Quantification of Magnetic Resonance Elastography for Tissue Shear Modulus using U-Net Trained with Finite-Differential Time-Domain Simulation

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Abstract : Magnetic resonance elastography (MRE) non-invasively assesses tissue elastic properties, such as shear modulus, by measuring tissue's displacement in response to mechanical waves. The estimated metrics on tissue elasticity or stiffness have been shown to be valuable for monitoring physiologic or pathophysiologic status of tissue, such as a tumor or fatty liver. To quantify tissue shear modulus from MRE-acquired displacements (essentially an inverse problem), multiple approaches have been proposed, including Local Frequency Estimation (LFE) and Direct Inversion (DI). However, one common problem with these methods is that the estimates are severely noise-sensitive due to either the inverse-problem nature or noise propagation in the pixel-by-pixel process. With the advent of deep learning (DL) and its promise in solving inverse problems, a few groups in the field of MRE have explored the feasibility of using DL methods for quantifying shear modulus from MRE data. Most of the groups chose to use real MRE data for DL model training and to cut training images into smaller patches, which enriches feature characteristics of training data but inevitably increases computation time and results in outcomes with patched patterns. In this study, simulated wave images generated by Finite Differential Time Domain (FDTD) simulation are used for network training, and U-Net is used to extract features from each training image without cutting it into patches. The use of simulated data for model training has the flexibility of customizing training datasets to match specific applications. The proposed method aimed to estimate tissue shear modulus from MRE data with high robustness to noise and high model-training efficiency. Specifically, a set of 3000 maps of shear modulus (with a range of 1 kPa to 15 kPa) containing randomly positioned objects were simulated, and their corresponding wave images were generated. The two types of data were fed into the training of a U-Net model as its output and input, respectively. For an independently simulated set of 1000 images, the performance of the proposed method against DI and LFE was compared by the relative errors (root mean square error or RMSE divided by averaged shear modulus) between the true shear modulus map and the estimated ones. The results showed that the estimated shear modulus by the proposed method achieved a relative error of 4.91%±0.66%, substantially lower than 78.20%±1.11% by LFE. Using simulated data, the proposed method significantly outperformed LFE and DI in resilience to increasing noise levels and in resolving fine changes of shear modulus. The feasibility of the proposed method was also tested on MRE data acquired from phantoms and from human calf muscles, resulting in maps of shear modulus with low noise. In future work, the method's performance on phantom and its repeatability on human data will be tested in a more quantitative manner. In conclusion, the proposed method showed much promise in quantifying tissue shear modulus from MRE with high robustness and efficiency.

Keywords : deep learning, magnetic resonance elastography, magnetic resonance imaging, shear modulus estimation
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