FedVCP: A Federated-Learning-Based Cooperative Positioning Scheme for Social Internet of Vehicles

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***Abstract*— Intelligent vehicle applications, such as autonomous driving and collision avoidance, put forward a higher demand for precise positioning of vehicles. The current widely used global navigation satellite systems (GNSS) cannot meet the precision requirements of the submeter level. Due to the development of sensing techniques and vehicle-to-infrastructure (V2I) communications, some vehicles can interact with surrounding landmarks to achieve precise positioning. Existing work aims to realize the positioning correction of common vehicles by sharing the positioning data of sensor-rich vehicles. However, the privacy of trajectory data makes it difficult to collect and train data centrally. Moreover, uploading vehicle location data wastes network resources. To fill these gaps, this article proposes a vehicle cooperative positioning (CP) system based on federated learning (FedVCP), which makes full use of the potential of social Internet of Things (IoT) and collaborative edge computing (CEC) to provide high-precision positioning correction while ensuring user privacy. To the best of our knowledge, this article is the first attempt to solve the privacy of CP from a perspective of federated learning. In addition, we take the advantages of local cooperation through vehicle-to-vehicle (V2V) communications in data augmentation. For individual differences in vehicle positioning, we utilize transfer learning to eliminate the impact of such differences. Extensive experiments on real data demonstrate that our proposed model is superior to the baseline method in terms of effectiveness and convergence speed.**

***Index Terms*— Collaborative edge computing (CEC), cooperative positioning (CP), federated learning, Internet of Vehicles.**

I. Introduction

RECENT years have witnessed a proliferation of social Internet-of-Things (IoT) techniques in supporting applications for smart cities. An intent-based traffic control system by investigating deep reinforcement learning (DRL) for 5G-envisioned IoCVs [1], which can dynamically orchestrate edge computing and content caching to improve the profits of the mobile network operator (MNO). This work is very forward-looking in combining 5G and artificial intelligence on the Internet of Vehicles. However, smart city, as an integrated system, relies largely on the interactions among edge users. Therefore, a new paradigm in existing edge computing is collaborative edge computing (CEC). Vehicle, is a basic and important class of edge computing device [2], attracts increasing attention in the fields of edge computing [1], [3]–[6]. The real-time precise positioning of vehicles enables various downstream applications, such as autonomous driving, collision avoidance, and lane-level positioning.

The most widely used positioning system in vehicle driving is global navigation satellite systems (GNSS), where edge devices receive broadcasts from multiple satellites and calculate the position of the vehicle. However, the positioning accuracy of GNSS in urban canyons ranges between 30 and 50 m [7] due to many factors, such as atmospheric conditions, systematic errors, and multipath. To improve the positioning accuracy, some works have studied sensor-rich vehicles (SRVs), which aim to incorporate more information perceived by extra sensors (e.g., radio frequency identification (RFID) [8], LiDAR [9], camera [10], and dead reckoning). Using collaborations of SRVs to improve location accuracy is promising because human mobility is a widespread social activity in cities. However, high-cost implementations of SRVs hinder its wide applications in CEC since only partial cars provide high-precision positioning data.

In order to solve the problem of vehicle positioning accuracy at a lower cost, many works have been proposed. Three main approaches are identified in the literature. The first is the cooperation-based methods, which aims to build the cooperation between vehicles and infrastructure or fused information, including cooperative positioning (CP) and vehicular cooperative positioning (VCP), as shown in Fig. 1. The second is edge computing-based methods. Li *et al.* [11] proposed RoadSide Equipment (RSE)-assisted lane-level positioning method, which utilizes commonly available received signal strength (RSS) data to improve GPS accuracy. Song *et al.* [12] proposed a CP framework that employs SRVs data and improves system security and robustness by building a blockchain. The latest advances have been achieved by embedding vehicle CP modules in the pipeline of deep feature learning to improve the accuracy of positioning. Li *et al.* [13] proposed a GPS error sharing framework based on vehicular

Manuscript received October 28, 2020; revised January 19, 2021; accepted February 22, 2021. Date of publication March 15, 2021; date of current version January 31, 2022. This work was supported in part by the National Natural Science Foundation of China under Grant 62072409 and Grant 62073295, in part by the Zhejiang Provincial Natural Science Foundation under Grant LR21F020003, and in part by the Fundamental Research Funds for the Provincial Universities of Zhejiang under Grant RF-B2020001. The work of Sajal K. Das was supported in part by the U.S. National Science Foundation (NSF) under Grant CNS-2008878, Grant SaTC-2030624, Grant CNS-1818942, and Grant OAC-1725755. *(Corresponding author: Guojiang Shen.)*

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Digital Object Identifier 10.1109/TCSS.2021.3062053

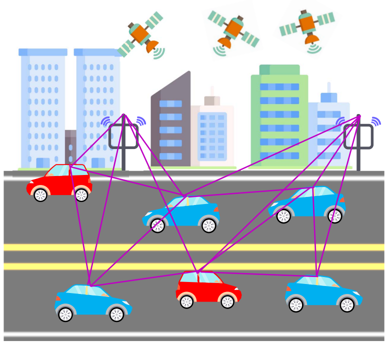

Fig. 1. CP scenario in VANET. The blue cars are CoVs. The red cars are equipped with high-precision sensors.

blockchain networks, and a deep neural network (DNN) is built to predict errors. Wang *et al.* [4] integrated imitation learning with vehicular edge computing for the first time, to the best of our knowledge, which is promising for online scheduling and computing. Hu *et al.* [14] presented a real-time positioning method for extended Kalman filter (EKF) and backpropagation neural network (BPNN). Though it seems reasonable to exploit edge computing and deep learning to enhance the accuracy of vehicle positioning, these existing methods still cannot cope with three levels of challenges effectively as follows.

1) In the accuracy level, most CP studies are incapable of addressing the positioning accuracy requirements of crucial intelligent transportation system (ITS) applications. For example, collision avoidance [15] and lane-level navigation need submeter accuracy. Therefore, more fine-grained location positioning methods are urgently needed.
2) At the user level, the privacy of vehicle GPS location data should be considered. Users tend to refuse to upload private location data, which makes centralized deep learning model training unfeasible.
3) In the application level, the SRV-based methods require high implementation cost, which is unpractical in the existing urban environment. It would be impractical to install enough sensors in all vehicles. For methods that use deep learning models, the uploading of vehicle location data inevitably takes up plenty of network bandwidth.

To address the above limitations, we propose a vehicle CP system based on federated learning (FedVCP). Our framework consists of three key components: 1) in the accuracy level, by maintaining a correlation model in a mobile edge computing node (MECN), the position error correction model is continuously updated iteratively to measure GPS error throughout the city; 2) in the user level, the federated learning method is adopted to protect the user privacy; users only need to upload the gradients used for model updates corresponding to the private data and download the latest model; and 3) in the application level, a federated learning algorithm is deployed in the GPS edge device rather than vehicle hardware upgrading. Moreover, we also try to make full use of the advantages of VCP to increase the accuracy of positioning through local vehicle-to-vehicle (V2V) communication. When using this method, more training data will be generated and more terminals can be involved in the training, and the convergence speed of the model will be accelerated. The main contributions of this article are as follows.

1) A vehicular cooperative position correction system based on federated learning is proposed. We design a DNN model in accordance with the system. This system fully utilizes the potential of CEC while protecting user data privacy, and the convergence speed and accuracy of the model have also been improved. To the best of our knowledge, this article is the first attempt to solve the privacy of CP from the perspective of federated learning.
2) We have explored the ability of VCP in local GPS error correction, maximized the role of SRVs, and let some common vehicles (CoVs) participate in data generation and model training tasks. This approach not only allows the system to operate normally with fewer SRVs but also represents the robustness of the system. For GPS errors caused by individual differences, a transfer learning method is applied.
3) Extensive experiments on real data demonstrate that our proposed method performs better in accuracy and convergence rate than the baseline method. In addition, we test the performance of the model in scenarios with different SRV ratios, and the results show that the model has favorable robustness.

The remainder of the article is organized as follows. The related work is described in Section II. In Section III, we introduce the problem to be solved and the overall framework. Details of the model implementation are presented in Section IV. The performance study is discussed in Section V, and the conclusion is drawn in Section VI.

II. Related Work

In this section, we review the existing research progress in vehicle positioning, federated learning, and transfer learning.

A. Vehicle Positioning

The development of ITS has spawned many promising IoT applications [16]–[22], such as navigation services, safe driving assistance, and autonomous driving technology. Accurate positioning information is a fundamental piece for these ITS applications. However, the positioning accuracy of the current GPS is not enough to meet the requirements of the above applications. Therefore, more accurate vehicle positioning technologies have attracted extensive attention. At present, the methods of enhancing vehicle positioning accuracy can be divided into three types: non-CP methods, CP-based methods, and error model sharing methods.

1) CP and Non-CP Methods: Differential GPS (DGPS) [23] and real-time kinematic (RTK) [24] are the best known in traditional CP. In DGPS, area-level errors caused by the atmosphere and ionosphere are broadcast to each user's GPS receiver to eliminate errors. However, DGPS cannot eliminate the error caused by the multipath effect. RTK can provide centimeter-level positioning accuracy when more than four satellites are visible, but it is not suitable for vehicle positioning due to vehicle dynamics and GPS signal blockage.

Traditional CP does not perform well in the complex urban environment. Thus, another method starts from the vehicle itself and make full use of abundant vehicle-mounted sensors to improve positioning accuracy. Ghallabi *et al.* [9] proposed a map-based localization using a multi-layer LiDAR to realize accurate self-vehicle localization. Sun *et al.* [25] used dead reckoning to solve location problem in non-GPS highway traffic environment. However, these sensors will not be available in all vehicles due to hardware costs.

2) Vehicular CP: Most modern CP systems are defined in vehicular ad-hoc network (VANET) [26], and these systems achieve precise positioning through V2V and vehicle-to-infrastructure (V2I) communications [such as dedicated short range communication (DSRC)]. In this article, we refer to such positioning methods as VCPs. When the GPS errors are expected to be reduced, VCP will try to use radio ranging technology to obtain its position relative to the accurately positioned vehicle or infrastructure. Familiar ranging methods are the time of arrival (TOA) [27], time difference of arrival (TDOA), RSS [28], round trip time (RTT), and angle of arrival (AOA). Alam and Dempster [15] review the VCP efforts and analyze their shortcomings; due to bandwidth and latency limitations, many methods are not feasible. Doppler-based range rating [29] seems can be viable in vehicular, but it has no ability to ranging from vehicles in the same direction.

3) Positioning With Machine Learning: In recent years, machine learning algorithms have been attempted to be applied to location tasks. The machine learning model learns the deep underlying relationship between position, state, and error from a global perspective, and the final model will benefit all users. Comparisons of the effects of basic machine learning algorithms and ensemble learning methods on indoor positioning tasks are introduced in [30]. Baek *et al.* [31] trained a multilayer perceptron (MLP) on past vehicle GPS trajectories to predict the current vehicle position. They find that even a single hidden layer was enough to complete the error estimate task. Li *et al.* [13] utilized DNN, edge computing, and blockchain to establish a GPS error evolution sharing framework. Machine learning algorithms perform well in error correction tasks, and our work follows these excellent characteristics. However, DNN-based methods do not solve the problems of privacy and network resource waste.

B. Federated Learning

Data exist in the form of isolated islands in most industries while most machine learning architectures require collected data. Federated learning, as a new machine learning framework, can solve the above problem while protecting data security and privacy. The original federated learning was presented in a series of works by Google [32]. Their initial idea was to train machine learning models and prevent data leakage when the data sets are distributed across multiple devices. Following this, Yang *et al.* [33] systematically introduced the definitions, architectures, and applications of federated learning framework.

Three categories of federated learning architectures are listed: horizontal federated learning, vertical federated learning, and federated transfer learning. Horizontal federated learning is applicable when data sets share the same feature space but have different samples. Vertical federated learning is applicable when two data sets share the same sample ID space but have different feature spaces. Federated transfer learning focuses on situations where two sets of data are not only different in the sample but also in feature space.

At present, the main research of federal learning focuses on privacy [34], security [35], and efficiency [36]. Federated learning is naturally close to edge computing, and the combination of federated learning and CEC is promising. In the vehicle positioning scene [37], federated learning provides fundamental privacy protection. It fits with our work.

C. Transfer Learning

Transfer learning aims to apply the knowledge learned from one domain's data to another domain with different data distributions and feature spaces. At present, transfer learning has made great progress in computer vision [38], [39] and reinforcement learning [40]. Yosinski *et al.* [41] quantified the transferability of features from each layer of a convolutional neural networks (CNN). "fine-tuning" and "frozen" are now widely used transfer learning methods. As for vehicle position correction, transfer learning can also improve positioning accuracy for each vehicle [13]. We adopt the idea of transfer learning in our work.

III. PRELIMINARIES

In this section, we first briefly state the vehicle positioning problem and then introduce the overall framework of FedVCP.

A. Problem Statement

1) Vehicle Positioning: In the urban traffic scene, we simply classify vehicles into CoVs $\mathcal{V}_c = \{v_i\}_{i=1,\dots,N}$ and SRVs $\mathcal{V}_s = \{v_j\}_{i=1,\dots,M}$. For the kth vehicle v_k at time t, no matter what set it comes from, objectively has a true geographic location $P^{kt} = [P_e^{kt} \;\; P_n^{kt}]$. P_e^{kt} and P_n^{kt} correspond to the eastern and northern coordinates in Universal Transverse Mercartor (UTM) for this location, respectively. However, P^{kt} is available only when $v_k \in \mathcal{V}_s$. In addition, GPS location P_{gps} is available to all vehicles. Thus, the problem to be solved is how to use $\{P_{\text{gps}}\}$ and $\{P^{kt}|v_k \in \mathcal{V}_s\}$ to approximate $\{P^{kt}|v_k \in \mathcal{V}_c\}$.

2) Error Prediction: P^{gps} is not accurate, which is mixed with errors. We refer to the errors caused by satellites, atmosphere, and multipath effect as regional errors $E^r = [E_e^r \;\; E_n^r]$. We train a model $\mathcal{F}_r$ (a neural network) to predict regional errors. In other words, we input P^{gps} into $\mathcal{F}_r$ and expect the output to be E^r. The error generated by the GPS receiver only affects the positioning of a single vehicle, which is called individual error E_i. Similarly, we expect that a model $\mathcal{F}_i$ can output E_i with the vehicle state information s^k as input.

B. Framework Overview

In order to solve the three problems faced by vehicle positioning: regional error correction, user trajectory data privacy, and individual positioning error, FedVCP uses the positioning correction model, horizontal federated learning framework, and the application of transfer learning three modules to correspond to the above problems, respectively. The overall process of the FedVCP framework is shown in Fig. 2.

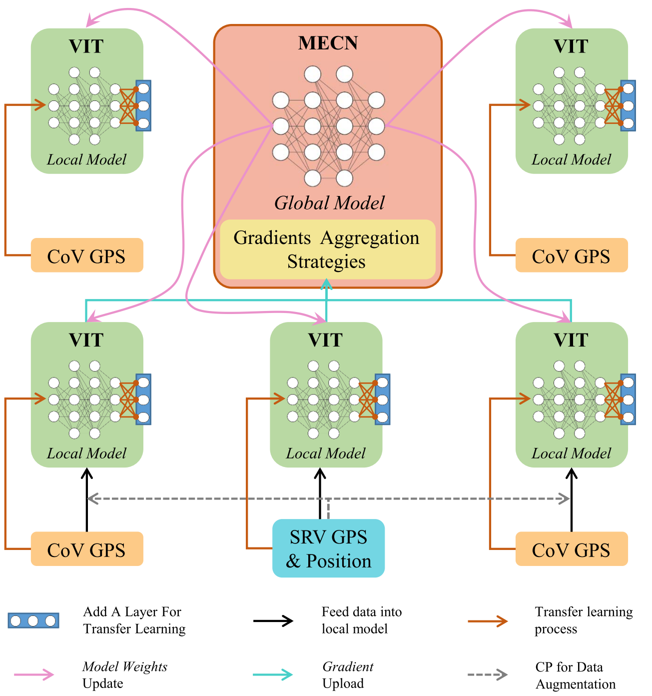

Fig. 2. Architecture of FedVCP. Local models are maintained in vehicle intelligent terminals (VITs), while MECN maintains the global model. Using private data, the local model uploads the gradient of the loss. The global model aggregates gradient information to update itself and the local model. In addition, the transfer learning process is carried out locally.

The MLP model is suitable for learning and correcting regional positioning errors due to its easy-to-implement characteristics and powerful feature extraction capabilities. Federated learning avoids the steps of user data collection to protect user privacy and can lead to results close to those of centralized model training. The use of transfer learning makes the model more customized. In addition, we consider the advantages of CP based on ranging and communication in solving local positioning and apply it to our framework.

IV. Methodologies

This section focuses on the methods in our study, including error analysis, error prediction model, model training, data augmentation, and the solution of individual error.

A. GPS Error Analysis

Generally, GPS errors are divided into systematic errors and random errors. The systematic errors mainly come from the satellite orbit and clock error, ionospheric delay and tropospheric delay, and receiver clock and positioning error. The random error mainly includes error caused by multipath effect and receiver noise [13]. Among the above errors, we refer to the errors caused by satellites, the atmosphere, and the multipath effect as regional errors E^r. The characteristic of regional errors is that the errors within the same region at similar time points are almost the same. We call the error generated by GPS receiver individual error E^i. In this article, we take no account of solving random errors.

The positioning error E can be decomposed into

$$E = E^r + E^i + E^\beta \tag{1}$$

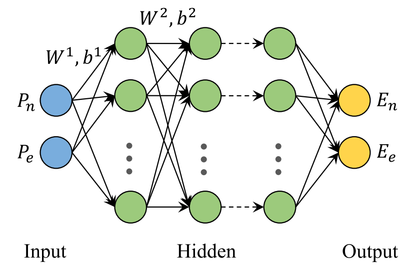

Fig. 3. MLP for error prediction.

where E^r and E^i are the regional errors and individual differences. E^β refers to the random error.

For vehicles u and v that are in the same area at a similar time, their relative error $\|\Delta E_{uv}\|$ is derived

$$\begin{aligned}
\|\Delta E_{uv}\| &= \|P_u - P_v\| - \|\hat{P}_u - \hat{P}_v\| \\
&\le \|(P_u - P_v) - (\hat{P}_u - \hat{P}_v)\| \\
&\le \|E_u - E_v\| \\
&\le \left\|\left(E_u^r + E_u^i + E_u^\beta\right) - \left(E_v^r + E_v^i + E_v^\beta\right)\right\| \\
&\le \left\|E_u^r - E_v^r\right\| + \left\|E_u^i - E_v^i\right\| + \left\|E_u^\beta - E_v^\beta\right\|
\end{aligned} \tag{2}$$

where E_u^r, E_v^r, E_u^i, and E_v^i are regional errors and individual differences of GPS positioning of vehicles u and v, respectively. P denotes the real position, and $\hat{P}$ stands for positioning given by GPS. As described above, $E_u^r \approx E_v^r$. Besides, E_u^β and E_v^β are random errors, and their value is relatively small. Thus, the relative error depends on individual differences

$$\|\Delta E_{uv}\| \le \left\|E_u^i - E_v^i\right\|. \tag{3}$$

B. MLP for Regional Positioning Error Prediction

In urban traffic scenarios full of landmarks nearby, SRVs can interact with the infrastructure through sensor ranging and other methods to obtain accurate GPS errors. However, CoVs fail to find errors. Moreover, the service range of the assisted positioning of the infrastructure cannot cover every location in the city, so it is difficult to promote the direct use of V2I assisted positioning. In addition, it can be concluded from the above analysis that the regional error represents the largest component of GPS errors, which means that only part of the error information in the area needs to be obtained to approximate the error of the entire area. The error prediction method for the entire city will be a huge nonlinear function.

Therefore, we hope that the error prediction model can simulate complex nonlinear mapping, and due to the time-varying nature of GPS errors, the model must have the ability to learn online. MLP meets the requirement of the error prediction model. When the assistant positioning is not available, SRVs and CoVs use the error prediction model to estimate the current GPS errors and correct their own positioning. All subsequent improvements in this article take MLP as the basic model of error prediction. Fig. 3 shows the details of the MLP error prediction model.

1) Input Layer: The GPS error prediction model takes east coordinate P_e and north coordinate P_n as the model input. The input vector of the model is expressed as $[P_e \;\; P_n]$.

2) Hidden Layers: The hidden layer of the model is the full connection layer, with rectified linear unit (ReLU) as the activation function.

3) Output Layers: Corresponding to the input of the model, the error of the east coordinate E_e and the error of the north coordinate E_n of the model are regarded as the output, and the output vector is expressed as $[E_e\ E_n]$.

We take u^k and v^k as the input and output of the kth hidden layer of the model, $\sigma(x) = \max(0, x)$ as the activation function, and W^k and b^k as the weight matrix and bias term of this layer, respectively. Then, the calculation process of this layer is given as follows:

$$\begin{aligned} v^k &= W^k \times u^k + b^k \\ u^{k+1} &= \sigma(v^k). \end{aligned} \tag{4}$$

C. Training Error Model With Horizontal Federated Learning

Although the cloud-based centralized training model can achieve acceptable results in GPS error correction tasks, this method faces two problems: 1) as private data, GPS trajectory data are almost impossible to collect and 2) even if some users agree to upload their data, it will consume a lot of network bandwidth. In this article, we propose a training method for an error prediction model based on federated learning, without uploading user data, so that the above problems can be solved.

Model training based on horizontal federated learning is different from traditional machine learning model training. It allocates training tasks to local terminals and MECNs. The local terminal is mainly responsible for the update of the local model parameters, the calculation of the loss value, and the gradient of the model weights. MECNs collect locally uploaded gradient information and use aggregation algorithms to fuse all gradients to update the global model. Then, MECNs deliver the new model weights to the local terminal. These processes will be repeated continuously until the model converges.

At the initial stage of the training, the weights of the global model are assigned to random values. The global model then sends the weights to the local, which updates the local model.

1) Local Procedure: Each local terminal inputs the local private data into the local model to predict the error, and the loss value is calculated by the mean square error (MSE) loss function the following equation:

$$J(\theta, x, y) = \frac{1}{2n}\sum_{i=1}^{n}(\hat{y} - y_i)^2 \tag{5}$$

$$\theta = \{W, b\}. \tag{6}$$

Then, the weight gradient of the last hidden layer is calculated as follows:

$$\frac{\partial J}{\partial W^L} = \frac{\partial J}{\partial v^L}\frac{\partial v^L}{\partial W^L} = (\hat{y} - y)(u^L)^T \odot \sigma'(v^L) \tag{7}$$

and

$$\frac{\partial J}{\partial b^L} = \frac{\partial J}{\partial v^L}\frac{\partial v^L}{\partial b^L} = (\hat{y} - y) \odot \sigma'(v^L) \tag{8}$$

where $\odot$ means the Hadamard product. By the chain rule, it is easy to get the partial of J with respect to v^l

$$\frac{\partial J}{\partial v^l} = \frac{\partial J}{\partial v^L}\frac{\partial v^L}{\partial v^{L-1}}\cdots\frac{\partial v^{l+1}}{\partial v^l}. \tag{9}$$

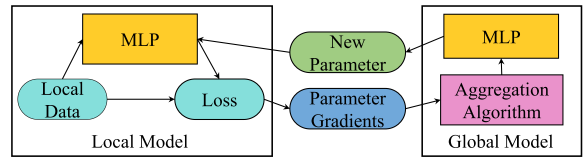

Fig. 4. Interactive iteration method of local model and global model in horizontal federated learning.

Algorithm 1 Gradient Aggregation Algorithm of Global Model

Input: The parameter set of the global model $\Pi = \{\pi^1, \pi^2, \cdots, \pi^K\}$, the gradients set $G = \{\nabla\pi_1, \nabla\pi_2, \cdot, \nabla\pi_\phi\}$, the learning rate η.

Output: The latest global model parameter set $\hat{\Pi} = \{\hat{\pi}^1, \hat{\pi}^2, \cdots, \hat{\pi}^K\}$

```
init Π̂ ← Π
init Ḡ ← {0}_{K×1}
# Calculate the average value of the gradient
for i ≤ φ do
    Ḡ ← Ḡ + ∇π_i
end for
Ḡ ← Ḡ/φ
# Updating the global model
for each π̂_j ∈ Π̂, each ∇π_j ∈ ∇Π do
    π̂_j ← π̂_j − η∇π_j
end for
return Π̂
```

The gradient of each parameter in the MLP can be easily derived as follows:

$$\frac{\partial J}{\partial W^l} = \frac{\partial J}{\partial v^l}\frac{\partial v^l}{\partial W^l} = \frac{\partial J}{\partial v^l}(u^l)^T \tag{10}$$

$$\frac{\partial J}{\partial b^l} = \frac{\partial J}{\partial v^l}\frac{\partial v^l}{\partial b^l} = \frac{\partial J}{\partial v^l}. \tag{11}$$

Finally, the gradients of all parameters are recorded as $\nabla\pi = \{\nabla\pi^1, \nabla\pi^2, \ldots, \nabla\pi^K\}$, and K represents the number of parameters of the model. The same process will be repeated m times. The average value $\nabla\pi_{\text{avg}}$ is calculated from the gradients obtained as the gradient of the upload.

2) Global Procedure: The global model collects gradients for model weight update from each local model. For each iteration of the global model, ϕ local models provide updated gradients for reference, that is, the gradients set $G = \{\nabla\pi_1, \nabla\pi_2, \ldots, \nabla\pi_\phi\}$. Each $\nabla\pi_i$ is a list of length K. After that, the global model uses an aggregation algorithm to integrate all the gradient information to update itself. The iterative update process is shown in Fig. 4.

In this article, we directly use the average value of the gradients as the gradient of the global model. The global model will be updated in a manner similar to stochastic gradient descent (SGD). The aggregation and model update process is shown in Algorithm 1. After the global model is trained for S rounds, the parameters are sent to the local model. The local model parameters are updated, and the next iteration starts.

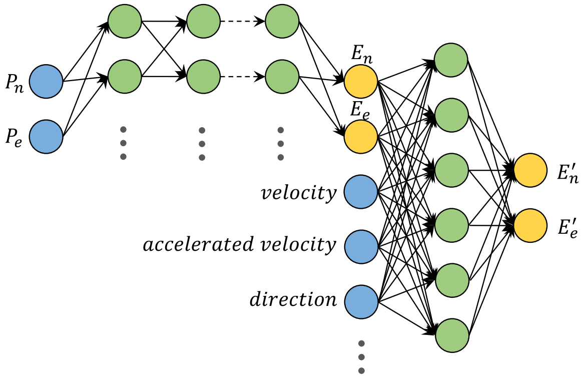

Fig. 5. FedVCP-TL model architecture.

D. Augmenting Data in a CP Way

Considering that, in current urban traffic scenarios, the amount of data provided by SRV may not be enough to make GPS error detection model training quickly converge, this article proposes a data augmentation idea based on ranging CP. In this way, CoVs no longer serve as pure model users; they also participate in data generation and model training.

When a CoV approaches an SRV, the SRV measures the relative position of the two vehicles and sends the relative position information and its own precise positioning information to the CoV. Subsequently, CoV approximates accurate positioning based on the abovementioned information. Therefore, CoVs are equivalent to possessing local training data and can have local models and participate in model training.

It is worth noting that, for CoV, too little data may be generated within a certain period of time. In this case, this part of the data should be abandoned and not participate in this round of training.

E. Handling Individual Errors With Transfer Learning

Among the components of GPS positioning errors, in addition to regional errors, there are individual errors. This type of error may be caused by various factors, such as receiver errors, vehicle location, or vehicle status. We use the idea of transfer learning to propose a model optimization for individual errors, called FedVCP-TL, as shown in Fig. 5.

In FedVCP-TL, first, the regional error prediction model is used to obtain the regional error; second, a new hidden layer is added to learn individual errors; finally, the vector of the regional error and vehicle state characteristics are concatenated as input, and the accurate error is used as the label.

In particular, since an individual error has no obvious area and time-varying characteristics, the training of an individual error prediction model does not need to be performed in real time. In this case, it is necessary to store the predicted value of the area error and the state of the vehicle, as well as the accurate error.

V. Performance Study

In this section, we introduce the source of experimental data and the simulation of data and show the settings of the comparative experiment. The results of simulation experiments prove the effectiveness of our proposed method and its robustness in different scenarios.

(a) (b)

Fig. 6. Visualization of raw data. (a) Road network. (b) Road network with trajectories.

TABLE I
Important Fields in Data Set and Descriptions

Field	Type	Example	Remark
DriverID	String	glox.jrrlltBMvCh8 nxqktdr2dtopmlH	Desensitized
OrderID	String	jkkt8kxniovIFuns 9qrrlvst@iqnpkwz	Desensitized
Timestamp	String	1501584540	unix timestamp, in seconds
Longitude	String	104.04392	GCJ-02 coordinate system
Latitude	String	104.04392	GCJ-02 coordinate system

A. Introduction to Data Set

The data set used in this article comes from the trajectory data of older drivers on the Didi express car platform in the second ring area of Chengdu in October 2016 of 65 km^2. The collection interval of trajectory points is 2–4 s. The track points have been tied to the road, ensuring that the data can correspond to the actual road information. The driver and order information is encrypted, desensitized, and anonymized. The data source is Didi Chuxing GAIA Initiative (https://gaia.didichuxing.com). We selected 100 vehicles' data from the trajectory data from 00:00 to 24:00 on October 1. The important fields in the data set and their descriptions are shown in Table I. We visualized the trajectory data and the road network corresponding to the data, as shown in Fig. 6.

For the latitude and longitude coordinates in the data set, we first convert them to the WGS84 coordinate system and then use UTM grid system to convert the latitude and longitude coordinates into east–north coordinates in meters. In order to simulate the regional characteristics of GPS error, we divided the studied urban area into 64 squares with sides of approximately 1 km. In our simulation experiment, we randomly generated regional errors, individual errors, and random errors from the Gaussian distribution the following equation:

$$f(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left[\frac{(x-\mu_1)^2}{\sigma_1^2} - 2\rho\frac{x-\mu_1}{\sigma_1}\cdot\frac{y-\mu_2}{\sigma_2} + \frac{(y-\mu_2)^2}{\sigma_2^2}\right]} \tag{12}$$

where $\rho = 0$ and $\sigma_1 = \sigma_2 = 1$. The range of these three errors is 10, 0.5, and 0.1 m.

TABLE II
COMPARISON OF LOSS OF VARIOUS GPS ERROR PREDICTION MODELS WITH DIFFERENT SRV RATIOS

SRVs %	Indicator	DNN	FedVCP	FedVCP*	FedVCP-TL
5%	MAE	0.24880	0.04610	**0.04318**	0.04379
	MSE	0.10615	0.00347	**0.00300**	0.00309
10%	MAE	0.10659	**0.03634**	0.04711	0.04726
	MSE	0.02365	**0.00212**	0.00362	0.00366
15%	MAE	0.07829	**0.03076**	0.03512	0.03559
	MSE	0.01059	**0.00147**	0.00193	0.00198
20%	MAE	0.06659	0.04437	**0.03501**	0.03507
	MSE	0.00692	0.00345	0.00192	**0.00191**
25%	MAE	0.04597	0.03226	0.03455	**0.03447**
	MSE	0.00338	0.00170	0.00194	**0.00192**
30%	MAE	0.05345	0.03612	0.02581	**0.02559**
	MSE	0.00424	0.00217	0.00109	**0.00106**

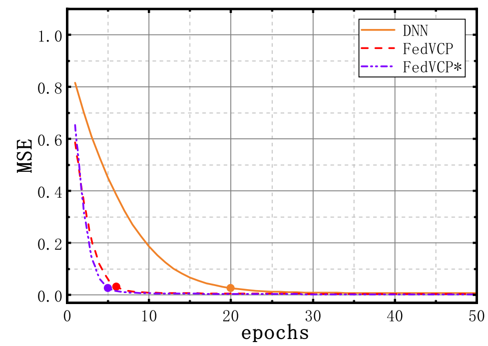

Fig. 7. Loss value curve during model training. This figure is the result when SRVs accounted for 20%.

B. Experimental Setup

In order to verify the effectiveness of our proposed method, a comparative experiment of DNN, FedVCP, FedVCP*, and FedVCP-TL is carried out. Specifically, (*) means that the strategy of data augmentation is used. For DNN and FedVCP, the same training set is used, while FedVCP* uses a data augmentation strategy, so the scale of the data set will be larger. FedVCP-TL is an extension of FedVCP*, adding training steps in the terminal.

The explanation here is that, in order to simplify the simulation of the data enhancement part based on vehicle collaboration, we treat vehicles in the same area as collaboration. Particularly, the actual cooperation will not span this far, but the number of vehicles used in the experiment is small, and the number of vehicles close to each other is also small, so we appropriately increased the scope of cooperation to obtain more reasonable results.

To simulate different urban traffic environments, we set up six sets of controlled experiments according to different proportions of SRVs, and their proportions of SRVs are 5%, 10%, 15%, 20%, 25%, and 30%.

For the comparison index of the experiment, we used the common regression model evaluation index MSE and mean absolute error (MAE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{13}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|. \tag{14}$$

C. Precision Analysis

Accuracy serves as a vitally important indicator in the GPS error prediction model. In this article, we use the loss values of both MAE and MSE to measure the accuracy of the model. According to the above experimental settings, the final accuracies of the model on the test set are obtained. The final results of the participating models are shown in Table II. It can be clearly seen that the performance of FedVCP and FedVCP* is very close to that of DNN, and even the accuracy of FedVCP is slightly improved compared to DNN. This indicates that the ability of the model obtained by federal learning is close to that of the model trained by traditional methods in the task of urban GPS positioning error prediction.

It can be observed that the performance of FedVCP* is slightly worse than the expectation. FedVCP* loses to FedVCP in 10%, 15%, and 25% of SRVs. We speculate that the condition that the local model training data of some vehicles are too few leads to overfitting of local model training. Then, the aggregation strategy of the global model does not take this problem into account and treats every local model equally.

In the FedVCP-TL experiment, positioning errors caused by vehicle states (such as velocity, acceleration, and direction) are rarely considered because it is difficult for us to know the specific causes of individual positioning errors and simulate such errors. Our experiment only considers the errors that are caused by the positioning receiver. The performance of FedVCP-TL, which uses transfer learning, performs better than FedVCP* when the proportion of SRVs is relatively higher. It indicates that FedVCP-TL has learned individual errors.

In general, the model FedVCP trained using the federated learning method can reach or exceed the DNN model trained in the cloud with the data being fully collected. FedVCP-TL, which adopts the transfer learning strategy, accomplishes its task of learning individual errors well when the collaboration scenario is good. Although FedVCP* using a data augmentation strategy is not perfect in accuracy, it is still within an acceptable range.

D. Convergence Rate Analysis

In addition to accuracy, the convergence speed is also an important indicator for GPS error prediction models. In the urban environment, the regional error of GPS is constantly changing, and the convergence speed of the model must be fast to cope with the rapidly changing GPS error. It is obvious that the GPS error prediction model will operate in real time. In this experiment, we do not consider the factors of upload speed and hardware performance but judge the speed of convergence by comparing the change of the loss value of each epoch. Each iteration of the model during training means that the model learns from all the training data and is updated once.

As can be seen from Fig. 7, DNN reaches convergence after training for about 30 epochs, while FedVCP completes the convergence of the model in 10 epochs. Not surprisingly,

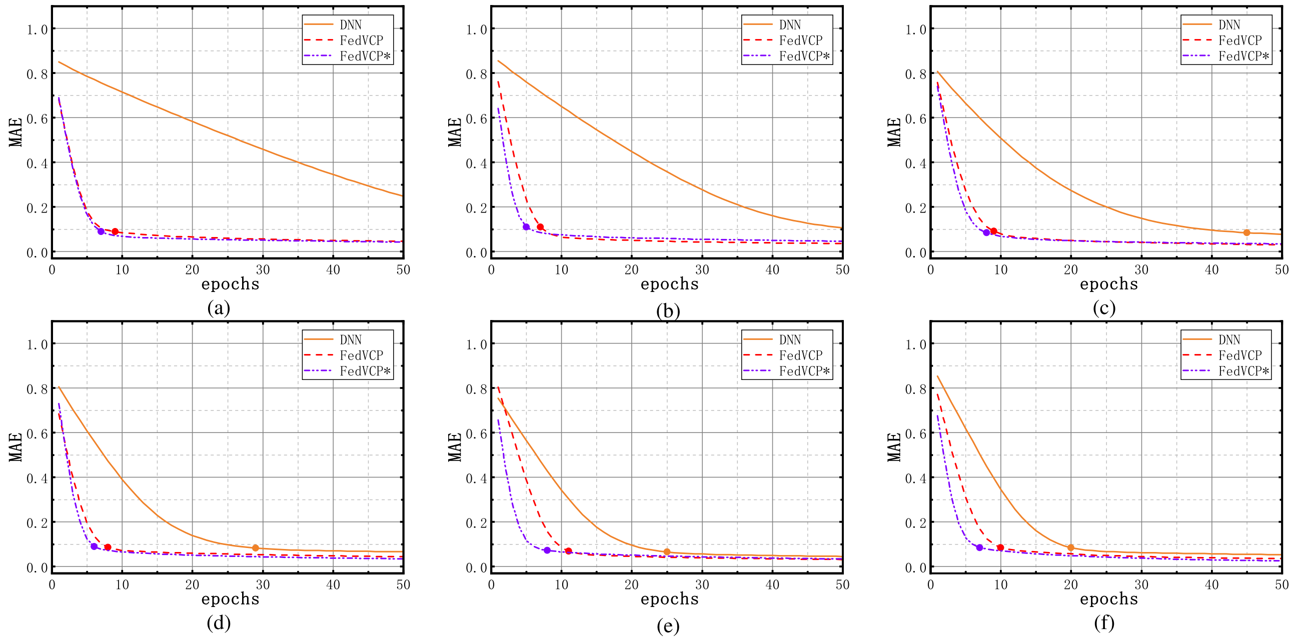

Fig. 8. Changes of MAE during training under different SRVs proportions. (a) 5%. (b) 10%. (c) 15%. (d) 20%. (e) 25%. (f) 30%.

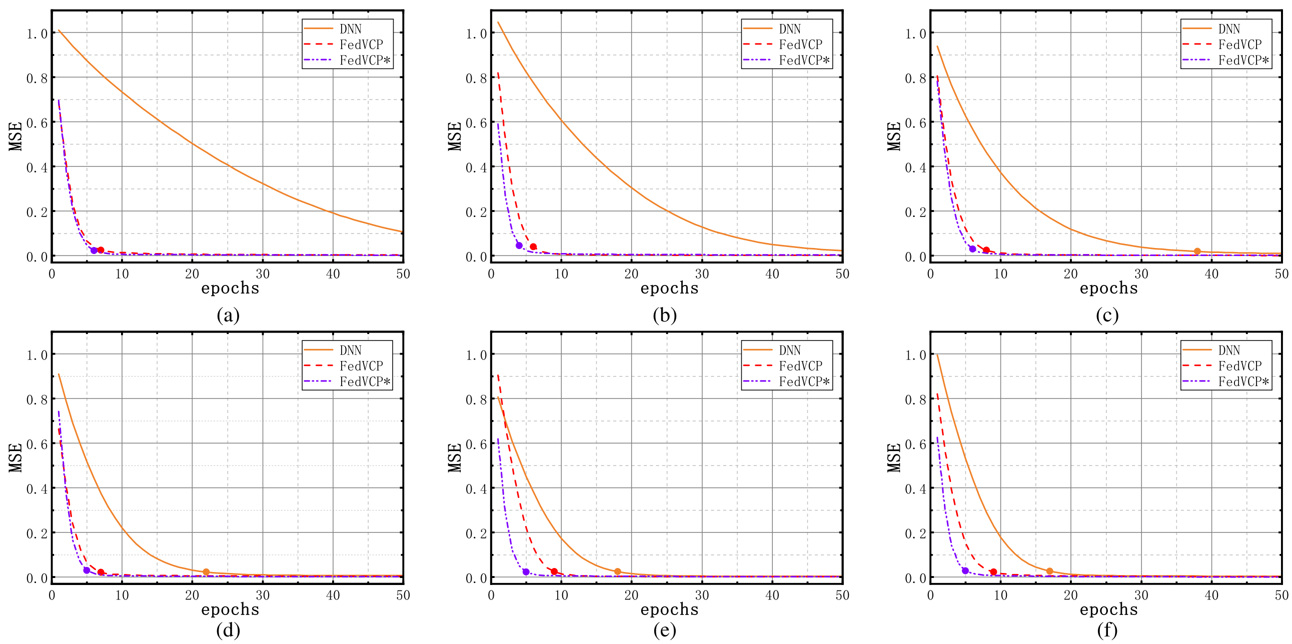

Fig. 9. Changes of MSE during training under different SRVs proportions. (a) 5%. (b) 10%. (c) 15%. (d) 20%. (e) 25%. (f) 30%.

FedVCP* failed to significantly surpass FedVCP in accuracy, but it surpasses FedVCP in convergence speed. The experiment shows that, under the condition of 100 vehicles participating in model training, on the one hand, the convergence speed of the model training method based on federated learning is much faster than that of centralized training. On the other hand, our proposed data augmentation strategy based on vehicle cooperation also played a role in accelerating model convergence.

In a real urban scene, the number of vehicles will be even larger, the regional error of GPS positioning will be more complicated, and the positioning data generated by vehicles can also be large. If the traditional model training method is used, the model training may be slow and consume a large amount of network bandwidth in data transmission. FedVCP performs backpropagation in the local model to calculate the gradient used for updating. This design is parallel from a global perspective and reduces the computation of the server and the overhead of data transmission. We speculate that the model will converge faster when more vehicles participate in model training.

E. Robustness Analysis

In order to verify the robustness of our proposed method in different urban traffic scenarios, we designed six groups of contrast experiments, covering the case where the proportion of SRVs ranges from 5% to 30%.

The experimental results are shown in Figs. 8 and 9. The MAE and MSE curves corresponding to DNN are very sensitive to the proportion change of SRVs. The smaller the proportion of SRVs, the slower the convergence rate of DNN is. It can be found that, regardless of the proportion of SRVs, the convergence speed of FedVCP and FedVCP* based on federated learning is much faster than that of DNN. Moreover, the convergence rate of the model trained by the federated learning method is not obviously affected by the environmental change. The performance of the model obtained by federated learning is comparable to that of the centralized training model, which shows the effectiveness of federated learning in GPS error prediction tasks. In different traffic scenarios, although the convergence speed will be slightly affected, the final loss of FedVCP and FecVCP* will both converge to an acceptable range, which shows the robustness of the model.

VI. Conclusion

In this article, we propose a novel vehicle CP framework named FedVCP. To the best of our knowledge, it is the first time that federated learning has been applied to vehicle CP. The implementation of federated learning solves the problem of data privacy and also stimulated the potential of cooperative edge computing. In addition, we use a data augmentation strategy based on cooperation to accelerate the convergence of the error prediction model. Then, we introduce the idea of transfer learning to further improve the positioning accuracy. Although our method performs well in simulation experiments, the real urban traffic environment is more complicated, and the effectiveness and robustness of the method need further discussion. In addition, how to use vehicle status information, such as speed, acceleration, and direction, more effectively is also a problem to be solved.

Acknowledgment

The authors would like to thank all the teachers and students in the lab for their help and support; during the COVID-19 epidemic, despite the inconvenience of isolation, they have provided the authors with valuable advice. They would like also to express their special thanks to Mengyuan Wang for his modifications to the article. Thanks to the data source: Didi Chuxing GAIA Initiative.

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