A Dynamic-Phase Extension for Model-Based Reconstruction of Breast Tumor Dynamic Contrast Enhanced MRI

B. K. Felsted[1], R. T. Whitaker[1], M. C. Schabel[2], and E. V. DiBella[2]
[1]School of Computing, University of Utah, Salt Lake City, Utah, United States, [2]Department of Radiology, University of Utah, Salt Lake City, Utah, United States

Introduction: A promising method for reconstructing a high quality sequence of images from rapidly acquired, under-sampled DCE acquisitions is the model-based reconstruction method—an algorithm that constrains the magnitude of the reconstructed time series to be consistent with a pharmacokinetic model. Here we extend the model-based reconstruction to include a physically based linear model that can account for phase changes due to field distortions from a gadolinium injection [1]. In some cases, neglecting these phase effects will lead to poor reconstructions at undersampling factors of R=8 and above. To estimate phase offsets from undersampled data, we investigate a physically based linear model that relates phase difference to magnitude difference. We use this phase model to extend the model-based reconstruction method to handle dynamic image phase.

Materials and Methods: The model-based reconstruction uses a compartmental model within each voxel of interest [2]:

$$g(x,t;\beta) = \left(\left| S_c^{(0)}(x) \right| + K^{trans}(x) \cdot C_p(t - t_0(x)) * e^{-k_{ep}(x)t} \right) \cdot e^{i\varphi(x,t;\beta)}$$

where g is the image's complex signal intensity (SI), x is short for spatial coordinate (x,y,z), $|S_0(x)|$ is the pre-contrast intensity, $\beta(x)$ a vector containing parameter maps of K^{trans}, k_{ep}, CA delay t_0, and dynamic image phase parameters, and $\varphi(x,t;\beta)$ the dynamic image phase model:

$$\varphi(x,t;\beta) = \varphi(x,t_b) + c(x) \cdot \left(u(x,t;\beta) - u(x,t_b;\beta) \right)$$

where $c(x)$ is the linear scale parameter, $\varphi(x,t_b)$ the measured baseline (post-contrast) phase taken at time t_b, and u is given by

$$u(x,t;\beta) = C_p(t - t_0(x)) * e^{-k_{ep}(x)t}$$

The model-based approach requires estimating 3 or 4 unknowns per voxel, whereas a fully sampled dataset contains around 50 datapoints over time per voxel. This vast asymmetry in knowns to unknowns can be exploited by model-based methods, provided that image phase dynamics are estimated with reasonably accuracy. If they are inaccurate, the Fourier transform of the trial reconstructions will not agree with the measured k-space data at each iteration, eventually offsetting the benefit of a high known to unknown ratio. Both a constant- and linear-phase model were applied to reconstruct two 4D breast DCE full k-space acquisitions, retrospectively undersampled at R-factors of 1, 4, and 8. Reconstruction errors were measured by comparing reconstructed magnitudes with the gold standard, an inverse Fourier transform of R=1 measured data. The method of Murase [3] was used for estimating kinetic parameters from reconstructions and the gold standard.

Results: Figure 1 shows that image reconstruction errors correlate spatially with dynamic image phase estimation errors. We have observed changes in image phase on the order of 0.5 radians for voxels of interest. When reconstructing with the constant phase model, these same voxels had substantial reconstruction errors. Figure 2 shows that the constant phase assumption resulted in a steep, erratic growth rate of error as R increased, whereas the linear phase model's errors remained relatively flat. Results from two other models are included for reference: a quadratic polynomial model (an extension to the linear-phase model), and a full-phase model (fixed to known phase). The constant- and full-phase models appear to do so well at R=1 because they have the fewest unknowns and phase is fixed to R=1 data.

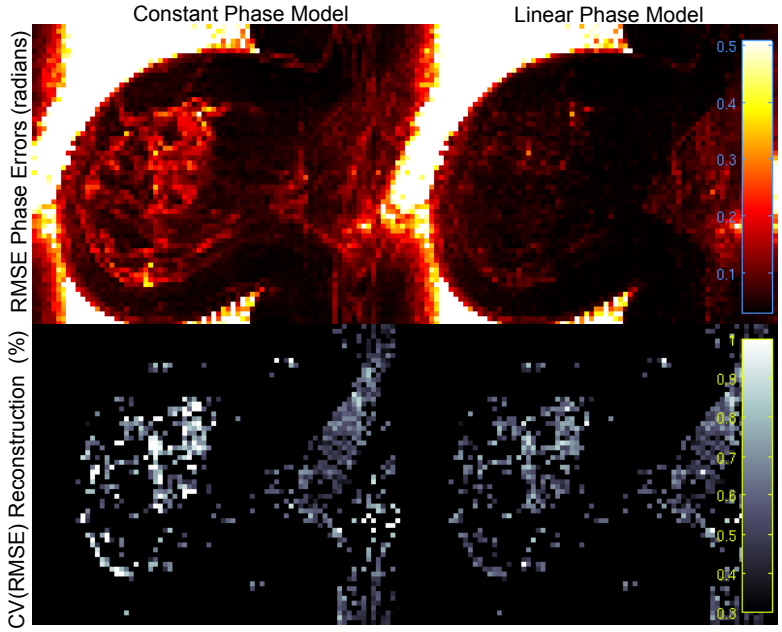

Figure 1: Voxel-wise image phase and magnitude reconstruction errors using an undersampling factor of R=8 (12.5% of k-space). Top left: Image phase RMSE errors from assuming constant phase (units of radians). Top right: Image phase errors after switching to a linear phase model. Bottom left: Image reconstruction error from assuming constant phase (in percentage). Bottom right: Image reconstruction error after switching to a linear phase model. Error is computed as RMSE or CV(RMSE)% over time.

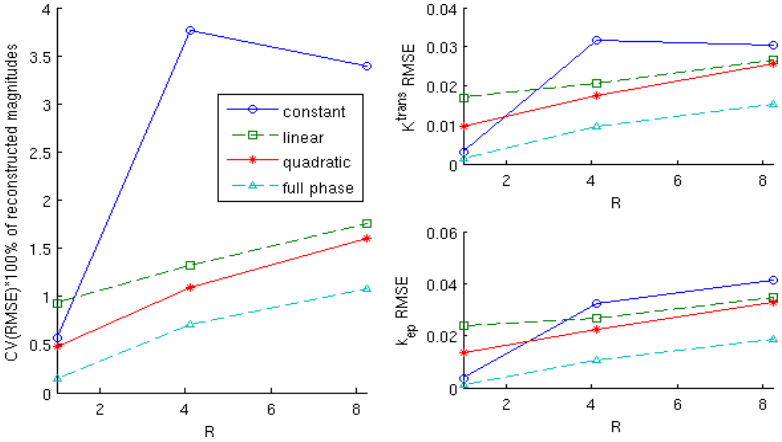

Figure 2: Comparison of reconstruction and parameter errors within the tumor for various R-factors from different phase models, the constant- and linear-phase models, as well as a quadratic-phase model and a gold standard full-phase model for comparison. The left plot shows CV(RMSE)% of reconstructions. The top- and bottom-right plots show RMSE for K^{trans}, k_{ep} in units of mmol/min and min^{-1}, respectively. Variable density undersampling was used.

Discussion: Although gadolinium's effects on the magnetic field are linear with concentration, the phase shifts are not spatially uniform due to a shift-variant convolution with a dipole field whose kernel varies spatially depending on the local geometry's angle made with B_0 [1]. The spatially varying field motivated the decision of using one scale parameter per voxel, as opposed to using one global scale parameter. Furthermore, the nonuniformities of the field evolve over time as the CA concentration changes. To account for this phenomenon, alternative modifications are possible; one includes a higher order polynomial, the results of which are shown in Figure 2 for the quadratic case. Thus far we have found in practice the linear model to provide the most expressive power; this is because it substantially reduces error in cases where the constant assumption breaks down and because it requires the estimation of only one additional unknown per voxel.

Conclusion: In the context of model-based reconstructions, while working at high undersampling factors, moderate dynamic phase shifts contribute to an appreciable portion of the error and thus should not be neglected. We have shown that a linear-phase model can reduce this source of error.

References: [1] Rochefort et al, Med.Phys. **35**(12) 2008. [2] Felsted et al, SPIE 72622S 2009. [3] Murase, MRM **51**:858-862 2004. [4] Tofts et al, JMRI 1999.