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Personalized Federated Learning Framework for Person Re-identification in MEC-enabled UAV Delivery Services

Yi Xu[1], Zhipeng Wang[1], Jonathan Kua[2], Haoyu Luo[3], Ruyi Guo[1], Xiao Liu[2]

1School of Computer Science and Technology, Anhui University, Hefei, China
2 School of Information Technology, Deakin University, Geelong, Australia
3 College of Mathematics and Informatics, South China Agricultural University, Guangzhou, China
08055@ahu.edu.cn; e22301221@stu.ahu.edu.cn; jonathan.kua@deakin.edu.au;
luohy@whu.edu.cn; guory@stu.ahu.edu.cn; xiao.liu@deakin.edu.au

***Abstract*—Unmanned Aerial Vehicle (UAV) based last-mile delivery is considered as a highly promising solution in smart logistics. To provide effective delivery service, it is crucial to ensure accurate positioning and identification of the UAV goods receiver in a timely fashion. However, insufficient data captured by onboard UAV cameras makes it challenging to guarantee the performance of those recognition models. Moreover, using data collected from public cameras and other devices for model training may lead to privacy concerns. To address these issues, this paper proposes a personalized federated learning framework named LP-Fed (Location-Aware Pixel Personalized Federated Learning) under the edge computing architecture. Building upon this framework, a person re-identification solution tailored to edge computing environment is implemented. This solution aims to enhance the precision of UAV-based goods receiver positioning and identification by leveraging multiple data sources while protecting data privacy. Specifically, LP-Fed employs a position-pixel attention module to adaptively aggregate the global models and local models, addressing feature disparities from various data sources at the edge. In addition, the introduction of model relevance indicators can dynamically adjust the aggregation weights of model parameters. Experimental results demonstrate that LP-Fed can significantly improve the model accuracy across eight representative person re-identification datasets while ensuring data privacy.**

Keywords—Personalized Federated Learning, UAV, Edge Computing, Person Re-identification

I. INTRODUCTION

In recent years, the rapid advancements of Artificial Intelligence (AI) has found widespread applications in smart logistics, and it is widely recognized as an effective means to enhance delivery efficiency and customer satisfaction [1-3]. In particular, intelligent Unmanned Aerial Vehicle (UAV)-based delivery has garnered significant attention due to several of its advantages, including rapid delivery, flexibility, cost-effectiveness, and environmental friendliness, hence making it a vital component for achieving efficient last-mile delivery [4-6]. Major e-commerce and logistics companies, such as JD.com, SF Express, and Amazon, have been driving research in UAV technology for product delivery in recent years [7-8]. Last-mile delivery is a critical aspect of smart logistics. It requires an efficient and accurate method to ensure UAVs can precisely locate and identify the target goods receiver, hence enabling a seamless and efficient logistics process. Person re-identification algorithms [9] are specialized techniques that are optimized for identifying individuals based on their appearance, including clothing, posture, facial features, and accounting for appearance variations across different scenarios and times. These optimizations have resulted in improved performance in personal identification. Consequently, many studies have employed person re-identification algorithms [10-11], and utilize data captured by UAV onboard cameras to train models for goods receiver identification. However, UAV deliveries are typically time-constrained, and the data captured by onboard cameras within this limited time frame is insufficient for accurate and efficient positioning/identification of goods receivers using inference models generated solely from this data. To enhance model accuracy, a viable approach is to share relevant data captured by street-level public and commercial cameras with UAV onboard camera data to expand the training dataset. Nevertheless, directly combining data from these diverse terminal devices to improve model performance can lead to severe privacy data leakage issues. In recent years, data privacy and security concerns have gained significant attention. With the rapid developments of the Internet of Things (IoT) and the surge in data, issues related to personal information privacy and digital security have become increasingly prominent. Regulations such as the European General Data Protection Regulation (GDPR) [12] and China's draft Data Security Management Measures impose higher requirements on data privacy protection. Consequently, data privacy protection significantly hinders the full utilization of data from these terminal devices.

Federated Learning (FL) is increasingly gaining attention as a solution that respects user privacy while handling large amounts of data. It enables collaboration among different individuals and organizations with terminal devices to train a global model without the need to share private datasets [13]. FL is also widely regarded as a positive step towards addressing the problem of isolated data islands. It employs encrypted distributed machine learning technology to ensure that parameters are encrypted during transmission between different parties, preventing unauthorized access [14]. FL aggregates these parameters into a global model, where all data is fully utilized while safeguarding data privacy. Through federated learning, it is possible to efficiently share street-level public camera data and commercial camera data with UAV-captured data to improve goods receiver identification while preserving data privacy. However, FL faces challenges in practice, one of which is the disparity in data distribution among different terminal devices. This arises from significant differences in angles, distances, lighting conditions, and image quality between various cameras and the UAV onboard camera in delivery scenarios. Consequently, the disparate

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distribution of data from multiple terminal devices poses challenges related to feature disparities in the data. Traditional FL methods, such as FedAvg [21], seek to achieve a high-quality global model through distributed training across clients, but these methods may fail to meet the local objectives of individual clients, leading some clients to opt-out of the FL process [18]. This is due to the difference in data distribution among clients, which is a key challenge in FL [16]. To address this issue, some research has proposed personalized Federated Learning (pFL) methods to mitigate differences in client data distribution within FL. Unlike traditional FL, which seeks to train a high-quality global model through distributed training across clients, pFL [19] enhances model performance, adapts to data heterogeneity, improves model specificity, and better protects privacy by training personalized models for each client. This makes FL more adaptable and efficient for different application scenarios and client requirements.

In the context of UAV-based smart logistics with the consideration of limited UAV computing power and other terminal devices, this paper proposes a personalized federated learning framework named LP-Fed. This framework incorporates the advantages of Mobile Edge Computing (MEC), including low latency, extensive coverage, and location awareness. LP-Fed adopts a Client-Edge-Cloud architecture, by leveraging multiple data sources to improve model performance while ensuring data privacy and security. In particular, to address the challenge of feature disparities in data from various edge segments in the UAV delivery scenario, we introduce the concept of model relevance in the local model aggregation phase of federated learning. By adapting aggregation weights for model parameters based on relevance indicators, we optimize the traditional federated learning model aggregation approach. In the global model update phase of federated learning, we employ a personalized training model method by adaptively aggregating the global model and local models using a pixel attention module, ensuring that the new round of local models aligns more closely with the edge data distribution, thereby enhancing model recognition performance. Given the extensive research on person re-identification in the UAV delivery domain, we implement a person re-identification solution tailored to edge computing scenarios based on the LP-Fed framework. We validate the effectiveness of our optimization methods across eight common pedestrian re-identification datasets.

The major contributions of this paper are as follows:

1. We proposed the novel LP-Fed framework based on the Client-Edge-Cloud architecture.

2. We designed a Model Parameter Adaptive Aggregation (PA) method to enhance federated learning local model aggregation.

3. We introduced a Pixel Attention Module-guided Personalized Update (PU) method for federated learning global model and local model aggregation.

The remainder of this paper is organized as follows: Section II provides an overview of related work, Section III details the LP-Fed framework and its specific algorithms, Section IV presents experimental results using eight typical pedestrian re-identification public datasets. Finally, Section V concludes the paper.

II. Related Work

A. Person Re-recognition

The goal of the person re-recognition algorithm is to retrieve images with the same identity from a large library based on image similarity [9]. The person re-identification algorithm is optimized specifically for person identification. It considers the appearance features of pedestrians, such as clothing, body shape, and facial features, etc., as well as the changes in the appearance of pedestrians in different scenes and times of day. This optimization focused on person identification, which makes it perform well in human identification. It is adaptable to a variety of different scenarios, including streets, shopping malls, airports, schools, and other places, and thus has a wide range of potential applications. Compared with traditional manual feature operators, deep neural networks can better extract representative features, which significantly improves the performance of person re-identification algorithms [20]. However, the dataset for person re-recognition contains images from different camera views. To train the person re-recognition model, a large amount of such data needs to be pooled. However, this also increases the potential privacy risk because these images contain personal information, identification information, and other sensitive information. The work in [17] effectively addresses the privacy risk caused by the mixing of person re-recognition data using federated learning. The proposed solution in [10] migrated the effective combination of federated learning with person re-identification algorithms to a UAV logistics scenario for goods receiver identification and proposed to lighten the model by using knowledge distillation. However, these camera devices are affected by various external factors in real deployments, including lighting conditions, camera shooting angle, sharpness and focus. These factors lead to significant differences in feature of images captured by different cameras. Therefore, a personalized Federation Learning (pFL) approach is needed to address the preservation of data privacy of person re-identification information.

B. Personalized Federation Learning

Federated Learning (FL) [13] is a distributed machine learning approach that trains machine learning models by using distributed data stored on different clients while avoiding the problem of client data leakage. Differences in client data distribution in FL is a key challenge [16], and personalized Federated Learning (pFL) has received much attention recently. Learning local models by using personalized (local) aggregation has been widely studied in pFL methods. Some of these studies have proposed that specific models for each client can be generated through personalized aggregation methods for client data distributions. For example, FedAMP [18] generates aggregated models for each client through an attention mechanism and personalized aggregation. On the other hand, FedPHP [19] utilizes historical local models to locally aggregate global and local models through rule-based moving averages and predefined weights (hyper-parameters). However, the existing personalized federated learning methods are not practiced on Re-identification (Re-ID)_ models, and the studies on personalization are focused on the stages where the model is sent from the global model to the local model for personalization. To improve the performance of the Re-ID model, we propose adaptively adjust the mixing weights of each edge-end model by using correlation metrics in the federated learning model aggregation stage, and adaptively

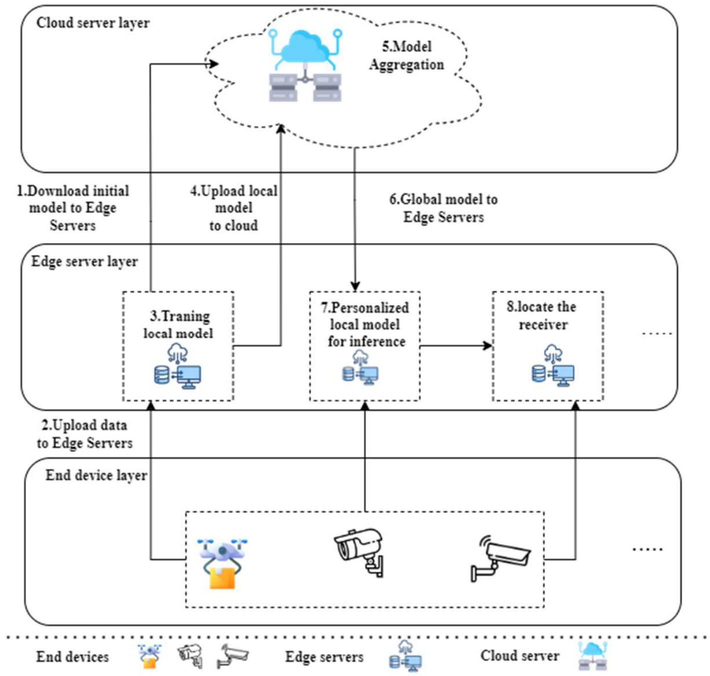

Fig. 1. Framework overview

aggregate the global and local models downloaded from the edge-end through the location pixel attention module, so that the aggregated personalized Re-id model is more suitable for the edge.

III. METHODLOGY

In this section, we introduce the LP-Fed framework which is based on a client-edge-cloud architecture developed to tackle the challenges related to the localization and identification of target recipients in UAV logistics scenarios. As illustrated in Fig. 1, our framework integrates multi-access edge computing (MEC), capitalizing on its merits of low latency, extensive coverage, and location awareness.

A. Framework

Fig. 1 illustrates the layered system design of the LP-Fed framework for UAV delivery scenarios. In this framework, urban distribution centers serve as cloud servers, whereas processing centers for different data sources serve as edge servers. For example, the data processing centers for UAV cameras are managed by logistics companies, the processing centers for neighborhood public cameras are handled by various public sectors, and the processing centers for commercial cameras are maintained by different companies. UAVs and neighborhood cameras are considered end devices.

This system is designed to enable effective data sharing to improve the efficiency and accuracy of drone delivery services. Each tier plays a key role in the overall delivery process and works collaboratively to achieve efficient logistics and distribution. Next, we describe the execution process of the LP-Fed framework.

(1) Initialization model: before the training process starts, the cloud server first assigns the initialization model to each client K .

(2) Data upload: The end devices $s=\{s_1,s_2,s_3,\cdots s_n\}$ upload the data to their edge servers to compose the local dataset $D=\{D_1,D_2,D_3\cdots D_n\}$.

(3) Local training: Each edge k trains the model θ_r^k .

(4) Model upload: Each edge uploads the trained model θ_r^k to the cloud server.

(5) Model Aggregation: The server adaptively aggregates the model parameters uploaded by each edge to obtain a new global model θ_{r+1} .

(6) Model distribution: The server distributes the global model to each edge and updates it to a personalized model for local data distribution as a new round of local models θ_{r+1}^k .

(7) Model inference: The edge server performs inference based on the local personalized model.

(8) Results execution: The edge servers use the results of model inference to localize the recipients.

During the training process, we make two improvements to federated learning. (1) when the cloud aggregates the local model as a global model, we use adaptive aggregation (PA) of model parameters at the edge end as a global model instead of the traditional weighted aggregation with the size of the data volume as the weight to be aggregated into a global model; (2) when the aggregated global model is downloaded from the cloud to the edge end, we perform Personalized Updating (PU) of the local model instead of the traditional federated learning cloud model is directly overwritten as a local model. This significantly improves the accuracy of the model. Next, we explain these optimizations in detail.

B. Edge-End Model Parameter Adaptive Aggregation

Traditional federated learning (FL) aggregation algorithms perform aggregation by weighting the aggregation according to the size of the data volume of each client [21]. In general, it is reasonable to assign higher weights to clients with larger datasets. However, there are differences in the quality and class of data across edge servers for UAV delivery. Relying only on the size of the data volume to determine the aggregation weights may lead to performance degradation. To further improve the practical effectiveness of the LP-Fed framework, we use adaptive aggregation of model parameters at the edge end. We use the correlation coefficient formula to calculate the correlation between the global and local models for each edge segment for the current round, i.e:

$$q_k = 1 - p_{corrcoef}(\theta_k^r, \theta^r) \tag{1}$$

where r denotes the number of communication rounds, $p_{corrcoef}$ is the correlation coefficient formula, θ_k^r denotes the client model parameters of the first r round, and θ^r denotes the global model of the first r round to predict the amount of knowledge is acquired at the edge end. To obtain higher quality information on different delivery areas, we assign smaller weights to the local models with higher correlation. The formula for adaptive aggregation of model parameters at each edge end into a global model is as follows:

$$\theta^{r+1} = \sum_{k=1}^{K} \frac{q_k}{q} \theta_k^r \tag{2}$$

where $q = \sum_{k=1}^{K} q_k$ is the sum of the correlation values between all edge-end local models and the global model for the current round. This approach gives less weight to the weighted aggregations where the edge-end models are more different from the current global model, thus extracting more knowledge from the edge-end that is different from the current model distribution, thus improving the quality of the global model.

C. Personalized Updating (PU) Local Model Approach

In our study, we propose the Personalized Updating (PU) approach. Unlike traditional federated learning where the global model directly replaces the local model and updates it (e.g., FedAvg [21]), we propose an element-level aggregation method using the pixel attention module to aggregate the global and local models. The aggregated model can be better adapted to the needs of each edge. Our personalized update formula is as follows:

$$\theta_i^{r+1} = \lambda \theta_k^r + (1-\lambda)\ \theta^{r+1} \tag{3}$$

The fusion weights λ are in the range of [0,1] and are obtained from the positional pixel attention module.

$$\lambda = \mathrm{sigmoid}\left(f_p(\vec{v}_p) \bullet f_i(\vec{v}_i)\right) \tag{4}$$

According to Fig. 2, we can convert the feature maps of the FL global and local models into vectors corresponding to the pixel positions, denoted as $\vec{v}_p$ and $\vec{v}_i$,respectively, then *sigmoid* the output of the function is expressed as the feature maps of the two models are multiplied pixel-by-pixel, and then normalized range to between [0,1]. The product operation corresponding to pixels captures the co-occurrence information between two pixel points. Through the product operation, if two feature maps have similar or similar element values at a certain position, their product results are larger; conversely, they are smaller. The product result can reflect the degree of correlation between two feature maps at each spatial location. This product operation is based on the element-level operation of the feature map, which effectively utilizes the structural information of the feature map in the spatial dimension.

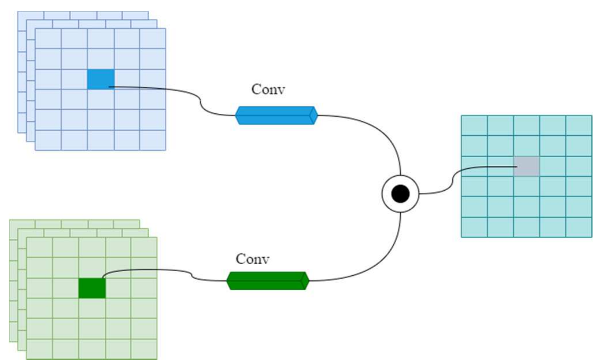

Fig. 2. Pixel attention guidance module

Algorithm 1 summarizes the algorithmic description of LP-Fed based on the above description.

Algorithm1: LP-Fed

Input: Local epoch E , batch size B , Round R ,
Number of clients N , selected clients K ,
learning rata η

Output: Local personalized θ_k^r of client K

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server:
  Initialize model θ^0 for each client k ;
  for each round r = 0 to R -1 do
    S_r ← (randomly select K );
    for each clients K ∈ S_r in parallel do
      θ_k^r ← ClientExecution( θ_k^r, k, r );
    θ^{r+1} ← Σ_{k∈s_r} (q_k / q) θ_k^r ;Parameter
      adaptive aggregation(PA)
    // Personalized update(PU)
    for each client K ∈ S_r do
      v_p ← feature maps from the θ_k^r ,
      v_i ← feature maps from the θ^{r+1} ;
      λ ← Sigmoid(f_p(v_p)•f_i(v_i));
      θ_K^{r+1} ← λθ_k^r + (1−λ)θ^{r+1} ;
  return θ^R , θ_k^R of each client k ;
Client Execution (θ, k, r ):
  B ← (divide local data into batches of size B );
  for each local epoch e = 0 to E−1 do
    for b ∈ B do
      θ ← θ − η∇ℓ (θ; b);
return θ
```

IV. Experimental Results

In this section, we first describe the experimental setup and dataset used; and then evaluate the effectiveness of our improved methods. Finally, we verified the effectiveness of each optimization through ablation experiments.

Datasets We use a typical eight-person re-identification public datasets in our experiments, and train each dataset as local data on an edge end. These datasets are used for benchmarking [17]. The statistics of the datasets are presented in Table 1. As shown in Fig. 3, these datasets are different in terms of the number of images, environment, identity number, and shooting angle. By using these datasets with different distributions to simulate a situation closer to a UAV distribution in a real scenario, the performance of the LP-Fed framework can be truly reflected.

TABLE I. THE STATISTICS OF EIGHT PERSON REID DATASETS.

Dataset	Identities	Images	Query	Gallery	Cameras
Market-1501[22]	751	12936	3368	19732	6
CUHK-03NP[23]	767	7365	1400	5332	2
CUHK-01[24]	485	1940	972	972	2
MSM-T17[25]	1041	32621	11659	82161	15
VIPe-R[26]	316	632	316	316	2
PRID-2011[27]	285	3744	100	649	2
iLIDS-VID[28]	59	248	98	130	2
3DPe-S[29]	93	450	246	316	2

The IDE model is a generalized baseline for person re-identification (Re-ID) [9]. We denote independent training as the training of person Re-ID on a certain dataset directly using the IDE model without any collaborative participation in FL with other clients. We can only prove the effectiveness of our approach if each client outperforms the independent training. We use a simple combination of federated learning and person re-recognition as a BASELINE to evaluate the effectiveness of our improvements. Therefore, we conducted two sets of experiments. In the first set of experiments we verified the effectiveness of LP-Fed by comparing LP-Fed, independent training and baseline methods. In the second set of experiments, we performed ablation experiments to verify the effectiveness of our proposed two-point optimization method for PA and PU.

Fig. 3. Sample images of eight datasets

Evaluation Metrics Cumulative Matching Characteristic curve (CMC) and Mean Accuracy Precision (mAP) are two important evaluation metrics for pedestrian re-identification. Cumulative Matching Characteristic curve (CMC) is a measure of the probability that the first K matches are successful. We only consider Rank-1, Rank-5, and Rank-10. where Rank-1 is the most important evaluation metric, while Rank-5 and Rank-10 are auxiliary evaluation metrics for evaluating the probability of successful matching for the first five and ten images. mAP is used to measure the average accuracy of matching, which is an important criterion for measuring the quality of a similar task model [17]. The algorithms used in our experiments are available online at https://github.com/wzpizz/LP-Fed.

Experimental Environment In conducting the experiments on evalutating the effectiveness of the LP-Fed framework, we simulate distributed federation training on a single NVIDIA GeForce GTX 3090 GPU. We used eight typical datasets, one for each edge and for training, which are collected from multiple camera views, simulating edge ends and collecting data from UAV cameras and other public cameras. In the LP-Fed framework, we use the IDE model with the ResNet-50 network as our model structure to perform FL. As described in [17], we set the number of local training rounds E=1, the batch size B=32, and performed 500 communication iterations.

A. *Performance Results*

We performed these experiements by comparing LP-Fed with independent training and baseline methods. Fig. 4 shows the results for Rank-1 accuracy on all datasets, Fig. 5 shows the results for the mAP metrics on all datasets, Fig. 6 shows the results for Rank-5 accuracy on all datasets, and Fig. 7 shows the results for Rank-1 accuracy on all datasets.

As shown in the results of Fig. 4 and 5, the Rank-1 accuracy and mAP of LP-Fed are higher than those of independent training on all datasets, which demonstrates the significance of adding our proposed LP-Fed framework to each edge end. The Rank-1 accuracy and mAP of LP-Fed are also higher than those of the baseline approach on all datasets, which verifies the effectiveness of our proposed two-point optimization for PA and PU. Moreover, it can also be seen in Fig. 4 that the Rank-1 accuracy of the independently trained approach is higher than that of the baseline approach on all five datasets, Market-1501, CUHK03-NP, CUHK01, MSMT17, and PRID2011, further proving the necessity of our two-point optimization of PA and PU.

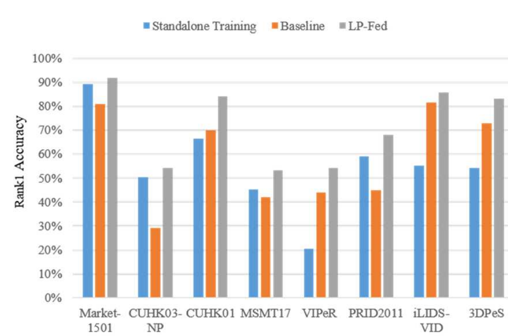

Fig. 4. Comparison of independent training, baseline, and LP-Fed performance (Rank-1 accuracy)

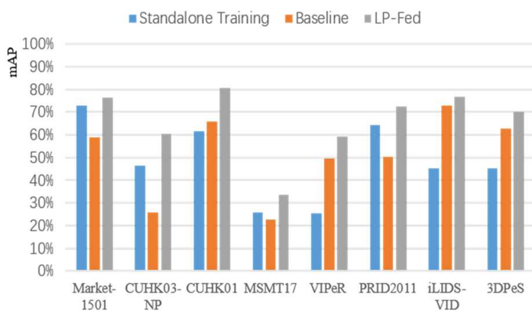

Fig. 5. Comparison of independent training, baseline, and LP-Fed performance (mAP)

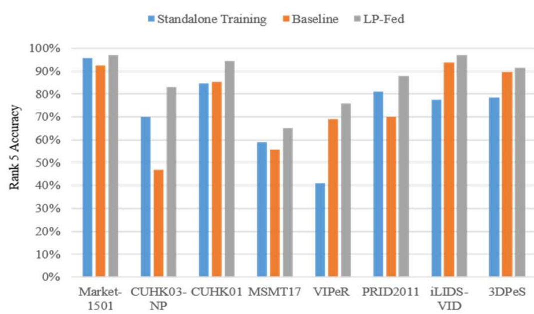

Fig. 6. Comparison of independent training, baseline, and LP-Fed performance (Rank-5 accuracy)

Fig. 7. Comparison of independent training, baseline, and LP-Fed performance (Rank-10 accuracy)

TABLE II. ABLATION EXPERIMENTS ON EIGHT TYPICAL PEDRSON RE-IDENTIFICATION DATASETS TO VERIFY THE IMPACT OF PA AND PU OPTIMIZATION METHODS

Datasets	LP-Fed	LP-Fed-PA	LP-Fed-PU
Market-1501	**0.917**	90.8	90.9
CUHK03-NP	**0.54**	51.4	51.2
CUHK01	**0.84**	80.5	82.2
MSMT17	**0.534**	51.7	53.2
VIPeR	**0.544**	52.8	52.2
PRID2011	**0.68**	60.0	65.0
iLIDS-VID	**0.847**	83.7	82.7
3DPeS	**0.829**	78.9	81.3

B. *Ablation Experiments*

To verify the impact of the individual optimization on the performance of the entire LP-Fed algorithm, we conducted an ablation study. We denote the de-embedded PA optimization method in LP-Fed as LP-Fed-PA, and we de-embedded the PU optimization method in LP-Fed as LP-Fed-PU. The experimental results are shown in Table II.

From the comparison results in Table II, we can see that the LP-Fed framework achieves the best performance. When we remove either the adaptive parameter aggregation optimization and the personalized update optimization on LP-Fed, the Rank-1 accuracy decreases regardless of the dataset used. These results proves the necessity of our two-point optimization approach for the LP-Fed framework.

V. CONCLUSION

In UAV-based delivery services, there are many open challenges such as the efficient localization and identification of goods receivers. This paper introduced a personalized Federated Learning (pFL) framework called LP-Fed based on the edge computing architecture, and leveraged the framework to implement a person re-identification (Re-ID) solution tailored to the edge computing environment. This solution aims to enhance the performance of Re-ID models by sharing data from various end devices while preserving data privacy. To address the challenge of disparate data distribution across a large number of end devices, LP-Fed incorporates two optimization approaches. Firstly, it adapts the aggregation of model parameters at the edge nodes by dynamically adjusting aggregation weights based on relevance metrics to optimize the traditional FL aggregation method. Secondly, it introduces a position-pixel attention module to adaptively aggregate the global model and local models so that the aggregated model can accommodate individual characteristics of each edge node for personalized updates. Comprehensive experimental results demonstrated that our framework can achieve significant accuracy improvements on many representative person re-identification datasets with varying data distributions. Therefore, with the proposed novel personalized federated learning framework, we can not only enhance the efficiency of UAV localization and goods receiver identification, but also effectively protect data privacy.

In the future, we plan to explore more effective model aggregation methods and personalized federated learning techniques to enhance the accuracy of FL models. We will also investigate the optimization methods to reduce the communication overhead for FL, and further improve the efficiency of the whole UAV delivery service.

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