A Federated Deep Unrolling Method for Lidar Super-Resolution: Benefits in SLAM

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***Abstract*—In this paper, we propose a novel federated deep unrolling method for increasing the accuracy of the Lidar Super resolution. The proposed framework not only offers notable improvements in Lidar-based SLAM methodologies but also provides a solution to the significant cost associated with high-resolution Lidar sensors. Particularly, our method can be adopted by a number of vehicles coordinated with a server towards learning a regularizer - a neural network - for capturing the dependencies of the Lidar data. To tackle this adaptive federated optimization problem effectively, we initially propose a deep unrolling framework, converting our solution into a well-justified deep learning architecture. The learnable parameters of this architecture are directly derived from the solution of the proposed optimization problem, thus resulting in an explainable architecture. Further, we extend the capabilities of our deep unrolling technique by incorporating a federated learning strategy. Our federated deep unrolling model employs an innovative Adapt-then-Combine strategy, where each vehicle optimizes its model and, subsequently, their learnable regularizers are combined to formulate a robust global regularizer, equipped to handle diverse environmental conditions. Through extensive numerical evaluations on real-world Lidar based SLAM applications, our proposed model demonstrates superior performance along with a significant reduction in trainable parameters, with 99.75% fewer parameters compared to state of the art lidar super-resolution deep neural networks. Essentially, this study is the first initiative to combine deep unrolling with federated learning, showcasing an efficient, and data-secure approach to automotive Lidar super-resolution SLAM applications.**

***Index Terms*—Deep unrolling, federated learning, interpretability, lidar, super-resolution.**

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I. Introduction

LIDAR Sensors are widely used in high-level autonomous vehicles as part of their perception systems, despite their high cost and moving parts. Due to the growing interest in autonomous driving, there are currently over 20 companies developing different types of lidar systems for autonomous driving applications, ranging from low-level to high-end capabilities [1]. With the continuous progress made over the years, a lidar-centric perception system is expected to mature in terms of model-based processing algorithms while satisfying at the same time requirements for the majority of autonomous vehicles (AVs) such as precise localization and accurate mapping of unknown surroundings. AVs frequently operate in environments characterized by constant changes, posing challenges to the creation of consistent maps. For instance, self-driving cars must possess the capability to consistently locate legal parking spots and identify safe passenger exit points, even in previously unexplored locations that lack accurate mapping data. The emergence of adaptive federated optimization in the field of Connected and Autonomous Vehicles (CAVs) has the capacity to transform such Lidar Based Simultaneous Localization and Mapping (SLAM) solutions [2], [3], [4].

However, two central challenges are currently restricting their broader implementation: the substantial cost of essential sensor equipment, including high-resolution Lidar (light detection and ranging) systems, and the prevalent skepticism towards deep learning methodologies, especially in high-stakes SLAM and multi-object detection and tracking applications. Large-scale deployment of such systems will only become feasible when the associated costs can be significantly reduced. Currently, the high expense is primarily due to costly sensor equipment (for instance, high-resolution Lidar systems) and the need for processing devices with advanced memory and computing capabilities [1]. Note that a 64-channel HDL-64E Lidar, typically employed for autonomous driving, costs roughly $85,000$\$. Conversely, a Lidar sensor with 16 channels is much more affordable, priced around $4,000$\$. Nonetheless, the lower resolution of the 16-channel sensor may impact its effectiveness in several autonomous driving applications, such as lidar based odometers and SLAM approaches [5].

In light of the above restrictions, a number of studies in the literature have delved into the use of more affordable sensors, for instance, a 16-channel Lidar, coupled with advanced super-resolution methodologies [6], [7], [8], [9], [10], [11], [12]. The ultimate objective is to enhance the data quality captured by low-resolution sensors, which can then serve as alternatives to costly high-resolution Lidar sensors. Two primary strategies have been explored to enhance the performance of low-resolution LiDAR sensor. The first category involves methods that integrate additional sensors. Such methods incorporate visual cameras [9], inertial measurement units (IMUs) [10], [13], or a combination of both [11]. The second category applies restoration methods, often deep learning-based super-resolution algorithms, either after initial range image calculation [6] or directly to the point cloud data [7], [8]. However, these methodologies depend on deep learning techniques which are often treated as black-box solutions. In particular, they generate complex neural networks characterized by an extensive amount of learnable parameters, thus necessitating substantial volumes of training data and lacking interpretability [14], [15]. Additionally, most lidar super-resolution techniques are based on pre-trained networks that are not updated in time, utilizing data recorded during the operation of the vehicles. Though, the data collected by each vehicle or even by a group of vehicles could facilitate continual learning paradigms, increasing the accuracy of the models in time. Building on this line of thought, federated learning [16] can serve as a continual learning methodology enabling collaboration between trusted agents and respecting at the same time privacy concerns. Again, the challenges in this case are related to the size of the state of the art super-resolution DNNs, posing significant communication and complexity challenges. Hence, designing efficient and explainable deep learning architectures that utilize the collaborative nature of FL is actually the (open) problem that is tackled in this paper.

To fill this gap, in this study, we aim to combine federated learning methods with analytical and well-justified optimization-based methods. This novel combination offers the advantages of both worlds: high performance due to the data offered by a number of cooperating agents as well as low-computational complexity and explainable model architectures. Specifically, our proposed method operates on range images directly derived from the lidar point clouds which are collected by different AVs that have the capability to communicate. Considering the unique local and non-local dependencies exhibited by 2D range images, our approach expands on recent studies that use learnable regularization terms in the form of suitable neural networks [17], [18]19, [19], [20]. These regularizers, derived from the training data of each AV, are adept at encapsulating more complex and unique characteristics of the data under consideration. Thus, the proposed method focuses on formulating a new well-justified optimization problem for the lidar super-resolution problem. This optimization problem consists of two interpretable components. The first component is a neural network derived by individual NNs of different AVs, which serves as a prior for the range images. The second component is a data consistency term that derives from the mathematical connection between the low and high resolution range images. To efficiently solve this problem the Half-Quadratic-Splitting (HQS) approach [21] is utilized.

Upon deriving an efficient iterative solver (e.g., based on the HQS) for the lidar super resolution problem, a model-based deep learning architecture is generated, via the utilization of the deep unrolling (DU) framework [20], [22], [23], [24], [25]. To elaborate, the derived solver is unrolled for a specific number of iterations, hence creating a structured neural network. Each layer within this network corresponds to a single iteration of our proposed algorithm. This DU technique facilitates end-to-end optimization of the model, thereby improving its ability to adapt to the problem at hand. The parameters of this model are directly mapped to the parameters of the well-understood optimization algorithm, resulting in an explainable framework that allows a clear understanding of its operation. In addition to offering superior levels of interpretability, the developed deep unrolling method showcase a compact structure and a reduced dependency on vast amounts of training data.

Additionally to the effective and interpretable model-based network, we propose a novel adaptation mechanism for cooperatively updating the regularizer deployed in a considerable number of vehicles, without sharing their own Lidar Data. In this context, our federated version of the deep unrolling methodology, allows each autonomous vehicle, equipped with its own low cost lidar sensor, to function as a distinct unit in a larger distributed learning network. Inspired by the distributed parameter estimation approaches [26], our approach follows the Adapt-then-Combine strategy. During the *adaptation* phase each vehicle employs its own private dataset to fine tune the local deep unrolling model by solving a local optimization problem. In the *combination* phase, the focus is on formulating a robust global regularizer, effectively encapsulating the information gathered from various vehicles operating in diverse environments.

The key contributions of this work can be summarized as follows:

- We propose a novel adaptive federated optimization mechanism for solving efficiently the lidar super-resolution problem. The proposed federated deep unrolling approach is the first attempt to solve collaboratively the lidar super resolution utilizing the benefits of FL and the DU frameworks. This combination captures the strengths of both frameworks: the superior performance afforded by data from collaborating agents and the benefits of low computational complexity and interpretable model architectures offered by the DU framework.
- Through comprehensive numerical evaluations, we demonstrate the superiority of our deep unrolling approach against various state-of-the-art methodologies in the context of lidar super-resolution problem. A great benefit that stems out of the proposed methodology is the fact that the individual deep unrolling networks contains 99.75% less parameters compared to other state-of-the-art deep learning networks. Moreover, the proposed mechanism is highly adaptable and can easily incorporate standard privacy-preserving mechanisms such as homomorphic encryption or differential privacy. In particular, we have evaluated the benefits of incorporating homomorphic encryption within the proposed FL-DU framework without negatively affecting the overall performance.
- We have also thoroughly studied the impact of the proposed federated DU-based Super resolution scheme in practical

and state of the art LiDAR based SLAM systems. More specifically, in order to provide a rigorous assessment, we integrated the proposed adaptive federated mechanism, utilizing the LeGO-LOAM system, a state of the art Lidar based SLAM that offers a real-time six-degree-of-freedom pose estimation and a generated 3D map. The reconstructed Lidar data achieved superior accuracy compared to other methods in various trajectories, highlight the effectiveness and superiority of the proposed approach in practical SLAM applications.

The remainder of this paper is organized as follows. In Section II, a detailed literature review and some preliminaries of related works are given regarding the deep unrolling framework, the lidar super-resolution problem and the federated learning. In the sequel, Section III formulates the problem under study and the proposed deep unrolling model. Section IV derive the proposed Federated Deep Unrolling method (FL-DU). Section V presents a series of extensive numerical results in the context of real world SLAM applications, that demonstrate the efficacy of the new algorithms. Finally, Section VI concludes the paper.

II. Related Work and Preliminaries

A. Deep Unrolling

The deep unrolling framework in an emerging research field with significant potential to numerous real-world inverse problems [20], [22], [23], [25], [27], [28], [29]. More formally, the deep unrolling approach transform effective optimization-based algorithms into computationally efficient and interpretable deep learning networks, where each iteration of the solver corresponds to one layer of the network [30].

To be more specific, in imaging systems inverse problems can be expressed as

$$\boldsymbol{Y} = \boldsymbol{S}\boldsymbol{X} + \boldsymbol{N} \tag{1}$$

where $\boldsymbol{Y}$ is the corrupted measurements of an signal $\boldsymbol{X}$, $\boldsymbol{S}$ denotes the forward operator and $\boldsymbol{N}$ is some noise. An effective way to estimate the desired signal $\boldsymbol{X}$ is to form an optimization problem

$$\arg\min_{\boldsymbol{X}} \ \frac{1}{2}\left\|\boldsymbol{Y} - \boldsymbol{S}\boldsymbol{X}\right\|_F^2 + \mu\mathcal{R}(\boldsymbol{X}) \tag{2}$$

where $\mathcal{R}(\cdot)$ is a regularization term, e.g. the total-variation (TV) semi-norm, or a learnable regularizer, aiming to promote the inherent properties of the under-examined signals [31]. Classic approaches to address this problem involve iterative solvers to estimate the solution, defined as $\boldsymbol{X}^{k+1} = g(\boldsymbol{X}^k, \boldsymbol{Y})$ to estimate a solution based on the Alternating Direction Method of Multipliers (ADMM) and HQS [32] methodologies. However, these methods can pose additional challenges in optimization problems. They often require parameter tuning and multiple iterations to converge to a satisfactory solution. In this context, a more effective solution can be realized using the deep unrolling paradigm. Particularly, a limited number of iterations from the derived iterative solver (e.g., HQS) are unrolled into a predefined number of iterations. This forms a structured neural network, with each layer representing a single iteration of the proposed algorithm.

Although the literature regarding the deep unrolling paradigm is rich in 2D classical image processing domain, its formulation and application in the automotive field, especially concerning Lidar super-resolution challenges in automotive scenes remains underexplored. In fact, in autonomous driving systems often encounter complex inverse problems that can potentially impact the performance of Simultaneous Localization And Mapping applications [33], [34], [35], [36]. In this study, we focus on the lidar super-resolution problem for automotive scenes by proposing a novel optimization problem and a deep unrolling network with state-of-the-art performance, low-computational complexity, and well-justified-explainable architecture. Significantly, the proposed DU model exhibits reduced number of trainable parameters i.e., $\mathbf{99.75}\%$ less parameters, as compared to other state-of-the-art deep learning methods.

Adopting a wider perspective, the deep-unrolling method provides numerous significant benefits in AV applications. In particular, compared to the classical deep learning approaches where their architectures derive from an ad-hoc manner [37], the proposed deep unrolling network have a clear connection with the under-examined problem and the considered optimization algorithm. This results in an explainable framework that allows a clear understanding of its operation. Understanding how a model operates can be vital for diagnosing and correcting any issues that could have safety implications [38]. For example, when a system exhibits sub-optimal performance, explanations assist engineers and researchers in identifying challenges, and potential areas of failure [38]. In addition, the developed deep unrolling method showcases a compact structure and a reduced dependency on vast amounts of training data. Therefore, the mathematical consistency and explainability in the proposed deep unrolling model become compelling attributes, amplifying the value and relevance of our work in real-world AV scenarios.

Finally, we leverage the structured design of our proposed deep unrolling framework to extend its capabilities further. Specifically, we propose a new federated learning framework, leading to an explainable deep learning models in the automotive domain.

B. Federated Learning in Automotive Domain

Although the Federated Learning framework has been extensively explored in numerous disciplines, e.g., signal processing, medical processing, its application in the autonomous driving domain remains under-investigated [16], [39], [40]. The current body of literature contains a limited number of works that investigate the benefits of FL in autonomous driving. For instance, study [41] used the FL scheme to examine the object detection problem in autonomous driving scenes. Additionally works in [42], [43] proposed methods for predicting the wheel steering angle in autonomous vehicles under the FL scenario. Theoretical aspects of federated learning, such as data distribution and non-i.i.d. nature of datasets, were explored in [2], [41]. Lastly, [44] developed a benchmark platform for semantic segmentation, incorporating multiple federated learning algorithms. It should be highlighted that the above approaches examine the federated learning framework only in the context of its application to specific problems, based on the FedAverage algorithm [45].

Our study differentiates from the existing literature in two important aspects. Firstly, we explore the novel problem of deep unrolling-based lidar super-resolution from a federated learning perspective, which has not been previously examined. By capitalizing on the distributed nature of federated learning, our approach enables the utilization of private lidar data gathered from diverse autonomous vehicles operating in different environmental conditions in order to improve the lidar slam solutions. Secondly, and more importantly, we propose a novel federated learning scheme based on the proposed deep unrolling formulation. We argue that the well-justified structure of the deep unrolling model can be fully utilized by the Federated learning strategy. Under the well justified structure of the deep unrolling model, the federated learning can be formulated as an Adapt-then-Combine approach. During the adaptation phase, each agent optimizes its local deep unrolling model, which is derived from the problem at hand. Subsequently, during the combination phase, agents upload only a portion of their local deep unrolling models – specifically the learnable regularizers – to a central server. The server then applies a fusion rule to the received learnable regularizers, deriving a global regularizer in the process. Thus, our proposed Federated Learning method seeks to learn a global regularizer that effectively captures the unique characteristics of each device's local private data. This global regularizer can then be efficiently integrated into local deep unrolling approaches to address the problem of Lidar super-resolution.

To the best of our knowledge, this is the first study that combines the deep unrolling strategy with the federated learning framework. This connection offers several practical advantages. Firstly, Firstly, the collaboration nature in the federated learning (FL) framework ensures both high performance and privacy.The deep unrolling method further enhances efficiency due to its compact model structure with fewer parameters, minimizing the communication load between devices and the central server and the computational resources that are required for training. Secondly, the interpretable architecture of the deep unrolling model enhances our understanding of the network's functions and the federated learning operation. Overall, the combination of the deep unrolling strategy with the federated learning framework not only improves efficiency but also enhances interpretability and privacy, making it a valuable approach for various applications.

C. Lidar Super-Resolution

In the field of lidar super-resolution, the majority of existing methods can be classified into two main categories.The first category involves methods that integrate additional sensors. Such methods incorporate visual cameras [9], inertial measurement units (IMUs) [10], [13], or a combination of both [11]. However, these methods have a significant drawback: they introduce increased computational complexity. This is primarily because their performance is heavily dependent on the accuracy of point cloud registration [7]. Additionally, the effectiveness of tight integration relies heavily on the precision of the IMU, which is often determined by its cost [7].

The second category involves the application of appropriate restoration methods to the noisy or low-resolution lidar data. In many instances, these approaches rely on the use of a deep learning-based super-resolution algorithm, which is applied either directly within the point cloud domain [7], [8], [46], or subsequent to the range-view domain, where the initial 3D point clouds are organized into 2D range images [6], [12].

Focusing on the studies [7], [8], [46] that process the raw 3D lidar point clouds to perform super resolution, these methods are usually computationally intensive as they require to find neighboring relationships among points [47]. The limited density of 3D point clouds derived from low resolution lidar sensors posses another major challenge, as they require complicated deep learning architectures and additional processing algorithms such as segmentation [8].

An alternative approach is to focus on the range image domain or range view, which involves projecting 3D point clouds onto 2D range images. This representation is more compact and provides a clearer insight into lidar point clouds, especially in handling the sparsity of raw 3D point clouds [48]. Methods such as [6], [12], utilize deep learning structures like the U-net-based network [6] or attention-based models [12]. Nevertheless, these deep learning architectures employed as black-box solutions they generate complex neural networks characterized by an extensive amount of learnable parameters. As a result they require substantial volumes of training data and often lack interpretability and explainability [14], [15].

In this study, we argue that the range view offers a distinct advantage. By converting 3D point clouds to 2D range images, we can identify and exploit the mathematical relationship that connects the low and high-resolution range images. Based on this relationship, we formulate a novel optimization problem that can be tackled using the deep unrolling framework. This approach offers adaptability, increased restoration performance, and computational efficiency while maintaining a clear understanding of the underlying processes.

Lastly, a significant distinction of our research from the existing literature is that most methods assume that the models are trained only once and they are not fine tuned in time utilizing data recorded during the operation of the vehicles. A further limitation of these methods is their lack of adaptability. Specifically, if there's a need to incorporate new information from other vehicles, it necessitates the transmission of new raw data to update the deep learning model. In contrast, we introduce an efficient federated learning framework based on the deep unrolling approach to address the above-mentioned challenges. In particular, the proposed method leverages data from distributed vehicles, mitigating privacy and communication challenges by exchanging only specific parts of the deep unrolling model namely, the learnable regularizer. This design

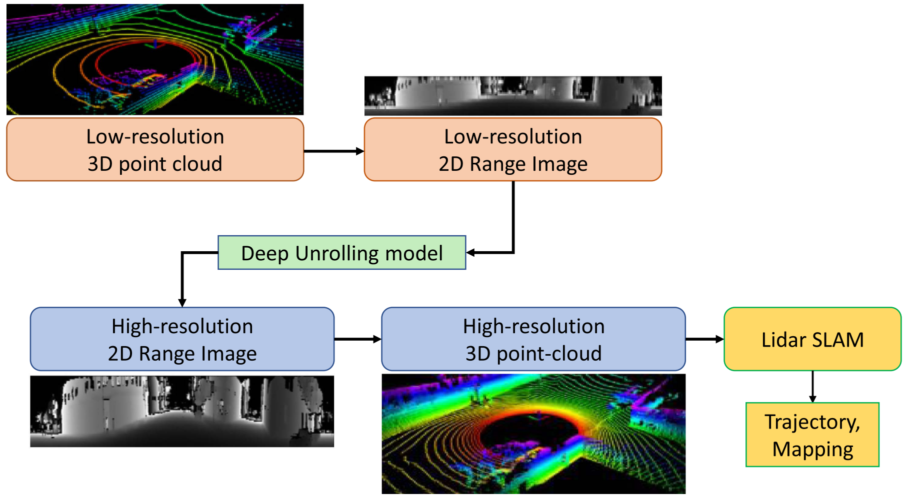


Fig. 1. Proposed Lidar super-resolution framework. Given a low-resolution 3D point cloud derived from a 16-channel lidar, it is project onto a 2D low-resolution range image. This image is provided as input to the proposed deep unrolling model (derived from the solutions of optimization problem (4), see also Section III-B2) to estimate the corresponding high-resolution range image. The estimated image is then transformed into 3D coordinates, thus producing the desired high resolution point cloud for the Lidar SLAM problem.

not only ensures data privacy but also enhances the adaptability of the proposed method, hence allowing it to efficiently integrate new information without the need for extensive data transfers. As a result, the overall effectiveness and flexibility of our system are substantially improved compared to traditional deep learning approaches.

III. The Lidar Super Resolution Problem and the Deep Unrolling Framework

In this section, we introduce the problem formulation regarding the lidar super-resolution problem and provide details how to design an efficient and explainable deep unrolling model. More specifically, Section III-A defines the mathematical relation between the low and high resolution lidar data. Utilizing the derived mathematical formulation, Section III-B presents the deep unrolling model to tackle efficiently the considered problem.

A. Lidar Super-Resolution: Problem Formulation

Assume a high-resolution point cloud generated by a 64-channel LiDAR sensor, resulting in the associated high-resolution range image $\boldsymbol{X} \in \mathbb{R}^{C \times M}$, where C signifies the vertical resolution (i.e., the total count of channels or lasers, for instance, $C = 64$), and M defines the horizontal resolution of the range image. The corresponding low-resolution range image $\boldsymbol{Y} \in \mathbb{R}^{c \times M}$, which retains the same horizontal resolution as X but includes only $c < C$ channels in the vertical resolution (e.g., $c = 16$), can be obtained using the degradation model below [6]:

$$\boldsymbol{Y} = \boldsymbol{S}\boldsymbol{X} + \boldsymbol{N} \tag{3}$$

where $\boldsymbol{S} \in \mathbb{R}^{c \times C}$ is a the downsampling operator that extracts only the c channels from the high-resolution range image and N denotes a zero-mean Gaussian noise term. With the low-resolution range image $\boldsymbol{Y}$ as input, our objective is to accurately estimate the high-resolution range image $\boldsymbol{X}$. Given the under-determined nature of this inverse problem, we suggest the following regularized optimization formulation

$$\arg\min_{\boldsymbol{X}} \ \frac{1}{2} \|\boldsymbol{Y} - \boldsymbol{S}\boldsymbol{X}\|_F^2 + \mu \mathcal{R}(\boldsymbol{X}) \tag{4}$$

comprised of a term that ensures data fidelity, and a learnable regularizer denoted as $\mathcal{R}(\cdot)$ which incorporates prior knowledge to capture the underlying structure of the range images. *Importantly, the learnable regularizer can be interpreted as a denoiser which can be replaced by a neural network where whose weights can be learnt using the training data*. Furthermore, μ stands for the penalty parameter that controls the importance of the learnable regularizer. By converting the estimated high-resolution range image into 3D coordinates, the desired high-resolution point cloud can be obtained. A visual representation of this workflow is provided in Fig. 1.

B. Deep Unrolling Framework

In this section, we provide details on the design of the proposed deep unrolling model based on the proposed HQS iterative solver.

1) HQS Iterative Solver: It should be highlighted that relation (4) constitutes a very challenging problem to be solved. To overcome this difficulty, we employ an alternating optimization (AO) scheme [32], splitting the main problem into two more tractable sub-problems, i.e., a least squares sub-problem and a denoising sub-problem. In accordance with this approach, we utilize the Half Quadratic Splitting (HQS) methodology [21] that is able to treat such issues.

In more detail, we introduce an auxiliary variable $Z \in \mathbb{R}^{C\times M}$ to problem (4), thus formulating it as follows

$$\begin{aligned} &\arg\min_{\boldsymbol{X}} \ \frac{1}{2}\left\|\boldsymbol{Y}-\boldsymbol{S}\boldsymbol{X}\right\|_F^2+\mu\mathcal{R}(\boldsymbol{Z}) \\ &s.t. \quad \boldsymbol{Z}-\boldsymbol{X}=0, \end{aligned} \tag{5}$$

Based on the above problem, the objective function that the HQS method aims to minimize is given by

$$\mathcal{L}=\frac{1}{2}\left\|\boldsymbol{Y}-\boldsymbol{S}\boldsymbol{X}\right\|_F^2+\mu\mathcal{R}(\boldsymbol{Z})+\frac{b}{2}\left\|\boldsymbol{Z}-\boldsymbol{X}\right\|_F^2 \tag{6}$$

where b denotes a penalty parameter that controls the importance of the learnable regularizer $\mathcal{R}(.)$. From relation (6) a series of individual sub-problems can be derived

$$\boldsymbol{X}^{(k+1)}=\arg\min_{\boldsymbol{X}}\frac{1}{2}\left\|\boldsymbol{Y}-\boldsymbol{S}\boldsymbol{X}\right\|_F^2+\frac{b}{2}\left\|\boldsymbol{Z}^{(k)}-\boldsymbol{X}\right\|_F^2 \tag{7a}$$

$$\boldsymbol{Z}^{(k+1)}=\arg\min_{\boldsymbol{Z}}\mu\mathcal{R}(\boldsymbol{Z})+\frac{b}{2}\left\|\boldsymbol{Z}-\boldsymbol{X}^{(k+1)}\right\|_F^2. \tag{7b}$$

The sub-problem in (7a) corresponds to a quadratic regularized least squares problem. The closed-form solution for this sub-problem is given as

$$\boldsymbol{X}^{(k+1)}=(\boldsymbol{S}^T\boldsymbol{S}+b\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y}+b\boldsymbol{Z}^{(k)}). \tag{8}$$

Additionally, problem (7b) can be expressed in the following form

$$\boldsymbol{Z}^{(k+1)}=\arg\min_{\boldsymbol{Z}}\frac{1}{2(\sqrt{\mu/b})^2}\left\|\boldsymbol{Z}-\boldsymbol{X}^{(k+1)}\right\|_F^2+\mathcal{R}(\boldsymbol{Z}) \tag{9}$$

From a Bayesian perspective, we can interpret sub-problem (7b) as a Gaussian denoiser [18], [20]. This implies that we can leverage a neural network $f_\theta(\cdot)$ as a denoising model, which can be trained using appropriate training data. Consequently, we can express (7b) as follows

$$\boldsymbol{Z}^{(k+1)}=f_\theta(\boldsymbol{X}^{(k+1)}) \tag{10}$$

It is worth noting that this neural network serves as the regularizer, or prior, that enforces specific properties learned from the training data on the predicted high-resolution range images. Hence, the HQS solver consists of two interpretable modules that is the data consistency solution for estimating the high-resolution range image (11a) and the denoising step in (11b)

$$\boldsymbol{X}^{(k+1)}=(\boldsymbol{S}^T\boldsymbol{S}+b\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y}+b\boldsymbol{Z}^{(k)}) \tag{11a}$$

$$\boldsymbol{Z}^{(k+1)}=f_\theta(\boldsymbol{X}^{(k+1)}) \tag{11b}$$

In the following, we propose a deep unrolling model. This model is established by unrolling the iterations of the local solver as depicted in (11), thus deriving an end-to-end interpretable deep architecture..

2) Deep Unrolling Model: In this section, we introduce an efficient and interpretable approach grounded in the Deep Unrolling (DU) framework. Instead of iterating over the map in (11) for a large number of iterations, the deep unrolling strategy is utilized. This method involves unrolling a limited number of K iterations, thus creating a K-layer deep architecture, as illustrated in Fig. 2. Specifically, we consider a small number of iterations, say K, of the HQS solver in (11) as layers of a deep learning model. Each iteration of the solver corresponds to a distinctive layer of the proposed structure, forming a K-layer deep learning network.

Algorithm 1: Deep Unrolling Model - Training Procedure.

Require: Low resolution range images Y, High resolution range images X,
Ensure: Deep unrolling model
Unroll the derived iterative solver for K iterations
for $k = 1 : K$ **do**
$\boldsymbol{X}^{(k+1)}=(\boldsymbol{S}^T\boldsymbol{S}+b\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y}+b\boldsymbol{Z}^{(k)})$
$\boldsymbol{Z}^{(k+1)}=f_\theta(\boldsymbol{X}^{(k+1)})$
end for
Optimize the deep unrolling model end-to-end using loss function (12)

In this scenario, the deep unrolling model's depth and parameters are highly **interpretable**, directly correlating with the underlying iterative algorithm. As shown in (11), each layer of the proposed model incorporates two interpretable modules: the closed-form solution derived from the data consistency term for the high-resolution range image estimation (11a), and the denoising process defined in (11b). The proposed deep unrolling network is depicted in Fig. 2.

After formulating the deep unrolling model, the next step necessitates the training of the learnable parameters of the deep unrolling model - specifically the neural network $f_\theta(\cdot)$ and the penalty parameter b. In order to achieve this, we aim to optimize the local deep unrolling model by minimizing a certain loss function, expressed as follows:

$$l(\theta)=\sum_{i=1}^{p}\left\|\boldsymbol{Z}_i^{(K)}-X_i\right\|_F^2. \tag{12}$$

where $\boldsymbol{Z}_i^{(K)}$ is the output of the proposed deep unrolling network given a low-resolution range image $\boldsymbol{Y}_i$ and $\boldsymbol{X}_i$ denotes the i^{th} ground truth high resolution range image. Algorithm 1 summarizes the formation of the deep unrolling model.

IV. Proposed Federated Deep Unrolling Method

In this Section, we formulate a novel Federated Deep Unrolling methodology (i.e., FL-DU). Inspired by the distributed parameter estimation approaches [26], we argue that the proposed FL framework can be expressed as an Adapt-then-Combine (ATC) strategy, thus utilizing the proposed optimization problem in (4). In particular, Section IV describes the Federated Deep Unrolling problem formulation and Sections IV-B and IV-C present the proposed adaption and combination steps of FL-DU framework.

A. Federated Deep Unrolling Framework

To mathematically establish the Federated Deep Unrolling (FL-DU) framework we consider a network of $\mathcal{N}$ edge devices (or agents) participating in the learning process. Each device

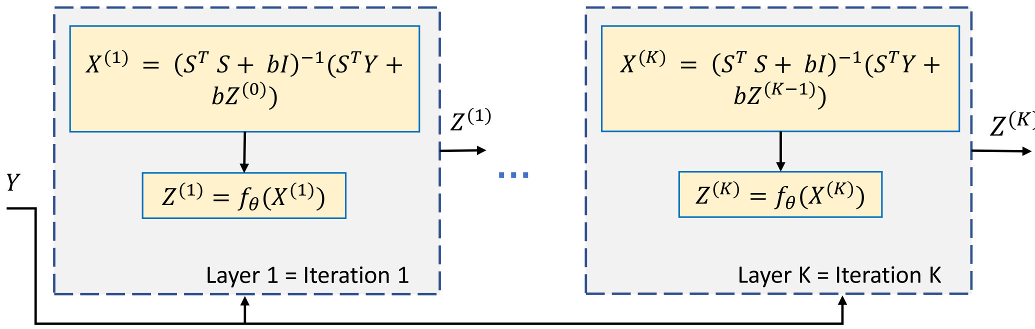


Fig. 2. Proposed Deep unrolling model. In particular, a small number of iterations, say K, of the local HQS solver in (11) are unrolled and treated as a deep learning architecture. Each iteration of the iterative solver is considered a unique layer of the proposed model, resulting in a K-layer deep learning architecture.

is identified by an index n within the set $\mathcal{N} = 1, 2, \ldots, N$, and holds a local dataset $\mathcal{D}_n = \{\boldsymbol{X}_n, \boldsymbol{Y}_n\}$. In this setup, $\boldsymbol{X}_n$ denotes the high-resolution range images, while $\boldsymbol{Y}_n$ represents the corresponding low-resolution range images. To simplify the notations, we assume that each local dataset is composed of one pair of high- and low-resolution range images.

Each agent aims to solve a local optimization problem utilizing the proposed problem formulation for the Lidar super-resolution in (4), defined as follows

$$\arg\min_{\boldsymbol{X}_n} \ \frac{1}{2} \|\boldsymbol{Y}_n - \boldsymbol{S}\boldsymbol{X}_n\|_F^2 + \mu_n \mathcal{R}_n(\boldsymbol{X}_n) \tag{13}$$

where $\mathcal{R}_n(\cdot)$ denotes to the learnable regularizer corresponding to the $n-$th agent.

The fact that the local agents utilize only their local data to address the proposed optimization problem may produce a local regularizer (prior) that is not able to generalize well in various environmental conditions. Thus this limitation may result in a local learnable regularizer ($\mathcal{R}_n(\cdot)$) that is only limited to capture dependencies of the range images generated from the local distribution. *To efficiently overcome this, the proposed federated deep unrolling framework allows agents to collaborate under the orchestration of a central server. Through this collaboration, they are able to learn a more robust regularizer, or prior, which exhibits greater generalization capabilities across diverse conditions.*

The goal of the server in this context is to solve the sum of the local optimization problems, i.e.,

$$\begin{aligned}
&\sum_{n=1}^{N} \left(\frac{1}{2} \|\boldsymbol{Y}_n - \boldsymbol{S}\boldsymbol{X}_n\|_F^2 + \mu_n \mathcal{R}_n(\boldsymbol{X}_n) \right) \\
&= \sum_{n=1}^{N} \left(\frac{1}{2} \|\boldsymbol{Y}_n - \boldsymbol{S}\boldsymbol{X}_n\|_F^2 \right) + \sum_{n=1}^{N} \left(\mu_n \mathcal{R}_n(\boldsymbol{X}_n) \right)
\end{aligned} \tag{14}$$

The optimization problem presented in (14) consists of two terms. The first term, known as the data consistency term, requires access to each agent's private local datasets. This part is crucial in maintaining the accuracy of the optimization. However, direct access to this local private data may raise privacy concerns. The second term represents the sum of the learnable regularizers corresponding to each agent. These regularizers are expressed as neural networks that capture the underlying structure in the data. Importantly, while the regularizers are learned using local data, they don't expose sensitive information. This makes them suitable for sharing with the server, which facilitates global optimization without compromising privacy.

In light of this, the proposed federated deep unrolling framework can be expressed as an Adapt-then-Combine (ATC) strategy [26], taking into account the above optimization formulation. Given the interpretable structure of the deep unrolling model, the proposed framework consists of two steps: adaptation and combination.

In the *adaptation* step, each agent aims to solve the optimization problem defined in (13). This step is designed to solve the proposed local optimization problem using the deep unrolling strategy and adapting the respective deep unrolling (DU) models to the specific characteristics of the local datasets from each autonomous vehicle (agent).

In the *combination* step, the focus is on merging the local learnable regularizers obtained from the deep unrolling models. This process results in a more powerful and robust global regularizer that effectively incorporates the information gathered from a diverse range of autonomous vehicles operating in different environmental conditions. By combining the local regularizers, the overall performance and generalization capabilities of the federated learning framework are enhanced.

The proposed approach provides the deep unrolling-based federated learning a clear and interpretable structure. The role of Federated Learning is to facilitate the merging of local learnable regularizers without compromising the privacy of individual datasets.

B. *Federated Deep Unrolling: Adaptation Step*

In the proposed approach, the adaptation step takes place within the local devices. In more detail, the adaptation step involves the following steps as we mentioned in Section III-B:

- Formulation of the optimization problem: Each edge device aims to minimize the objective function defined in (4) to estimate the high-resolution range image based on the low-resolution range image and system matrix $\boldsymbol{S}$.

- Local HQS iterative solver: The optimization problem is solved using the HQS iterative solver, which iteratively estimates the high-resolution range image and performs denoising. This iterative solver serves as the basis for the deep unrolling model.
- Creation of the local deep unrolling model: A K-layer deep architecture is formed by unrolling a small number of iterations of the HQS solver. Each layer corresponds to an iteration, making the model highly interpretable. The learnable parameters, including the denoiser weights, are trained using an end-to-end approach.

1) Local HQS Solver and Deep Unrolling Model: Focusing on the devices' side, at the t-th communication round each device n aims to solve the following optimization scheme (see, also (13)), i.e.,

$$\arg\min_{\boldsymbol{X}_n} \ \frac{1}{2}\left\|\boldsymbol{Y}_n - \boldsymbol{S}\boldsymbol{X}_n\right\|_F^2 + \mu_n \mathcal{R}_n(\boldsymbol{X}_n) \tag{15}$$

where $\mathcal{R}_n(\cdot)$ denotes to the learnable regularizer corresponding to the $n-$th agent.

Similar to the procedure described in Section III-B1, each agent n employs the HQS methodology to tackle the local optimization problem in (15), thus forming the following local objective function

$$\mathcal{L}_n = \frac{1}{2}\left\|\boldsymbol{Y}_n - \boldsymbol{S}\boldsymbol{X}_n\right\|_F^2 + \mu_n \mathcal{R}_n(\boldsymbol{Z}_n) + \frac{b_n}{2}\left\|\boldsymbol{Z}_n - \boldsymbol{X}_n\right\|_F^2 \tag{16}$$

Recall that the solution of this optimization problem consists of two interpretable modules that is that is the data consistency solution for estimating the high-resolution range image (11a) and the denoising step in (11b). Thus, at each communication round t, the local device n solves the following iteration map

$$\boldsymbol{X}_n^{(k+1)} = (\boldsymbol{S}^T\boldsymbol{S} + b\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y_n} + b\boldsymbol{Z_n^{(k)}}) \tag{17a}$$

$$\boldsymbol{Z}_n^{(k+1)} = f_{\theta_n}(\boldsymbol{X}_n^{(k+1)}) \tag{17b}$$

Local Deep Unrolling model: However, as we mentioned in Section III-B2, instead of solving the above iterative map for a large number of iterations, each device employs the deep unrolling strategy, thus unrolling a small number of K iterations and creating a K-layer deep architecture, as depicted in Fig. 2. Having formed the local deep-unrolling model the device n employs some version of the stochastic gradient descent to train it end-to-end using some loss function as in (18).

Note that the learnable parameters of the local deep-unrolling model are the weights of the denoiser $f_{\theta_n}(\cdot)$ denoted as θ. Thus, during the *adaptation step*, an agent updates the local deep unrolling model, which consists of the equations in (17) as follows:

$$l_n(\theta_n) = \left\|\boldsymbol{Z}_n^{(K)} - X_n\right\|_F^2. \tag{18}$$

where $\boldsymbol{Z}_n^{(K)}$ is the output of the proposed deep unrolling network given a low-resolution range image $\boldsymbol{Y}_n$ and $\boldsymbol{X}_n$ denotes the ground truth high resolution range images.

C. Federated Deep Unrolling: Combination Step

After all participating edge devices $n \in N$ have updated their local deep unrolling models, the next step is the *combination* step. The objective of this step is to learn an appropriate regularizer (prior) that captures the unique characteristics of the range images by utilizing local information from the agents. Due to the structure of the local deep unrolling (DU) models, the devices only upload to the server the neural network $f_{\theta_n}(\cdot)$ responsible for the denoising process in (17b). Subsequently, the server combines all the local denoisers using a fusion rule, as follows

$$f_{\theta_g} = \sum_{n=1}^{N} a_n f_{\theta_n} \tag{19}$$

where f_{θ_g} denotes the global denoiser (regularizer) and a_n stand for combination weights. Consequently, the server transmits the global denoiser back to the local devices. These devices initialize the denoisers of the local deep unrolling models (i.e., (11b)) with the received global denoiser. This procedure is repeated for T communication rounds.

Hence, the FL-DU algorithm can be written as an agent Adaptation step, which involves the local data consistency term (20a) and the local denoiser (20b) (solved by unrolling these equations using the proposed deep unrolling strategy) and a Combination step (20c):

$$\boldsymbol{X}_n = (\boldsymbol{S}^T\boldsymbol{S} + b_n\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y_n} + b_n\boldsymbol{Z_n}^{(k)}) \tag{20a}$$

$$\boldsymbol{Z}_n = f_{\theta_n}(\boldsymbol{X}_n) \tag{20b}$$

$$f_{\theta_n} = \sum_{n=1}^{N} a_n f_{\theta_n} \tag{20c}$$

Fig. 3 illustrates the proposed FL-DU framework. Additionally, Algorithm 2 summarizes the proposed approach.

V. Performance Analysis

To evaluate the effectiveness of the proposed deep unrolling model and the federated deep unrolling framework, a series of experiments were carried out in the context of LiDAR super-resolution. The aim was to upscale data from a 16-channel LiDAR to a 64-channel LiDAR by a factor of 4. Furthermore, we assessed the benefits of our proposed method on a LiDAR SLAM system based on the LeGO-LOAM algorithm [49]. The LiDAR SLAM experiments were conducted on a developed simulation framework [50]. The primary objectives of the experimental results include:

- Designing an interpretable deep unrolling model that exhibits state-of-the-art performance and significantly lower complexity compared to other state-of-the-art approaches.
- Demonstrating the advantages of formulating a federated learning framework that utilizes the deep unrolling strategy, called Federated Deep Unrolling.
- Evaluating the benefits of incorporating homomorphic encryption within the proposed FL framework without negatively affecting the models performance.

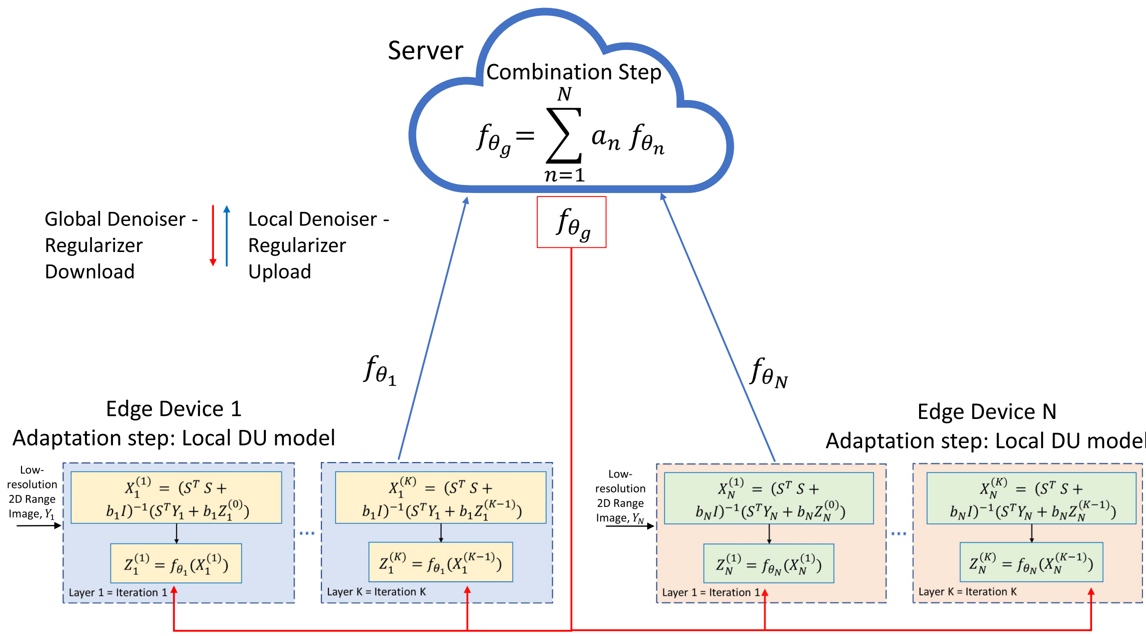


Fig. 3. Proposed end-to-end Deep unrolling-based Federated Learning approach. This strategy contains two key parts i.e., the adaptation and the combination step. In the adaptation step, each agent updates its local deep unrolling model using the local data consistency term (20a) and the local denoiser (20b). This process ensures adaptation to the specific characteristics of the agent's dataset. In the Combination part, the server combines the outputs of all local denoisers using a fusion rule (20c). This creates a global denoiser (regularizer) that captures knowledge from diverse local datasets.

- Illustrating how the super-resolution problem can be useful in a real-world application, such as a LiDAR SLAM system.

A. Dataset

Training Data: Regarding the training, we employed the same dataset presented in study [6]. A 64-channel lidar, OS-1-64, was simulated in the CARLA Town 1 and Town 2 scenes, matching the Ouster dataset field of view (33.2°). For the same scene, a 16-channel lidar, OS-1-16, was simulated to generate low-resolution point clouds. Both high- and low-resolution point clouds were projected onto range images [48], resulting in 7000 pairs of 64x1024 and 16x1024 images. The images were then normalized to a range of 0-1 for training. Note that Town 2 scene contains a variety of environmental settings, resulting in a rich dataset that simulates the diverse experiences vehicles may encounter.

Testing Data: To validate the performance of the proposed FL architecture, the real-world Ouster lidar dataset was utilized. This dataset comprises 8825 scans collected over a 15-minute drive in San Francisco using an OS-1-64 3D lidar sensor. The high-resolution point clouds were converted into 64x1024 range images, and 16 rows were extracted to create 16x1024 low-resolution images. These data pairs were utilized to assess the architecture's performance in recovering high-resolution 3D point clouds from low-resolution inputs.

B. Implementation Details

1) Proposed Deep-Unrolling Model: Concerning the proposed lidar super-resolution model, the number of unrolling iterations was set to $K = 6$, thus leading to 6-layer deep network architecture. During the end-to-end training procedure, we employed the Adam optimizer with batch size equal to 6. Furthermore, the learning rate was set to $1e-03$ and the number of epochs to 100.

Neural Network Architecture (regularizer-denoiser): Regarding, the neural network $f_\theta(\cdot)$ in (20b), we used a 5-layer CNN network, where each layer consists of 64 filters with size 3×3. Moreover, we employed the ReLU as activation and drop-out rate equal to 0.05. Initially, using pairs of noisy and ground truth high resolution range images, the CNN network (denoiser) was pre-trained adopting the ADAM optimizer with learning rate equal $1e-03$ and batch size equal to 6 for 100 epochs. After the initialization stage, the derived CNN network was used to initialize the weights of the corresponding CNN denoiser of the proposed deep unrolling model for the end-to-end training procedure. Finally, note that at inference time, similar to study [6], we employed a Monte-Carlo drop-out method [51] as a post-processing technique to remove unreliable range predictions.

2) Federated Learning Scenario: In our experiment, we examined a network made up of 10 autonomous vehicles, each functioning as a distinct agent. The training data previously mentioned was partitioned into 5 unique blocks. Each block was sourced from different locations within the CARLA simulator, thereby representing varied environmental conditions.

During the local training on the edge devices, we utilized 5 epochs with a learning rate of $1e-04$ and a batch size of 6. Additionally, we determined the number of communication rounds between the central server and the edge devices to be $T = 50$. The local models were trained using the Adam optimizer.

Algorithm 2: Proposed Federated Deep Unrolling Framework.

Require: number of communication rounds M, local private datasets $\mathcal{D}_n = \{\boldsymbol{X}_n, \boldsymbol{Y}_n\}$ for $n = 1 \dots N$.
Ensure: Global denoiser
for each communication round $t = 1 : T$ **do**
  Edge device side: Adaptation step
  for each device $i = 1 : N$ **do**
    Unroll the derived iterative solver for K iterations
    for $k = 1 : K$ **do**
      $\boldsymbol{X}_{n,t} = (\boldsymbol{S}^T\boldsymbol{S} + b_n\boldsymbol{I})^{-1}(\boldsymbol{S}^T\boldsymbol{Y_n} + b_n\boldsymbol{Z_{n,t}}^{(k)})$
      $\boldsymbol{Z}_{n,t} = f_{\theta_{n,t}}(\boldsymbol{X}_{n,t})$
    end for
    Optimize the deep unrolling model end-to-end using loss function (18)
    Due to the structure of the local deep unrolling (DU) models, the devices only upload to the server the neural network (prior-denoiser) $f_{\theta_{n,t}}(\cdot)$ responsible for the denoising process in (20b).
  end for
  Server side: Combination step
  Compute the new global denoiser (prior): $f_{\theta_{g,t}} = \sum_{n=1}^{N} f_{\theta_{n,t}}$
  Send the global model to all edge devices to initialize the local denoiser with the global denoiser
end for

3) Secured Federated Learning: In literature, several studies have explored the use of privacy-preserving techniques such as Homomorphic Encryption [52], [53], [54] within the realm of classical federated learning. Our goal is to demonstrate how security mechanisms, such as Homomorphic encryption, can be easily integrated to enhance the security of the proposed Federated deep unrolling method, without negatively affecting the models performance. To this end, we used homomorphic encryption based on the Tenseal library [55]. In the context of the proposed federated deep unrolling system, multiple vehicles collaborate to improve a global model during the combination step, while keeping their training data local. However, sharing information between these agents or with a central server can lead to potential privacy breaches. Herein lies the importance of using HE. It enables each client to encrypt their trained denoiser (prior) parameters before sending them to a central server for aggregation. Thus, the agents need to encrypt only the denoising step in (20b) from their local deep unrolling models. Due to the special properties of HE, the server can perform computations directly on these encrypted parameters to generate an encrypted global model. This method ensures that the server, while able to aggregate the model updates and further distribute them, never has access to the raw data or individual model parameters, maintaining the privacy of each participant in the federated deep unrolling process. Finally, even though the aggregated encrypted model is then decrypted, the privacy is still preserved since vehicles have access only to the aggregated model not the individual ones.

TABLE I
QUANTITATIVE RESULTS- CENTRALIZED SOLUTIONS

Dataset	Method	L1 loss	Number of parameters (milions)
Ouster	Linear	0.0324	-
	Cubic	0.0467	-
	SR-ResNet [56]	0.0231	$35M$
	SRAE [6]	0.0214	$30M$
	centralized DU	**0.0208**	$\mathbf{0.1M}$

C. Lidar Super-Resolution Performance on Raw Data: Centralized Solutions

In this Section, we compared the proposed deep unrolling method with several other methodologies, including the baseline linear and cubic interpolation approaches, the well-established super-resolution SR-ResNet model [56] in classic image processing, and the state-of-the-art lidar-based super-resolution SRAE model [6] under the centralized scenario. Specifically, a central server gathers all available data from distributed edge devices to train the lidar super-resolution models.

Table I presents a summary of the reconstruction results, demonstrating that the proposed deep unrolling method outperforms other approaches in terms of L1-loss. The proposed method not only provides quantitative gains, but it also requires substantially fewer parameters compared to the deep learning methodologies. This advantage is attributed to the well-defined architecture derived from the optimization problem in (4). Particularly, the proposed model contains $\mathbf{99.75}\%$ fewer parameters than the SR-ResNet and SRAE approaches, making it an ideal choice for real-world applications with computational and storage constraints.

The aforementioned advantage of the proposed deep unrolling model can be attributed to its architecture, which has been derived from an optimization problem, thereby retaining the concise structure of the optimization-based solution. In addition to the benefits mentioned above, this model also demonstrates its effectiveness in situations where communication efficiency is of paramount importance, such as in federated learning (FL) scenarios. *The lower number of parameters in the model helps to minimize communication overhead, further enhancing its suitability for practical applications, including those that involve FL.*

D. Lidar Super-Resolution Performance on Raw Data: Federated Learning Solutions

To thoroughly evaluate the advantages and possibilities of our proposed federated deep unrolling framework, called FL-DU with and without the homomorphic encryption part, we compare it with the following approaches:

- centralized-DU: This represents our deep unrolling model used in a centralized context, where a central server gathers data from distributed edge devices to train the lidar super-resolution model.
- centralized-SRAE: Since the SRAE method [6] was found to be the top-performing competitor, we include it in our comparison.

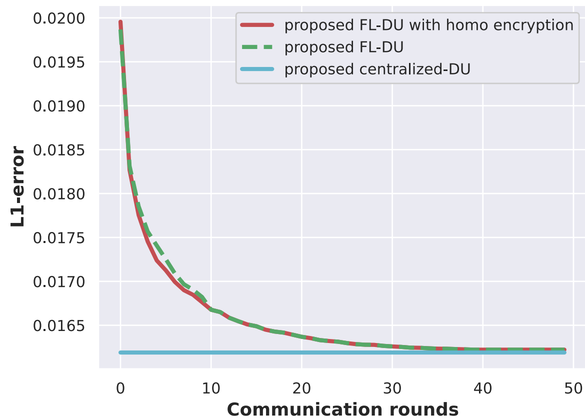


Fig. 4. L1 loss of the derived global model from the proposed deep unrolling FL scheme with and without homomorphic encryption vs communication rounds along with the best accuracy achieved by the centralized deep unrolling model.

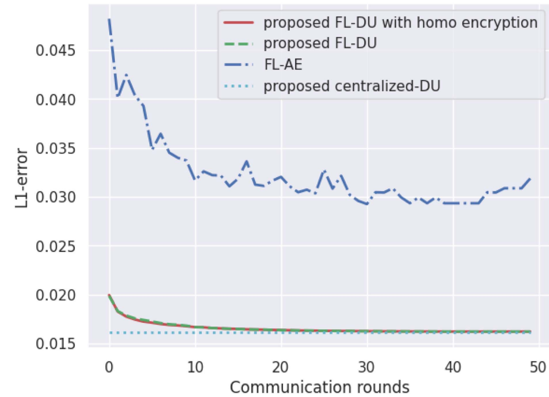


Fig. 5. Loss of the derived global model from the proposed deep unrolling FL scheme with and without homomorphic encryption vs communication rounds against the classical federated learning framework with the SRAE model denoted as FL-SRAE.

TABLE II
QUANTITATIVE RESULTS - FEDERATED LEARNING

Dataset	Method	Data training size	L1 loss
Ouster	proposed FL-DU with encryption	700 per client	0.0211
	proposed FL-DU	700 per client	0.0210
	FL-SRAE	700 per client	0.0357
	proposed centralized-DU	7000	0.0208
	centralized-SRAE	7000	0.0214

- FL-SRAE: Additionally for completeness purposes, we also consider a straightforward federated learning scenario [57], where edge devices utilized the deep neural network proposed in study [6].

Comparison with the centralized methods: As we can see from Fig. 4 and Table II the proposed FL-DU method is able to achieve similar performance against the centralized solution. Crucially, the proposed method necessitates only a limited number of communication rounds between the server and local agents, along with a mere five epochs of local training per round, to converge effectively to the centralized solution. Although, the centralized scheme attains marginally superior quantitative results, it necessitates the exchange of considerable amounts of data, thus imposing a considerable burden on the communication links between edge devices and the central server, and raising data privacy concerns. In contrast, the proposed FL-DU scheme provides an efficient solution that overcomes these issues by requiring agents to share only their local denoisers (or priors) from the respective deep unrolling models, which capture detailed information regarding the structure and dependencies of the range images.

Another important aspect that stems from the proposed federated unrolling strategy is the fact that we can incorporate any privacy preserving strategy. Interestingly, the FL-DU with the homomorphic encryption achieves the same convergence behavior as compared to the FL-DU without the encryption part.

Comparison proposed FL-DU with the federated learning methods:

As illustrated in Fig. 5 and Table II, the proposed FL-DU method considerably outperforms the comparative federated learning approach that uses a state-of-the-art deep learning model. This superiority is observed in both accuracy and convergence rate. Notably, our method achieves similar results to the centralized solution while requiring fewer communication rounds. Despite vehicles working with limited training data, the global model, which is derived from our FL-DU method, delivers a performance that aligns closely with the centralized solution. On the other, the performance of the compared FL-AE method fails to converge to the centralized solution. The vast parameter space of the SRAE model cannot be effectively optimized with limited data, thereby resulting in subpar performance.

The superiority of the proposed FL-DU method can be attributed to the fact that the proposed federated unrolling framework contains local deep unrolling models with concise structure requiring less data. The concise structure of the local deep unrolling models can be verified considering that these models contain $\mathbf{99.75}\%$ fewer parameters compared to the SRAE model, making it an ideal choice for real-world applications.

Overall, the above results verify the efficacy of the proposed federated deep unrolling framework. The FL-DU approach, enables vehicles to obtain more accurate and computationally efficient models by leveraging information from diverse datasets obtained from various autonomous vehicles. This information is used to learn a global prior for the range images. The derived prior, functioning as a denoiser, is subsequently applied to the local deep unrolling models, in order to tackle the lidar super resolution problem. The proposed framework provides the deep unrolling-based federated learning a clear and interpretable structure. In particular, the role of Federated Learning is to facilitate the merging of local learnable regularizers without compromising the privacy of individual datasets.

E. Impact of Lidar Super-Resolution on Lidar Based SLAM Approaches

In order to thoroughly assess the effectiveness of our proposed deep unrolling model, along with the federated learning approach, we examined its applicability in a real-world automotive scenario. To do this, we utilized the LeGO-LOAM [49] system,

TABLE III
LIDAR SLAM: ABSOLUTE POSE ERROR W.R.T TRANSLATION PART (m)

Metrics	Ouster: 2600 scans					Ouster: 6000 scans				
	Lidar-16	centralized SRAE [6]	proposed centralized-DU	proposed FL-DU	FL-SRAE	Lidar-16	centralized SRAE [7]	proposed centralized-DU	proposed FL-DU	FL-SRAE
mean	6.84	15.97	**3.86**	4.39	39.2	299.90	48.29	**26.06**	31.54	110.47
rmse	8.52	18.52	**4.42**	4.74	35.12	316.82	61.73	**27.85**	33.20	135.78
max	23.61	43.04	15.69	**10.02**	71.60	479.02	183.42	**51.33**	52.15	389.45

which is a Lidar based SLAM mechanism that offers real-time six-degree-of-freedom pose estimation and a generated 3D map. We tested it on two sequences from the Ouster dataset:

- The first sequence consists of 2600 consecutive scans, representing a relatively simple trajectory followed by the vehicle.
- The second sequence is composed of 6000 scans that correspond to a more challenging trajectory with short, closely spaced loops.

The primary goal of the Lidar SLAM is to deliver real-time six-degree-of-freedom pose estimation for ground vehicles equipped with 3D lidar sensors. The system achieves this by extracting planar and edge features and subsequently utilizing them to calculate different components of the six-degree-of-freedom transformation between consecutive scans. To investigate the influence of the Super Resolution (SR) approach on such a SLAM system, we conducted a performance comparison of the LeGO-LOAM algorithm using for distinct inputs:

- High-resolution 3D point clouds reconstructed with the proposed centralized-DU method
- High-resolution 3D point clouds reconstructed using our proposed FL-DU approach. In this case, we solely utilized the federated learning scenario with homomorphic encryption, as our findings demonstrated that it achieved practically the same performance as the corresponding federated learning scenario without the encryption part. In more detail, the point clouds were reconstructed using the derived model from the 50-th communication round of the FL-DU framework.
- low-resolution 3D point clouds generated by a 16-channel lidar sensor
- High-resolution 3D point clouds reconstructed using the centralized SRAE method [6].
- High-resolution 3D point clouds reconstructed using the Federated Learning method that uses the deep learning model of the SRAE method [57].

For our analysis, we employed error metrics from earlier studies [58], [59]. The results, including the output metrics, the cumulative distribution function (CDF) of Absolute Pose Error (APE) translation, and trajectory heatmaps, are presented in Table III and Figs. 6, 7. The reference pose (trajectory) for these results is derived from a 64-channel lidar.

In our analysis, as illustrated in Figs. 6 and 7, we observe that both the proposed centralized-DU and FL-DU methods consistently outperform the 16-channel lidar and the SRAE [6] across all the examined trajectories. This highlights the superior accuracy of our reconstructed 64-channel lidar data compared to the state-of-the-art SRAE method [6] and the FL-SRAE approach.

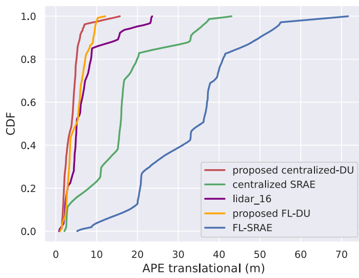
Additionally, although the 16-channel lidar provides satisfactory results during the simple trajectory (2600 scans, see Fig. 6), in the more challenging trajectory (6000 scans), which contains close loops, the 16-channel lidar is not able to follow the reference trajectory (see Fig. 7). This can be justified by the fact that the LeGO-LOAM method relies on the availability of the edge and planar features to estimate the vehicle transformation, and thus it fails to generate robust features from the sparse point cloud derived from the 16-channel lidar.

In comparison to the traditional federated learning approach (i.e., FL-SRAE), our proposed Federated Deep Unrolling framework consistently demonstrates superior results across both trajectories. It's important to note that the local models used in the FL-SRAE approach consist of more than 30 million parameters. This not only imposes significant communication constraints but also necessitates an extensive and diverse set of training examples for these models, which local agents often lack, resulting in subpar performance. Conversely, our proposed FL-DU method, owing to its mathematical formulation, incorporates deep unrolling models with a concise structure. These models can be effectively trained with considerably fewer training examples. Thus, the FL-DU method is not only more efficient but also more practical in scenarios with data limitations, further highlighting the advantages of our approach.

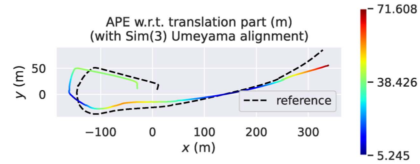
Finally, our proposed FL-DU approach delivers results comparable to the centralized-DU method. The comparable performance of these two models, despite the reduced data exchange and privacy enhancement offered by the federated approach, indicates the potential of FL-DU as a practical and efficient method in real-world applications. In conclusion, our findings strongly support the efficacy and efficiency of our proposed deep unrolling models (both centralized and federated) as cost-effective solutions in real-world automotive scenarios.

F. Ablation Analysis: Impact of Communication Rounds on the Performance of FL-DU

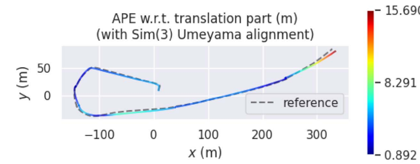
To further demonstrate the benefits of the proposed federated deep unrolling framework, in this section, we conducted an experimental analysis focused on the impact of the number of communication rounds exchanged between the server and the local agents. Specifically, we investigate how these rounds within the federated deep unrolling framework can influence the performance of Lidar SLAM. To this end, we examined the performance of three distinct models that emerged from the 6th,



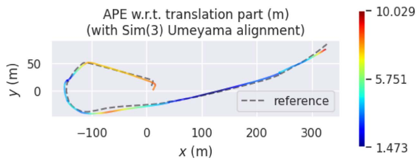
(a) CDF of APE translational



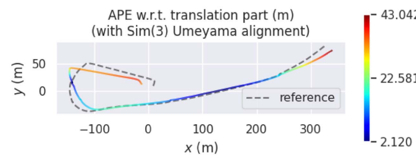
(b) FL-SRAE heatmap [57]



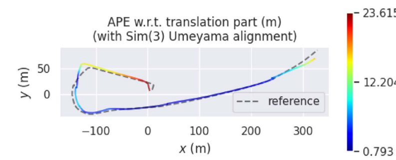
(c) Proposed centralized-DU heatmap



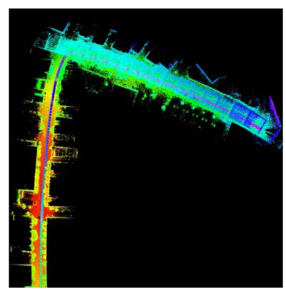
(d) Proposed FL-DU heatmap



(e) Centralized SRAE [6] heatmap



(f) Lidar-16 heatmap



(g) Mapping derived from the output of Lego-Loam using the FL-DU method.

Fig. 6. CDF and heatmaps for the centralized DU method, the proposed FL-DU framework using the DU model derived from the 50-th communication round, the 16-channel Lidar, the method SRAE [6] and the FL-SRAE approach using as reference trajectory the path derived from the lidar with 64 channels regarding the first path with the 2600 scans. We have also prepared a supplementary demonstration video[1] that visually illustrates the quality of the reconstructed point clouds derived from the proposed FL-DU method.

TABLE IV
LIDAR SLAM: ABSOLUTE POSE ERROR W.R.T TRANSLATION PART (m) - IMPACT OF DIFFERENT COMMUNICATION ROUNDS OF THE PROPOSED FEDERATED DEEP UNROLLING FRAMEWORK

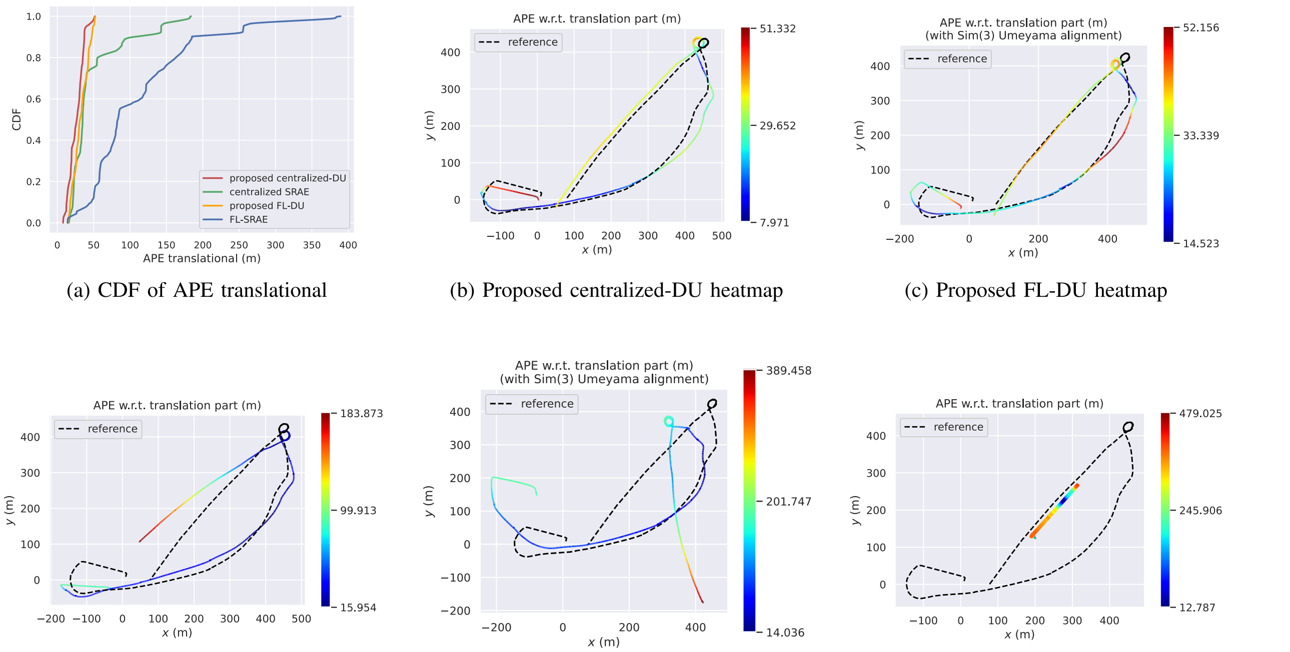
	Ouster: 2600 scans				
Metrics	FL-DU round 6	FL-DU round 20	FL-DU round 50	centralized DU	centralized SRAE [6]
mean	21.15	7.10	4.39	**3.86**	15.97
rmse	22.37	8.30	4.74	**4.42**	18.52
max	43.70	20.28	**10.02**	15.69	43.04

20th, and 50th rounds of the federated deep unrolling framework. Additionally, we compared the proposed FL-DU approach against the state-of-the-art centralized SRAE method [6] and the proposed centralized DU approach.

Fig. 8 and Table IV summarize the results, showcasing the consistent enhancement in performance metrics, including mean error, root mean square error (rmse), and maximum error, as the number of communication rounds in the FL-DU model increases. Specifically, the model derived from the 50th round surpasses the performance of models from earlier rounds, ensuring that the iterative communication within the federated deep unrolling framework indeed contributes positively towards its efficacy.

Incorporating deep unrolling models during the adaptation phase of the FL-DU framework brings forth multiple advantages. Firstly, these models possess a concise structure, resulting in reduced communication overhead between the server and local agents. This reduction is due to the relatively small number of parameters compared to other state-of-the-art deep learning models. Secondly, the FL-DU framework requires a minimal number of communication rounds to converge to the centralized deep unrolling solution. Notably, it only takes 20 rounds for the FL-DU framework to surpass the performance of the centralized autoencoder (SRAE) solution. This efficiency in terms of both communication rounds and model parameters highlights the advantages of the FL-DU framework in federated learning settings.

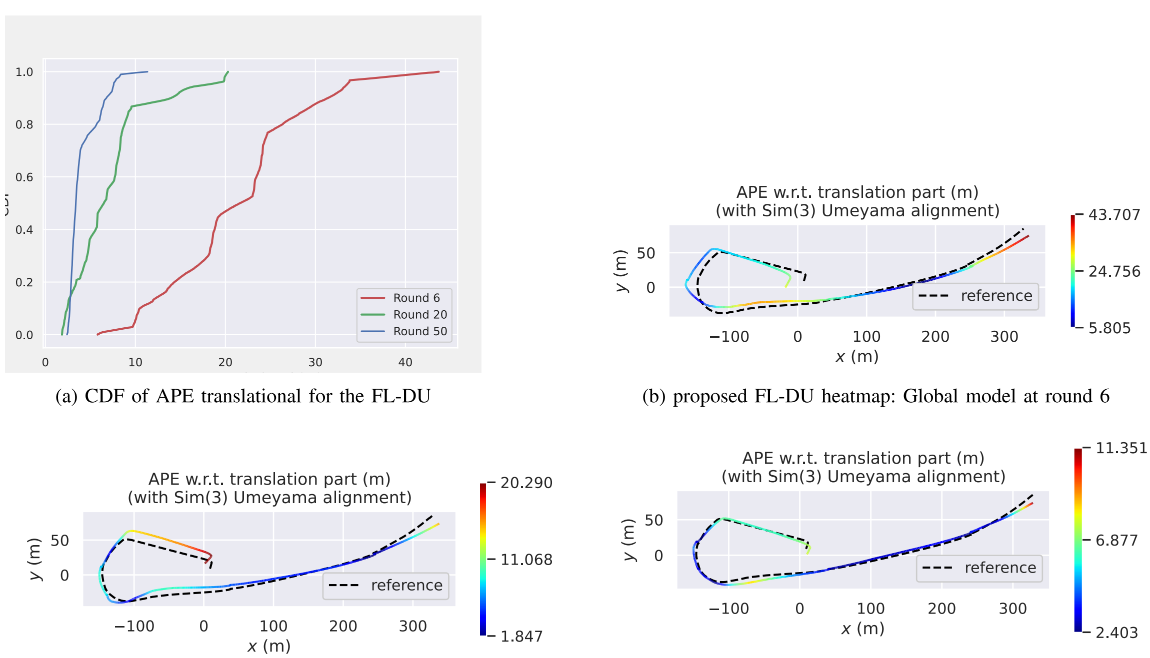
[1]The demonstration video of the FL-DU method can be accessed at https://www.youtube.com/watch?v=Fp_nBrD6NiY



(a) CDF of APE translational (b) Proposed centralized-DU heatmap (c) Proposed FL-DU heatmap

(d) centralized SRAE [6] heatmap (e) FL-SRAE heatmap [57] (f) Lidar-16 heatmap

Fig. 7. CDF and heatmaps for the centralized DU method, the proposed FL-DU framework using the DU model derived from the 50-th communication round, the 16-channel Lidar and the method SRAE [6] using as reference trajectory the path derived from the lidar with 64 channels regarding the first path with the 6000 scans. Note that in the CDF plot, the 16-channel Lidar was excluded due to its insufficiency to yield satisfactory comparative results.



(a) CDF of APE translational for the FL-DU (b) proposed FL-DU heatmap: Global model at round 6

(c) proposed FL-DU heatmap: Global model at round 20 (d) proposed FL-DU heatmap: Global model at round 50

Fig. 8. CDF and heatmaps for the proposed FL-DU method for different communications rounds i.e., round 6, 20, 50 regarding the first path with the 2600 scans. We have also prepared a supplementary demonstration video[2] that visually illustrates the effectiveness of our proposed method in different communications rounds.

VI. Conclusion

The paper proposes a new approach for enhancing automotive Lidar super-resolution for simultaneous localization and mapping (SLAM) by addressing the high cost associated with high-resolution Lidar sensors. The method introduces an adaptive federated optimization approach, which involves multiple vehicles coordinated with a central server to learn a regularizer (a neural network) capable of capturing the intricate features and attributes of the Lidar data.

[2]The demonstration video regarding the impact of FL-DU rounds can be accessed at https://www.youtube.com/watch?v=Fp_nBrD6NiY

To effectively tackle the adaptive federated optimization problem, the adaptation part is based on a deep unrolling framework that converts an iterative convex optimization solver into a deep learning architecture, with the learnable parameters directly derived from the solution of the optimization problem. The capabilities of the deep unrolling technique are further extended by incorporating a combination step, combining the regularizers from the different collaborative vehicles towards creating a robust global regularizer capable of handling diverse environmental conditions.

The proposed mechanism is extensively evaluated through numerical experiments on a real-world Lidar-based SLAM application. The results demonstrate superior performance compared to other centralized deep learning based methods, while also achieving a significant reduction in trainable parameters. In fact, the proposed Super resolution model exhibits 99.75% fewer parameters compared to prevailing centralized deep learning based approaches. This study represents the first integration of deep unrolling with federated learning, presenting an efficient, explainable, and data-secure approach for automotive Lidar super-resolution and perception applications.

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