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A Multi-branch Deep Learning Architecture for Microwave-Ultrasound Breast Imaging

Vahab Khoshdel * (1), Pedram Mojabi(2), and Joe LoVetri (1)
(1) University of Manitoba, Winnipeg, Canada; e-mail: vahab.khoshdel@umanitoba.ca; Joe.LoVetri@ umanitoba.ca
(2) University of Calgary, Calgary, AB (pedram.mojabi@ucalgary.ca)

Abstract

A novel deep convolutional fusion architecture with multiple branches is proposed to address the challenges posed by electromagnetic inverse scattering problems. Traditional inverse scattering techniques suffer from various difficulties, including strong ill-conditioning, high computational cost, and intrinsic nonlinearity. To overcome these challenges, a multi-branch convolutional neural network (CNN) is proposed for reconstructing two-dimensional (2D) images of breast permittivity in order to detect tumors. The proposed architecture, which is influenced by objective-function methods, inputs scattered-field data and ultrasound-derived breast mask as prior information to reconstruct images of permittivity. The architecture consists of two branches, a decoder-only branch and a convolutional branch, to handle inputs of different formats. The final reconstructed 2D image is obtained by fusing the outputs of these two branches. The CNN is trained using eight numerical MRI-based breast models. Results demonstrate that the proposed approach provides high-quality imaging for high-contrast objects of interest. This work opens up a new avenue for real-time quantitative microwave imaging using deep learning.

1 Introduction

Microwave imaging has been widely used for various imaging applications, including breast cancer detection and treatment monitoring [1], subsurface prospecting [2], and stored-grain monitoring [3]. However, the associated quantitative inverse scattering problem is ill-posed and nonlinear, making it challenging to obtain highly accurate reconstructions of the complex-valued permittivity. To address this challenge, different techniques have been developed in the past few decades; however, they often require computationally expensive iterative techniques, particularly when imaging highly inhomogeneous scatterers with high contrast values. Despite the advancements made in recent years, images containing reconstruction artifacts still remain a great challenge, particularly in biomedical imaging, where the resolution is lower compared to other modalities.

The field of deep learning has seen a significant expansion in recent years, and convolutional neural networks (CNNs) have emerged as a particularly powerful tool for solving a wide range of scientific and engineering problems. These include applications in natural language processing, computer vision, and speech recognition [4]. CNNs have also been applied to medical imaging [5, 6], with notable achievements in the areas of segmentation, detection and classification. The use of deep learning techniques in medical imaging has been well-investigated for many common modalities [7]. CNNs are a type of deep neural network that is specifically designed to handle image data as inputs, which makes them particularly suitable for image-based applications.

In recent years, researchers have explored the utilization of machine learning techniques in the context of electromagnetic inverse problems with the aim of improving the performance of microwave imaging (MWI). The state-of-the-art deep-learning-based MWI techniques can be broadly categorized into two groups. The first group encompasses the utilization of CNNs in combination with traditional algorithms to enhance the performance of electromagnetic inversion. This includes the use of deep learning as a prior or regularization term [4] or as a post-processing method for denoising and artifact removal [8, 9]. Both have been shown to improve the performance of traditional methods [10, 11]. The second group of techniques involves the direct reconstruction of an image from measurement data using deep learning techniques. While there have been promising studies on the use of deep learning techniques for the direct reconstruction of images from measurement data in other imaging modalities, such as MRI [12] and ultrasound [13], there remains a significant need to investigate the application of deep learning to the inverse problem in microwave imaging. Recent research by Li *et al.* has demonstrated the potential of using deep neural networks for nonlinear electromagnetic inverse scattering, but their work has been limited to simple homogeneous targets with low contrast and two-dimensional (2D) inverse problems [14]. Khoshdel *et al.* have also developed a multi-branch deep convolutional fusion architecture that aims to solve electromagnetic inverse scattering problems to reconstruct 3D images of the moisture distribution in stored grain [15].

In an effort to reduce the amount of prior information required by the ML model to solve electromagnetic inverse scattering problems compared to our previous research [15], in this study a novel convolutional neural network (CNN) architecture is proposed to directly reconstruct two-dimensional (2D) permittivity images of the breast. To accomplish this, a homogeneous background was taken into account during the generation of scattered field data, in addition prior images of an ultrasound-derived breast mask provide information only regarding the shape and location of the breast. The proposed CNN learns to find and locate the cancerous breast tumors from sensor-domain data, represented as a complex-valued array of transmitter-receiver measurements, to a 2D image of the permittivity. The trained CNN model achieves a higher imaging quality compared to traditional inversion techniques in microwave imaging. Additionally, the use of trained CNN models enables the application of microwave imaging for quasi-real time monitoring by eliminating the reconstruction time.

3 Neural network architecture

The proposed architecture is a multi-branch convolutional neural network (CNN) designed to reconstruct two-dimensional images of the permittivity map of the breast. The proposed Architecture is inspired by our previous research on reconstructing 3D images of the grain's moisture distribution. The model accepts the real and imaginary components of microwave scattered-field data at multiple frequencies as its primary input. It is worth noting that in this paper, a homogeneous background medium with a relative complex permittivity of 23.3-j18.46 is used as the assumed background for the incident field to determine the scattered field data.
This work draws inspiration from studies that demonstrate the improved performance of incorporating prior information as an inhomogeneous numerical background that modifies the incident/scattered field decomposition [16, 17]. That work shows the importance of different levels of information considered as background information in the success of traditional inverse techniques. Thus, with the goal of decreasing the ML model’s reliance on prior information, ultrasound-derived breast mask is herein utilized as prior information. Fig 1 shows the schematic of the proposed architecture.

To integrate this into the proposed model, the first branch takes in the scattered-field data, and the second branch is a several convolutional layers, which inputs the prior image [5]. The outputs of both branches, *i.e.* the decoder-only branch and the U-Net, are then combined through a linear combination, which is parameterized. The proposed Convolutional Neural Networks (CNNs) were implemented using Python 3.9.1 and Keras 2.11.0 with Tensorflow backend. A Mac Studio machine equipped with Apple M1 Max chip was employed as the computing platform. To achieve a suitable scale, the convolutional layer weights were initialized using the Xavier initialization method. The CNN was trained using an Adam optimizer with a batch size of 5 over a total of 50 iterations. To mitigate the risk of overfitting, a four-fold cross-validation strategy was employed.

4 Dataset

Eight numerical tumorless MRI-based breast models are used to create the data sets [20,21]. For each model, we create fifty images by adding different numbers, locations, and sizes of tumors. Each breast phantom is also rotated 11 times. Therefore, each breast model has 600 unique phantoms, and the total number of phantoms for eight models is 4800.
It is assumed that each breast phantom is surrounded by 30 transceivers. The microwave scattered data for each pair of transmitter and receiver pairs is collected at three frequencies (f = [1, 1.5, 2] GHz). The relative complex permittivity of 23.3−j18.46 is used as a background medium.

5 Results

We demonstrated the performance of our proposed method for reconstructing 2D images of permittivity by presenting several random examples from the test dataset featuring zero, one, or two tumors from various breast models.

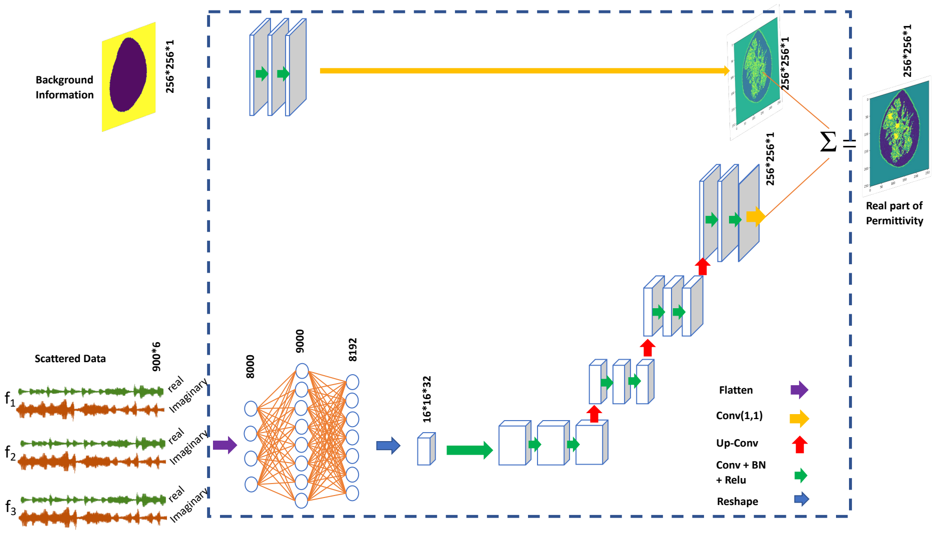

Figure 1. Schematic of the proposed architecture. The inputs to the network are the normalized real and imaginary parts of scattered-field data for three different frequencies and ultrasound-derived tissue regions as an image, and the network is trained to output the corresponding true 2D permittivity map.

Figure 2 illustrates the reconstructed images produced by the CNN and shows the network's capability to identify tumors and eliminate the typical artifacts of traditional inverse methods. Given that the CNN was trained on a dataset of eight MRI breast models, we evaluated the generalization of the trained CNN to a completely new breast model by testing the model's performance on the new model. Figure 3 illustrates the performance of the trained CNN when the inputs for a new breast model are scattered-field data and prior information image. Results show that the model cannot reconstruct tumors for new models. It is noteworthy to mention that, in comparison to our previous research on stored-grain imaging [16], we have attempted to decrease the amount of prior information required by the model. This has been achieved not only through the utilization of prior images as masks, which provide information solely regarding the shape and location of the breast, but also through the consideration of a homogeneous background in the generation of scattered field data. In future work, we will investigate improving the generalizability of the model by increasing the number of breast models. The techniques learned from the present approach will form the basis of extending it to data collected using our 3D dual-mode US/MW experimental imaging system.

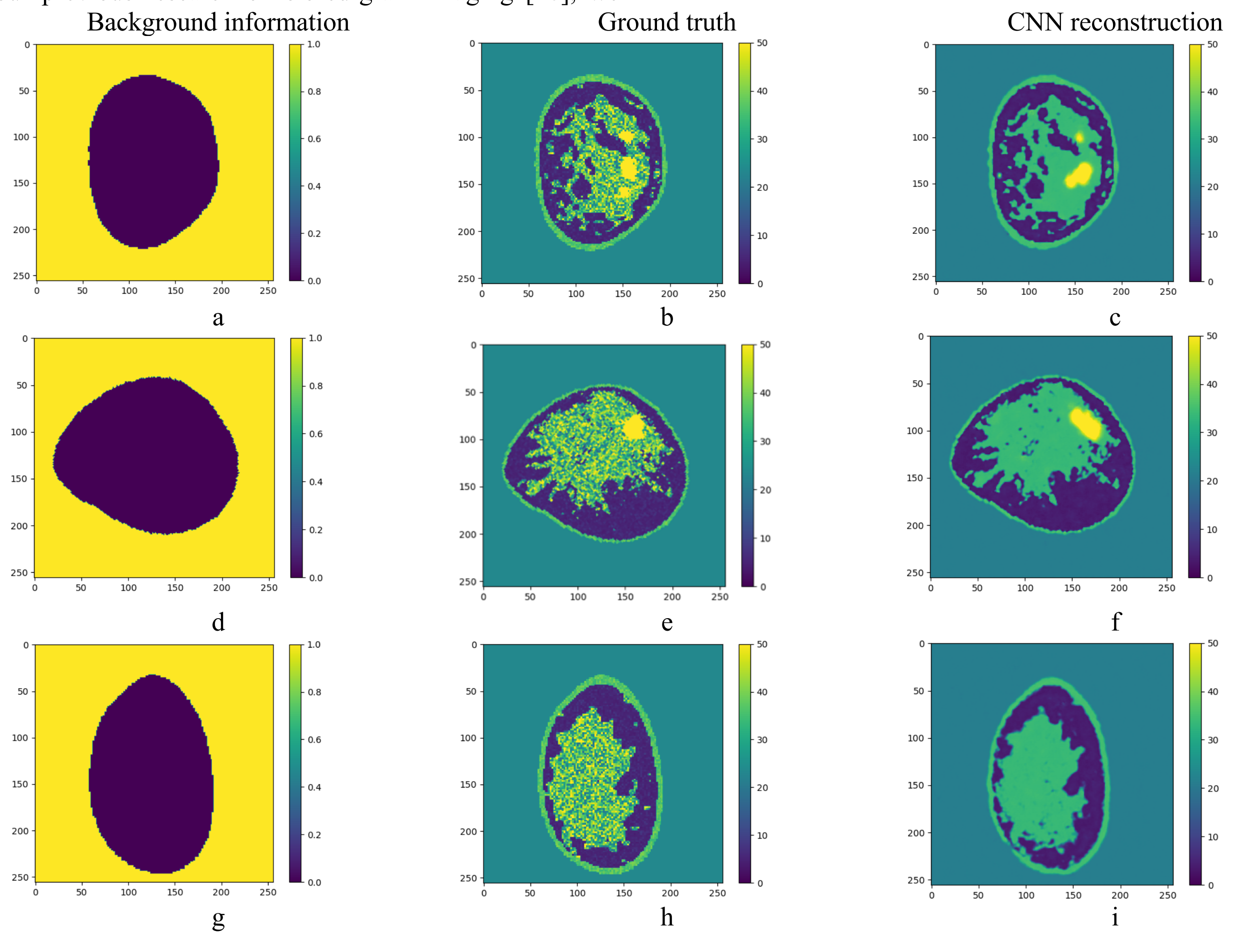

Figure 2. The real part of CNN reconstruction results for particular examples with two, one and no tumor. (a, d, g) The Background information as input, (b,e,h) Ground truth. (c,f,i) CNN reconstruction.

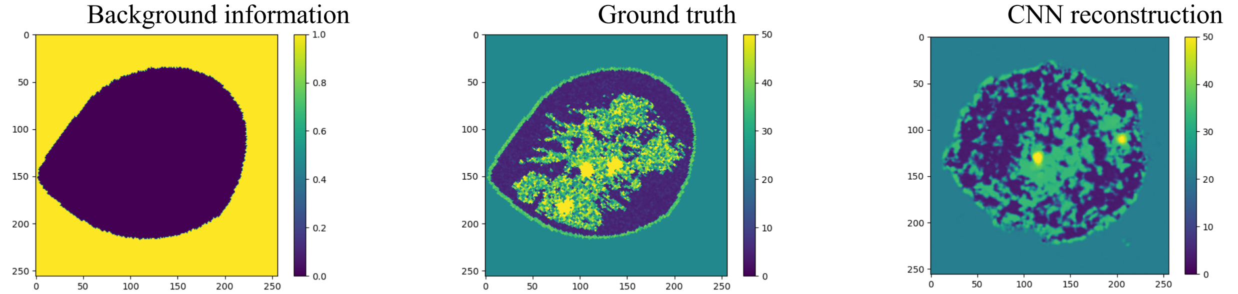

Figure 3. The real part of CNN reconstruction results for particular examples from a totally new breast model.

6 Conclusion

In conclusion, our study has shown that Convolutional Neural Network (CNN) architectures can effectively solve the electromagnetic inverse scattering problem. The proposed through the implementation of physical property imaging using electromagnetic scattered-field data. We have demonstrated the direct imaging of breast tissue permittivity from scattered-field data without the need for traditional reconstruction techniques. The results indicate architecture utilized both raw scattered-field data and prior information in the form of ultrasound-derived breast mask to successfully find and locate the tumors. The training of the CNNs was conducted using a synthetic dataset of 4800 breast phantoms, which were generated with a randomized number, size, and location of tumors. This work highlights the potential for CNNs to be a valuable tool in the imaging of physical properties in medical applications as well as any other application which need real-time imaging.

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