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Acceleration of Magnetic Resonance Fingerprinting Reconstruction Using Denoising and Self-Attention Pyramidal Convolutional Neural Network

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PURPOSE

Magnetic resonance fingerprinting (MRF) based on echo-planar imaging enables whole-brain imaging to rapidly obtain T1 and T2* relaxation time maps. Reconstructing parametric maps from the MRF scanned baselines by inner-product method is computationally expensive. We aimed to accelerate the reconstruction of parametric maps using a deep learning model.

MATERIAL AND METHODS

The proposed approach uses a two-stage model that first eliminates noise and then regresses the parametric maps. Parametric maps obtained by dictionary matching were used as a reference and compared with the prediction results of the two-stage model. MRF scans were collected from 32 subjects. Figure 1 is the schematic of the proposed model.

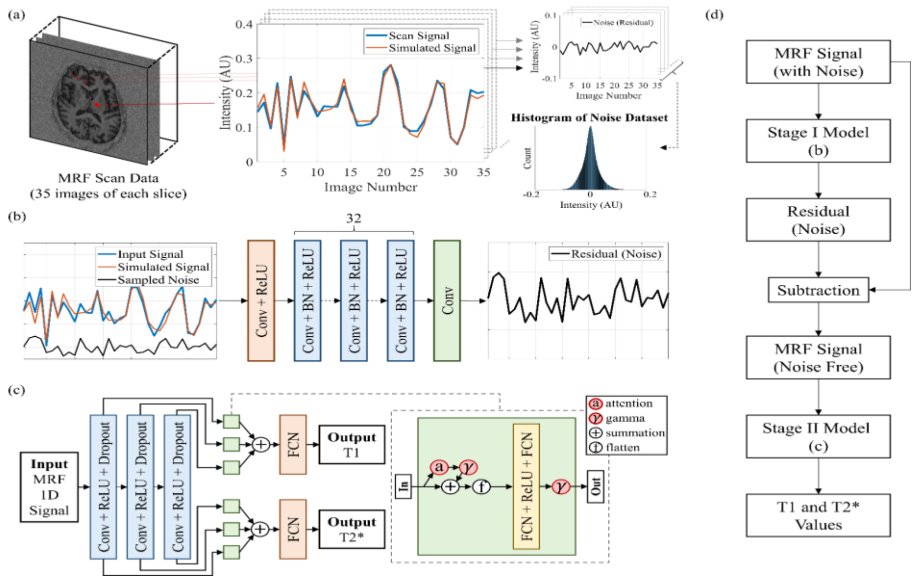

Figure 1. Schematic of the noise collection, denoising CNN, pyramid model, and flowchart of the two-stage model. (a) Collection of the noise dataset. AU = arbitrary unit. (b) Denoising CNN. (c) Weighted pyramid dual-path CNN with attention. (d) Flowchart of the successive process of the proposed model.

RESULTS

The signal-to-noise ratio increased significantly after the noise removal by the denoising model. For prediction with scans in the testing dataset, the mean absolute percentage errors between the standard and the final two-stage model were 3.1%, 3.2%, and 1.9% for T1, and 2.6%, 2.3%, and 2.8% for T2* in gray matter, white matter, and lesion locations, respectively. Figure 2 depicts a single slice from a patient with multiple sclerosis for the tissue masks, FLAIR, standard and predicted maps for T1 and T2*, and their corresponding difference maps.

CONCLUSIONS

Our proposed two-stage deep learning model can effectively remove noise and accurately reconstruct MRF parametric maps, increasing the speed of reconstruction and reducing the storage space required by dictionaries.

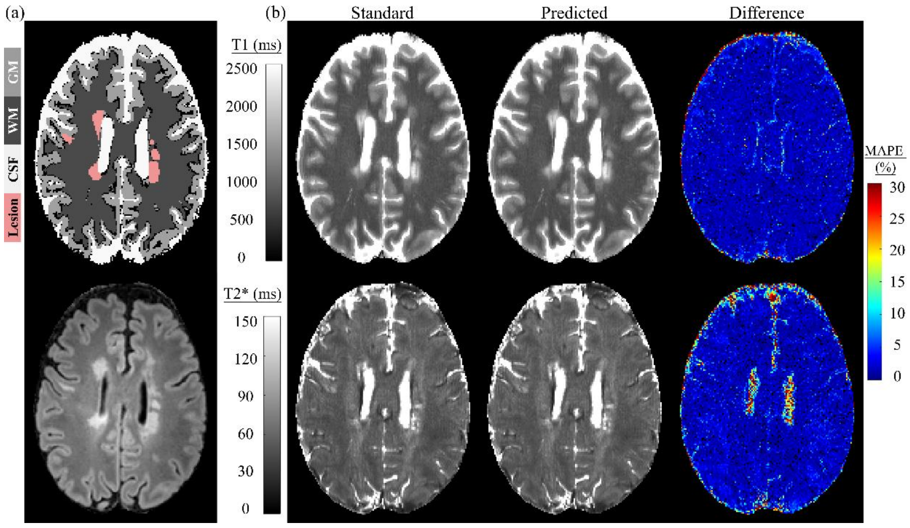

Figure 2. Magnetic resonance fingerprinting parametric maps of a single slice in a patient with multiple sclerosis matched by the simulated dictionary (standard) and predicted by the proposed model. (a) Top is the tissue masks; bottom is the FLAIR. (b) Standard maps by dictionary matching, predicted maps by the proposed two-stage model, and difference maps between them.

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