Providing Location Information at Edge Networks: A Federated Learning-Based Approach

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Abstract

Recently, the development of mobile edge computing has enabled exhilarating edge artificial intelligence (AI) with fast response and low communication costs. The location information of edge devices is essential to support the edge AI in many scenarios, like smart home, intelligent transportation systems, and integrated health care. Taking advantage of deep learning intelligence, the centralized machine learning (ML)-based positioning technique has received heated attention from both academia and industry. However, some potential issues, such as location information leakage and huge data traffic, limit its application. Fortunately, a newly emerging privacy-preserving distributed ML mechanism, named federated learning (FL), is expected to alleviate these concerns. In this article, we illustrate a framework of FL-based localization systems as well as the involved entities at edge networks. Moreover, the advantages of such a system are elaborated. On the practical implementation of it, we investigate the field-specific issues associated with system-level solutions, which are further demonstrated over a real-world database. Moreover, future challenging open problems in this field are outlined.

Introduction

Recently, the advance in wireless communication technologies and artificial intelligence (AI) has promoted orders-of-magnitude increases of interconnected smart devices, that is, internet of things (IoT). To provide smart context-aware services with massive data generated at the network edge, mobile edge computing (MEC) has been developed rapidly [1]. By sufficiently exploiting the communication/computing resources at edge networks, MEC enables ultra-low latency, high-bandwidth, and real-time edge AI.

The position information of edge devices is a cornerstone to enable sound and real-time operations of the edge network. On one hand, position information can be utilized across all layers of the communication protocol stacks to design and optimize the communication system at edge networks [2]. On the other hand, position information is naturally indispensable on the application of location-based services (LBS), such as navigation, target tracking, recommending system and mobile game. As the era of Beyond 5G (B5G) and IoT arrives, brand-new LBS will emerge in a wide range of application areas [3], including industry 5.0, smart home, intelligent transportation systems, and so on. For example, after acquiring self-positioning, the industrial robot is able to cooperate with others in a highly automated way. Therefore, how to accurately predict the location is always a key component to support edge AI.

As the rapid development of AI, machine learning (ML) technologies have played an important role in providing position information in complex environments [3]. ML-based localization consists of two phases: the off-line phase and the on-line phase. In the off-line phase, a ML model is trained by learning the relationship between the location-dependent measurements and related positions. In the on-line phase, the trained model is used to predict the real-time position of a device by requiring the location-dependent measurement of it.

Although ML-based localization has received extensive attentions, there are two critical issues that limit its practical applications: privacy concerns and huge data traffic. Traditional centralized learning based technologies require uploading raw data (measurements and related positions) of participated devices, named clients hereinafter, to a central server, which generates huge data traffic especially in large-scale systems. Also, in this process, position information is exposed directly, and may be intercepted by an adversary.

Recently, a distributed ML mechanism, named federated learning (FL) [4] has gathered tremendous interests. In FL, local ML models are trained at clients where training data is generated, and a global ML model is generated in the central server by aggregating the local models. This cooperative learning is completed by exchanging local model parameters rather than the massive raw data that contains privacy information. With the potential of addressing the issues of privacy concerns and huge data traffic, FL-based localization has been researched and has shown considerable prediction performance [5–7].
In this article, we first illustrate the process of FL-based localization at the edge network, and highlight the involved entities and their operations. Different from existing works [5–7], we also point out three inherent issues including measurement heterogeneity, environmental variation and 3D localization. This article aims to discuss these vital aspects in the field of FL-based localization and provide system-level solutions. The remainder of this article is organized as follows. In the next section, the framework of FL-based localization at the mobile edge network is illustrated and its main advantages are elaborated. Then we focus on three field-specific challenges when implementing FL-based localization, and provide potential solutions. Subsequently, some key opening problems that deserve future researches are discussed. Finally, conclusions are drawn.

**FL-Based Localization System at the Edge Network: Procedures and Advantages**

In this section, we first illustrate the framework of FL-based localization system at the edge network by two steps as shown in Fig. 1, and then elaborate main advantages of the proposed framework.

**Stage One: Fingerprint Database Construction**

The first stage of FL-based localization is to construct training databases, usually termed as fingerprint database. Specifically, active edge devices perform a site survey over the area of interest (AoI) assisted with access points (APs), as illustrated in Fig. 1. APs are deployed at fixed positions and broadcast signal for location sensing. Ambulatory edge devices pass a certain number of positions in the AoI while reading the location-dependent patterns, such as received signal strength of AP signals at each position. Finally, each edge device stores several data pairs as local fingerprint database, consisting of the measurements of AP signals (features) and corresponding measuring positions (labels). We next describe the properties of the two involved entities.

APs refer to any fixed devices that are able to emit the signal used for location sensing, mainly including WiFi, Bluetooth, ultra-wideband (UWB), radio-frequency identification (RFID), and ultrasound [3]. The type of AP signal determines the advantages and disadvantages of the localization system directly. Among them, WiFi based localization system has developed most widely and achieved most successful application due to low hardware cost [3].

**Stage Two: Federated Learning Process**

Fingerprint databases are constructed at edge devices in the site survey, and can be used to train a localization engine under the FL framework. In this manner, local clients collaborate in training a ML model under the coordination of a central server with communication of model parameters. A complete picture of FL structure at the edge network is depicted in Fig. 1. The FL is an iterative process, and the procedures at each round of FL contain the following four steps.

**Local Fingerprint Database Training:** Each client updates the local model in parallel based on the global model parameters, received from the central server. Updates are completed by optimizing the local model parameters to minimize the training loss over a local fingerprint database.

**Local Localization Model Uploading:** Each client transmits the updated local model parameters to a central server.

**Global Aggregation:** The central server aggregates the received local models according to the calculated weights, and updates the global model.

**Global Localization Model Broadcasting:** The central server broadcasts the updated global model parameters to selected clients for the next round of learning.

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**Figure 1.** Schematic diagram of FL-based localization at the edge network.
The distributed nature of FL ensures system resilience and service continuity of edge networks where unbalanced computing and communication resource is witnessed. In FL, each client learns its local model in parallel at each epoch, and it is possible to optimize the FL process under the heterogeneous resources constraints with advanced techniques.

The above steps are repeated until convergence where the update of global model grounds to a halt. Finally, the last model can be put into use in the on-line phase. We next illustrate the properties and operations of involved entities in FL at the edge network.

**Clients** train the local model over fingerprint database and upload the updated local model parameters to the central server. Therefore clients are equipped with logging, computing, storage, and communication entities. There are two types of clients in the edge network. The edge device that has done the site survey can participate in the FL as a local client. Moreover, trustful edge servers can become a local client as long as having access to the fingerprint databases of edge devices. To further protect the privacy of these fingerprint databases, we can utilize the differential privacy or encryption based techniques to prevent the privacy leakage [8]. By undertaking the learning task from some communication/computation-limited edge devices, the edge servers enable a reliable and real-time learning process.

The central server refers to the cloud server, equipped with high-speed computing, cache/storage and communication entities. Cloud server aggregates the local training model uploaded from distributed clients to update the global model and distributes it to all clients. Note that the aggregation is usually a low-complexity operation like averaging, so the cloud server can synchronously handle other tasks.

**WHY FL-BASED LOCALIZATION?**

In what follows, we will elaborate the irresistible reasons of choosing the above FL-based localization system, compared to traditional localization technologies.

**Data-Based Localization:** The fingerprint databases collected in the site survey match the underlying mechanism of the complex environment on the AoI. Learning the fingerprint databases in FL-based localization rather than building the signal propagating model as in model-based localization is more suitable for complex environments where many edge devices may be located in.

**Large-Scale Application:** In the online phase, any edge device in the AoI can infer its position after receiving the converged global model from the central server. Note that the devices are not limited to FL clients. Moreover, the neuronic network model or Gaussian process model are two representative inference engines in FL-based localization [5]. The on-line location inference of such engines usually takes extremely short response and low computing resource. It can be concluded that the universal, low-latency and low-complexity location inference enables the large-scale application of such engines at the edge network.

**Privacy-Preserving and Communication-Efficient Mechanism:** In FL, the cooperation of distributed clients is achieved through communication with a central server, and only local localization model parameters instead of raw data are transmitted. This mechanism can save extra communication resources for both clients and the central server, compared to the centralized ML. Note that communication resource is crucial to provide better quality of service (QoS) for users in edge networks. Moreover, such cooperative mechanism greatly avoids the leakage of location information of clients from its fingerprint database to the external third-party. It is essential to promote the application of location-aware services. Because the highly sensitive location information and the personal behavior reflected by it can be utilized by adversaries or eavesdroppers, causing potential troubles and risks [6].

**Liberation of the Central Server:** In FL, the central server acts as an assistant that helps aggregate the local models trained by local clients, and does not need to perform the complex model training task. Therefore, only a small share of computing resources in the central server is occupied by FL-based localization, and the central server can synchronously handle other vital tasks at the edge network.

**Coordination of Unbalanced Resource:** The distributed nature of FL ensures system resilience and service continuity of edge networks where unbalanced computing and communication resource is witnessed. In FL, each client learns its local model in parallel at each epoch, and it is possible to optimize the FL process under the heterogeneous resources constraints with advanced techniques [9].

**FL-BASED LOCALIZATION ACROSS DIFFERENT DOMAINS**

In this section, we first discuss two important and practical issues for implementing the FL-based localization, and then provide a system-level solution.

**Issues Description**

**Measurement Heterogeneity:** In the site survey, different types of edge devices are used to detect and measure AP signals. Their different hardware facilities such as build-in sensors result in inconsistencies of the detection and measurement at the same position and time. Therefore, the fingerprint databases collected by different type of devices may follow non-independent identically distributed (non-iid). Note that there are many factors causing the measurement heterogeneity between clients, such as temperature and humidity, in this issue, we only focus on different types of devices.

**Challenges:** FL aims to generate a generalized model for balancing the requirement of each client. Due to the severe measurement heterogeneity, the FL model may be unsatisfactory when applied on the target type of device. A common idea is to train an extra type-specific FL model under the cooperation of target edge devices. However, the fingerprint data collected by a single type of devices may be insufficient, so that training a model over the insufficient dataset may cause the over-fitting problem.

**Environmental Variation:** Another practical factor is the substantial environment variation in the AoI in different time phases. Signal propagation environment in the AoI always changes over the time, caused by unpredictable activities of...
humanity, movements of objects, and even the variation of temperature and humidity. Besides, some APs may be shifted to different locations. All these factors result in the distribution discrepancy of fingerprint measurements over the AoI between different time phases.

**Challenges:** The existing FL model is trained by a large number of data collected at the time phase of the site survey, and thus it only specializes in learning the feature during that time phase. Applying the existing FL model directly to predict locations in different time phases may be unsatisfactory. A common idea is to retrain an extra time-specific FL model over new fingerprint databases, which are collected at the target time phase. However, re-collecting massive fingerprint data is highly-cost and time-consuming. Therefore, the newly collected fingerprint data is usually insufficient to retrain the time-specific FL model.

**A Federated Transfer Learning-Based Approach**

In essence, the mentioned two issues can be integrated as the statistical heterogeneity between training domain and application domain. In the issue of measurement heterogeneity, the training domain refers to the mixed fingerprint data distribution on diverse devices, while the application domain refers to that on the target type of devices. In the issue of environmental variation, the training domain means the fingerprint data distribution during the time phase of the site survey, while the application domain means that at the target time phase.

Transfer learning (TL), which focuses on transferring the knowledge learned from the source domain to different but related target domain [10], is greatly suitable for this scenario. Therefore, utilizing TL in the FL-based localization, that is, federated transfer learning (FTL)-based localization, seems to be a great solution. FTL has been developed recently and successfully applied to provide personalized AI in multiple regions, including smart hearth, human mobility prediction, and so on [11].

Then, we propose a hybrid federated transfer learning-based localization scheme (H-FedTLoc), which enjoys general knowledge sharing from traditional FL and meanwhile specific knowledge owned from target-specific training. The key idea is to transfer the global FL model, trained by large-scale data on source domain to sub-global FL models, which will be fine-tuned over small-scale trainable data on target domains. Different from existing FTLs that focus on local personalization [11], the proposed H-FedTLoc focuses on local-global personalization using a two-layers FL framework. The details are illustrated as follows.

As shown in Fig 2, the whole process consists of the following three steps:

- **Global FL:** each participant collaborates in training a high-quality global model with the assistance of the central server in a FL manner.
- **Model transfer:** after global FL, the central server transfers the global model to a sub-global model built for further personalization on target type of devices.
- **Sub-global FL:** the central server transmits the sub-global model to clients, which have access to the target database (fingerprint database collected by target type of device).

**FIGURE 2.** Schematic diagram of H-FedTLoc across devices.

FL-based 3D Localization

Positioning in a three-dimensional (3D) case, i.e., a multi-floor building, has attracted extensive attention. However, a direct predicting of the three dimensional position of a device in a multi-floor building usually has poor precision, and an effective approach is to predict in two steps [12]. In the first step, a ML-based classifier is used to determine the height of the location, for example, which floor the device locates on. In the second stage, the two-dimensional (2D) position of the device on the located floor is predicted. Based on this, an extension of the FL-based localization to 3D cases is proposed, which is straightforward and handy to implement.

In the off-line phase, to construct local fingerprint databases, a site survey is conducted in the multi-floor building by clients. After the site survey, a floor classifier is first learned with the coordination of all local clients in this building under the FL framework. Then for each floor, a 2D localization model is learned by local clients on the floor. In the on-line phase, using the floor classifier and floor-specific ML models, the position of device can be predicted quickly. Therefore, FedLoc-3D consists of a FL-based floor classifier and 2D localization models.

**Heterogeneous Scenario**

Different from the centralized 3D localization, FL-based 3D localization suffers from extreme...
unbalanced data distribution between local databases. It is non-trivial for some clients, such as robots to do cross-floor site survey. For a client such as a smart phone carried by a person, performing cross-floor site survey is time-consuming and labor-costing. Therefore, usually, a client is only active on a single floor in the building during the site survey. In the multi-class floor classify task, each local database may only consists of one-class data, causing serious statistical heterogeneity. To this end, a simple but elegant FL-based training scheme, namely federated one-vs-all (FedOVA) [13], is introduced to predict the located floor of devices.

FedOVA aims to decompose a multi-classification task into multiple binary classification tasks under the FL framework. The procedure of FedOVA-based floor classifier is illustrated in Fig. 3. Specifically, for a L-floor building, totally L binary classifiers are learned, each of which specializes on a single but different floor. Such classifier aims to output the probability of locating on the focused floor or not. In the off-line phase, totally L models are trained independently. Note that, each client takes local update on the whole L binary classifiers. In the aggregation step, the central server aggregates the floor-specific models separately. In the on-line phase, a device can input its real-time fingerprint measurement to the trained L classifiers, and then obtain the probabilities of locating on each floor in the building. Naturally, the floor with the max probability is selected as the prediction result.

**Experimental Results**

In this section, we provide experimental results on a widely utilized real-word database, named UJIIndoorLoc [12] to demonstrate the aforementioned issues and associated solutions.

**Database Description:** UJIIndoorLoc is collected at three buildings with four or more floors of the Jaume I University (UJI) that covers almost 110000 m2. It provides 21049 sampled points where 19938 is for training and 1111 is for validation, which is conducted by more than 20 people and 25 different devices during several months. The fingerprint measurement in this database is the received signal power (RSS) of WiFi signals.

**Basic Settings:** The 4-floor build with identification equal to 1 is selected for 3D cases and the floor with identification equal to 1 in this building is selected for 2D cases. For 2D cases, the client amount is set to be 8 while for 3D cases, the client amount is set to be 16. TensorFlow libraries are utilized to implement the learning process by a MLP network. For model training, the initial and also the most common FL scheme, that is, Federated Averaging (FedAvg) [4] is used here.

**Measurement Heterogeneity**

The discussed issues of measurement heterogeneity caused by different types of devices are well verified in the UJIIndoorLoc since RSS values measured by different type of smart phones are obviously inconsistent at the same position and time. Note that in this scenario, each client only owns one device. Three focused methods including FedLoc, N-FedLoc and our proposed H-FedTLoc, are investigated in this subsection. FedLoc means training a FL model with all types of devices without transfer, and N-FedLoc represents newly training a FL model over trainable data on target type of devices.

Test MAE on the target type of device (one type of device that participate in the federated training) via training epochs is provided in Fig. 4a. As seen, after transferring the global model to the sub-global model in H-FedTLoc, the prediction error can be reduced significantly within few rounds of epochs. Besides, it may be advantageous to perform the model transfer at an earlier epoch for enjoying a faster performance improvement. At the final round (400 epochs), the proposed H-FedTLoc reduces the prediction error substantially compared to FedLoc and achieves an almost 20 percent performance gain over N-FedLoc.

**Environmental Variation**

The discussed issues of environmental variation is well verified in the UJIIndoorLoc since the distribution of RSS values measured at different time phase are obviously inconsistent. The interval between the source time phase and the target time phase is about one month in this setting.

The aforementioned three methods are also compared in this subsection. Differently, FedLoc means training a FL model over data collected at the source time phase (source trainable data), and N-FedLoc represents training a FL model over trainable data collected at the target time phase (target trainable data).

Figure 4b illustrates test MAE at target time phase via training epochs with various quantity ratios of target trainable data to source trainable data. This result indicates that the performances of H-FedTLoc and N-FedLoc improve as the amount of target trainable data increases. Moreover, in both scenarios, the performance of the proposed H-FedTLoc surpasses FedLoc obviously and reduces the prediction error substantially compared to N-FedLoc.
In this subsection, we only focus on the FL-based classifiers in the 3D case. After predicting the floor, the localization task becomes a 2D one, which has already been discussed. We consider two scenarios. In the homogeneous scenario (scenario A), each client collects local database across the floors in the building. In the heterogeneous scenario (scenario B), each client only collects local database on a single floor. Figure 5 shows the testing accuracy versus global training epochs. As can be observed, FL-based classifier converges fast and has a near-centralized accuracy in the scenario A but performs poorly in the scenario B. In the scenario B, the test accuracy of the FedOVA-based classifier surpasses the FL-based classifier obviously at the epoch of 400.

**Challenges and Open Research Topics**

**Label-Less FL-Based Localization via Crowdsourcing**

Recently, fingerprint crowdsourcing has been extensively studied, which relieves the burden of site survey from professional surveyors to common users such as mobile devices in a participatory sensing manner [14]. But there arises an important issue that is common users may be unwilling or unable to explicitly label fingerprint data with the location information as the professional surveyors do in the site survey. Therefore, most or whole fingerprint data is unlabeled in localization via crowdsourcing.

A common idea to address this issue by performing location annotation with little user intervention. In this way, several systems have been designed by using the inertial sensors of devices with the aid of a floor plan or without [14]. However, existing schemes are centralized, labeling isolated local fingerprint databases with little user intervention for FL-based localization via crowdsourcing deserves further works.

In [6], authors propose a centralized indoor localization method using pseudo-label (CRNP) which leverages the power of unlabeled fingerprint data, and then incorporate CRNP and FL-based localization system. Inspired by this, exploiting more effective semi-supervised/unsupervised learning in FL-based localization system can be investigated as future directions.

**Heterogeneous Spatial Distribution**

On the practical implementation of FL-based localization, unbalanced client behaviors emerges due to the differences of built-in hardware and located areas on the AoI. Such unbalanced behaviors including sampling intervals, sampling amount and trajectories of each client will result in the spatial heterogeneity of local databases [7]. Such spatial heterogeneity leads to unbalanced quality between local databases. Generally, it is more reasonable to distribute larger aggregation weights to local model trained over higher-quality fingerprint databases rather than averaging them in FedAvg [4].

Authors in [7] characterized the local database quality by the area of sampling convex hull and showed the effectiveness of distributing the aggregation weights according to the characterized qualities directly. However, this method only focuses on the sizes of local sampling areas but ignores the relative spatial relationship of these areas. Designing more comprehensive aggregation weights from both theory and practice deserves further works.

**Non-IID Cases in FL-Based Localization**

The non-iid cases are practical and inevitable in the FL-based localization. In this work, we consider three forms of non-iid data scenarios in localization, measurement heterogeneity, environmental variation and heterogeneous 3D localization. In addition, heterogeneous spatial distribution [7] is also a non-iid data scenario. Besides the technologies we introduced, many techniques in the FL framework are responsible for handling the...
Getting location information with fast response is crucial to some time-sensitive servers such as intelligent transportation systems. Reducing the time delay of FL-based localization is necessary since the FL may converge slowly with non-iid data or unbalanced resources.

**Time-Sensitive FL-Based Localization**

Getting location information with fast response is crucial to some time-sensitive servers such as intelligent transportation systems. Reducing the time delay of FL-based localization is necessary since the FL may converge slowly with non-iid data or unbalanced resources. Many technologies are researched to reduce the time delay of distributed ML, including designing gradient descent optimizer and coordinating/optimizing the computing/communication resources [15]. Absorbing these technologies in FL-based localization methods is expected to provide location information with fast responses as a further direction.

**Conclusion**

In this article, the framework of FL-based localization at the edge network as well as its advantages has been illustrated. On the practical implementation, we have illustrated three inherent issues including measurement heterogeneity, environmental variation and 3D localization as well as provided system-level solutions. The effectiveness of these system-level solutions have been demonstrated on the real-world UJIIndoorLoc database. Finally, we have outlined other challenging problems which deserve further researches.

**Acknowledgments**

This work was supported in part by the National Natural Science Foundation of China (Nos. 62071234, 62071289, 61972093, 62171217 and under Grant no. 62002170), the Major Science and Technology plan of Hainan Province under Grant ZDKJ2021022, the Scientific Research Fund Project of Hainan University under Grant KYQD(ZR)-21008, the National Key R&D Program of China under Grant 2018YFB180110 and the China Postdoctoral Science Foundation under Grant no. 2021M691540.

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