Indoor Path Loss Prediction Leveraging Radio Tomographic Maps

Pham Q. Viet and Daniel Romero
Dept. of Information and Communication Technology, University of Agder, Grimstad, Norway.
Email:{viet.q.pham,daniel.romero}@uia.no.

***Abstract*—Accurate path loss prediction is crucial for indoor localization, tracking, and navigation. In this paper, we propose an approach for indoor path loss prediction in the ICASSP 2025 signal processing grand challenge [1]. The results show that our approach has close performance to the state-of-the-art methods.**

***Index Terms*—Indoor, path loss, prediction.**

I. Introduction

Accurate path loss prediction is crucial for indoor localization, tracking, and navigation.

In this paper, we propose an approach for indoor path loss prediction. The approach consists of two steps. First, model-based predictions are obtained by considering the free-space loss, the transmittance, and the loss due to the radiation pattern and orientation of the transmitter. The predictions are then improved by means of neural networks. The results show that the proposed approach has close performance to the state-of-the-art methods.

Sec. II formulates the problem. Our proposed approach is then presented in Sec. III and evaluated in Sec. IV. Finally, Sec. V concludes the paper. The code and data will be published on www.radiomaps.org.

Notation: Lowercase (uppercase) boldface letters represent column vectors (matrices). Equality by definition is denoted as $\triangleq$. $\|.\|$ denotes the ℓ_2 norm. Sets are denoted by caligraphic uppercases.

II. Problem formulation

This section presents the problem of indoor path loss prediction of the challenge.

Let $\mathcal{R} \subset \mathbb{R}^2$ encompass the Cartesian coordinates of all points in a 2D indoor environment of a floor inside a building. $\mathcal{R}$ is discretized into a grid $\mathcal{G} \subset \mathcal{R}$ of $N_x \times N_y$ locations where N_x and N_y are respectively the number of locations in the x and y dimensions. $\Delta_x = \Delta_y = \Delta$ are the spacing between adjacent grid points in the x and y dimensions.

Let $\boldsymbol{r}_{\text{Tx}} \in \mathcal{G}$ denote the location of a transmitter (Tx) whose frequency f, radiation patterns (loss by angle) $p(\alpha)$, $\alpha \in [0, 2\pi]$, and orientation $\beta \in [0, 2\pi]$ are known. $t(\boldsymbol{r})$ and $r(\boldsymbol{r})$ are respectively the transmittance and reflectance coefficients at location $\boldsymbol{r} \in \mathcal{G}$.

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A *path loss map* is a function that returns an approximation $s(\boldsymbol{r})$ of the true (or target) path loss $\tilde{s}(\boldsymbol{r})$ between the Tx at $\boldsymbol{r}_{\text{Tx}}$ and $\boldsymbol{r}$.

$\forall \boldsymbol{r} \in \mathcal{G}$, given $\boldsymbol{r}_{\text{Tx}}, p(\alpha), \beta, f, t(\boldsymbol{r})$, and $r(\boldsymbol{r})$, the problem is to predict $\tilde{s}(\boldsymbol{r})$.

III. Proposed approach

This section presents the proposed approach for the path loss prediction. The approach consists of two steps. First, a model-based method is used to approximate the path loss. The approximation is then improved by means of neural networks.

A. Model-based Prediction

A model-based prediction of the path loss is obtained by considering the free-space loss, the transmittance, and the loss due to the radiation pattern and orientation of the Tx.

- Let $s_{\text{free}}(\boldsymbol{r})$ be the free-space loss between the Tx at $\boldsymbol{r}_{\text{Tx}}$ and $\boldsymbol{r}$. $s_{\text{free}}(\boldsymbol{r})$ is given by

$$s_{\text{free}}(\boldsymbol{r}) \triangleq 20 \log_{10} \left(\frac{4\pi d(\boldsymbol{r}) f}{c} \right), \tag{1}$$

  where $d(\boldsymbol{r}) \triangleq \max\left(\|\boldsymbol{r} - \boldsymbol{r}_{\text{Tx}}\|, \epsilon\right)$ is the distance between $\boldsymbol{r}_{\text{Tx}}$ and $\boldsymbol{r}$, ϵ is a sufficient small positive number, and c is the speed of light.
- Motivated by the tomography models in [2], [3], transmittance loss $s_{\text{tran}}(\boldsymbol{r})$ caused by transmitting through walls is given by

$$s_{\text{tran}}(\boldsymbol{r}) \triangleq \frac{1}{d(\boldsymbol{r})} \int_{\boldsymbol{r}_{\text{Tx}}}^{\boldsymbol{r}} t(\bar{\boldsymbol{r}}) d\bar{\boldsymbol{r}}, \tag{2}$$

- Loss by radiation pattern and orientation of the Tx is given by

$$s_{\text{rad}}(\boldsymbol{r}) \triangleq p\left(\alpha(\boldsymbol{r}) + \beta\right), \tag{3}$$

  where $\alpha(\boldsymbol{r})$ is the angle between the line connecting $\boldsymbol{r}_{\text{Tx}}$ and $\boldsymbol{r}$ and the x-axis.

The proposed model-based prediction is then given by

$$s_{\text{mod}}(\boldsymbol{r}) = s_{\text{free}}(\boldsymbol{r}) + s_{\text{tran}}(\boldsymbol{r}) + s_{\text{rad}}(\boldsymbol{r}). \tag{4}$$

B. Residual Prediction

1) Overview: Since it is challenging to model and to trace the reflection, data-driven methods arises as a promising solution to further improve the model-based prediction $s_{\text{mod}}(\boldsymbol{r})$.

Let $\tilde{s}_{\text{res}}(\boldsymbol{r}) \triangleq \tilde{s}(\boldsymbol{r}) - s_{\text{mod}}(\boldsymbol{r})$ be the target residual loss that is the difference between the target loss and the model-based prediction. We train a neural network to predict the residual loss $\tilde{s}_{\text{res}}(\boldsymbol{r})$. Let $F_{\boldsymbol{\theta}}$ be a neural network whose parameters are collected into $\boldsymbol{\theta}$. The network takes as input a feature vector $\boldsymbol{x}(\boldsymbol{r}) \triangleq [s_{\text{mod}}(\boldsymbol{r}), t(\boldsymbol{r}), r(\boldsymbol{r}), d(\boldsymbol{r}), p(\alpha(\boldsymbol{r})), s_{\text{free}}(\boldsymbol{r}), s_{\text{tran}}(\boldsymbol{r}), s_{\text{rad}}(\boldsymbol{r})]^\top \in \mathbb{R}^8$ and returns the approximate $F_{\boldsymbol{\theta}}(\boldsymbol{x}(\boldsymbol{r}))$ of the residual loss $\tilde{s}_{\text{res}}(\boldsymbol{r})$ at location $\boldsymbol{r}$. Our predicted path loss is then given by

$$s(\boldsymbol{r}) = \min(\max(s_{\text{mod}}(\boldsymbol{r}) + F_{\boldsymbol{\theta}}(\boldsymbol{x}(\boldsymbol{r})), 0), \delta_{\text{s}}), \tag{5}$$

where δ_{s} is a parameter imposing the maximum path loss.

2) Architecture: Let $B(K)$ be a *convolutional block* that sequentially consists of: 1) a $K \times K$ convolutional layer with 8 input channels and 32 output channels, 2) a *LeakyReLU* layer, 3) a $K \times K$ convolutional layer with 32 input channels and 8 output channels, 4) a *LeakyReLU* layer, and 5) a residual connection from the input to the output of the block.

Our network is then a sequence of: a 1×1 convolutional layer with 8 input channels and 8 output channels, $B(K)$, $B(1)$, $B(K)$, $B(1)$, $B(K)$, and a 1×1 convolutional layer with 8 input channels and 1 output channel. The loss function is the sum of the squared error between the predicted and the true residual losses.

IV. Experiments with Synthetic and Real Data

This section evaluates the performance of the proposed approach. $K = 5$, unless stated otherwise. The maximum loss δ_{s} is 200 dB. The performance metric is the root mean square error (RMSE) defined as

$$\text{RMSE} \triangleq \sqrt{\mathbb{E}\left[\frac{1}{|\mathcal{G}|}\sum_{\boldsymbol{r}\in\mathcal{G}} |\tilde{s}(\boldsymbol{r}) - s(\boldsymbol{r})|^2\right]}, \tag{6}$$

where the expectation is over maps.

Experiment 1: This experiment compares the target map with its model-based prediction. Fig. 1 shows the target map and its model-based prediction for task 1, frequency 1, antenna 1, building 1, and sample 3 in the training set. It can be observed that the model-based prediction is close to the target map.

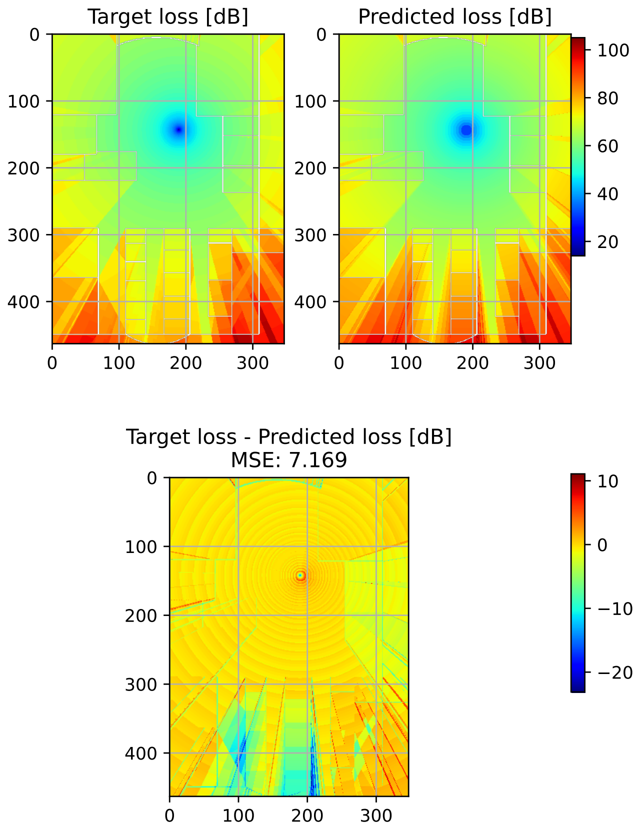

Fig. 1: Comparison of the target map with its model-based prediction.

Experiment 2: This experiment evaluates the performance of the proposed approach on the test set. Fig. 2 shows the test results, which are available at https://indoorradiomapchallenge.github.io/results.html. Currently, we are ranked 7th.

- It can be observed that our RMSEs for tasks 1 and 2 are quite close to the top teams. However, our RMSE in task 3 is not that close. This is due to the limited time. We only managed to train neural networks for tasks 1 and 2. Our test results for task 3 are based on the model-based predictions, which do not take into account the reflection.
- Also due to the limited time, we heuristically set the maximum loss δ_{s} to 200 dB for all tasks. The results can be further improved if δ_{s} is chosen so that it minimizes the RMSE for each task in the training set.

V. Conclusions

References

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RESULTS (RMSE)

Method	Task 1	Task 2	Task 3	Final (Weighted)
Wenlihan_Lu_HKUST(GZ)	7,87	**10,1**	**10,09**	**9,427**
Bin_Feng_SIA	**7,84**	10,15	10,26	**9,501**
TerRaIn **Marco Skocaj, Mengfan Wu, Mate Boban**	8,09	10,94	11,54	**10,325**
Li_Xin_NTU	8,38	11,53	11,06	**10,397**
Cheick_Tidiani_Orange	9,66	10,62	12,53	**11,096**
Weiming_Huang_CUHK	9,62	12,19	11,91	11,307
Viet_QuoC_UIA	8,47	11,89	17,86	13,252

Fig. 2: Test results.