Deep Learning Assisted Microwave Imaging using MRI Data

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Microwave imaging can be used for biomedical applications, such as breast cancer diagnostics, and more recently, for thermal therapy monitoring. However, due to the ill-posed and nonlinear nature of the microwave inverse scattering problem, it is still a major challenge to reconstruct high quality dielectric images for medical purposes. In microwave imaging, the total number of measurements is usually substantially smaller than the total number of unknowns, which makes the problem under-determined. Moreover, the total electric field and the dielectric contrast within the volume integral equation used to solve the inversion problem are both unknowns and coupled together, which makes the problem nonlinear. Many efforts have been spent to address these two issues separately. Specifically, regularization techniques, such as the Tikohonov regularization, sparsity, and spatial prior regularization, have been used to choose a preferred solution in accordance to the prior knowledge of the image. Iterative methods, such as Born and distorted Born iteration methods, have been used to iteratively solve the nonlinear inverse scattering problem. However, currently there are still no methods that can overcome the nonlinearity of high contrast microwave inverse scattering.

One obvious, but not always easy, approach to address both the problems of nonlinearity and an under-determined system is to start with a solution that is already very close to the true solution. This is, in general, not a straightforward task. We propose to acquire this approximate microwave imaging solution from magnetic resonance imaging (MRI) data and to use convolutional neural networks (CNNs) to learn the mutual information between MRI and microwave images from existing databases such as the University of Wisconsin MRI and microwave breast image pairs. This approach is based on the assumption that there exists mutual information between magnetization relaxation time from MRI images and dielectric values from microwave images. The CNN approach is chosen because of its strength to retain local shape and structure information (different type of tissues should have similar structures in MRI and microwave images) as well as the capability to learn the nonlinear relationship between individual pixel values (relaxation time and dielectric). After building this neural network, we can input the MRI image and generate an approximate microwave image, which contains all of the mutual information between tissue magnetization relaxation time and the dielectric constant. Then the derived microwave images are used as the starting solution for solving the microwave inverse scattering problem. This step refines the image and can develop microwave tissue properties that are not captured by MRI. To increase the accuracy of the neural network, a larger number of training samples with increased dielectric mapping accuracy that are currently available are eventually needed. One approach is through active learning, which feeds the microwave images generated at the last stage back into the neural network as training samples. These images contain not only the unique feature of microwave images, but can also include the mutual information between MRI and microwave, which has not been fully learned by the neural network. In this talk, we will demonstrate the MRI images inferred dielectric images through our customized CNN. We will also compare the final microwave imaging results with and without using MRI inferred dielectric image priors.