4 January 2025 ·

Qeios

Peer Review

Review of: "Deep Learning-Based CKM Construction with Image Super-Resolution"

Yi Zheng[1]

1. College of Artificial Intelligence, Jianghan University, Wuhan, China

This paper presents an innovative and effective approach to constructing Channel Knowledge Maps (CKMs) using deep learning-based super-resolution techniques SRResNet. By bridging concepts from image processing and wireless communication, the authors provide a creative solution to the challenge of building high-resolution CKMs from sparse measurement data. The results demonstrate strong performance across multiple datasets and metrics, making this work a valuable contribution to the field of environment-aware communications in next-generation wireless networks. The paper is well-organized, the methodology is rigorously validated, and the findings hold both theoretical and practical significance. But if the author could pay attention to the following suggestions, it may enhance the value of this paper.

Suggestions and Recommendations:

1. **Comparison with Other Advanced Models and Ablation Studies:** Include more comparisons with state-of-the-art deep learning models, such as RadioUNet[1] or RadioGANs[2] and etc., to emphasize the relative advantages of SRResNet in CKM construction. For instance, provide detailed side-by-side comparisons of SRResNet, RadioUNet, and RadioGANs. This would highlight SRResNet's performance advantages in terms of prediction accuracy and generalization capability. And evaluate all models across multiple datasets and varying SR factors (e.g., 2×, 4×, 8×) to showcase the robustness of SRResNet in different conditions. Then, present visualizations of reconstructed CKM maps for the same test samples to qualitatively demonstrate the fidelity of SRResNet compared to the other methods. Moreover, I suggest to analyze the specific architectural choices in SRResNet to explain why it outperforms alternatives.

doi.org/10.32388/R2D0VG

2. **Handling Noisy or Non-Uniform Data:** Discuss potential methods for addressing noise and non-uniform distribution in sparse measurement data, as this would enhance the real-world applicability of the proposed method. It could apply data augmentation like adding controlled noise or creating non-uniform sparsity patterns in training data to simulate real-world conditions and improve model robustness. And It also can introduce loss functions that penalize noise-related artifacts (Noise-Aware Loss Functions), such as total variation loss or perceptual loss, to enhance the model's resilience to noisy inputs.
3. **Dataset Diversity:** Explore the use of more diverse datasets or real-world measurement scenarios, such as RSRPSet at IEEE DataPort (10.21227/4ba2-tg21), to validate the generalizability and robustness of the proposed method.

References

1. ^*Ron Levie, Çağkan Yapar, Gitta Kutyniok, Giuseppe Caire. (2021). RadioUNet: Fast Radio Map Estimation With Convolutional Neural Networks. IEEE Trans. Wireless Commun., vol. 20 (6), 4001-4015. doi:10.1109/twc.2021.3054977.*
2. ^*Yi Zheng, Ji Wang, Xingwang Li, Jiping Li, et al. (2023). Cell-Level RSRP Estimation With the Image-to-Image Wireless Propagation Model Based on Measured Data. IEEE Trans. Cogn. Commun. Netw., vol. 9 (6), 1412-1423. doi:10.1109/tccn.2023.3307945.*

Declarations

Potential competing interests: No potential competing interests to declare.