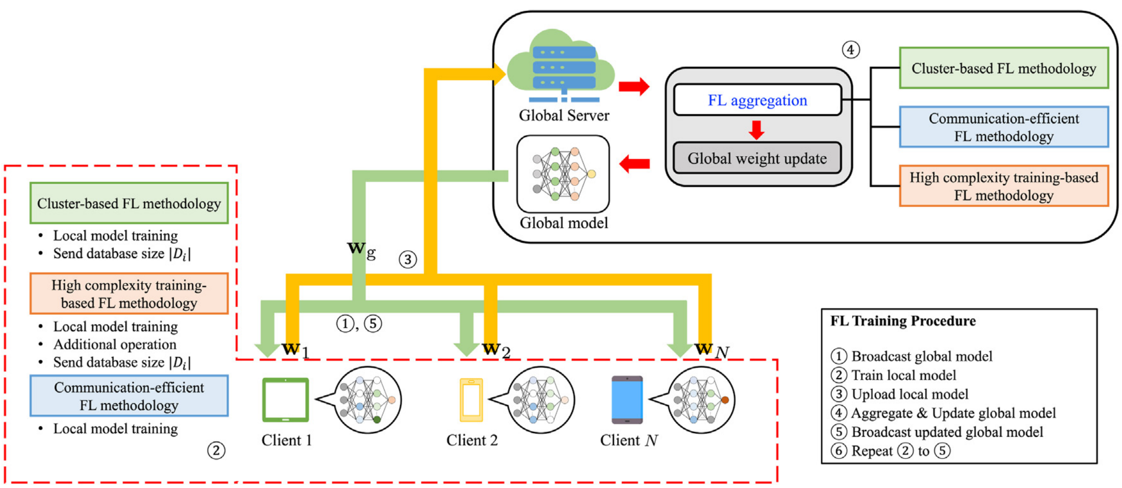

Fig. 2. An illustration of federated learning training procedure.

for non-IID [14]. In non-IID databases, there is a high possibility that global model aggregation does not work appropriately because each local client trains the model in a different direction. Also, performance degradation is inevitable when using the non-IID database measured under device heterogeneity, and different amounts of training data [21–23].

The technique proposed in this paper incorporates a fingerprinting-based indoor localization with DL, leveraging FL. Generally, fingerprinting-based indoor localization operates in two phases; namely, offline and online phases as illustrated in Fig. 1. In the offline phase, the fingerprinting-based indoor localization generates a radio-map database of various signal information collected at a specific reference locations. These signal information includes RSS, Channel State Information (CSI), AoA, and ToA. In the online phase, the fingerprint-based indoor localization estimates the location of the information collected by operating a matching algorithm using the information collected in the new location and the database configured in the offline phase. In the general FL process, we solve the optimization problem of finding a global model by integrating multiple local models.

This process can be mathematically expressed as the following loss function $\mathcal{L}(\mathbf{w})$ minimization problem:

$$\min_{\mathbf{w}} \mathcal{L}(\mathbf{w}) \text{ where } \mathcal{L}(\mathbf{w}) = \sum_{i=1}^{N} p_i \mathcal{L}_i(\mathbf{w}_i, \mathcal{D}_i). \tag{1}$$

where N is the number of participating local clients and $\mathbf{w} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_N]$ contains the model weight. $\mathcal{L}(\cdot)$ is global loss function, $\mathcal{L}_i(\mathbf{w}_i, \mathcal{D}_i)$ is the local loss function of the ith client trained with their own database $\mathcal{D}_i$, and p_i is a relative weight parameter for each client, with $\sum_i p_i = 1$. To minimize the global loss function $\mathcal{L}(\mathbf{w})$, the general FL training process includes the following steps, as shown in Fig. 2.

Since the FL procedure is iterative until convergence, the superscript (t) denotes the tth learning round in the formula.

Table 1
Federated learning-based indoor localization methodologies.

Perspective	FL technique	Localization metric	Communication overhead		Computation overhead		Localization performance
			Local	Server	Local	Server	
Cluster-based methodology	FLoc [24]	Accuracy (%)	High	Low	Medium	Medium	Low
	FedAMP [25]		Low	High	Low	High	Medium
	FedAMP-F [25]		Low	High	Low	High	High
Training-based methodology	FedProx [14]	RMSE (m)	High	Low	High	High	High
	PSO-PFL [26]		Medium	Low	High	High	High
Communication -efficient methodology	FedAvg [27]	RMSE (m)	Medium	Low	Low	Low	Medium
	FL with reliability [27]		Low	Low	Low	High	High
	FedLWC		Low	Low	Low	Medium	Medium–High

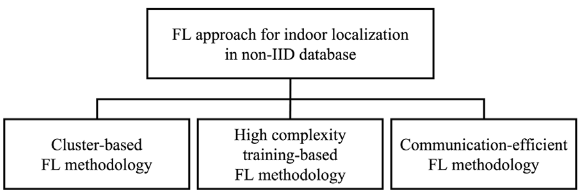

Fig. 3. Perspective of FL approach for indoor localization.

- *Initialize task*: The server identifies local clients to participate in the FL training process.
- *Broadcast global model* : The server broadcasts a randomly generated global model parameter $\mathbf{w}_{\mathrm{g}}^{(t)}$ to participating local clients.
- *Train and upload local model* : After receiving broadcast global model $\mathbf{w}_{\mathrm{g}}^{(t)}$, each client trains local model $\mathbf{w}_i^{(t)}$ using local database $\mathcal{D}_i$ and sends updated local model $\tilde{\mathbf{w}}_i^{(t)}$ to server.

$$\begin{aligned} \mathbf{w}_i^{(t)} &= \mathbf{w}_g^{(t)}, \\ \tilde{\mathbf{w}}_i^{(t)} &= \mathbf{w}_i^{(t)} - \eta \bigtriangledown \mathcal{L}_i(\mathbf{w}_i^{(t)}), \end{aligned} \tag{2}$$

where η is the local learning rate.

- *Aggregate and update global model* : The server aggregates the local models $\tilde{\mathbf{w}}_i^{(t)}$ from clients to make new global model $\tilde{\mathbf{w}}_g^{(t)}$ and sends the updated global model $\mathbf{w}_{\mathrm{g}}^{(t+1)}$ to the clients for the next round.

$$\mathbf{w}_{\mathrm{g}}^{(t+1)} = \tilde{\mathbf{w}}_{\mathrm{g}}^{(t)} = \sum_{i=1}^{N} p_i^{(t)} \tilde{\mathbf{w}}_i^{(t)}, \tag{3}$$

where p_i is averaging weight factor for ith local model with $\sum_{i=1}^{N} p_i^{(t)} = 1$.

3. FL methodologies for indoor localization

In this section, we classify FL techniques for indoor localization into three main perspectives, as illustrated in Fig. 3. Each perspective divided into *Cluster-based FL methodology*, *High complexity training-based FL methodology*, and *communication-efficient FL methodology* shows the characteristics shown in Table 1. The FL techniques for indoor localization corresponding to each perspective are described below.

3.1. Cluster-based FL methodology

In this section, we present cluster-based FL methodologies for indoor localization. In the cluster-based FL methodologies, the collected information space is divided into several predefined clusters. After that, classification is performed using the FL-based learning model for localization. We introduce two FL indoor localization studies as below, FLoc [24] and FedAMP-based algorithm [21,25]. FLoc [24] is the first work to solve the privacy security problem by applying the FL technique to the fingerprinting-based localization scenario. However, unlike general DL-based fingerprinting localization studies, FLoc does not simply use a Multi-Layer Perceptron (MLP) model consisting of multiple hidden layers as a training structure. Instead, FLoc uses a DNN structure combined with a modified Deep AutoEncoder (DAE).

Therefore, this DAE structure shows excellent noise reduction and feature extraction performance and improves localization performance. Unlike other studies that find the optimal FL aggregation method for a better global model update, FLoc does not describe the aggregation method. Instead, FLoc describes the global model update process that a new local model adds for the global model update when a new client enters the indoor area. Perhaps the FL aggregation weight is expected to be proportional to the number of clients. To prevent performance degradation when using the non-IID database, the Federated Attentive Message Passing (FedAMP) [21] algorithm applies privacy-preserving personalized models. Using a personalized model is equivalent to using a specialized fine-tuning method, where the global model is fine-tuned using the client's personalized model [28].

The proposed AMP mechanism encourages similar local clients to collaborate more with each other. As each FL learning round proceeds, AMP repeatedly promotes collaboration between similar local model weights, thereby improving the characteristics of personalized models. The FedAMP algorithm is applied to FL indoor localization based on Wi-Fi RSS fingerprint collected in a non-IID environment [25]. In addition, authors improve localization performance in complex environments where the performance of FedAMP decreases by combining the FedAMP algorithm and the Bayesian data fusion method for probabilistic classification [29].

3.2. High complexity training-based FL methodology

The high complexity training-based FL methodologies for indoor localization are discussed in this section. The methods discussed below use high complexity operations in the local model training process and the FL aggregation process in the global server. The CNN, LSTM structure, and FedProx [14] are applied to fingerprinting localization using Wi-Fi CSI [30]. Using the collected CSI, each device participating in FL learning is trained to minimize the local objective function, including the proximal term. As a result, [30] shows that the localization performance calculated by the RMSE metric increased by 25% on average compared to before the FL technique was applied.

To overcome FedAvg's non-IID performance degradation, two personalized FL techniques called a mixture of Experts (MoE), and knowledge distillation (KD) are applied to local training; the FL aggregation method using pseudo label information, is applied to the global server. According to the previous studies, the local model's performance improvement leads to the FL algorithm's performance improvement by high-complex local training. As another approach, a high-performance FL technique called a Prediction-based Semi-supervised Online Personalized Federated Learning (PSO-PFL) had been proposed in [26].

3.3. Communication-efficient FL methodology

In this section, we present communication-efficient FL methodologies for indoor localization. In communication-efficient FL methodology, the FedAvg algorithm compensates for the communication overhead performance. In addition, they propose several improved FL aggregation algorithms through additional operations on the global server. We introduce an FL indoor localization study using model reliability [27] and propose an FL aggregation algorithm based on Layer-wise local model Weight Change (FedLWC). Existing NN has a limitation in that they cannot express uncertainty which means the probability of making a wrong decision. Charles Blundell et al. [31] use Bayesian Neural Networks (BNN) as a method to remove uncertainty in NN.

In addition, Yarin Gal et al. [32] propose an algorithm using Monte-Carlo (MC) dropout to solve the resource-intensive problem of directly applying Bayesian networks. NN model reliability (uncertainty) is applied to FL indoor localization based on Wi-Fi RSS fingerprint collected in a non-IID environment [27]. The server performs a two-step operation to apply the FL with the model reliability algorithm. In the first step, the server acquires uncertainty information by calculating the variance of the localization error based on MC dropout using the local model and validation database. In the next step, the server obtains reliability information by taking the reciprocal of the acquired uncertainty information and finally applies the FL algorithm through the normalization process.

We propose a new FL aggregation method called a federated learning aggregation algorithm based on Layer-wise local model Weight Change (FedLWC), based on the basic idea from the study of [33] that the local database size is not optimal and does not accurately reflect the characteristics of each local model. Because this method does not use the local database size information that FedAvg sends to the global server, it can gain some communication overhead. We can get more precise averaging weight factor $p_{i,LWC}^{(t)}$ for proposed algorithm's global model update in (3), by using local model's LWC calculated *layer-wise Euclidean Distance (ED)* between $\tilde{\mathbf{w}}_i^{(t)}$ and $\mathbf{w}_i^{(t)}$ as follows:

$$d_i^{(t)} = \sum_{\ell=1}^{L} \frac{d_{i,\ell}^{(t)}}{H_\ell}, \qquad d_{i,\ell}^{(t)} = \|\tilde{\mathbf{w}}_{i,\ell}^{(t)} - \mathbf{w}_{i,\ell}^{(t)}\|, \tag{4}$$

where $d_{i,\ell}^{(t)}$ is ED of the ℓth layer of the ith local model weight and the global model weight at (t)th training round. $d_i^{(t)}$ denotes a weighted average of $d_{i,\ell}^{(t)}$ according to H_ℓ. H_ℓ denotes the number of neuron parameters constituting each layer that is determined as a network structure.

After calculating LWC for each N client at the server, $p_{i,LWC}^{(t)}$ averaging weight factor of the ith client is determined based on N LWCs as below:

$$p_{i,LWC}^{(t)} = \frac{d_i^{(t)}}{\sum_{i=1}^{N} d_i^{(t)}}. \tag{5}$$

A large value of $d_i^{(t)}$ means that a larger change occurred when training the same global model. This means that the local model converges faster compared to other local clients. Accordingly, it is reflected in the aggregation with more weight. Finally, the aggregated global model weight $\tilde{\mathbf{w}}_g^{(t)}$ in (3) can be computed as:

$$\mathbf{w}_g^{(t+1)} = \tilde{\mathbf{w}}_g^{(t)} = \sum_{i=1}^{N} p_{i,LWC}^{(t)} \tilde{\mathbf{w}}_i^{(t)}, \tag{6}$$

According to the above studies, applying the exact characteristics of the local model to FL aggregation leads to the performance improvement of the FL algorithm while taking advantage of the low communication overhead.

4. Performance comparison of federated learning-based localization techniques

This section presents the simulation setup and performance comparison of existing FL-based localization techniques. Specifically, this section analyzes the cluster-based FL localization techniques, Table 1, and the effect of DL with FL on the convergence.

4.1. Simulation setup

4.1.1. Wi-Fi RSS database configuration

A Wi-Fi database collected from an indoor building environment is usually used for fingerprinting localization. The UJIIndoorLoc database [34] is one of the popular Wi-Fi RSS databases for fingerprinting-localization studies. The database includes about 21,000 RSS samples from 390 m in length to 270 m in width over four floors for training and testing

Table 2
Number of Wi-Fi RSSI data according to Phone ID.

ID	Number of data	ID	Number of data
1	507	9	4835
2	610	10	192
3	1383	11	841
4	1596	12	374
5	913	13	980
6	440	14	724
7	498	15	1091
8	4516	16	437

Table 3
Parameters for regression FL localization simulation.

Parameters	Value
Network structure	1024 × 512 × 128
Loss function	Mean Absolute Error
Activation function	Sigmoid × 3, Linear
Optimizer	Adam
Learning rate	0.001
Round	50
Batch	20
Epoch	20

from a total of 520 Wi-Fi APs. For data collection, this research used 24 smartphones using Android OS with different characteristics (such as software and hardware) to collect RSS. Table 2 shows that different smartphones collected different numbers of data from a minimum of 192 to a maximum of 4835 to construct the training database. Therefore, non-IID characteristics according to differences in data amount, device heterogeneity, and collection environment characteristics are remarkable.

4.1.2. FL model structure

All FL techniques in Section 3.1 and Section 3.3 use the DNN architecture for performance evaluation. The rest of the common simulation parameters for the regression method are shown in Table 3.

FL techniques using the regression method compute the error between the estimated location and the actual test data of the server using the Root Mean Square Error (RMSE) metric to compare the performance of the localization algorithm. They present the localization performance compared to FedAvg, FL with model reliability [25], non-FL model with DNN, and kNN with $k = 4$ [34]. FL technique using classification method computes class prediction accuracy. The localization performance compared to the non-FL model with DNN, FedAvg, FedAMP, and FedAMP-F has present in [25]. Those models are DNN structures having two hidden layers with [256, 16] neurons using ReLu activation. They evaluate FL performance by changing the number of clients participating in FL learning and the number of location classes to be classified.

4.2. Discussion

4.2.1. Cluster-based FL localization techniques

This section presents the indoor localization performance comparison of existing ML methods using a non-IID database as summarized in Table 4. The localization performance is expressed in the form of the percentage value how accurately the test database is classified into a predefined cluster. We have compared the DNN, FedAvg, FedAMP, and FedAMP-F under the different non-IID data settings. The simulation proceeds by changing the number of data collection regions L and the number of clients participating in FL learning M. First, the overall performance decreased when M was fixed, and L was increased. This is because the number of training data for each region is reduced.

Table 4
Classification accuracy performance comparison of cluster-based FL localization techniques [25].

	DNN	FedAvg	FedAMP	FedAMP-F
$L = 10$, $M = 6$	90.0%	86.0%	87.0%	91.5%
$L = 20$, $M = 6$	74.5%	73.0%	67.5%	74.0%
$L = 10$, $M = 18$	90.0%	82.0%	81.0%	87.0%

Similarly, the performance decreased even when L was fixed, and M was increased for the same reason. In all cases, FedAMP performance decreased significantly compared to FedAvg, but FedAMP-F showed the best performance among FL methods by fusing the Bayesian probabilistic classification [29]. Although the FedAMP technique in [25] requires a lot of computation on the global model to improve localization performance. However, it is not much different from the FedAvg, so it is more practical to use a simpler FedAvg.

4.2.2. The effect of DL with FL on the convergence

We compared various methods (FedAvg, FedLWC, and FL with model reliability) to obtain global model weights for FL. Fig. 4 shows the indoor localization performance compared to FedAvg, FL with model reliability (dropout), a non-FL model with DNN, and kNN. The difference in performance is observed to be insignificant compared to the increase in computation on the global server. In the case of a non-FL model with DNN, since the server collects all data and there is no model weight aggregating process, localization error is constantly calculated as 5.61 m at every round. In addition, the kNN also shows the localization error is constantly calculated as 7.18 m at every round. Compared to DNN and kNN, the localization error of three FL techniques decreases and converges to 7.76 m in FedAvg, 7.11 m in FedLWC, and 6.06 m in FL with the dropout method (maximum performance when applying dropout ratio 0.1) at round 50. FedAvg performance is measured higher than FedLWC until round 20. However, after that, FedLWC decreases slightly faster and converges to better performance.

5. Conclusion and future directions

This tutorial presented a tutorial on DL with an FL-based indoor localization method for non-IID fingerprinting databases. To this end, this paper explained systematic approaches for addressing privacy concerns and performance degradation issues in non-IID fingerprinting databases. For this purpose, the methods presented in this paper involved

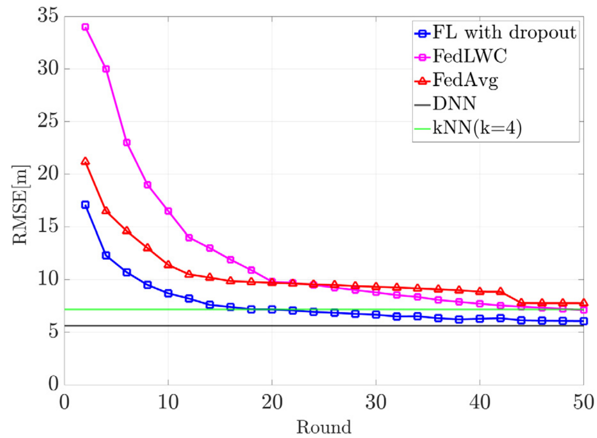

Fig. 4. The effect of DL with FL on the convergence.

the application of a personalized layer, model reliability, and layer-wise local model weight change information to FL. This tutorial summarized FL-based indoor localization studies into three FL-based techniques: high-complexity training for performance improvement of local training models, exact characteristics of the local model for global model aggregation, and Bayesian data fusion for probabilistic clustering, to improve FL-based indoor localization performance. Additionally, this tutorial prospects that privacy and security are the key points in the future development of the IoT application market. FL is a representative distributed learning technique that addresses privacy and security concerns. Therefore, the importance of the FL-based techniques is expected to increase.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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