

Digital Beamforming for MRI Systems

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Introduction

Purpose

Phased array MRI systems require efficient algorithms to combine the complex-valued individual coil images into a single composite image. The primary goal of any such image reconstruction algorithm is to improve the SNR by obtaining an optimal weighting vector which may be computed over a small Region of Interest. We present here a Digital Beamforming algorithm which offers potential advantages over previously existing reconstruction methodologies

Prior art

Root Sum of Squares (RSS) Method

- This method described in [1] by Roemer *et al*, involved a very simple reconstruction strategy.
- The reconstructed image pixel was obtained as the l_2 norm of the vector formed by the individual pixel values from the various receiver coils.
- Combining the images as a sum-of-squares results in high SNR as long as at least one of array coils has high SNR.

Adaptive reconstruction of phased array MR imagery

- This method described in [2] by Walsh *et al*, offers superior SNR recovery in the darker regions of the Field of View (FOV) when compared to its predecessors (see e.g. RSS method)
- It involves obtaining an optimal vector \mathbf{m} by solving the eigenvalue problem for the matrix $\mathbf{R}_n^{-1}\mathbf{R}_s$, where \mathbf{R}_s and \mathbf{R}_n are respectively, the signal and noise correlation matrices
- These correlation matrices can be computed pixel by pixel or over specific Region of Interest.
- It is the widely used reconstruction strategy in present day clinical MR systems to combine phased array MR images.

Our Contribution

The reconstruction method proposed by Walsh *et al* uses a matched filter based approach to suppress artifacts and improve SNR in the dark regions of the FOV by adaptive nulling. This was achieved by computing the noise covariance matrix from a region in the FOV where motion and/or flow artifacts were present. However, this technique does not take into account the transmitter and receiver geometries, and the near field directivities of the array coil elements.

Directivity of a coil element determines the fraction of the element excitation power that reaches a particular image pixel and also the reverse, the fraction of the pixel protons emitted power received by a particular coil element. In our current approach, the Receive-only beamforming (RxBF) algorithm utilizes the transmit and receive element directivity patterns at each pixel in computing a spatially-varying weight vector for combining the complex image data from different receiving elements.

Receive-only Beamforming

Problem Formulation

For an n_c -element MR phased array, the complex image pixel value in the image space, obtained from the p -th receiver can be modelled using the relationship between the NMR signal and the spin density function ρ as,

$$I_p(x, y) = \mathbf{h}^+(x, y) \mathbf{m}_{tx} D_p^-(x, y) \rho(x, y) + v(x, y) \quad (1)$$

where $D_p^-(x, y)$ is the p -th receiver directivity at location (x, y) , $\mathbf{h}^+(x, y) = [D_1 D_2 \dots D_{n_c}]$ is the array directivity at (x, y) , and \mathbf{m}_{tx} is the $n_c \times 1$ transmit excitation vector (assuming the n_c elements are operating in transmit-receive mode). Also the noise function $v(x, y)$ is assumed to be independent complex valued Additive White Gaussian Noise (AWGN). Equation (1) can be vectorized (for $p = 1, 2 \dots n_c$) and written more compactly as,

$$\mathbf{I}(x, y) = \mathbf{H}(x, y) \rho(x, y) + \mathbf{v}(x, y) \quad (2)$$

where $\mathbf{H}(x, y) = \mathbf{h}^+(x, y) \mathbf{m}_{tx} \mathbf{h}^-(x, y)$, and the receiver directivities at a point (x, y) are encapsulated by the vector $\mathbf{h}^-(x, y)$. When we have AWGN with variance σ_v^2 , using Equation (2), the spin density function can be estimated by a linear minimum-mean-square estimator [3] of $\rho(x, y)$ given $\mathbf{I}(x, y)$,

$$\hat{\rho}(x, y) = \frac{\mathbf{H}^H}{\|\mathbf{H}\|_2^2 + S\hat{N}R^{-1}(x, y)} \mathbf{I}(x, y) \quad (3)$$

Here, $S\hat{N}R = \hat{\sigma}_\rho^2 / \hat{\sigma}_v^2$ is a local estimate of the SNR. It is clear that, Equation (3) yields a SNR-regularized spatial inverse filter with respect to the array directivity vector \mathbf{H} . Equation (3) is applied at all points in the FOV where the estimated SNR is greater than a certain threshold and at all other points we reduce the pixel value by a constant factor. This SNR thresholding prevents noise amplification in pixels outside the skull where there is no signal component.

Image Acquisition and Methods

- The transmitter and receiver directivities were estimated by computational methods using Remcom software for a 7T MRI system with a 16-element elliptical array geometry (as shown in Fig 1).

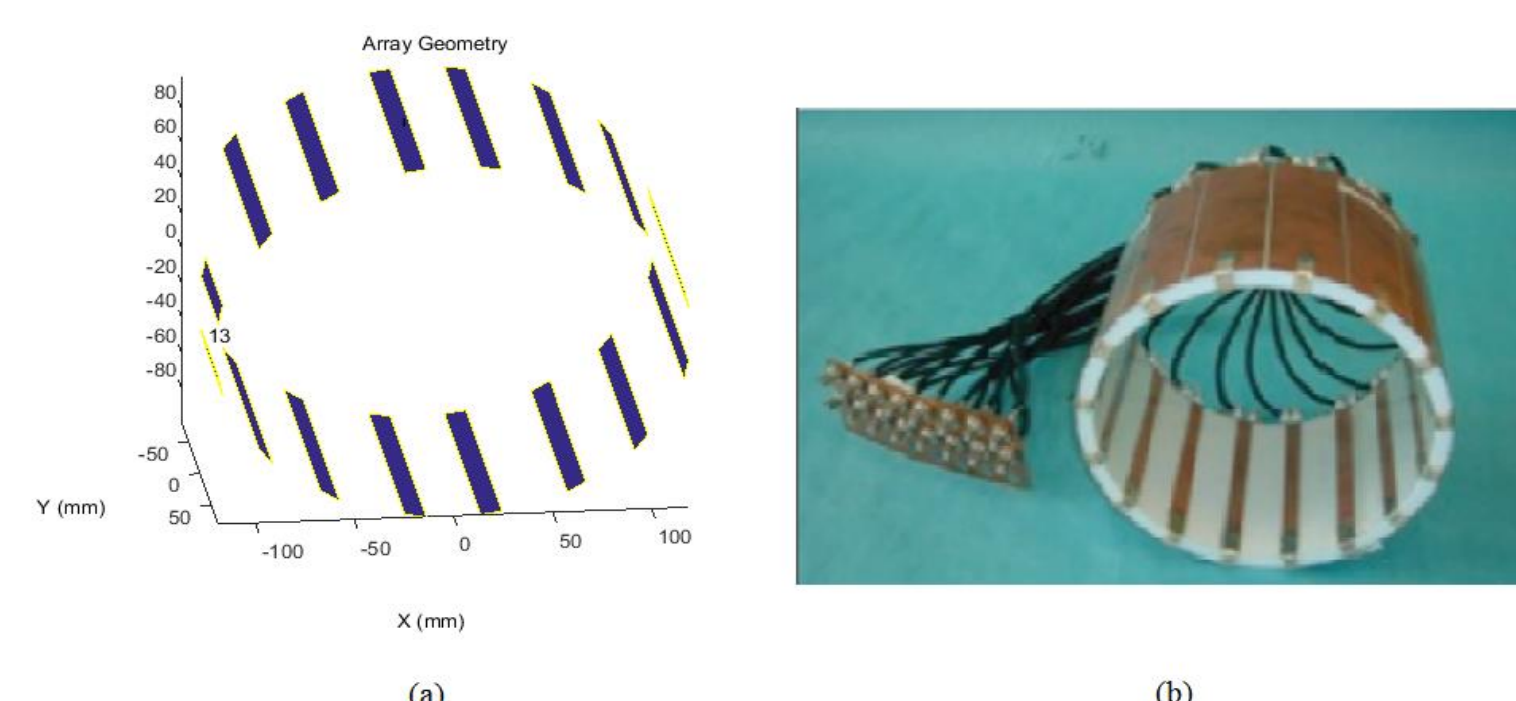


Figure 1: (a) Elliptical Array Geometry modelled in Matlab (b) Photograph of the TEM microstrip RF coil, showing the transmission line elements.

- The modelled elliptical coil used to image a human brain is of size $24\text{cm} \times 20\text{cm}$ with 16 TEM microstrip resonators (14 of which are 16cm long and the other two are 7.5cm long).
- The simulation for image acquisition was run for an All-Transmit mode (with all the 16 transmitters ON) for the following parameters: $T_R = 0.05$, $T_E = 0.005$ and flip angle, $\alpha = 30^\circ$.

Results

Comparison of our Results

The adaptive reconstruction method proposed by D.O.Walsh *et al* and the RxBF algorithm described above were run on this data set and the resulting reconstructions are shown in Figure 2. The conventional reconstruction in Figure 2(a) shows darker regions (with lower SNR) near the center of the brain. Reconstruction using the RxBF algorithm shown in Figure 2(b) clearly exhibits enhanced signal levels and uniform contrast throughout the image FOV. Anatomical details like the ventricle structure are much clearer in the reconstruction using the RxBF algorithm.

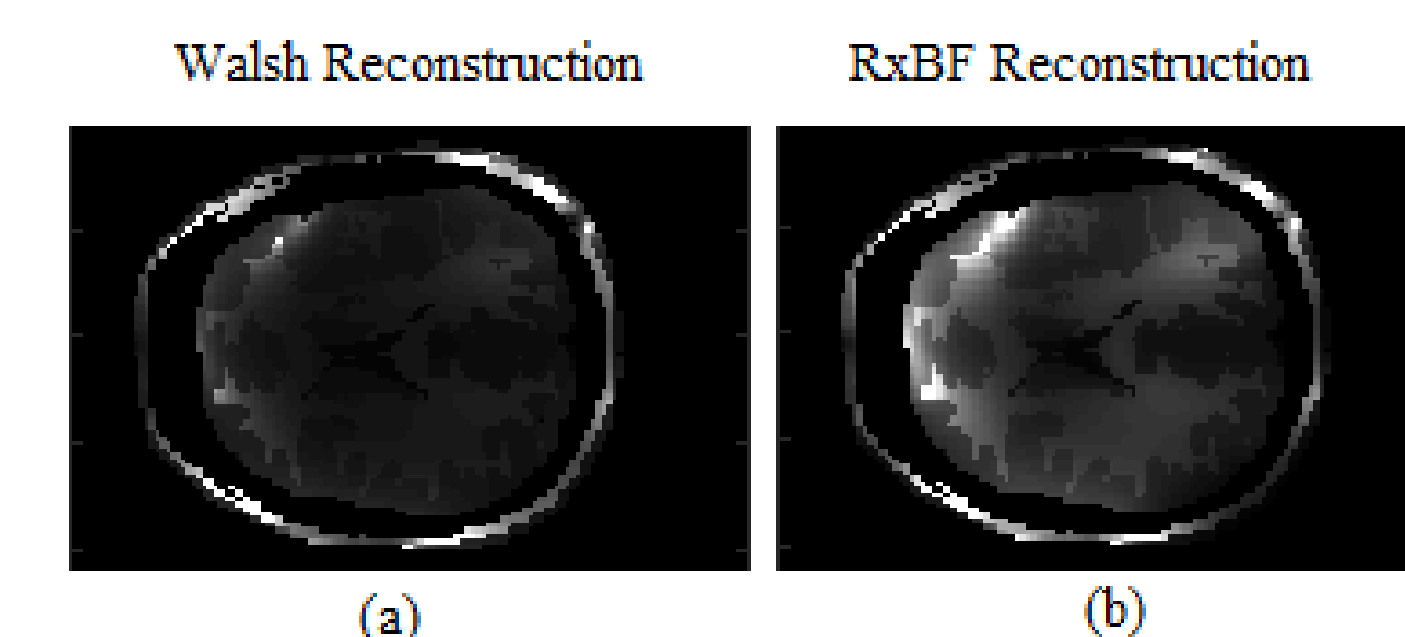


Figure 2: Reconstructed brain MR images obtained using (a) Adaptive reconstruction described by Walsh *et al*, and (b) RxBF algorithm described above

Conclusion

Incorporating the directivities of array elements for image reconstruction in Phased array MRI systems seems to produce improved results when compared to existing techniques. The improvements demonstrated above can be achieved with no additional changes to the existing hardware or imaging sequences of current MRI systems. If the element directivities in free space are computed beforehand and tabulated, such a reconstruction scheme is extremely practical and beneficial.

References

- [1] P. B. Roemer, *et al*. "The NMR Phased Array", Mag. Reson. Med, vol. 16, pp. 682-690, 2000
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