A Multi-Task Learning Model for Super Resolution of Wireless Channel Characteristics

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Abstract—Channel modeling has always been the core part in communication system design and development, especially in 5G and 6G era. Traditional approaches like stochastic channel modeling and ray-tracing (RT) based channel modeling depend heavily on measurement data or simulation, which are usually expensive and time consuming. In this paper, we propose a novel super resolution (SR) model for generating channel characteristics data. The model is based on multi-task learning (MTL) convolutional neural networks (CNN) with residual connection. Experiments demonstrate that the proposed SR model could achieve excellent SR performances in mean absolute error and standard deviation of absolute error. Advantages of the proposed model are demonstrated in comparisons with other SOTA deep learning models. Ablation study also proved the necessity of multi-task learning and techniques in model design. The contribution in this paper could be helpful in channel modeling, network optimization, positioning and other wireless channel characteristics related work by largely reducing workload of simulation or measurement.

Index Terms—Wireless channel modeling, ray-tracing (RT), super resolution (SR), multi-task learning (MTL), convolutional neural network (CNN),

I. INTRODUCTION

Thanks to the fast advances in the fifth generation (5G) wireless communication, our world is stepping into the era of Internet of Everything (IoE) [1]. To enable ultra-low latency and high reliability communication services in dense connected areas like urban districts, accurate wireless channel model is a necessity. Correct knowledge of the propagation channel is also critical for radio coverage estimation, network optimization and for many related applications [2]. Naturally, channel modeling is seen as the foundation for planning and optimizing communication and related systems [3].

Channel modeling is the process of characterizing the propagation principles of radio waves in realistic environments, and provides insight theoretical guidance for the design, deployment and optimization of communication systems. Generally, stochastic channel modeling (SCM) and ray-tracing (RT) based deterministic modeling are two main modeling approaches [4]. For SCM, channel characteristics like path loss (PL), propagation condition (line of sight or non line of sight), delay spread, angular spreads and Rician K-factor are required to generate channel coefficients and thereafter to

model the wireless channel. Massive channel measurements in different environments, which are usually time-consuming and expensive, must be conducted to obtain the necessary channel characteristics data [5]. On the other side, RT based modeling approach can generate accurate channel data if given precise propagation environment and configuration, but at the cost of high computational complexity and enormous calculation time [6]. Therefore, a fast and reliable channel characteristics data generation method will effectively address the limitations above.

One of the promising solutions is machine learning (ML) method. The recent surge of ML is revolutionizing almost every branch of science and technology, including wireless channel modeling. The wireless channel is a time-varying nonlinear system, which contains multi-dimensional information in time, spatial and frequency domain. Machine learning has very powerful learning and inferring capabilities. It can automatically learn from channel data so that the structural relationship between data in complex environments can be extracted to approximate nonlinear systems. Moreover, machine learning is very efficient in mining information from high dimensional data, which can significantly expedite data processing.

Current research in this area are still inadequate. Most of recent works focused on predicting only one of the channel characteristics like PL (Radio Coverage Prediction) [2]. The input is mostly restricted to building information, satellite image [7], map [8] and just one of the characteristics. Few works attempt to estimate several channel characteristics at the same time. As for ML methods, traditional algorithms such as Random Forests (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) as well as Deep Learning (DL) methods such as Convolutional Neural Network (CNN) [8], Transformer [9] and Generative Adversarial Network (GAN) [10] are frequently employed. Also, the estimation targets are usually restricted to one or two characteristics. In general, few works have studied Multi-Task Learning (MTL) models for generating channel characteristics data with several characteristics as input. The connection between different characteristics awaits to be exploited.

In this paper, instead of prediction or estimation, we propose a super resolution (SR) model for channel characteristics.
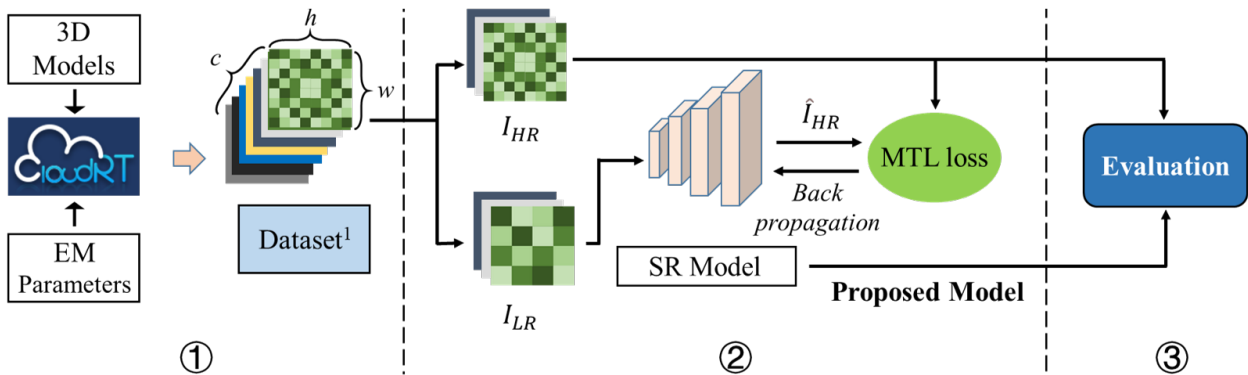
Fig. 1: The overview of proposed residual network based MTL SR model for wireless channel characteristics. ① RT simulation and dataset generation. ② The SR model training process. ③ Evaluation.
Dataset[1]: Channel characteristics dataset

The model is based on MTL CNN with residual connection. Overview of our work is shown in Fig.1. Given 3D models of urban areas and the corresponding EM parameters, CloudRT platform outputs channel characteristics dataset and the dataset is used for SR model training. Data from the dataset are degraded into low resolution data as input. Original high resolution data are used as the ground truth. MTL loss is employed to better balance multi tasks. We evaluate our proposed SR model by ablation study and comparisons with other DL models. Specifically, we make the following contributions:

- In dense urban areas, RT simulation by self developed CloudRT was conducted and channel characteristics dataset are constructed based on simulation results.
- A residual network based MTL SR model is proposed. Weighted masks are added in loss function. Homoscedastic uncertainty is employed to balance the single task losses during training. Residual connection and *iterative up-and-down* technique are implemented in CNN blocks for better SR performances.
- Training process and results of evaluation are provided. The proposed SR approach generally performs better than other SOTA DL models. Comparing with baseline, the proposed approach could achieve very good SR results in all channel characteristics targets and deteriorate significantly less than baseline with larger scale factor. Ablation study proved that the techniques in training and model design are necessary.

II. SIMULATION AND DATASET CONSTRUCTION

This section describes the procedures of RT simulation and dataset construction. In this paper, we used self developed CloudRT [11] [12] platform to generate channel characteristics data.

RT approach is widely used to generate accurate channel characteristics in a specific environment. Based on 3D electronic map and electromagnetic (EM) parameters provided by ITU-R P.1238-7, RT simulation is conducted in dense urban areas on CloudRT platform. More than 100 simulation regions are manually selected from urban areas of four major

TABLE I: RT Simulation configuration

Carrier frequency	3.55 GHz
System bandwidth	100 MHz
Frequency resolution	1 MHz
Antenna	Omni-directional vertical polarization
Simulation range	1 km×1 km
Tx location	30 - 50 m above the ground
Rx location	2 m above the ground

TABLE II: Channel Characteristics Dataset

Characteristic	Normal Range	NaN Value	Unit
PL	[-200,0)	200	dB
K_p	(-30,0]	100	dB
DS	(0,500)	-100	ns
ϕ	[0,360)	-360	°
θ	[0,180)	-180	°
LOS/NLOS	-1/0	1	

cities in China: Beijing, Shanghai, Hangzhou and Xi'an. The simulation regions are 1km × 1km squares with 3D electronic map resolution of 200 × 200. Transmitter (Tx) is located on one of the high buildings near the center of simulation region, and a large LOS area should be maintained. The receivers (Rx) are located 2 meters above ground, uniformly distributed by distance of 5 meters on the horizontal plane. Only receivers outside buildings are considered in simulation. Table I summarizes the simulation configuration and details of it can be found in [13].

$$K_p = \frac{\sum_{i=1}^{N_r} P_i - P_0}{\sum_{i=1}^{N_r} P_i} \qquad (1)$$

The channel characteristics dataset is constructed based on RT simulation results. Definitions of path loss (PL), root mean squared (RMS) delay spread (DS), RMS azimuth (ϕ) angular spread of arrival, RMS elevation (θ) angular spread of arrival, line of sight (LOS) and non line of sight (NLOS) follows the usual. We redefined Racian-K factor as multi-path power ratio K_p in (1), where P_i and P_0 is the power of ray i and ray of

direct propagation. In LOS area, K_p is the ratio of power of all rays except P_0 to the total power. In NLOS area, K_p is equal to zero. K_p is continuous in both LOS and NLOS areas thus suitable for ML. The 6 characteristics are also SR targets in this paper. We use PL, K_p, DS, ϕ, θ, LOS/NLOS as the abbreviations or symbols of the channel characteristics and SR targets, as shown in TABLE II. Values which are far beyond ordinary thresholds in communication systems are set as the minimum (PL, K_p) or the maximum (DS) of corresponding normal range. NaN value represents the channel characteristics data of receivers which locate inside buildings. NaN value should be void but set as real number out of normal range so that ML model is able to distinguish. A data in channel characteristics dataset is a 200 by 200 tensor with 7 channel (including building heights). The input data are processed by down-sampling by certain scale factor and up-sampling by interpolation so that the shape remains the same. In total, 753 data were generated and combined to construct the dataset.

III. METHODOLOGY

A. Problem Definitions and Terminologies

Super-resolution is a notion of recovering High Resolution (HR) data from the Low Resolution (LR) data [14]. The LR data mostly originates from HR data with a process of degradation:

$$I_{LR} = \mathcal{D}(I_{HR}; \delta) \qquad (2)$$

where I_{LR}, I_{HR}, $\mathcal{D}$, δ denote LR data, HR data, degradation process which is usually unknown, and parameters of degradation such as scaling factor. Usually I_{LR}, I_{HR} are the input training data and the ground truth correspondingly.

SR can be described as the model of recovering I_{LR} to I_{HR}. The recovery (approximation) result is denoted as $\hat{I}_{HR}$. $\mathcal{F}$ represents the recovery model with parameters θ. Take DL as the example, $\mathcal{F}$ is the neural network while θ is the weights and other related parameters in the neural network.

$$\hat{I}_{HR} = \mathcal{F}(I_{LR}; \theta) \qquad (3)$$

To this end, the objective of SR is as follows:

$$\hat{\theta} = \arg \min_{\theta} \mathcal{L}(\hat{I}_{HR}, I_{HR}) + \lambda \Phi(\theta) \qquad (4)$$

where $\mathcal{L}$ is the loss function between recovery result $\hat{I}_{HR}$ and ground truth I_{HR}. Φ is the regularization term with parameters θ and λ is the weight factor. The best SR model would minimize the loss to the least with respect to θ.

B. Residual Network based Multi-Task Learning Model

The proposed residual network based MTL model consists of two parts: *backbone* part and *fine-tune* part, as in Fig. 2. The *backbone* part is to extract high-dimensional features from input data while the fine-tune part focuses on each of the tasks to achieve the best SR performances.

The CNN block contains two convolutional layers with activation function ReLU. The size of data during convolution remains 200×200. The number of CNN blocks N is
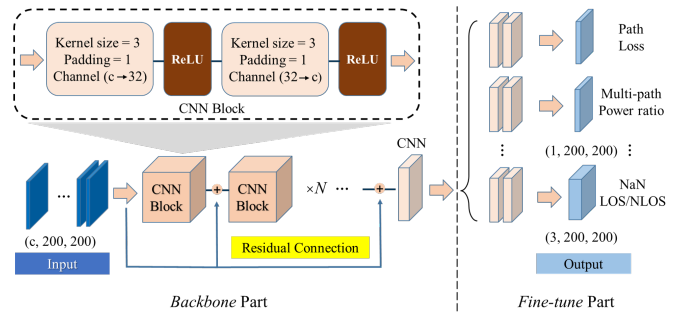

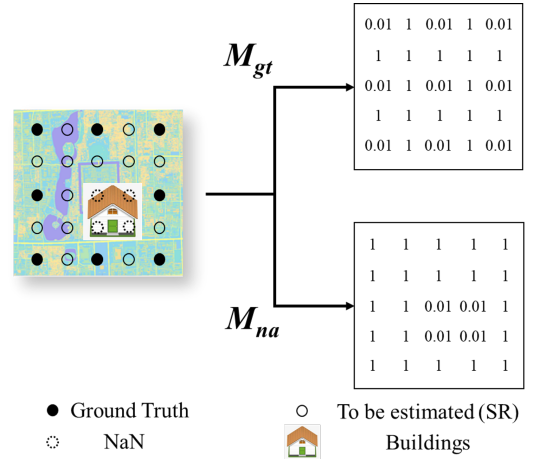Fig. 2: The overview of proposed MTL CNN model with residual connection

Fig. 3: An illustration of M_{gt} and M_{na}. Mask values are all set as 0.01. The background is electronic map of Tiananmen Square in Beijing, China.

set to be 3 in our work, but a larger number of blocks may also achieve excellent SR performances based on our previous experiments. To be noted, the numbers of channels in convolutional layers are set to be *iterative up-and-down*, as shown in the illustration of CNN block. The *iterative up-and-down* technique can filter irrelevant information in input data. Residual connection is also necessary for good SR performances. Several CNN blocks are concatenated with residual connection to construct the *backbone* part. In *fine-tune* part, 6 lightweight models are designed for the corresponding targets. Lightweight models are two layer CNN like in CNN block but number of channels remain fixed. We also observed a little bit better performances of SR with other models in *fine-tune* part. Note that for NaN/LOS/NLOS, outputs of the *fine-tune* nets are the probabilities of corresponding propagation conditions.

C. Loss Functions and Evaluation Metrics

As explained in Section II, only receivers outside the building are considered in simulation. As a result, NaN values are given real number to guarantee that the input data is a regular matrix or tensor. Also, there will always be some

ground truth values (elements) in the matrix of input data. However, both NaN values and ground truth values are trivial in SR process. To keep the loss function continuous and to help ML models concentrate on SR values of desired positions, weighted loss is introduced as the mask of NaN values M_{na} and the mask of ground truth M_{gt}, which are illustrated in Fig. 3.

Several kinds of loss functions and evaluation metrics such as *pixel loss*, and *content loss* are widely used in image SR tasks. Differently, only *pixel loss* is accepted in channel characteristics SR task. According to previous experiments, L1 (norm) loss is employed for training as it performs better than L2 loss and peak signal noise ratio (PSNR).

There are 6 SR targets in this paper as mentioned in section II. For LOS/NLOS, SR process is essentially to classify between LOS and NLOS area. For the rest targets, the SR process are regression. Due to the difference between classification and regression, the loss functions are categorized into two scenarios where L1 norm are used for regression and cross entropy are used for classification, as in (7) and (8). The loss function $\mathcal{L}_m$ in training can be described as follows:

$$\mathcal{L}_m(\hat{I}, I) = \begin{cases} loss_{ce}(\hat{I}, I), & \text{if target } m \text{ is LOS/NLOS} \\ loss_{l_1}(\hat{I}, I), & \text{others} \end{cases} \quad (5)$$

where $\hat{I}$ and I are SR recovered data and ground truth. Before the calculation of loss function, both $\hat{I}$ and I should be weighted by *Hadamard Product* with M_{gt} and M_{na}:

$$I_{weighted} = I_{original} \circ M_{na} \circ M_{gt} \quad (6)$$

n, h, w, represents the number of values to be estimated (SR) and side lengths of input data. k stands for the class among LOS/NLOS/NaN in (8).

$$loss_{l_1}(\hat{I}, I) = \frac{n}{(hw)^2} \sum_{i,j} |\hat{I}_{i,j} - I_{i,j}|_1 \quad (7)$$

$$loss_{ce}(\hat{I}, I) = -\frac{n}{(hw)^2} \sum_{i,j} I_{i,j,k} \log \hat{I}_{i,j,k} \quad (8)$$

During the pre-train stage, homoscedastic uncertainty [15] is employed to balance the single-task losses as in (9). Not only the weights in neural networks W but also noise parameters $\boldsymbol{\sigma}$ are trainable and updated through standard back propagation during training.

$$\mathcal{L}_{MTL}(W, \boldsymbol{\sigma}) = \sum_m \frac{\mathcal{L}_m}{2\sigma_m^2} + \sum_m log(\sigma_m) \quad (9)$$

The evaluation metric is much simpler than training loss. Basically, values of receiver located in building areas (NaN values) and ground truth values are not included in calculation. The metric for evaluating SR performance of LOS/NLOS is classification accuracy. For the rest targets, mean absolute error (MAE) and standard deviation of absolute error (SDE) are regarded as the metrics.

IV. EXPERIMENTS

A. Training Configuration and Implementation

In this work, DL training are performed by PyTorch 1.10.2 on a work station with 1 NVIDIA GeForce RTX 3090 GPU, Intel Core i9-9900K CPU and 32 GB DDR4 RAM.

The training process are divided into two stage: *pre-train* stage and *fine-tune* stage. In *pre-train* stage, (9) is used as the loss function for back propagation and weights of the entire SR model are updated. Next, in *fine-tune* stage, only weights of *fine-tune* part in the SR model are updated while *backbone* part remains unchanged. The purpose of this design is to obtain a general feature extractor (*backbone* part) for channel characteristics SR. By doing so, it's very fast and convenient to concatenate lightweight models for specific tasks when comparing with DL models aiming at only one channel characteristic.

Data augmentation is employed to the training set for enhancing diversity of the inputs. The training set is transformed by rotation of 90, 180 and 270 degree as well as horizontally and vertically flipping. As a result, the training dataset is incremented by 5 times.

The proposed SR model is trained for 100 epochs in both of two stages. The learning rate is set as 0.00001. Adam optimizer is used for gradient descent. Batchsize is set as 1. The channel characteristics dataset is randomly split into training set and test set by ratio of 7:3. Experiments with scale factor 2, 4 and 8 were conducted.

B. Backbone Part

As mentioned above, *backbone* part of the proposed SR model is regarded as a general feature extractor. The comparison of DL models is summarized in Table III. Our proposed SR model could achieve 3.26 dB for MAE of PL with scale factor 2. Under the same configuration, several kinds of DL models including ResNet50, vision transformer (ViT) [16] and GAN-SR [17] were tested. Performances of these SOTA DL models are not satisfying. For *backbone* part, ResNet50 is the best in tested DL models but the MAE is around 7-8 dB. After several experiments of ViT by changing the number of transformer encoder and the number of heads in attention layer, the best result of MAE is around 8 dB. Performances of GAN are much worse than CNN and ViT. The best results of GAN is higher than 12 dB for MAE. Moreover, few experiments show that the loss of generator and the output of discriminator (probability that $\hat{I}_{HR}$ is real) converge at the end. Nash equilibrium between generator and discriminator could hardly be reached. For other targets, SR results of these DL models are also much worse than those of the proposed model.

The reasons of why SOTA DL models doesn't work well are analyzed. First, the data size of channel characteristics dataset is much smaller than popular computer vision datasets like CIFAR-10, ImageNet and MINST. Second, texture, style and smoothness of images should be considered in image SR but not regarded as objectives in characteristics SR task. As a result, deeper models with larger number of parameters are more

(a) Path Loss   (b) K_p (c) RMS ϕ Spread

(d) Accuracy of LOS/NLOS Classification   (e) RMS Delay Spread   (f) RMS θ Spread
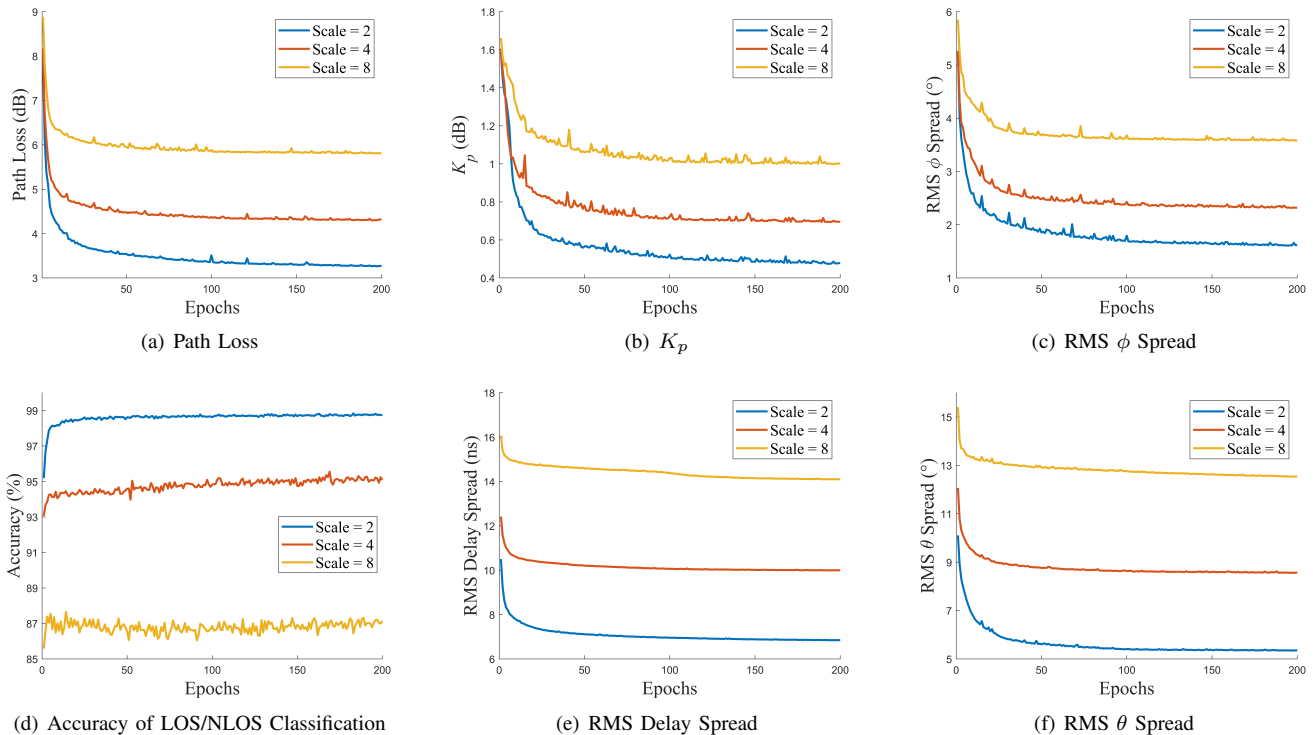
Fig. 4: MAE and classification accuracy of 6 SR targets during training process.

liable to over-fitting. The comparison of SR performances and model complexity are presented in Table III. For the proposed model, both the number of parameters (Params) and floating point of operations (FLOPs) are much smaller than other DL models.

TABLE III: Comparison of Deep Learning Models

	Proposed Model	ResNet50	ViT	GANSR
Params / k	**4.25**	8610	13040	28670
FLOPs / GMac	**0.34**	2.58	10.33	12.42
MAE of PL / dB	**3.26 (best)**	7-8	7-8	>12

C. Performance of Proposed Model

MAE and classification accuracy of 6 SR targets during training process are shown in Fig. 4. Clearly for six targets, the MAE and classification accuracy of SR are decreasing during training and converge at the end. In *pre-train* stage (1-100 epochs), MAE and classification accuracy decrease very quickly with some minor jitters due to MTL loss. This indicates that the proposed model and MTL loss is effective as a feature extractor to achieve fairly good SR performances with multi inputs and tasks. In *fine-tune* stage (101-200 epochs), few jitters are observed. MAE and classification accuracy decrease slowly to converge at the end so that better SR performances could be achieved in *fine-tune* stage. We also observed that given scale factor as 8, the classification accuracy of LOS/NLOS jitters greatly. We will look into this part in future research.

In general, the best SR results achieved by the proposed model is demonstrated in Table IV and Table V. Compared with bilinear interpolation, both MAE and SDE of the proposed model is far smaller. Moreover, SR performances of the proposed model deteriorate significantly less than bilinear interpolation when scale factor is relatively larger (4 or 8).

D. Ablation Study

Ablation study was conducted to investigate the effectiveness of MTL and techniques in the proposed model. **MTL** represents the proposed model without residual connection and *iterative up-and-down* technique. It is set as the baseline model for comparison. **STL** means the baseline model with only single task (PL) during training.

Table VI demonstrates the cumulative performance gain of MAE and SDE in ablation study. The evaluation metric is PL. Apparently, SR of single task learning is incomparable to MTL. **RES** Residual connection and *iterative up-and-down* technique could reduce MAE and SDE for 20% on average. **DA** could also enhance SR performance in some extent. It's noticed that the enhancement of **DA** and **RES** decreases much when scale factor are large (4 and 8).

V. CONCLUSION

In this paper, a novel residual network based MTL model is proposed for SR of wireless channel characteristics. RT simulation was conducted and channel characteristics dataset were constructed based on simulation results. Weighted masks are introduced in loss function which can help better fit randomly

TABLE IV: Comparison of MAE between Proposed model and Bilinear Interpolation

Scale \ Targets		PL	K_p	DS	ϕ	θ	LOS/NLOS
2	Proposed	3.26	0.47	6.84	1.6	5.34	98%
	Bilinear	16.58	6.73	13.46	12.97	16.6	85%
4	Proposed	4.29	0.69	9.99	2.31	8.55	95%
	Bilinear	26.76	11.06	20.41	21.13	26.53	72%
8	Proposed	5.80	0.99	14.09	3.57	12.53	87%
	Bilinear	36.77	15.54	27.9	29.71	36.92	65%
Unit		dB	dB	ns	°	°	Acc.

TABLE V: Comparison of SDE between Proposed model and Bilinear Interpolation

Scale \ Targets		PL	K_p	DS	ϕ	θ
2	Proposed	5.04	0.89	10.06	4.29	9.84
	Bilinear	31.69	13.55	18.18	23.75	27.57
4	Proposed	6.61	1.19	13.61	5.92	14.33
	Bilinear	43.24	18.75	24.94	32.72	38.41
8	Proposed	8.30	1.55	16.94	8.00	18.13
	Bilinear	51.15	22.46	30.23	39.27	46.2

TABLE VI: Cumulative Performance Gain of MAE and SDE Compared to Baseline Model

	MAE			SDE		
	2	4	8	2	4	8
+ DA	+36%	+26%	+18%	+26%	+14%	+8%
+ RES	+28%	+20%	+13%	+20%	+12%	+7%
+ MTL	0	0	0	0	0	0
STL	-149%	-170%	-124%	-167%	-221%	-205%

STL: Single task learning
RES: Residual connection and *iterative up-and-down* technique
DA: Data augmentation

distributed building regions. A general MTL model with two stage training methods are proposed. The proposed model could achieve SR results of PL with MAE of 3.26 dB and 98% classification accuracy of LOS/NLOS areas given scale factor as 2. It also outperforms other SOTA DL models and the reasons are discussed. The proposed model demonstrates huge advantages in channel characteristics SR tasks especially when scale factor is relatively large. Ablation study also proved the necessity of residual connection, *iterative up-and-down* techinque and multi-task learning. In future, we will continue the study of channel characteristics SR problem by refining proposed MTL model on network structure and MTL loss function. Relations between upper bounds of SR performances and scale factor will also be explored.

References

[1] J. CAO, L. XU, R. Abdallah, and W. SHI, "An os for internet of everything: Early experience from a smart home prototype," *ZTE Communications*, vol. 15, no. 4, pp. 12–22, 2019.

[2] S. Mohammadjafari, S. Roginsky, E. Kavurmacioglu, M. Cevik, J. Ethier, and A. B. Bener, "Machine learning-based radio coverage prediction in urban environments," *IEEE Transactions on Network and Service Management*, vol. 17, no. 4, pp. 2117–2130, 2020.

[3] F. Xiao, X. Xie, Z. Li, Q. Deng, A. Liu, and L. Sun, "Wireless network optimization via physical layer information for smart cities," *IEEE Network*, vol. 32, no. 4, pp. 88–93, 2018.

[4] D. He, K. Guan, J. M. Garcia-Loygorri, B. Ai, X. Wang, C. Zheng, C. Briso-Rodriguez, and Z. Zhong, "Channel characterization and hybrid modeling for millimeter-wave communications in metro train," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 12 408–12 417, 2020.

[5] Y. d. J. Bultitude and T. Rautiainen, "Ist-4-027756 winner ii d1. 1.2 v1. 2 winner ii channel models," *EBITG, TUI, UOULU, CU/CRC, NOKIA, Tech. Rep*, 2007.

[6] X. Wang, D. He, K. Guan, B. Ai, J. M. García-Loygorri, and C. Briso-Rodríguez, "Hybrid channel modeling for intra-wagon communication in millimeter-wave band," in *2020 14th European Conference on Antennas and Propagation (EuCAP)*, 2020, pp. 1–5.

[7] L. Wu, D. He, B. Ai, J. Wang, H. Qi, K. Guan, and Z. Zhong, "Artificial neural network based path loss prediction for wireless communication network," *IEEE Access*, vol. 8, pp. 199 523–199 538, 2020.

[8] R. Levie, C. Yapar, G. Kutyniok, and G. Caire, "Radiounet: Fast radio map estimation with convolutional neural networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 6, pp. 4001–4015, 2021.

[9] Y. Tian, S. Yuan, W. Chen, and N. Liu, "Radionet: Transformer based radio map prediction model for dense urban environments," *arXiv preprint arXiv:2105.07158*, 2021.

[10] L. Guo, Y. Zhang, and Y. Li, "An intelligent electromagnetic environment reconstruction method based on super-resolution generative adversarial network," *Physical Communication*, vol. 44, 2021.

[11] D. He, B. Ai, K. Guan, L. Wang, Z. Zhong, and T. Kürner, "The design and applications of high-performance ray-tracing simulation platform for 5g and beyond wireless communications: A tutorial," *IEEE Communications Surveys Tutorials*, vol. 21, no. 1, pp. 10–27, 2019.

[12] K. Guan, D. He, and Z. Zhong, "Cloudrt: A chinese example of open science infrastructure and services," *Cultures of Science*, vol. 4, no. 4, pp. 217–226, 2021. [Online]. Available: https://journals.sagepub.com/doi/abs/10.1177/20966083221084142

[13] Z. Zhang, X. Wang, D. He, Q. Huang, and D. Liu, "Ray-tracing simulation and analysis of 5g channel characteristics in dense urban areas," in *2022 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting*, Accepted.

[14] Z. Wang, J. Chen, and S. C. H. Hoi, "Deep learning for image super-resolution: A survey," *IEEE Trans Pattern Anal Mach Intell*, vol. 43, no. 10, pp. 3365–3387, 2021. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/32217470

[15] A. Kendall, Y. Gal, and R. Cipolla, "Multi-task learning using uncertainty to weigh losses for scene geometry and semantics," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7482–7491.

[16] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, and S. Gelly, "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, 2020.

[17] C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, and Z. Wang, "Photo-realistic single image super-resolution using a generative adversarial network," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, Conference Proceedings, pp. 4681–4690.