Indoor Localization System for Seamless Tracking Across Buildings and Network Configurations

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***Abstract*—WiFi localization systems have become increasingly popular owing to the ubiquity of WiFi-enabled devices. However, traditional WiFi networks were not originally designed for localization purposes, and changes to the Access Point locations can significantly drop localization performance. Moreover, these systems are unable to generalize models trained in one building to other buildings due to dependencies on building characteristics and their WiFi configurations. To address this challenge, we propose *GlobLoc*: the first global indoor positioning system that can function in any environment in a plug-and-play manner without requiring recalibration. Towards this end, we introduce a novel concept called the "virtual environment" in which users are tracked rather than the physical counterpart. This enables the localization model trained on one environment to function in another, regardless of changes occurring in the network environment, as they share the same virtual environment. Our experiments demonstrate that *GlobLoc* outperforms existing state-of-the-art propagation- and fingerprinting-based systems by at least 65%. This superior accuracy is due to its robustness to changes in the WiFi environment and its adaptability to different building configurations.**

***Index Terms*—Deep Learning-based localization, WiFi-based indoor positioning, Virtual mapping, Global indoor positioning**

I. Introduction

Indoor localization systems have emerged as a popular topic in recent years, gaining considerable attention due to their widespread applications in location-based services and other domains. Various techniques have been employed to develop indoor localization systems using sensor measurements or signal propagation models (e.g., WiFi, BLE, ultra-wideband, cellular) [1]–[7]. Sensor-based systems have utilized the measurement of the Inertial Measurement Unit on smartphones with pedestrian dead-reckoning to track user location. However, this approach is plagued by noisy measurements and calibration issues that restrict its ubiquity despite being independent of building infrastructure.

WiFi-based systems have been the most prevalent approach, thanks to the broad coverage of WiFi and the support of the IEEE 802.11 standard by most mobile devices. WiFi-based systems can be, in general, classified into propagation- and fingerprinting-based techniques [8]–[13]. Propagation-based techniques aim to model the relationship between the received signal strength and distance without the need for site surveying. While these models do not require calibration, their accuracy is inferior to that of fingerprinting techniques. In contrast, fingerprinting techniques utilize recorded WiFi access point (AP) signatures, or fingerprints, to estimate device location. These signatures represent the received signal strength indicator (RSSI) of the surrounding APs that are used to train Machine/deep learning models to learn the relationship between the received signals and user location. Deep neural networks have been shown to achieve state-of-the-art performance in WiFi-based indoor localization when big data and computing power are available, as they capture the joint RSSI distribution across all APs [8]–[12]. However, obtaining such big data for training models requires tedious data collection, which increases with the use of complex deep-learning models. Furthermore, the collected data are susceptible to changes in the RSSI values due to network change or maintenance (i.e., APs distribution or replacement).

To address this issue, some techniques attempt to reduce data collection overhead while providing the required amount of training data using data augmentation techniques [14]. Another possible way is by leveraging external hardware for automatic labeling while the users are performing war-driving, e.g., [15]–[18]. However, these techniques cannot solve the problem completely as they still require data collection upon any changes, such as network maintenance, which can alter the number of installed APs as well as their locations and types. As a result, retraining the localization model with fresh data becomes necessary. This hinders the use of the trained model in other buildings and/or other network configurations, significantly affecting the global scalability of the localization system.

In this paper, we propose *GlobLoc*: an adaptable deep learning-based localization system designed to overcome the limitations of recalibration (e.g., data collection and retraining) in traditional machine learning-based systems when network configuration or building conditions change. By utilizing a building's WiFi network and a convolutional neural network (CNN), *GlobLoc* establishes a novel adaptable method that achieves highly accurate localization performance. In *GlobLoc*, the deep neural network is trained using images generated from perceived WiFi scans within the building. Unlike conventional fingerprinting, the generated images are independent of the building and access points and can be

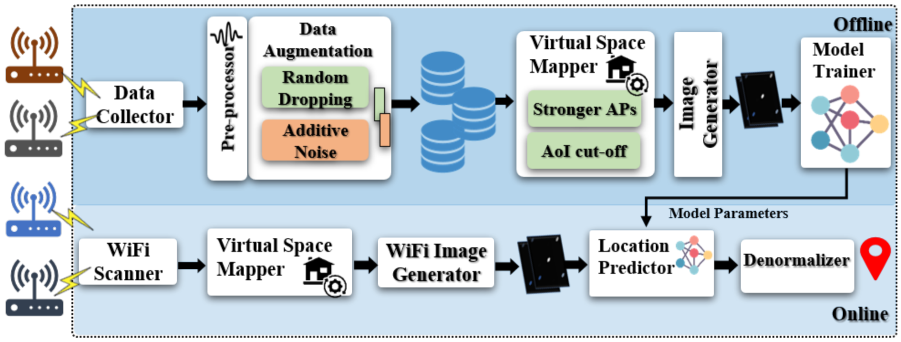

Fig. 1. The *GlobLoc* system

reused across different buildings. This is achieved by introducing the concept of a "virtual space" which is obtained by employing spatial mapping and normalization of the physical space, ensuring building independence. Additionally, given that the generated images do not contain AP IDs, thus they are AP-independent. This approach differs from traditional fingerprinting where each AP ID is mapped to its respective RSSI, making the fingerprint useless in case of a network variation or migration to a new building. Both building- and AP-independence allow *GlobLoc*'s training to be independent of the physical building in which the data was collected. This makes *GlobLoc* generalize to different buildings, thereby eliminating the high deployment and maintenance overhead associated with traditional fingerprinting-based techniques due to the collection and re-collection of the fingerprint; while at the same time providing enough training data to train the data-hungry deep neural networks. Moreover, *GlobLoc* relies solely on ubiquitous WiFi signals, making it accessible for off-the-shelf devices.

We implemented and evaluated our system in a realistic testbed comprising six laboratories, incorporating diverse network configurations with different AP locations and densities. The results confirmed that *GlobLoc* consistently achieved a median location error of 1.8m in normal conditions and 2.6m when the AP locations were changed and their density was altered. This level of accuracy surpasses the performance of state-of-the-art systems in the same testbed by more than 65%.

The rest of this paper is organized as follows: Section II discusses related work. In Section III, an overview of the *GlobLoc* system is presented, emphasizing its various functionalities. Then, in Section IV, we delve into the different modules, providing a detailed description. Section V presents the evaluation of *GlobLoc*. We finally conclude the paper in Section VI.

II. Related Work

In this section, we present a survey of the relevant literature related to our *GlobLoc* system. We divide the discussion into two main axes: Accuracy and Adaptability.

A. Accuracy-Targeting Systems

Research on WiFi-based localization has gained momentum, relying on the relationship between RSSI and distance from APs. RADAR [19] uses fingerprinting techniques but assumes deterministic RSSI, which is invalid. Horus [9] models signal strength as a time-dependent probability distribution. IncVoronoi [20] builds a propagation model using Voronoi diagrams, eliminating fingerprinting. On the other hand, deep learning has recently gained popularity in indoor localization due to its ability to improve accuracy. WiDeep [21] trains denoising autoencoders on noisy data and uses probabilistic frameworks. Passifi [22] focused on enhancing the security of WiFi-based localization against location spoofing attacks. LiPhi [15] reformulates localization as a classification problem and enhances the accuracy using the centroid method. MagttLoc [23] boosts the WiFi localization performance by integration with the Magnetic field and processing the measurements with a Recurrent Neural Network. However, these approaches improve the localization performance within a specific environment but struggle to generalize with network or building changes.

In contrast, GlobLoc is designed for robust generalization across various environments, ensuring accurate localization regardless of the specific setting.

B. Adaptability-Targeting Systems

Achieving adaptability in WiFi indoor positioning systems is a challenge due to the complexity of indoor environments and the dynamics of WLAN networks. Early approaches, such as RedPin [24] and EARIL [25], utilized fingerprinting and statistical models but incurred high computational costs. Alternative strategies exploited spatial correlation among WiFi signals [26]. Machine learning techniques have also gained attention, with ML-based solutions [27] and Adaptive Genetic Algorithm [28] offering enhanced adaptability. LiPhi [15] employs a two-step approach using crowdsourcing and transfer learning. However, these approaches often rely on external hardware or data collection, leading to deployment costs.

On the contrary, GlobLoc achieves dynamic adaptability by training the localization model in a virtual space, decoupling it from physical constraints. This decoupling allows GlobLoc to seamlessly adapt to various environments without costly external hardware or continuous data collection.

III. System Overview

Fig. 1 depicts the overall architecture of *GlobLoc*. The system operates in two stages: an offline training stage and

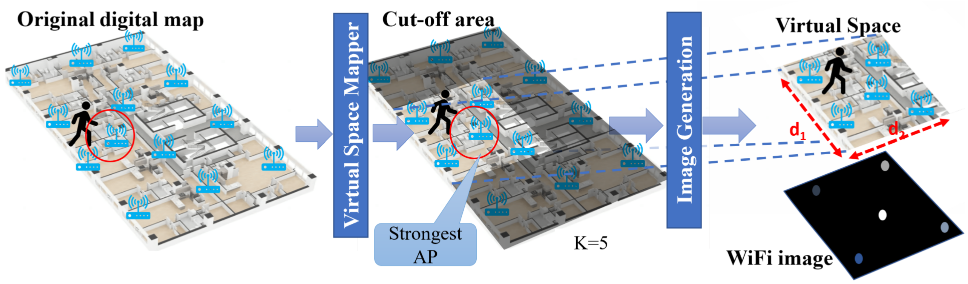

Fig. 2. Virtual space mapper and image generation

an online tracking stage. In the offline stage, *GlobLoc* collects WiFi scans at predefined reference locations in the source environment using our Data Collector App. Each scan contains RSSI values of each AP visible to the user's device and is annotated with the user's location where the scan is collected. The **Pre-processing** module processes this data and generates an RSSI feature vector, which is further augmented with artificially generated samples. Next, the **Virtual Space Mapper** module maps the locations of the user and APs from the physical space to the virtual space coordinate system. This step is essential to enable building-independent localization and reduce building dependencies. Subsequently, the **Image Generator** module converts the WiFi scans into so-called "WiFi images" where APs are represented in pixels in an image. These environment-independent images are used by the **Localization Model Trainer** module to train a convolutional neural network for estimating the user's location in the virtual space. This type of training is called environment-independent localization using transferable features. As a result, the trained model remains valid even if used with another set of APs or AP distribution or in other buildings without the need for retraining from scratch. In the online stage, the user captures a WiFi scan in an unknown location and environment. The **Virtual Space Mapper** and **Image Generator** modules process the scan, creating an environment-independent input for the trained localization model. The model estimates the user's location in the virtual space, which is then converted to the coordinates of the physical target building or network configuration. This enables accurate and efficient indoor localization, regardless of the user's environment or network settings.

IV. The *GlobLoc* System

In this section, we provide a detailed description of each system module.

A. Pre-processing and Data Augmenter

This module maps the captured WiFi signals to their corresponding feature vectors. To achieve this, *GlobLoc* scans the detectable WiFi access points and records their RSSI readings. This module also enhances the generalization ability of the localization model in the virtual space by utilizing data augmentation techniques to generate synthetic training samples. *GlobLoc* employs two augmentation methods: Random Dropping and Additive Noise.

Random Dropping: One of the primary challenges faced by our system is the need to adapt to changes in the WLAN infrastructure setup. If the model is trained with a specific set of strongest APs, it may become outdated if those APs are no longer available due to maintenance or other factors. To address this issue, we employ randomly dropping APs to simulate situations where some APs are no longer available. By taking the strongest available APs as features and replacing any dropped AP with the next strongest one, we ensure that our model can perform accurately even when certain APs are unavailable. This approach helps our system avoid relying on a specific set of APs. It trains the model with multiple views of the strongest APs for each location, thus boosting its generalization ability. By simulating different scenarios through the random dropping of APs, *GlobLoc* can generate a more diverse training dataset, resulting in a more robust and adaptable model.

Additive Noise: In wireless communication systems, the RSSI measurements are essential for estimating the distance between a transmitter and a receiver. However, when both devices are stationary, the RSSI measurements can change significantly due to multiple factors. These include instantaneous changes in the environment, such as opening a door, and the noisy wireless channel characterized by multipath and fading. To account for these variations in RSSI measurements, *GlobLoc* generates synthetic noisy WiFi scans by adding white Gaussian noise to the original scans S The noise is drawn from a normal distribution with a mean of zero and a standard deviation that is determined empirically. The resulting noisy scans help to train localization models to be more robust to variations in the RSSI measurements.

B. Virtual Space Mapper

The Virtual Space Mapper is a crucial component of our system, responsible for generating transferable features that enable our localization model to generalize to different WLAN infrastructure configurations and buildings. The feature vector generated by the pre-processor module is highly dependent on a specific environment, with a particular distribution of APs identified by their MAC addresses. This dependence on specific APs limits the model's ability to generalize to different configurations. To overcome this limitation, *GlobLoc* employs a novel approach of identifying APs by their locations instead of their MAC addresses[1]. By replacing the MAC address with the location of the AP, *GlobLoc* reduces the dependency on a specific set of APs and increases the model's transferability across different WLAN infrastructures.

While replacing MAC addresses with AP locations in our system is an effective way to enhance the transferability of the feature vector, it is still subject to limitations based on the size and dimensions of the source environment. This presents a challenge to the model's ability to generalize to different target buildings with varying spatial configurations. To address this challenge, *GlobLoc* introduces a novel building-independent virtual space concept that enables the system to overcome this limitation. The virtual space is a common coordinate system to which the locations of the user and APs are mapped, regardless of their physical location. In this way, the virtual space provides a standardized frame of reference that eliminates the dependence on the source environment's size and dimensions. Obtaining this space begins with selecting the k strongest APs out of a total of m APs covering the entire environment. This selection is because the strongest APs are likely to provide the most reliable and stable signal strength measurements, which can help improve the accuracy of the localization model. In addition, by selecting only a subset of APs, the computational complexity of the model training and online inference can be significantly reduced without compromising accuracy.

Then, *GlobLoc* cuts out an area of the building defined as the spatial rectangle area ($d_1 \times d_2$) surrounding the strongest k APs, as shown in Fig. 2. This can be justified as the user most likely exists in this area. Additionally, by localizing the user in a smaller area, the received signals are less affected by the complex factors of cluttered environments such as walls and furniture, improving the model's ability to generalize to different environments. Finally, the location of the user and APs are mapped to the coordinates of this virtual space. This allows training the localization model on one environment and applying it to fit other unseen environments, providing greater flexibility and versatility in deployment scenarios.

C. The Image Generator

The Image Generation module converts WiFi scans of the APs to WiFi images that are later input to *GlobLoc*'s CNN for training or location prediction.

The process of image generation based on the WiFi scan is illustrated in Fig. 2. For each scan in the virtual building B_v, an image is created with width $w_{im} = d_1$ and height $h_{im} = d_2$. This image represents the plan/top view of the virtual space. Dimensions of the base image are in pixels, where each pixel represents half a meter in real life. The image (all black) is then colored based on the RSSI of visible APs in the virtual space; the higher the RSSI, the brighter the pixel

[1]The locations of access points can be easily obtained from available floorplan information or estimated using crowd-sourcing methods [15] or using Location Configuration Information/Location Civic Report (LCI/LCR) protocol that returns AP locations.

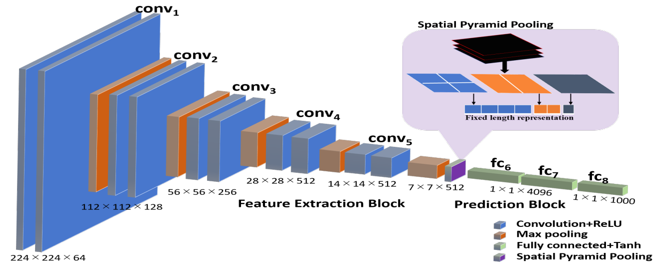

Fig. 3. The *GlobLoc* localization model architecture

color. A linear transformation is applied to convert the RSSI to a gray-scale pixel intensity between 0 and 1 according to: $I(\text{ap}) = \frac{S(\text{a}) - \text{rss}_{\text{min}}}{\text{rss}_{\text{max}} - \text{rss}_{\text{min}}}$.

Where $I(a)$ is the pixel intensity of AP ap, $S(a)$ the RSSI of AP a and rss_{min} and rss_{max} are the minimum and maximum possible RSSI values for any AP, respectively. For each visible AP a, the obtained pixel intensity value $I(a)$ is used to color the pixel in the image representing the virtual space location of this specific AP. This process is repeated for all scans in the original and augmented datasets and the resulting sub-images of each scan to build the training and testing images of the model.

D. The Localization Model Trainer

This module is responsible for leveraging the configuration-independent features of both the collected and augmented data to train a deep neural network and find its optimal parameters. Specifically, this module trains a CNN to predict the user's location in the virtual space using WiFi images. CNNs are well-suited for handling 2D image data, making them an appropriate choice. However, it is important to note that the WiFi images used in this context may have different sizes. This variation in size is a result of dynamically cutting off the virtual space based on the building layout and the location of APs. Therefore, we design the network to handle this issue.

In this module, the CNN architecture employed consists of a feature extraction block and a prediction block (as shown in Fig. 3). The former involves five cascaded feature extraction blocks, each composed of two convolutional layers followed by a max-pooling layer. These convolutional layers aim to extract meaningful features from the input WiFi images, leveraging the power of CNNs in handling 2D image data. The rectified linear unit (ReLU) activation function is used as an activation function for the convolutional layers, introducing non-linearity and enhancing the network's representational capacity. However, a challenge arises when dealing with varying-sized input WiFi images. While CNNs can handle such variations, the resulting feature maps have different sizes, which poses a problem for the subsequent prediction block that requires a fixed input size. To address this issue, spatial pyramid pooling [29] is employed. Spatial pyramid pooling divides the feature maps into multiple fixed-size sub-regions and performs pooling operations independently on each sub-region. This allows the network to capture local and global

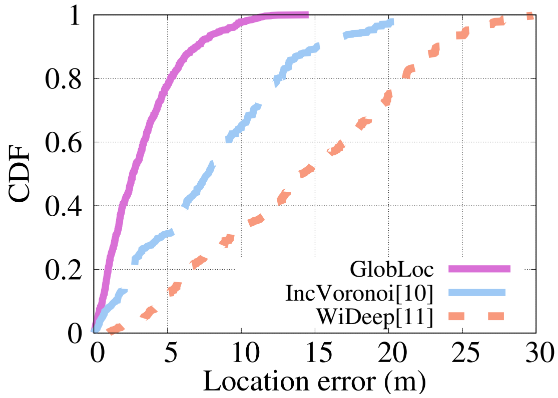

Fig. 4. CDF of error distance in case of changing 5 APs locations.

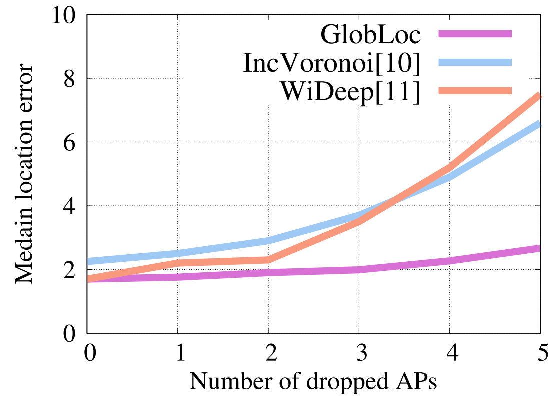

Fig. 5. The localization error when the number of dropped APs changes.

information regardless of the input size. In other words, it enables the network to have a fixed-length representation regardless of the spatial dimensions of the input feature maps. To apply spatial pyramid pooling, the feature maps generated by the last feature extraction block are divided into a predefined number of levels. Each level represents a different spatial resolution or sub-region size. For example, the levels represent grids of different sizes: a coarse grid covering the entire feature map, a finer grid covering half of the feature map, and an even finer grid covering a quarter of the feature map. For each level of the spatial pyramid, a max pooling operation is performed on the corresponding sub-regions. This pooling operation can be max pooling or average pooling, which aggregates the features within each sub-region into a fixed-length representation. The resulting pooled features from all levels are then concatenated to form a compact and informative representation of the entire feature map.

These features are fed to the predictive block which consists of three fully connected hidden layers. We use the hyperbolic tangent function (tanh) for the fully connected layers. The output layer consists of two neurons corresponding to the user's location in the virtual space. Therefore, the problem is formalized as a regression problem. Thus, we use a linear activation function for the output layer and mean square error (MSE) as the loss function. The use of spatial pyramid pooling allows the effective training of the prediction model and ensures its ability to capture both fine-grained details and high-level context, regardless of the spatial dimensions of the feature maps.

Once the CNN is trained, it is used in the online phase by the *Location Predictor* module to estimate the user's location.

E. The Online Location Predictor

During the online stage, *GlobLoc* is capable of locating the user in real-time, even in environments with arbitrary network configurations. The user's phone scans the surrounding APs, along with their RSSI, while the user is in an unknown location. The system then defines the area the user is in as covered by the k strongest APs. Using the virtual space mapper module, *GlobLoc* extracts the virtual space using APs information and maps the located APs into it. This module generates an image representation of the virtual space where each AP is located in its corresponding location and assigned its captured RSSI.

Finally, *GlobLoc* feeds this image representation to the trained localization model to estimate the user's location in the virtual space coordinate system. The estimated location is then mapped to the physical space coordinate system by reversing the normalization process of the virtual space mapper. This process allows for accurate real-time localization of the user, making *GlobLoc* a valuable tool in a variety of applications

V. Evaluation

In this section, we present the evaluation of the *GlobLoc* system in a real-world indoor testbed. Our experiments were conducted across six laboratories located on our university campus, encompassing a total net area of $629m^2$ with different furniture arrangements.

A. Data Collection

To evaluate the performance of our system, we conducted data collection by walking around the testbed with three mobile devices (Google Pixel XL, HTC One, and Asus Zenfone). To facilitate ground-truth profiling, the same application runs synchronously on all mobile devices with one device dedicated to controlling ground-truth collection for all devices. The application's visual interface is designed to depict the testbed floor plan in the foreground of the master device. The user tags her current location on the displayed testbed as a ground truth which is triggered by a long tap on the map interface. The collected data consists of RSSI measurements from the WiFi APs located in the testbed, along with the corresponding ground-truth coordinates of the mobile device. In total, the testbed contains 31000 scans. Specifically, we assigned the ground-truth coordinates for 310 fingerprint locations, where 100 WiFi scans were collected at each location. The spacing between each fingerprint location was around $1m$. We used this data to train and evaluate our system, as well as to compare its performance against other state-of-the-art indoor localization systems including WiDeep [21], and IncVoronoi

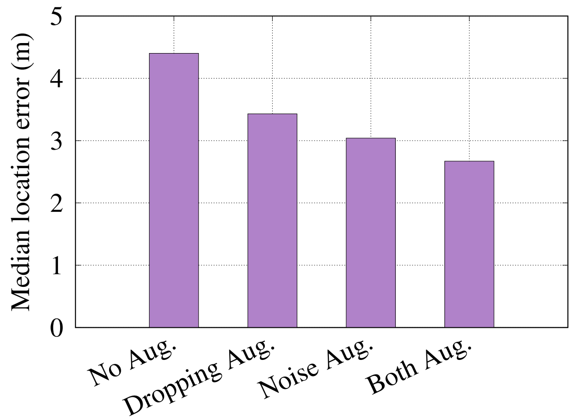

Fig. 6. Effect of Different Data Augmentation Techniques

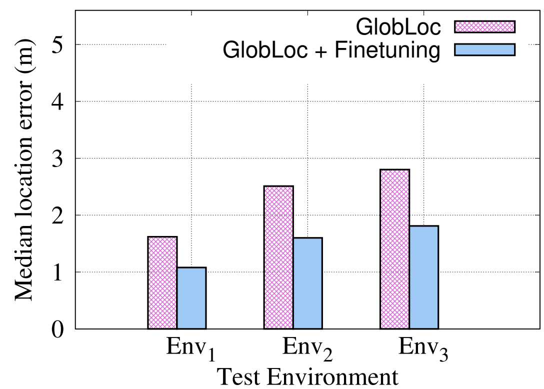

Fig. 7. *GlobLoc*'s performance across different unseen environments.

[20]. To perform the evaluation, we used the accuracy metric that represents the median localization error.

B. Effect of Changing Network Configuration

1) AP Location: We conducted an experiment to study the effect of changing the location of APs on the robustness of *GlobLoc* compared to other state-of-the-art indoor localization systems, namely WiDeep [21], and IncVoronoi [20]. The experiment was conducted in six laboratories; each is equipped with eleven APs. The system was trained on a base configuration while the APs have specific locations and tested on five new configurations by changing the location of five access points. The CDF of the distance error of our system versus the other systems is shown in Fig. 4. The figure shows the superiority of *GlobLoc* over the WiDeep [21], and IncVoronoi [20] techniques with 81% and 65%, respectively. This result can be explained by noting that the compared schemes build propagation and fingerprinting models that assume fixed APs locations in a specific environment, which cannot be ensured in practical scenarios. On the contrary, *GlobLoc* excels in its ability to adapt to any environment by efficiently mapping it to a virtual space. This adaptive approach enables the trained model to operate effectively, resulting in superior localization performance.

2) Effect of AP density: In this section, we investigate how the number of APs affects the localization performance of systems. Figure 5 illustrates the impact of dropping APs on the median localization error. The results indicate that *GlobLoc* achieves the best localization error of 1.67m when no APs are dropped, outperforming other systems. However, when one AP is dropped, the error slightly increases to 1.75 meters, and the error further rises to 2.67 meters when five access points are dropped. Importantly, *GlobLoc* consistently outperforms other systems by at least 20% in scenarios where 1 to 5 access points are dropped. This can be attributed to the fact that the compared schemes were trained using all APs and did not allow for changes in network configurations or a reduction in the number of access points. As a result, these schemes fail to generalize well under scenarios with reduced APs. On the other hand, the proposed system demonstrates robustness due to its design, which includes the random dropping augmentation technique and training the model using a reduced number of APs in the virtual space.

C. Importance of Data Augmentation

In this section, we investigate the impact of the two data augmentation techniques on *GlobLoc*'s localization accuracy. Fig. 6 shows that both techniques independently improved the localization accuracy by at least 30%. However, when both techniques were combined, a 39% improvement was achieved. It is noteworthy that the random dropping of APs allows the simulation of scenarios where APs are missing or no longer available (a realistic situation in many practical settings). Additionally, the incorporation of RSSI noise mimics real-world signal variations that are inherent in wireless signal propagation or instantaneous changes in the environment, such as a door opening or closing event. By employing both methods, the *GlobLoc* model becomes more robust and capable of handling these situations.

D. Evaluating Performance Across Different Environments

In this section, we evaluate the generalization capability of *GlobLoc* across different buildings. The model was trained using data from three laboratories and subsequently tested in three distinct unseen laboratories (Env_1, Env_2, Env_3) in an independent manner. The results shown in Fig. 7 demonstrate the system's commendable performance and flexibility to operate in previously unseen environments. Env_1 achieves a comparable performance of 1.63, similar to the training environments. However, Env_2 and Env_3 exhibit slightly increased errors due to their larger spaces and complex signal propagation caused by furniture. Despite these challenges, the system's performance remains acceptable, with a median error below 3 meters, even without any model calibration for the unseen environments. Furthermore, fine-tuning the model using only 5% of the samples from each target environment leads to a significant improvement in performance, as depicted in Fig. 7. This highlights the system's generalization capability, even without calibration, and its capacity to adapt to various target environments using minimal data.

VI. Conclusions

In conclusion, our proposed system, *GlobLoc*, offers a novel solution to the challenge of changes in network configuration in WiFi-based localization systems. By introducing the concept of virtual space and leveraging transferable features, *GlobLoc* can perform accurate localization even with varying AP distributions. Furthermore, the data augmentation module in our system plays a critical role in improving the performance of *GlobLoc*. By generating synthetic data to increase the diversity and quantity of training data, the module reduces the risk of overfitting and improves the generalization ability of the model. Our experiments on real-world datasets from six different laboratories validate the effectiveness of *GlobLoc* and its potential to advance the field of WiFi-based localization. *GlobLoc* provides a solid foundation for developing localization systems that can operate in diverse deployment environments, and we believe it will inspire future research in this area.

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