Demo: Meta2Locate: Meta Surface Enabled Indoor Localization in Dynamic Environments

Qinpei Luo Ziang Yang Boya Di Chenren Xu

Peking University

Introduction

The **received signal strength (RSS) fingerprint** approach is one of the most cost-efficient and widely-used approaches for indoor localization. It first selects multiple sample points in the room and collects RSS from several access points (AP) to form a fingerprint map. Thus, by comparing the RSS values from the user with the map, we can locate the position of the user.

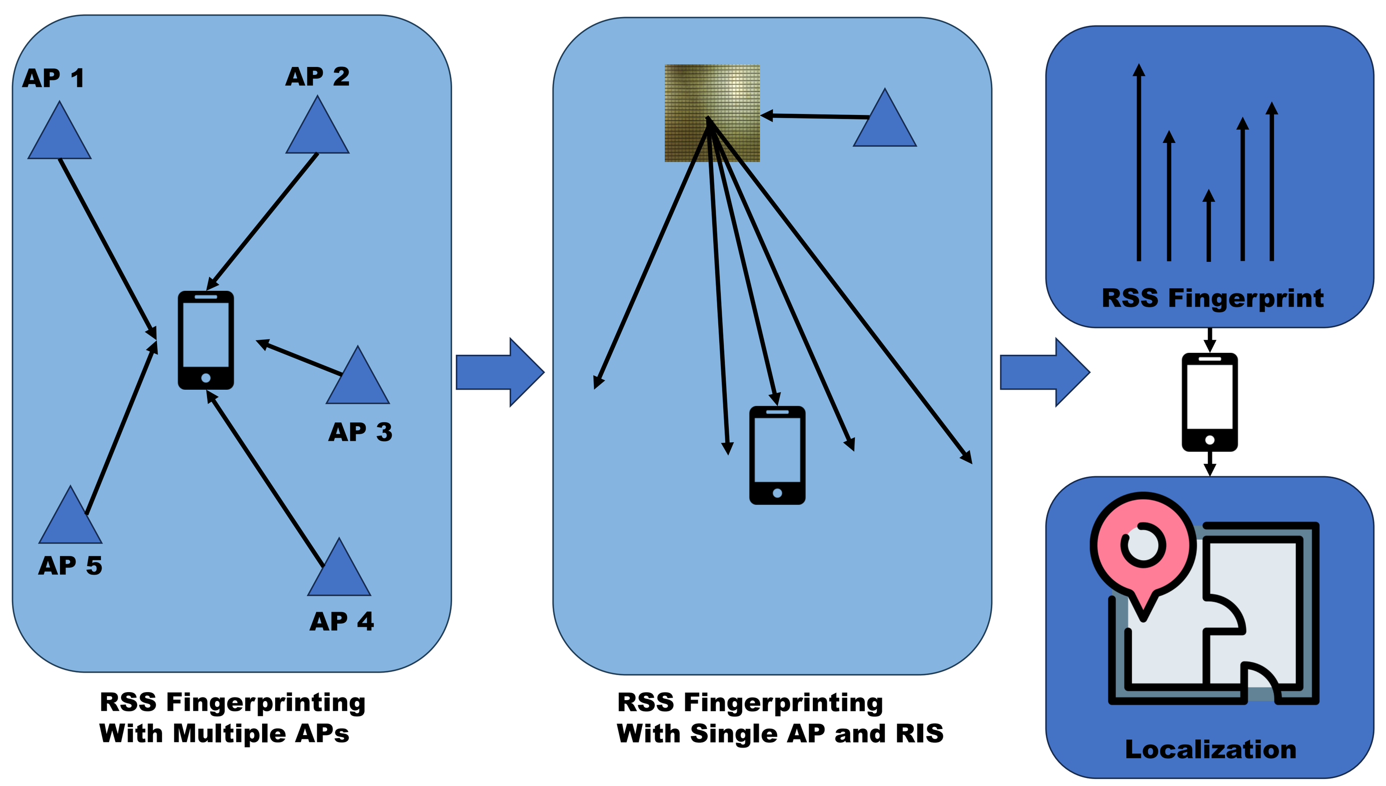

Figure 1. An illustration of RSS fingerprint for indoor localization

However, there exist two challenges when implementing the RSS fingerprints method for indoor localization in practice:

- **Multiple APs:** Systems based on traditional RSS fingerprint mapping often require multiple APs to form the fingerprint, which brings a burden of extra devices as typically we do not have that many closely spaced APs deployed in a single room or building.
- **Dynamic Environment:** In real indoor wireless environments, the RSS fingerprints are very noisy and time-varying due to the shadowing and multi-path effect. Thus, once the environment has changed, it is necessary to recollect the RSS fingerprints, which costs a lot of effort and time.

Methodology

To tackle the aforementioned issues, first, we choose to use Reconfigurable Intelligent Surface (RIS), a planar sheet consisting of numerous electrically tuneable elements, to generate the RSS fingerprint. By configuring RIS elements, it can change the phase shifts of the reflected signal to obtain multiple RSS values to form the fingerprint map using only a single AP.

As for the challenges brought by the dynamic environment, we carefully designed the mapping module between RSS fingerprints and the user's location. In detail, we propose a meta-learning method implemented in the mapping module based on a novel weighting scheme for RSS fingerprints collected from different environments.

- We first conduct the meta-learning phase with all the data collected at different times to build a meta-model, i.e., a generalized convolutional neural network (CNN), followed by the online learning phase where we re-train the meta-model with only 20% of data in a new environment.
- Evaluated by the data collected with the above system under the time-varying environment, our proposed approach achieves better localization accuracy compared to other benchmark methods trained by fewer data, lowering mean localization error by 21.5%.

System Overview

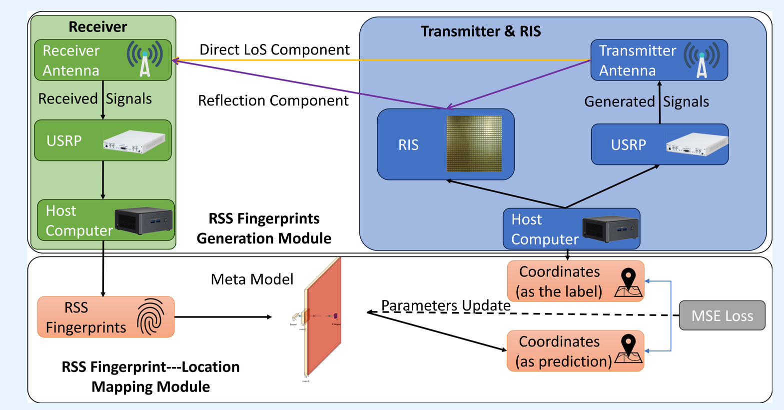

Figure 2. Architecture of *Meta2Locate*

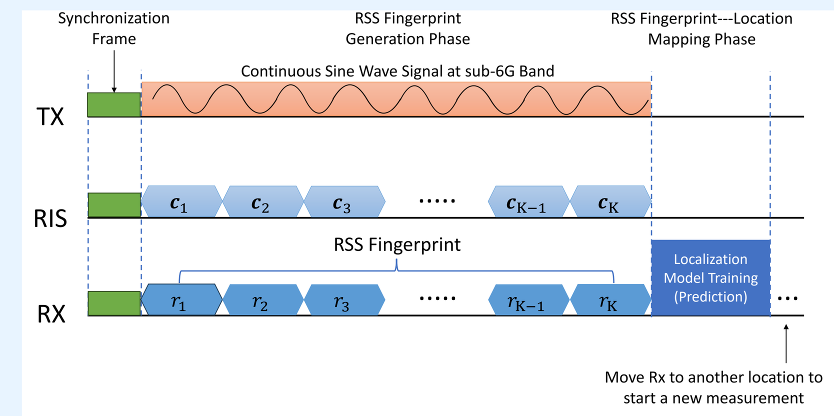

Figure 3. A cycle of the protocol for *Meta2Locate*

The system architecture of proposed *Meta2Locate* is shown in Fig. 2, which is divided into two sub-modules: *RSS fingerprints generation* and *RSS fingerprint—location mapping*.

The *RSS fingerprints generation* module mainly has the following three components:

- **Transmitter&RIS**: The transmitter is placed on the right side of the room along our self-designed RIS depicted by Fig. 4(c), which consists of 28*28 elements and works at the sub-6G band centered by the frequency of 5.5 GHz. As shown in Fig. 4(b), it combines the RIS, control circuits and transmit antenna together to reconfigure the wireless environment. It also includes a Universal Software Radio Peripheral (USRP) to generate transmit signal and is controlled by a host computer, which also controls the configuration of RIS.
- **Receiver**: The receiver of the system is deployed on a robot as in Fig. 4(d). It is equipped with a USRP connected to a host computer, which records RSS from the USRP.
- **Data Collection**: As shown in Fig. 4(e), we divided the plane of the room into grids and choose multiple points to collect data. The blue × data points are collected as the training set, while the red · points form the test set. All the black × and · points are not sampled due to the obstacles and restrictions of the environment. In the process of data collection, we move the car to each point and change the configuration of RIS 10 times and record the corresponding RSS as the fingerprint. The protocol of *Meta2Loate* is shown in Fig. 3.

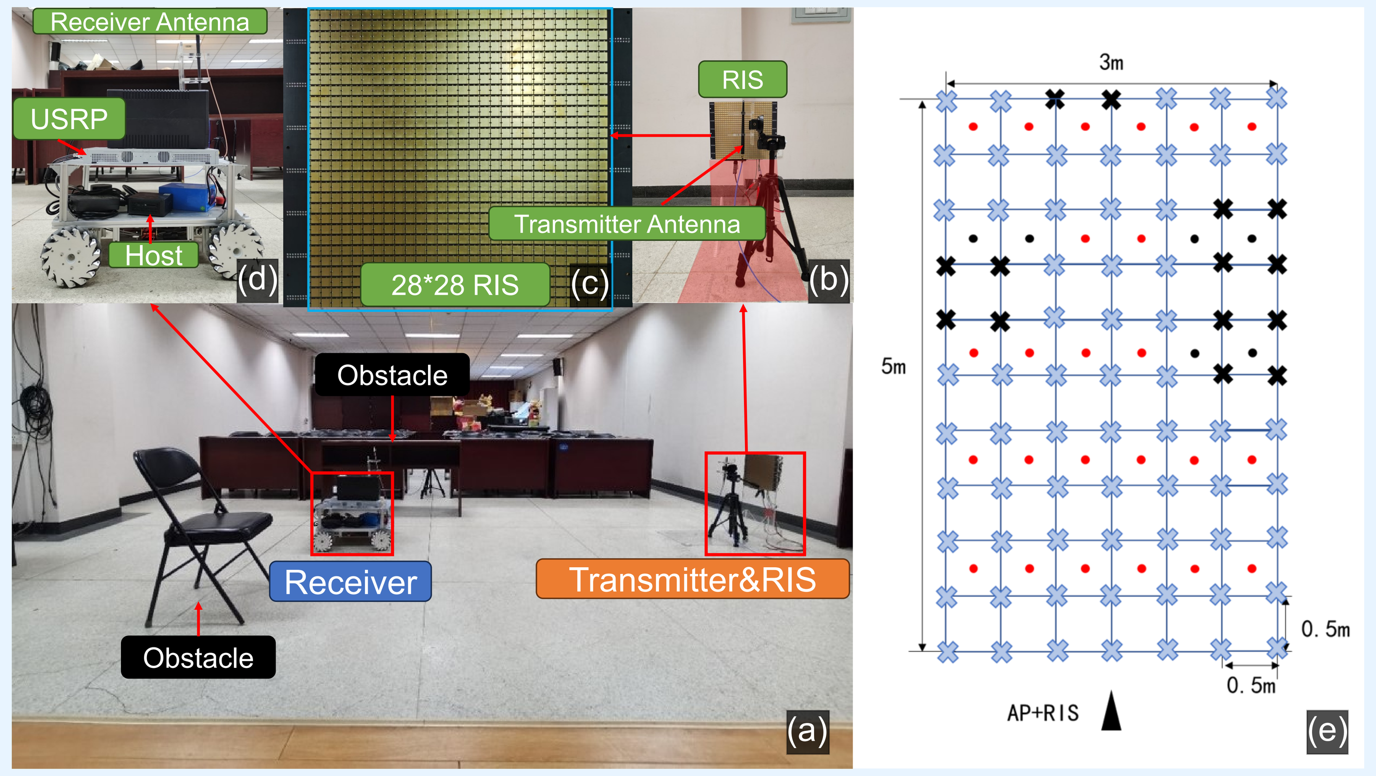

Figure 4. (a) Layout of *Meta2Locate*, (b) Transmitter&RIS, (c) RIS, (d) Receiver, (e) Collection map

As shown in Fig. 3, for measurement at each location, the Tx first transmits a synchronization frame to the RIS and Tx to initialize the measurement. Then, in the RSS fingerprint generation phase, the host computer keeps generating the sine wave signal to the USRP, meanwhile changing the configuration of the RIS as $\{\boldsymbol{c}_1, \boldsymbol{c}_2, \cdots, \boldsymbol{c}_K\}$ to acquire K different beam patterns. Thus, the receiver can record K RSS values and turn them into a fingerprint, in the form of a vector as $\boldsymbol{r} = \{r_1, r_2, \cdots, r_K\}$. With the collected RSS fingerprints, we can either train a localization model by the practical locations of Rx or use the model to predict Rx's locations.

Experimental Result

We define the *task* $\mathcal{T}_i$ as building up a mapping function in a specific wireless environment numbered by i.

$$\boldsymbol{f_\theta}(\boldsymbol{r}) = (x, y),$$

where (x, y) refers to the location of the Rx, and $\boldsymbol{\theta}$ represents the parameter of the mapping function. We randomly select one task as the *test task* and use others as the *training tasks*, in which each task consists of a training set and task set collected by *Meta2Locate*. With the test task, We evaluate our proposed method and other benchmarks as illustrated in Table. 1.

Table 1. Proposed and Benchmark methods

Method	Trained by the training tasks	Fraction of used training set from the test task for re-training
Proposed	✓	20%
CNN-1		100%
CNN-2	✓	0%
CNN-3		20%
KNN		20%

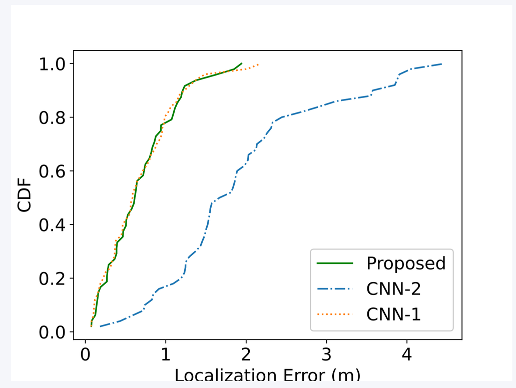

Figure 5. The CDF curve of localization error

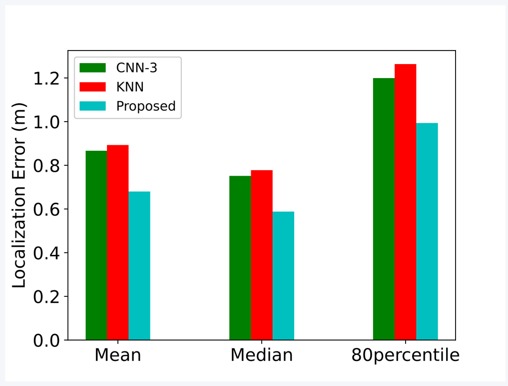

Figure 6. Evaluation of localization error

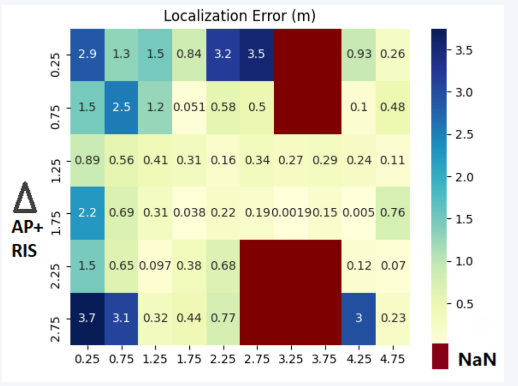

Figure 7. Heatmap of the localization error

In Fig. 5, we first show the CDF curve of the localization error comparing our proposed method with the other two benchmarks: (1) *CNN-1* trained by 100% of the training set from the *test task*, (2) *CNN-2* trained by the *training tasks* but without retraining of the *test task*. The comparison between *CNN-1* and *CNN-2* verifies the **variability of the wireless environment** and the **necessity of recollecting data for retraining**. The result also shows that our proposed method can **achieve a close performance compared to the CNN model trained by more data**.

Fig. 6 compares the localization error of our proposed approach with the other two benchmarks, (1) *CNN-3*; (2) a k-nearest-neighbor (KNN) model named *KNN*. Both of the two benchmarks are trained from scratch using only 20% of the training set from the *test task*. Evaluated by the test set, the results show that **our proposed approach outperforms traditional CNN and KNN with the same downsampled training data, improving the mean, median and 80 percentile error by 21.5%, 21.7% and 17.0% respectively**.

Fig. 7 depicts the heatmap of the localization error using the test set from the *test task*, where the data of blocks colored by wine red are NaN due to restrictions of the environment. It can be seen that data points in the first column tend to have higher errors. One possible reason is that **these points are closer to AP and RIS, where the variation of the electromagnetic environment is more acute**. Besides, the localization error of data points from the first row is also higher. It can be explained by the **limitation of the scan angle of the RIS, as it is harder for it to direct the beam to these points**.

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luoqinpei@pku.edu.cn