

Multi-Contrast Reconstruction using Neural Network for Higher Acceleration

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Introduction

MRI can offer images with various contrasts by controlling imaging parameters. Clinical diagnosis requires several examinations to present various characteristics of organs, which are very time-consuming. To reduce total imaging time, many techniques have been proposed. Among them, parallel imaging techniques utilize sensitivity difference between multichannel RF coils. However, it is difficult to apply these techniques to higher acceleration due to SNR degradation. In this study, it is a key concept that each image in clinical protocols has different contrast, but shares similar structure information. The concept is helpful for reconstructing each contrast image from subsampled multi-contrast data. We propose a reconstruction model based on artificial neural network (ANN) to allow to use higher acceleration factors and compared its performance with GRAPPA.¹

Materials and Methods

Data source: Three typical sequences such as T1-weighted (T1w), T2-weighted (T2w) and fluid attenuated inversion recovery (FLAIR) sequences in brain protocol are frequently used. For the three sequences, brain MR images from five subjects were obtained using Siemens Magnetom Verio 3T system with 12 channel head coil. Imaging parameters for the experiments are given as FOV = 220×200mm², matrix size = 384×216, slice thickness = 5mm, TR/TE = 558/10ms (T1w), TR/TE = 5000/90ms (T2w), and TR/TE/TI = 9000/97/2500ms (FLAIR).

Model design: A flowchart of the proposed method is shown in Fig 1a. Full k-space data are subsampled and parallel imaging techniques are applied according to the subsampling pattern. Each intermediate image with different contrast is divided into overlapping blocks and each voxel in the block is used as inputs for an ANN model. All inputs and outputs are normalized before applying the proposed ANN model. Multilayer perceptron is implemented as shown in Fig 1b. One hidden layer and hyperbolic tangent function for activation are used, and it can be represented as follows:

$$C_k = \sum_{j=1}^{n_H} w_{kj} \tanh\left(\sum_{i=1}^{n_I} w_{ji} C'_i + b_0\right) + b_1$$

where C'_i is normalized input voxel, and C_k normalized output voxel. Back propagation algorithm is implemented to train weight values (w_{kj}, w_{ji}) and bias values (b_0, b_1) with the given values of the number of hidden neurons (n_H) and the number of inputs (n_I). Finally, a reconstructed image is obtained by denormalizing.

Performance evaluation: Artifact power (AP) is calculated for inside of the object.² High-frequency error norm (HFEN) is additionally calculated to quantify the reconstruction result of edge.³ K-fold cross validation is performed for training and testing. The proposed ANN model is applied to single contrast (SC) and multi contrast (MC) reconstructions, whose input images are single contrast image and multiple contrast images, respectively.

Results

As shown in Fig 2a, AP of GRAPPA is exponentially increasing with respect to the reduction factor. SC and MC in low acceleration factor show small gain. However, the higher the reduction factor is, the bigger the gain is. Fig 2 proves the advantage in utilizing sharable information among different contrast images. The proposed method guarantees the quality of the reconstructed image even in higher acceleration in Fig 3. According to Fig 2b, the proposed ANN model plays a role of not a smoothing filter but an approximator to reduce noise, while maintaining details of the image.

Discussion and conclusion

The proposed method shows possibility of higher acceleration. Conventional parallel imaging technique was combined with ANN, and various contrast images were simultaneously and mutually used for reconstruction. This framework can be applied to various reconstruction techniques like partial Fourier reconstruction algorithms and multi-band imaging techniques. In addition to multi contrast images, phase and location information could be additionally used as inputs of ANN model for better results.

Reference

1. Wang Z, et al. Improved Data Reconstruction Method for GRAPPA. MRM. 2005;54:738-742.
2. Yutzy S, et al. Improvements in Multislice Parallel Imaging Using Radial CAIPIRINHA. MRM. 2011;65:1630-1637.
3. Ravishanker S, et al. MR Image Reconstruction From Highly Undersampled k-Space Data by Dictionary Learning. IEEE TMI. 2011;30:1028-1041.

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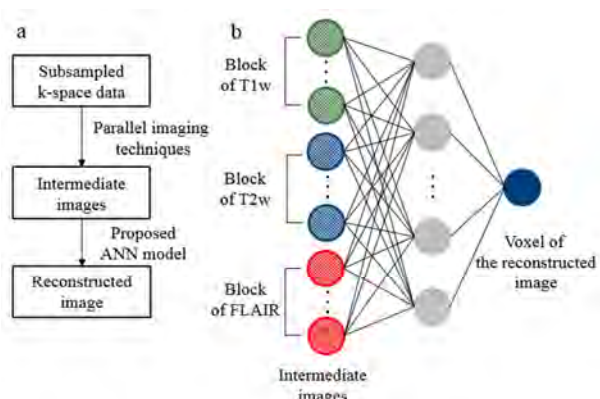


Figure 1. (a) Flowchart of the proposed method, and (b) Schematic diagram of multilayer perceptron.

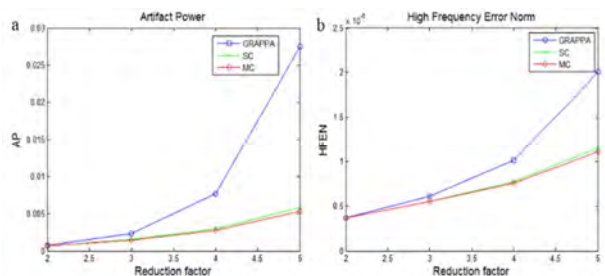


Figure 2. (a) AP, and (b) HFEN of the proposed method and GRAPPA.

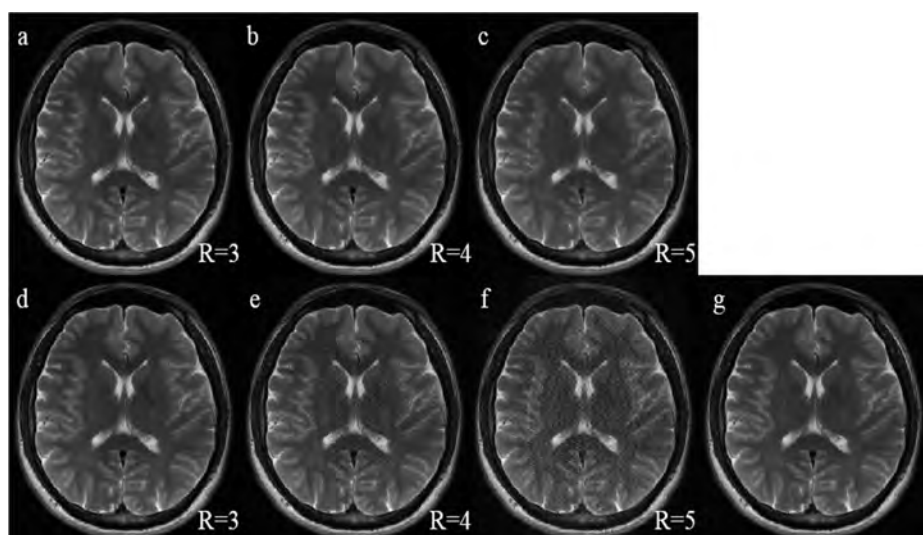


Figure 3. (a-c) the proposed method, (d-f) GRAPPA with respect to the reduction factor, and (g) reference (full-sampled image).