

Deep Learning for Solving Inverse Scattering Problems in Breast Cancer Imaging

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In this paper, we propose a novel deep learning-based framework to address the inverse scattering problem in breast cancer imaging. A convolutional neural network (CNN) is trained on synthetic data to reconstruct dielectric property maps from scattered microwave signals. Our results demonstrate that the proposed approach achieves high reconstruction accuracy, effectively suppresses artifacts, and localizes tumors with high precision. This work highlights the potential of deep learning in revolutionizing microwave imaging for breast cancer detection.

Microwave imaging has garnered attention as a safe, low-cost, and non-invasive alternative. By exploiting the contrast in dielectric properties between healthy and malignant breast tissues, microwave imaging offers high sensitivity to tumor detection. However, its clinical application is hindered by the complexity of solving the inverse scattering problem, which involves reconstructing tissue dielectric properties from scattered microwave signals. Traditional methods, such as the Born approximation and compressive sensing, are computationally expensive and prone to artifacts, particularly in heterogeneous tissues.

Recent advancements in deep learning have shown promise in overcoming these challenges. Deep learning frameworks can leverage large datasets to learn complex mappings between input signals and target outputs, making them ideal for addressing inverse problems. In this study, we propose a deep learning-based approach for solving the inverse scattering problem in breast cancer imaging. Our framework integrates simulated datasets to train a convolutional neural network (CNN) for accurate reconstruction of tissue dielectric properties.

The proposed method consists of three main stages: data generation, neural network design and training, and evaluation. Synthetic data were generated using Computer Simulation Technology (CST), which provided realistic datasets of microwave scattering. Breast phantoms were modeled with accurate dielectric properties based on literature, and tumors of various sizes and locations were embedded to simulate realistic scenarios. Preprocessing involved normalizing the scattered microwave signals between 0 and 1 for numerical stability and reducing dimensionality with Principal Component Analysis (PCA) to retain the most significant information.

The neural network architecture consisted of a convolutional neural network (CNN) designed to map scattered microwave signals to dielectric property maps. The input layer accepted normalized frequency-domain signals, while convolutional layers extracted spatial and frequency-based features. Residual blocks were incorporated to address vanishing gradient issues and enhance feature propagation. The output layer produced either 2D or 3D maps of dielectric properties. The network was trained using a mean squared error (MSE) loss function, optimized with the Adam optimizer at a learning rate of 0.001. Performance evaluation metrics included Structural Similarity Index (SSIM) to measure similarity between reconstructed and ground-truth images, Peak Signal-to-Noise Ratio (PSNR) to quantify reconstruction quality, and Localization Accuracy to assess tumor detection performance. These metrics ensured a robust and reliable assessment of the proposed method's effectiveness.

In this presentation, we will showcase the results of the proposed deep learning-based framework for solving inverse scattering problems in breast cancer imaging. Qualitative analysis further underscores the effectiveness of the proposed method. Visual inspection of the reconstructed dielectric property maps reveals that the CNN successfully suppresses artifacts and produces high-resolution images of tumor regions.