Uncertainty Nonlinearly Guided Learning Framework for Full-wave Inverse Scattering

Siyuan He and Zhun Wei
College of Information Science and Electronic Engineering, Zhejiang University, Hangzhou, China

Abstract— In the electromagnetic inverse scattering problem, deep learning schemes have achieved significant successes. Nonetheless, due to insufficient interpretability, well-trained neural networks may still have poor predictions in individual samples or regions, posing risks for practical applications. Recently, uncertainty has been introduced into neural networks to quantify possible errors along with predictions. Whether the uncertainty information can be used to further optimize the network has attracted attention. In this work, we propose an uncertainty-nonlinearly-guided learning framework for the full-wave inverse scattering problem. By introducing uncertainty into the loss function through nonlinear transformation, the learning framework can optimize the network for specific targets, such as paying attention to the edge parts or background parts.

Specifically, we adopt a network structure that decouples prediction and uncertainty to avoid interference between the two variables. We divide the training process into three phases. Firstly, we separately train a prediction network based on the dominant current (DC) method and adopt mean square error (MSE) as the loss function. Then, we train the uncertainty network using the DC inputs and prediction networks, adopting the assumption of Gaussian distribution, and using the negative logarithm of the Gaussian probability density function as the loss function. During this process, the network parameters of the prediction network are frozen. In the third step, we use uncertainty to optimize the network and adopt the uncertainty-guided-loss (UDL) we proposed. Experimental results show that our framework can achieve ideal optimization results for different objectives. Optimization of high-uncertainty areas can improve the prediction of edge parts, predict some results where the original prediction failed, and improve the overall structural similarity (SSIM). Targeting low uncertainty areas can significantly reduce the noise in the background.

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