

A neural network approach for non-Cartesian k-space parallel imaging reconstruction

N. Sinha¹, S. Jana¹, and M. Saranathan¹

¹Indian Institute of Science, Bangalore, Karnataka, India

Introduction: Parallel MR Imaging utilizes implicit or explicit knowledge of coil sensitivity functions to reconstruct unaliased images from undersampled multicoil data. Image based methods such as SENSE [1], k-space based methods such as GRAPPA [2] and hybrids [3] have been proposed. Most of these techniques have focused on Cartesian trajectories. With increasing popularity of non-Cartesian trajectories like radial, spiral due to their inherent over-sampling of low k-space, there is a felt need for adapting parallel imaging to these sampling methods. However, due to the complex nature of the aliasing PSF for non-Cartesian trajectories, parallel imaging reconstruction has proved non trivial. We propose a novel algorithm using neural networks (NN) to reconstruct non-Cartesian undersampled data.

Theory: In this paper, neural networks are used to reconstruct unaliased images from multicoil non-Cartesian undersampled k-space data. The basic idea is to use NN to “learn” the aliasing process caused by non-Cartesian undersampling (effected by reducing angles or interleaves) and then use it to unalias the undersampled images. Neural networks require training data to help determine their weights. We used the low resolution central k-space data itself to train the NN. For radial imaging, even for undersampled cases, unaliased low resolution images can be reconstructed using data within a specific Nyquist radius. For the spiral case, this strategy fails for undersampling factors greater than 2, necessitating the use of variable density trajectories with more densely sampled cores. Low resolution k-space data are undersampled and the aliased images fed to the NN to estimate the optimal weights based on the fact that the unaliased low resolution image is known *a priori*. Because the aliasing pattern for low k-space and full k-space are similar, the same weights are used to reconstruct an unaliased image by optimal combination of the aliased high resolution images.

Methods: All simulations and reconstructions were performed using MATLAB. Phantom data were obtained using a 8-channel head coil and a gradient echo spiral pulse sequence (16 interleaves, 3096 samples per interleaves) on a GE 1.5Texcite scanner. Re-gridding on a 2X grid was performed as in [4] using a Kaiser-Bessel window of width 2.5 and all reconstructed images were cropped to a 256x256 grid. For the radial case, a synthetic phantom was created (180 projections, 128 points) and the same sensitivity function as the spiral case used to simulate a multicoil acquisition. Undersampling was achieved by discarding interleaves or projections suitably, determined by the undersampling factor. For spirals, a central disk of radius $k_{max}/10$ was densely sampled by using a larger number of turns. Low resolution unaliased images were generated using the densely sampled low k-space and combined to obtain an unaliased multicoil image using the root-sum-of-squares combination. The architecture of the neural network is shown in Figs. 1a-b. It consists of an input layer with 18 neurons, a hidden layer with 98 neurons, and the output layer with 1 neuron. At each pixel position, the intensity of the coil-aliased images is split into their real and imaginary parts. The position co-ordinates are concatenated, making up the 18-dimensional feature vectors ($8 \times 2 + 2$). The neural network was trained until the resulting training error is 0.001. Typically, convergence occurred in 1000 iterations and took 1.5 min. on MATLAB running on a 2 MHz Pentium PC. In the training phase, feature vectors derived from the low resolution aliased coil images are used. The target in this phase is the already known low-resolution multicoil image. This phase determines the weights connecting the neurons, and defines the neural network. In the reconstruction phase, feature vectors were derived from the high-resolution aliased coil images, and an estimate of the desired unaliased high resolution multicoil image is obtained. After obtaining the NN estimate of the true image, the central k-space for each coil is substituted by the acquired central k-space data for all coils and the final output image recomputed, in order to improve the reconstruction SNR.

Results: The proposed NN method was first verified by reconstructing Cartesian undersampled data and the image quality was comparable to conventional SENSE reconstruction (not shown for lack of space). Reconstruction results using spiral data undersampled by a factor of 4, and radial data undersampled by a factor of 6 are shown in Fig 2. The error images and the aliased combinations are also shown for both cases. It can be seen that the NN has effectively removed aliasing in both cases. Fig 3 shows a comparison of sample profiles through the full k-space and reconstructed images, for the spiral case.

Conclusions: We have demonstrated a NN based technique to reconstruct spirally and radially undersampled multicoil data, for acceleration factors up to 4 and 6, respectively. Neural networks were used to learn the transformation needed to generate the unaliased multicoil image, using the aliased coil images. There are no assumptions made about the nature of the transformation or about the sampling trajectories and no tweaking of any convergence parameters was done. While NN have been used for estimating coil sensitivities [5], this is the first demonstration of the use of NN for parallel imaging reconstruction with no *a priori* assumptions.

References: 1) Pruessmann et al. MRM 42:952–962 (1999) 2) Griswold et al. MRM 47:1202–1210 (2002) 3) Kyriakos et al. MRM 44 : 301-308 (2000) 4) Jackson et al. IEEE TMI. Vol 10, No. 3 pp 473-478 (1991) 5) Buehrer et al. Proc. ISMRM 14 (2006)

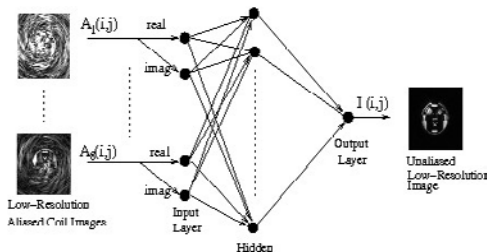


Fig. 1a. Training phase

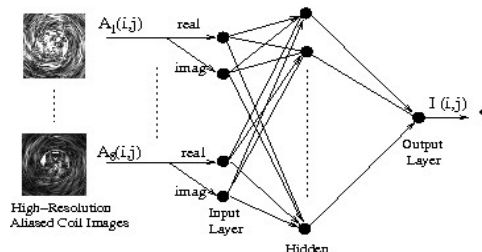


Fig. 1b. Reconstruction phase

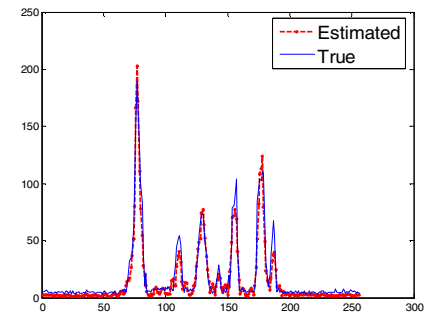


Fig. 3. Comparison of a line profile through the NN reconstructed (undersampled k-space) data (Fig. 2B) and corresponding unaliased reconstruction (full k-space) for spiral sampling.

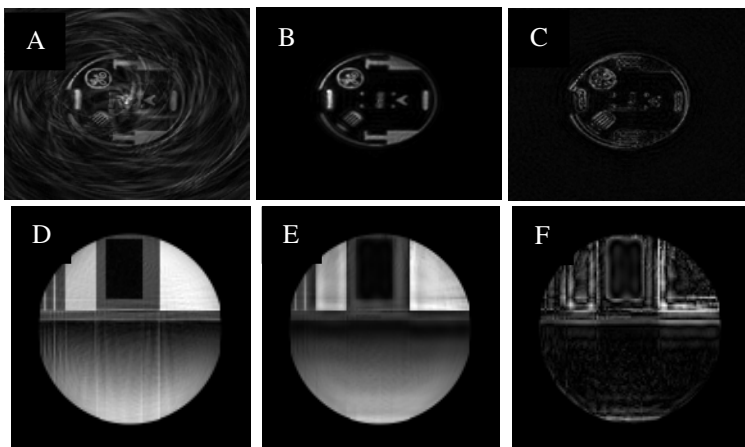


Figure 2. Comparison of NN reconstructions for spiral and radial under-sampled multicoil data.

A : Root Sum of Squares image of aliased acquisitions (4 interleaves)
 B : NN Reconstructed image using 4 interleaves; scale:[0-255]
 C : Spiral error image; scale:[0-80]
 D : Root Sum of Squares image of aliased acquisitions (30 projections)
 E : NN Reconstructed image using 30 projections; scale:[0-255]
 F : Radial error image; scale:[0-60]