Federated Learning-Based Localization with Heterogeneous Fingerprint Database

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Abstract—Fingerprint-based localization plays an important role in indoor location-based services, where the position information is usually collected in distributed clients and gathered in a centralized server. However, the overloaded transmission as well as the potential risk of divulging private information burdens the application. Owning the ability to address these challenges, federated learning (FL)-based fingerprinting localization comes into people's sights, which aims to train a global model while keeping raw data locally. However, in distributed machine learning (ML) scenarios, the unavoidable database heterogeneity usually degrades the performance of existing FL-based localization algorithm (FedLoc). In this paper, we first characterize the database heterogeneity with a computable metric, i.e., the area of convex hull, and verify it by experimental results. Then, a novel heterogeneous FL-based localization algorithm with the area of convex hull-based aggregation (FedLoc-AC) is proposed. Extensive experimental results, including real-world cases are conducted. We can conclude that the proposed FedLoc-AC can achieve an obvious prediction gain compared to FedLoc in heterogeneous scenarios and has almost the same prediction error with it in homogeneous scenarios. Moreover, the extension of FedLoc-AC in multi-floor cases is proposed and verified.

Index Terms—Federated learning, fingerprint-based localization, heterogeneous database, geometric characteristic.

I. INTRODUCTION

The explosion of smart devices and the ever-growing sensing and computing technologies have motivated the development of indoor location-based services (LBS) [1]. With the coming of beyond 5G (B5G) and internet of things (IoT), LBS becomes indispensable. However, it is challenging to achieve high localization accuracy using traditional localization approaches. For example, the weak signals emitted from satellite cannot work well in indoor environments, making global navigation satellite system unserviceable. Moreover, other empirical and model-based technologies mismatch the underlying mechanism of complex indoor environments. Owning the ability of remedying these defects, the technique of received signal strength (RSS) fingerprint-based indoor positioning has received increasing attentions [2].

An attractive solution for such localization is the centralized machine learning (ML) algorithm [3]. In the off-line phase, a site survey is performed with clients by measuring the strength pattern of signals at different sampling positions in the area of interest (AoI). Such signals are emitted from access points (APs), including WiFi, Bluetooth, Zigbee, etc. Then, a ML model is trained in the server to map the RSS vector and the corresponding measuring position. In the on-line phase, a user can query its position by inputting the real-time measured signal pattern to the trained model.

However, in the off-line phase, clients are required to send the raw data to the server for model training, causing disclosure of clients’ position information. The privacy protection issue severely hinders the promotion and scalability of LBS [3]. Besides, with a large-scale raw data and client amount, the gathering process leads to a high communication cost.

To alleviate the over-loaded communication cost and protect the client privacy, federated learning (FL) has been introduced to the fingerprint-based localization system [4]–[6]. The gist of FL is to learn a global model in a distributed manner while keeping raw data locally, and only model parameters are exchanged between clients and server. Therefore, FL-based localization is a promising approach to address the above-mentioned challenges. The existing FL-based localization algorithms [4]–[6] are based on Federated Averaging [7]. However, it shows that the heterogeneous nature of fingerprint database limits the prediction performance of these algorithms.

In detail, in practical fingerprint-based localization applications, database heterogeneity usually emerges due to the unbalanced client behaviour. For example,

1) Smart devices may have different hardwares, e.g., battery, sensor and computing unit.
2) Different environmental factors like obstacles may differ sample states of smart devices.
3) Smart devices may be ordered/taken by different owners, causing various moving states.

Such unbalanced behaviours will result in unbalanced sampling characteristics in the AoI, e.g., sampling intervals, sampling amount and trajectories. Consequently, the database heterogeneity is generated, which is mainly reflected by the spatial distribution of sampling positions in the AoI. Therefore, the heterogeneous characteristic of fingerprint database should not be omitted in the design of localization algorithms, which has been neglected in existing FL-based localization algorithms [4]–[6]. In this paper, we first characterize the heterogeneity of the fingerprint database, and then a novel heterogeneous FL-based localization algorithm with the area
of convex hull-based aggregation (FedLoc-AC) is proposed. To
the best of our knowledge, this is the first work to characterize
the heterogeneity of fingerprint database and design FL-based
localization algorithm with it. The main contributions of this
paper are summarized as follows:

1) The fingerprint database heterogeneity exists in dis-
tributed localization tasks. To characterize it, we associate
the heterogeneity with the spatial distribution of sampling
positions, and propose a computable heterogeneous char-
acteristic, i.e., the convex hull of sampling positions.

2) To improve the localization accuracy, a novel FL-based
localization algorithm, named as FedLoc-AC, is proposed
by elaborating the proposed heterogeneous characteristic
of fingerprint database. Besides, the convergence property
of the FedLoc-AC is provided. Moreover, the adaption of
FedLoc-AC in multi-floor cases is proposed.

3) We conduct extensive experiments to verify the effec-
tiveness of the proposed heterogeneous characteristic. In
addition, experimental results, including real-word and
3D cases show the proposed FedLoc-AC can achieve
considerable prediction gain compared to FedLoc in het-
erogeneous scenarios and has almost the same prediction
error with it in homogeneous scenarios.

The rest of this paper is structured as follows. In Section II,
we describe the process of FL-based localization and address
the problem of fingerprint database heterogeneity. In Section
III, the fingerprint database heterogeneity is characterized, and
then the FedLoc-AC is proposed based on it. We present
experimental results in Section IV, and conclude this paper
in Section V.

II. FL-BASED LOCALIZATION

A. Fingerprint Database Construction

Consider a fingerprint-based indoor localization with the
assistance of \( N \) clients and \( L \) APs in the AoI. These APs
are deployed at fixed positions to broadcast WiFi beacons.
The clients here refer to smart devices equipped with sensing,
logging, storage, computing and communication entities. To
perform the site survey in the AoI, each client moves to a
certain number of positions to read the strength pattern of
received signals emitted from APs. The RSSs sampled by
the \( i \)-th client at a position can be formulated in a vector form as

\[
x_i = [RSS_{i,1}, RSS_{i,2}, \cdots, RSS_{i,L}],
\]

(1)

where \( RSS_{i,j} \) denotes the measured RSS at the \( i \)-th client,
from the \( j \)-th AP.

After finishing the site survey, the \( i \)-th client storages \( M_i \)
data pairs, consisting of measured RSSs and corresponding
positions. Subsequently, a local database, denoted as \( D_i \)
is constructed at the \( i \)-th client, which is expressed as

\[
D_i = \{(x_1^i, y_1^i), (x_2^i, y_2^i), \cdots, (x_M^i, y_M^i)\},
\]

(2)

where \( y_i \) is the corresponding measuring position of \( x_i \).

Fig. 1: Block diagram of FL-based localization. Stage I:
Fingerprint database construction (the green points represent
the sampling positions in the site survey and the dotted line
is the edge of corresponding convex hull). Stage II: The FL
work flow.

B. Federated Learning Process

In this subsection, we present the process of training a mul-
tiple perceptron (MLP) model for localization in a federated
manner.

For ease of understanding, a complete picture of FL frame-
work is depicted in Fig. 1. The FL process consists of
information interactions between the central server and clients
with \( T \) global epochs. At the \( t+1 \)-th round, the process of
such a FL system contains the following four steps:

- **Local training:** each client completes the local update on
the global model \( w^t \), received from the central server.
The update is based on optimizing the model over the
local fingerprint dataset. The mean absolute error (MAE)
is selected as the local loss function, defined as

\[
\mathcal{L}_i(w) = \frac{1}{M_i} \sum_{m=1}^{M_i} l_i(x_i^m, y_i^m; w),
\]

(3a)

\[
l_i(x_i^m, y_i^m; w) = \|F(x_i^m; w) - y_i^m\|_2,
\]

(3b)

where \( w \) is the model to be optimized and \( F \) is the
model function. The local update is finished by \( E \) steps
of stochastic gradient descent at \( w^t \) with a learning rate
\( \eta \). Let \( w_i^{t+1} \) denote the local updated model of the \( i \)-th
client.

- **Parameters uploading:** all clients transmit the local up-
dated model to the central server.

- **Model aggregation:** the central server aggregates the
uploaded local model and generates new global model, expressed as

\[
w_i^{t+1} = \sum_{i=1}^{N} p_i w_i^{t+1},
\]

(4)

where \( p_i \) represents the aggregating weight of the \( i \)-th
client with \( \sum_{i=1}^{N} p_i = 1 \).
• **Parameter broadcasting:** the central server broadcasts the aggregated $w^{t+1}$ to all clients for the next round of learning.

### C. Fingerprint Database Heterogeneity

The objective function in the FL-based localization can be formulated as

$$\mathcal{L}(w) = \sum_{i=1}^{N} p_i \mathcal{L}_i(w).$$

(5)

It implies that $p_i$ plays an important role in the prediction performance of trained model.

In practical applications, database heterogeneity usually emerges due to unavoidable unbalanced device behaviours. Therefore the FL-based localization should be designed by considering this vital factor. Furthermore, the aggregating weights should be determined by the heterogeneity characteristic of fingerprint databases. As illustrated in Fig. [1](#), the spatial distribution of sampling positions is an important heterogeneity characteristic. For example, even with the same data size, the coverage area of fingerprint database differs from each other. In the next section, we will characterize the spatial distribution of fingerprint database by a well-known definition of convex hull [3].

Then we will elaborate this characteristic to the aggregating design of FL-based localization.

### III. THE PROPOSED FEDLOC-AC

#### A. Heterogeneous Characteristic of Fingerprint Database

In Fig. [2](#) we further explain the heterogeneous characteristic of fingerprint database, i.e., the spatial distribution of sampling positions. In detail, in the online phase, a user at position $y$ is querying its position by inputting its real-time measured RSS vector to a MLP model, which is trained by the fingerprint database $\mathcal{D}$ in the off-line phase. Let $y'$ denote the single measuring position in $\mathcal{D}$ and $\mathcal{D}(y')$ denote the set of whole sampling positions in $\mathcal{D}$. Without loss of generality, the average prediction error at position $y$, denoted as $e(y)$, is proportional to the minimum distance between $y$ and $\mathcal{D}(y')$, expressed as

$$e(y) \propto d_{\min}(y; \mathcal{D}(y')) = \min_{y' \in \mathcal{D}(y')} \| y - y' \|_2.$$  

(6)

After illustrating the effect of the spatial distribution to the estimation of a single position, we will expand it to the whole AOI. Since the mainly concerned performance of the trained model is the average prediction accuracy over the AOI, a comprehensive performance metric is given by

$$\mathcal{E} = \int_{y \in \text{AoI}} e(y) f(y) dy = \frac{1}{S} \int_{y \in \text{AoI}} \int_{y' \in \mathcal{D}(y')} e(y) dy,$$  

(7)

where $f(y)$ is the probability density function of user position in the AOI and $S$ is the area of the AOI. We consider a uniform distribution of user position here. Substituting (6) into (7), we obtain

$$\mathcal{E} \propto \int_{y \in \text{AoI}} \min_{y' \in \mathcal{D}(y')} \| y - y' \|_2 dy,$$  

(8)

By doing so, the fingerprint database with a larger overlay area will contribute more to the global training model. The proposed algorithm is outlined in Algorithm [1](#). Note that we simplify the client as $Cl$.

**Remark 1:** The authors in [10](#) have derived the convergence property of federated learning theoretically. We find that the convergence property of FedLoc-AC follows [10](#) by some adjustments. More details can be found in the appendix.

**Remark 2:** Compared with the FedLoc [5](#) in computational complexity, the FedLoc-AC needs the $i$-th client to compute $S_{Cl}$, additionally, whose complexity is $O(D_i)$. Due to the co-existing federated learning process in FedLoc and FedLoc-AC, such additional cost is negligible.

### C. Extension to 3D Cases

Recently, positioning in a 3D case, especially a multi-floor building has attracted extensive attentions. However, predicting
Algorithm 1: Heterogeneous FL-based localization

Input: $T$, $w^0$, $\eta$, $E$, $D_i$ $\forall i$
Output: $w^t$

Preparation:

while $C_l \in C_1, C_2, \ldots C_l N$ do

Find out the convex hull of $D_l$, denoted as $C_i$,
using Melkman algorithm \[9\]
Compute the area of $C_i$, i.e., $S_{C_i}$
Send $C_i$ to the central server

Initialization: $t = 1$.

while $t \leq T$ do

Local training process:

while $C_l \in C_1, C_2, \ldots C_l N$ do

foreach $e \in 1, 2 \ldots E$ do

$w \leftarrow w - \eta \nabla L_i(w)$

$w_i^t \leftarrow w$

Upload parameters $w_i^t$

Model aggregating process:

Update the global model parameters $w^t$ as

$w^t = \sum_{i=1}^{N} \frac{S_{C_i}}{\sum_{i=1}^{N} S_{C_i}} w_i^t$

The central server broadcasts global model parameters

$t = t + 1$

IV. EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the proposed algorithm, compared with the centralized MLP and FedLoc [8] under different scenarios. Besides, the effectiveness of the proposed heterogeneous characteristic is verified.

Experimental Environment: To construct typical and straightforward scenarios clearly, the simulated dataset are synthesized. The AoI is an indoor environment with $50 \times 50$ m$^2$. There are four WiFi nodes fixed at the corner of the AoI, emitting electromagnetic wave with power $P_0$. The propagation of electromagnetic wave in the AoI is simulated according to the radio-channel propagation model in [11]. The related wireless propagation environment is set as follows. The transmit power of each AP is 10 dBm, and the received power loss at the 1 m reference distance is $-30$ dBm. To simulate the complicated indoor environment, the path loss is set to range from 3 to 8 and the variance of noise is set to range from 2 to 8 in the AoI.

We consider both homogeneous and heterogeneous scenarios. In heterogeneous scenario, we consider a typical unbalanced device behaviors, causing fingerprint database heterogeneity, i.e., moving velocity. The details are showed as follows.

Homogeneous scenario: The data collection and model training are completed by 8 clients. Starting from the vertexes of the rectangle AoI, each client moves with a velocity of 0.5 m/s with a sampling interval of 3 s. At each sampling position, the sample is obtained after averaging over 10 measurements. After sampling at 200 positions, each client constructs the local fingerprint database, and then cooperates with a central server to train a global model. The test database is generated at randomly positions in the AoI for 1200 times.

Heterogeneous scenario: The basic settings maintain the same with the homogeneous scenario, while a half of the participated clients act as stragglers with a limited moving velocity of 0.05 m/s, resulting in unbalanced sampling spacing.

Learning Structure: TensorFlow libraries are utilized to implement the learning process by a MLP network. The MLP is trained using SGD consisting of a single hidden layer with 64 hidden units, where ReLU units are selected as active function. We set $T = 300$, $E = 40$, and $\eta = 0.00001$.

A. Verifications of the Heterogeneous Characteristic

In this subsection, we verify the conclusions in Section III.A through Monte Carlo simulations.

Firstly, the positions of 1800 user data are randomly generated in the AoI, and then the corresponding RSS vectors are measured. For each user data, the prediction error of the MLP model and the minimum distance between the user position to fingerprint positions are stored as a pair. Fig. [3(a)] is a statistical version of the 1800 data pairs. As seen, the average prediction error is in proportion to the minimum distance.

Secondly, we generate 1000 fingerprint databases randomly. For each fingerprint database, the area of convex hull and the MAE of test database are stored as a pair. Fig. [3(b)] is a statistical version of the 1000 data pairs. It demonstrates
that the average MAE is in inverse proportion to the area of convex hull of fingerprint database.

B. Prediction Performance of Proposed FedLoc-AC

Fig. 4 shows the testing MAE of focused approaches versus global epochs under the designed scenarios. In the heterogeneous scenario, the FedLoc-AC (the proposed algorithm) surpasses the FedLoc obviously in terms of the prediction accuracy with similar convergence rate. At the final round, the FedLoc-AC can achieve a 20% performance gain compared with FedLoc. This improvement is reasonable. The fingerprint database of clients with stronger moving abilities are more representative to reflect the environment of the AoI. The proposed FedLoc-AC distributes larger weights to the stronger clients in the model aggregation while FedLoc averages the aggregating weights. In the homogeneous scenario, the proposed FedLoc-AC has almost the same performance with the FedLoc since the aggregating weights in FedLoc-AC are near average. Through converging under more rounds than the centralized learning, the FedLoc-AC can keep raw data locally.

C. Real-world 3D cases

The real-word dataset named UJIIndoorLoc is adopted to evaluate the proposed method and its extension version. The experimental data is sampled in the four-storey building with "BUILDINGID" equal to 0 in the UJIIndoorLoc database. We select the the training subset for model training and the validation subset for test.

Fig. 6: Testing MAE of focused methods versus global epochs with UJIIndoorLoc database.

The client amount in the building is set to be 20. For floor classifier, we select MLP network as the classifier, consisting of a single hidden layer with 1024 hidden units, where ReLU units are selected as active function. Softmax units are selected as active function in the output layer. The learning is achieved by SGD with $\eta = 0.000001$ and $E = 20$. For floor-specific localization, the MLP is trained by SGD consists of two hidden layers with 128 $\times$ 128 ReLU units. We set $E = 40$, and $\eta = 0.00001$.

Fig. 5 shows the testing accuracy of FL-based classifier and centralized classifier versus global epochs. As seen, the test accuracy of FL-based classifier rivals the centralized benchmark.

When the floor is predicted by the FL-based classifier, to further predict the specific position on the floor is just the 2D case we focused on. Fig. 6 shows the test error of focused approaches versus global epochs on the floor with id equal to 1 in this building. This result demonstrates the prediction superiority of the proposed FedLoc, consisting with Fig. 4.

D. extension to 3D case

V. CONCLUSION

In this paper, we have focused on FL-based localization that trains a global model in a cooperative and distributed manner without exposing the raw data of clients. Considering the practical database heterogeneity, a novel FedLoc-AC algorithm has been considered, which aggregates the client model according to the proposed heterogeneous characteristic, i.e., the area of convex hull. Experimental results have verified the effectiveness of the heterogeneous characteristic and confirm the prediction superiority of FedLoc-AC, compared to the existing FedLoc. Improving the FedLoc-AC by finding more effective aggregating weights deserves further research.

APPENDIX: CONVERGENCE BOUND OF FedLoc-AC

For theoretical analysis, the assumptions of the local loss function are listed as follows.

Assumption 1: We assume the following for the $i$-th client:
1) $L_i(w)$ is convex.

1Also, we consider both homogeneous and heterogeneous scenarios. In the homogeneous scenario, the training database are random distributed to 8 clients. In the heterogeneous scenario, a half of clients act as stragglers, whose local training databases have limited cover area in the AoI.
2) \( \mathcal{L}_i(w) \) is \( \rho \)-Lipschitz, i.e., \( \| \mathcal{L}_i(w) - \mathcal{L}_i(w') \| \leq \rho \| w - w' \| \) for any \( w, w' \).

3) \( \mathcal{L}_i(w) \) is \( \beta \)-smooth, i.e., \( \| \nabla \mathcal{L}_i(w) - \nabla \mathcal{L}_i(w') \| \leq \beta \| w - w' \| \) for any \( w, w' \).

We also define the following metric to capture the divergence between the gradient of a local loss function, defined in [3], and the gradient of the global loss function, defined in [5].

**Definition 1:** For any \( i \) and \( w \), we define \( \delta_i \) as an upper bound of \( \| \nabla \mathcal{L}_i(w) - \nabla \mathcal{L}(w) \| \), i.e.,

\[
\| \nabla \mathcal{L}_i(w) - \nabla \mathcal{L}(w) \| \leq \delta_i.
\]

We also define \( \delta \equiv \frac{\sum_i S_i \delta_i}{\sum_i S_i} \).

The difference between the Definition 1 and the counterpart in [10] are the definition of \( \delta \), in where the proposed aggregation with heterogeneous databases are considered.

Following [10], when \( \eta < \frac{1}{\beta} \), we have

\[
L(w^T) - L(w^*) \leq \frac{1}{2 \eta \phi T} + \frac{1}{4 \eta^2 \phi^2 T^2} + \frac{\rho h(E)}{\eta \phi E} + \rho h(E),
\]

where \( \phi \equiv \omega (1 - \frac{\delta^2}{2}) \), \( \omega \equiv \min_i \frac{1}{\| w(t-1) - w_i \|} \) and \( h(x) \equiv \frac{1}{\beta} ((\eta \beta + 1)x - 1) - \eta x \) for any \( x \neq 0, 1, 2, \ldots \).

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