URSI GASS 2021, Rome, Italy, 28 August - 4 September 2021

Convolutional neural networks and microwave-ultrasound data fusion for breast imaging

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Breast cancer is most common among females. Different imaging modalities have been investigated for breast imaging, such as X-ray, ultrasound, MRI and microwave. Among them, microwave and ultrasound are non-invasive, non-ionizing and low-cost. Microwave is preferred since providing high-contrast images, yet resolution is low due to the relatively large wavelength; ultrasound can produce high-resolution images with low contrast. Thus, it is of great interest to fuse these two modalities to produce images with both high contrast and high resolution. Fusion can be achieved by simultaneous inversion in the imaging process, or by successive imaging with the result of one modality used as prior in the inversion of another modality, or by fusion of two images after imaging procedure. Here the first method is investigated. Several algorithms have been proposed for joint inversion, based on physical or empirical relations between different parameters [1] or on structure similarities [2].

Recently, convolutional neural networks (CNN) have been investigated for inverse scattering problems [3, 4] and have shown great potential. In this work, we use convolutional neural networks (CNN) to achieve joint inversion of microwave and ultrasound. The CNN structure is based on two-stream CNN [5], proposed to utilize both temporal and spatial information as the inputs of two CNNs and then fused by a classifier for video recognition. Similarly, two networks are built for ultrasound and microwave data, resp., and convolutional kernels shared for these two sets of data after their features are combined at some level. Every pixel of the output image is classified into a tissue type class by a softmax classifier. Realistic breast models used to generate datasets are from the UWCEM Breast Phantom Repository [6]. Tumors with random size and position are added into different slices from these models. Synthetic data are obtained by solving the forward scattering problem with a Method of Moments. Data augmentation technique is used to enlarge the dataset with random rotation and flipping. Different noise levels are added to microwave and ultrasound data. Considering the class imbalance that the number of pixels in a tumor is much smaller than of other tissue types, a weighted loss function is introduced to give a higher penalty when a pixel in tumor is misclassified. The well-known Adam optimization algorithm is used to train the network. Comparison is also conducted with one-stream case where microwave and ultrasound data are considered as different channels.

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