Augmented Reality-Empowered Network Planning Services for Private Networks

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Abstract—To support Industry 4.0 applications with haptics and human-machine interaction, the sixth generation (6G) requires a new framework that is fully autonomous, visual, and interactive. In this paper, we propose a novel framework for private network planning services, providing an end-to-end solution that receives visual and sensory data from the user device, reconstructs the 3D network environment and performs network planning on the server, and visualizes the network performance with augmented reality (AR) on the display of the user devices. The solution is empowered by three key technical components: 1) vision- and sensor fusion-based 3D environment reconstruction, 2) ray tracing-based radio map generation and network planning, and 3) AR-empowered network visualization enabled by real-time camera relocalization. We conducted the proof-of-concept in a Bosch plant in Germany and showed good network coverage of the optimized antenna location, as well as high accuracy in both environment reconstruction and camera relocalization. We also achieved real-time AR-supported network monitoring with an end-to-end latency of about 32 ms per frame.

I. INTRODUCTION

Impacted by the ever-increasing global spending on smart manufacturing, the total addressable market for private networks is forecast to increase from $3.7 billion in 2021 to over $109.4 billion in 2030, according to a report by ABI Research [1]. However, the state-of-the-art network services remain old-fashioned. For example, the network planning service providers rely on either the floor plan uploaded by the customer or the site survey measured by the technician on-site. Not only are such services costly in both time and human resources, but they also provide a limited user experience. Moreover, the modern flexible and modular production systems require network planning solutions that can be quickly and easily adapted to new network environments triggered by dynamically changing batches of individual products.

Extended reality and digital twin can be promising technologies to facilitate autonomous and interactive network services in the 6G era [2], [3]. However, most of the works have tackled them from the perspective of which challenges they raise with respect to future network systems [4], while few of the works consider them as a means to help build truly user-centric, interactive cyber-physical network systems [5]. A few works have proposed conceptual AR-based frameworks for various small-scale network solutions. For example, WiART [6] takes inputs from beam-steerable reconfigurable antennas and enables users to select desired antenna radiation patterns in the mobile app and observe their effects on link performance.

However, the AR visualization is limited to the antennas and their radiation patterns within a short distance. In [5], the authors proposed to scan an indoor apartment environment to a vector facet model and use it for wireless signal propagation prediction with ray tracing. Then, an AR application is applied to visualize the prediction in the form of holograms with an AR headset. However, the performance is limited by the lack of information about the obstacles for radio propagation. Also, the solution is relied on licensed AR applications and expensive commercial AR headsets.

To provide autonomous, visual, and interactive service for private network planning with low-cost mobile devices, we propose in [7], [8] a novel service platform empowered by vision- and sensor fusion-based 3D radio environment reconstruction and AR-assisted network visualization. The goal is to make the invisible radio network visible, and to provide truly user-centric gamified interface to improve the user experience. The service platform receives video/image sequence and inertial measurement unit (IMU) data from user device via a mobile user interface (UI), reconstructs the 3D radio environment based on the received data, approximates the radio propagation model, and demonstrates the optimized network planning solution on UI with AR as shown in Fig. 1.

To the best of the authors' knowledge, we provide the first end-to-end interactive AR-empowered solution to private network planning. Our contributions are summarized as follows.

• On the client side, we developed an Android app that sends visual and sensory data from the mobile
device to the server, receives model and localization data from the server, and performs local rendering and haptic function.

- On the server side, we implemented the following functions: 1) our developed 3D environment reconstruction algorithm called Simultaneous Localization and Mapping with Object REcognition (SLAMORE) [9], that can detect, track, localize, and reconstruct the major obstacles for electromagnetic waves, 2) network planning policy assisted by ray-tracing application, and 3) our developed real-time camera relocalization algorithm [10] based on deep learning and sensor fusion to enable the AR features.

- We demonstrated the proof-of-concept (PoC) of the end-to-end solution with standard Android mobile device and edge server in a real industrial environment – a Bosch plant in Germany.

II. System Architecture

The proposed interactive, AR-supported network planning service platform includes three main techniques: 1) mapping and 3D environment reconstruction, 2) ray tracing-based radio map generation and network planning, and 3) real-time camera relocalization for AR. Because the remote service tackles real-time AR performance when monitoring and interacting with the network, we need to allocate different functions in either the mobile device or the server based on their computational, transmission, and latency constraints. After extensive experiments and tests, we design the system architecture of the end-to-end solution as shown in Fig. 2.

In the first step (mapping), the user runs our app on a mobile device and the app sends the captured visual and sensory data to the server. The server receives the data and calls the mapping function – our developed SLAMORE algorithm [9] – to detect, track, localize, and reconstruct the major obstacles for electromagnetic waves. In this way, the server reconstructs an “extracted” version of the environment customized for radio propagation. In the second step (network planning), with the haptic function, the user can specify the preferred area for access point (AP) deployment, and sends the information to the server. The server generates radio map with ray tracing based on the reconstructed 3D environment, and performs network planning policy constrained by the user specified area. Then, the server sends the environment model, the proposed AP deployment position(s), and the corresponding generated radio map(s) to the user. The data is saved in the local storage and can be retrieved locally to enable a haptic interaction with the virtual 3D model of the network environment. In the final step (AR-supported network monitoring), the server trains a multi-input deep neural network (DNN) for camera relocalization [10] based on the previously collected data and the generated environment in the mapping step. The user sends in real-time the visual and sensory data to the server, and the relocalization model takes it as input and estimates the 6D camera pose (including 3D position and 3D orientation) as output. The server then sends the estimated camera pose to the user device, and the app computes rendering locally and projects the augmented radio map on the captured camera view.

Note that in our previous works [9], [10], we have provided technical solutions to 3D radio environment reconstruction and real-time camera relocalization, respectively. In this paper, we focus on the system design of the end-to-end solution. Moreover, while the previous works conducted experiments only in the office environment, in this paper we demonstrate the most recent results of the PoC in a Bosch plant in Germany.

III. End-to-End Solution

A. Data Collection

The app running on the mobile device captures in real-time the RGB camera stream and the motion sensor measurements including timestamp, 3D angular rate, 3D linear acceleration, and 4D quaternion from the device, and sends them to the server via real-time transport protocol (RTP) (details of the
implementation will be given in Section IV-I. These measurements are used for both 3D environment reconstruction and camera relocalization algorithms.

On the server, to facilitate SLAMORE and reconstruct an obstacle-aware radio propagation environment, a labelled dataset of objects in the industrial environment needs to be pre-collected. One may argue that in practice the pretrained set of object classes can be too large for recognizing all obstacles in the new environments. However, because we target private networks, we can train multiple sets of classes for different types of customers. For example, automotive manufacturing plants from various manufacturers possibly have deployed similar types of equipment, thus we can create a large dataset for this specific type of customers.

B. Mapping and 3D Radio Environment Reconstruction

Most of the mapping and environment reconstruction methods, such as 3D scanning or simultaneous localization and mapping (SLAM) algorithms, provide complex reconstructed model by creating ultra-dense 3D point cloud (a collection of points defined by a given coordinate system) and recovering smooth nonlinear surfaces [11]. However, for radio propagation environment reconstruction we cannot afford such complexity: modeling radio propagation maps, e.g., by using ray tracing [12], can be computationally extremely expensive if it is based on a complex environment. Thus, to customize an environment reconstructor for 3D radio propagation modeling, we target on the following problem:

How to efficiently reconstruct an “extracted” industrial radio propagation environment that achieves good accuracy yet eases the task of 3D radio propagation modeling?

To this end, we propose a feature- and object-based monocular SLAM algorithm called SLAMORE, which can efficiently detect, track, localize, and reconstruct the major obstacles for electromagnetic waves, and reconstruct a 3D map composed of detected space boundaries and reconstructed obstacles. SLAMORE is built on the basis of a state-of-the-art visual-inertial SLAM algorithm ORB-SLAM3 [13]. However, ORB-SLAM3 reconstructs the environment with sparse 3D point cloud and the output point cloud does not provide the information needed for radio propagation modeling, such as real world coordinates and scale, object segmentation, and surface material. To overcome this challenge, we propose SLAMORE with the following new features: 1) We train a customized convolutional object detector for a defined set of objects in certain radio propagation environment. The label includes class of the objects, 3D shape and size, and surface material. 2) The object detector is embedded in the mapping thread for each keyframe. A series of steps is designed in the parallel thread for new object creation and object culling and merging. 3) We solve the major problem in ORB-SLAM3 when using low-cost and low-frequency IMU sensors from mobile device – recovery of the real world coordinates and scale – by using the side information contained in the class labels of the recognized objects and by filtering the IMU measurements.

With these new features, we can extract sufficient but not overwhelming information about the environment, which can be further used as input for efficient radio propagation modeling. Due to the limited space, we refer the interested readers to our previous work [9] for the technical details.

C. 3D Radio Map Generation and Network Planning

Because ray tracing for radio propagation modeling is a well-studied topic, we can use existing algorithms or software development kits (SDKs) to compute the radio map such as WinProp [14] and WISE [15]. Also, to further reduce complexity, various shooting-and-bouncing ray tracing algorithms [16] can be applied. Because our reconstructed environment is customized for radio propagation, it enables much more efficient ray tracing computation, comparing to the complex 3D scan composed of huge nonlinear triangular meshes.

As for the network planning, to provide a good coverage by optimizing the position of AP, we consider the gradient-based search over a grid space of the candidate AP positions. Because of the interactive interface and haptic functions, the users can specify their preferred deployment areas, e.g., limited area on the ceiling. Thus, we can generate a discrete search space with tractable size. Then, we can start from $N$ randomly chosen initial positions and perform gradient-based search for each of them, and choose the one with the best coverage over all converged positions from the $N$ trajectories. Note that this is an iterative process, i.e., we need to compute the radio map for each adaptive AP position, thus a fast yet accurate ray tracing computation is crucial for reducing the complexity. SLAMORE well fulfills the task because it extracts sufficient but not overwhelming information about the environment, which enables faster ray tracing computation and more efficient searching.

D. Real-Time Camera Relocalization and Augmented Reality

To enable the AR features, e.g., overlaying the virtual network models on the 2D images captured by camera, we need to estimate the camera pose in real time. Therefore, we are interested in solving the following problem:

At each time frame $t$, given camera captured image array $I(t) \in \mathbb{R}^{w \times h \times 3}$, where $w$ and $h$ are the image width and height in pixel respectively, and the extracted feature vector from motion sensors $\mathbf{m}(t) \in \mathbb{R}^n$, what is the corresponding camera pose $\mathbf{p}(t) := [l(t), \mathbf{o}(t)]$ composed of camera location $l := [x, y, z]$ and orientation $\mathbf{o}$?

Note that the orientation $\mathbf{o}$ can be written in the form of 3D rotation vector $\mathbf{r} := [x_r, y_r, z_r]$ or its equivalent 4D quaternion $\mathbf{q} := [q_x, q_y, q_z, q_w]$. The quaternion $\mathbf{q}$ needs to be normalized to unit length, thus the camera pose is still 6-degree of freedom (DoF) when $\mathbf{o} = \mathbf{q}$. 

![Fig. 3: Multi-input DNN for real-time camera relocalization](image-url)
To solve the problem, we propose a multi-input DNN with both image and sensor data as inputs to estimate the camera pose as shown in Fig.3 The training data can be obtained from the data previously collected for SLAMORE, including the video and IMU data sequence and the corresponding camera pose in the world coordinates transformed by SLAMORE. Due to the limited space, we omit the details here but refer the interested reader to our previous work [10].

After deriving the estimated camera pose in the world coordinates, denoted by location $l_w \in \mathbb{R}^4$ and rotation $R_{cw} \in \mathbb{R}^{3 \times 3}$ (rotation matrix from the camera coordinates to the world coordinates, converted from orientation $o$), we can project any 3D point of radio map $x_w$ in world coordinates into the pixel system $(u, v)$ as below:

$$
\begin{bmatrix}
u' \\
w'
\end{bmatrix} = KR_{cw}^T [x_w - l_w], \quad (1)
$$

$$
u = u'/w \quad \text{and} \quad v = v'/w, \quad (2)
$$

where $R_{cw}^T = R_{wc}$ indicates the rotation matrix from the world to the camera coordinates, and $K \in \mathbb{R}^{3 \times 3}$ is the camera intrinsic matrix.

IV. PROOF-OF-CONCEPT

We conducted the experiment in a Bosch plant in Germany, and selected an area of 15m x 10m. The applied antenna model is Nokia FW2HC integrated omni antenna with antenna gain of 4.7 dBi. We use Nokia 6 as the mobile device and the edge server is equipped with 4 Nvidia Tesla K80 GPUs for SLAMORE and DNN training and inference.

1) Data Collection and Communication Protocols

Our developed Android app captures RGB camera stream with a resolution of 480p and the motion sensor measurements including timestamp, 3D angular rate, 3D linear acceleration (from accelerometer), and 4D quaternion (from Android attitude composite sensors which derive the rotation vector from the physical sensors accelerometer, gyroscope, and magnetometer). We use RTP to carry the video stream compressed by codec. The sensory data is also included in the RTP packets along with the video stream.

2) 3D Radio Environment Reconstruction

To test SLAMORE, we have taken 5 video sequences which provides in total 80596 frames. To pretrain the object detector, we have manually labelled 300 keyframes with 25 classes of machines and objects in the industrial environment. The object detector is initialized with the SSD MobileNetV2 backbone model from Tensorflow 2 Object Detection API and finetuned with our created training data. We are able to achieve 87.2% mean average precision. An example is given in Fig.4. Our SLAMORE algorithm has achieved an mean absolute percentage error (MAPE) for object position estimation of 3.4 ~ 5.2%.

In Fig.5 on the left side we show the outputs from the state-of-the-art ORB-SLAM3, including the map points as the black points and the estimated camera positions as the red trajectory, with inaccurate alignment with the world coordinates and without object segmentation. The poor alignment is caused by the noisy measurements from the low-cost IMU sensors embedded in mobile device. On the right side we show the reconstructed environment and obstacles, and the map points associated to the distinct obstacles using SLAMORE.

3) 3D Radio Map Generalization and Network Planning

In this experiment, we use WinProp [14] to compute the radio map with ray tracing technique. The generated radio maps of the optimized antenna position at different heights 0.1m, 1m and 1.5m are shown in Fig.5

4) Real-Time Camera Localization

Either rotation vector (radians) $r \in \mathbb{R}^3$ or quaternion $q \in \mathbb{R}^4$ can be used to represent the camera orientation. In Table I we compare between the output features $r$ and $q$ when using different loss functions: 1) $W_{Euc\_Euc}$: weighted sum of location Euclidean distance and quaternion Euclidean distance, and 2) $W_{Euc\_Ang}$: weighted sum of location Euclidean distance and quaternion angle error. Table II shows that using quaternion $q$ as output and including angle error in the loss function provides the best performance. The average inference time per frame is 3.87 ms.

TABLE I: Comparison of loss function and output features

| Loss Function | Orientation Error | Location Error |
|---------------|------------------|----------------|
| $W_{Euc\_Euc}$ | 0.0327 | 9.2124 cm |
| $W_{Euc\_Ang}$ | 0.0637 | 10.3272 cm |
| $W_{Euc\_Euc}$ | 8.2937 cm | 3.2562 |

5) Performance of the End-to-End Solution

For the AR-empowered network visualization, we achieve the end-to-end latency (including data processing, data trans-
mission, control message transmission, and deep learning-based model inference) of 31.83 ms per frame, i.e., frame rate of over 30 fps. We can also interact with the virtual 3D model as shown in Fig. 7(a) or monitor the network with an AR view in real time as shown in Fig. 7(b).

V. CONCLUSION

We proposed a novel framework for private network planning service, providing an end-to-end solution that receives visual and sensory data from the mobile device, reconstructs the 3D network environment and performs network planning in the server, and visualizes the network and its performance with AR on the mobile device. Several building blocks were developed and implemented: 1) SLAMORE algorithm to reconstruct customized radio propagation environment, 2) ray tracing-based radio map generation and network planning, and 3) deep learning- and sensor fusion-based real-time camera relocalization to enable the AR features. Finally, we conducted the PoC of the proposed end-to-end solution in a real industrial plant and showed good coverage of the optimized antenna location, as well as the high accuracy in both environment reconstruction and camera relocalization. We also achieved the real-time end-to-end latency of less than 32 ms per frame for the AR-empowered network monitoring.

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