4D MAP Image Reconstruction of MRI Data

J. Hinkle[1], G. Adluru[2], E. DiBella[2], and S. Joshi[1]
[1]Scientific Computing and Imaging Institute, University of Utah, Salt Lake City, Utah, United States, [2]Utah Center for Advanced Imaging Research, University of Utah, Salt Lake City, Utah, United States

Introduction

Conventional MRI reconstruction techniques are susceptible to artifacts when imaging moving organs. To avoid such artifacts gating using a navigator echo or electrocardiogram signal is often employed in the scanning protocol. A series of gated 3D images are then played as a cine loop or further processed and brought into correspondence using deformable image registration techniques for modeling motion. However, the gating algorithm can prolong the acquisition significantly and reduce signal to noise ratio, while increasing the acceptance window of the gating protocol leads to unacceptable motion artifacts. In this work, we take an alternate approach and develop an iterative image reconstruction algorithm that accommodates organ motion in the formulation. We use a maximum a-posterior (MAP) paradigm that uses the raw time-stamped data to simultaneously reconstruct the images and estimate deformations in anatomy. The algorithm eliminates artifacts by avoiding the gating processes and increases signal-to-noise ratio (SNR) by using all of the collected data. This framework also facilitates the incorporation of fundamental physical properties such as the conservation of local tissue volume during the estimation of the organ motion.

Methods

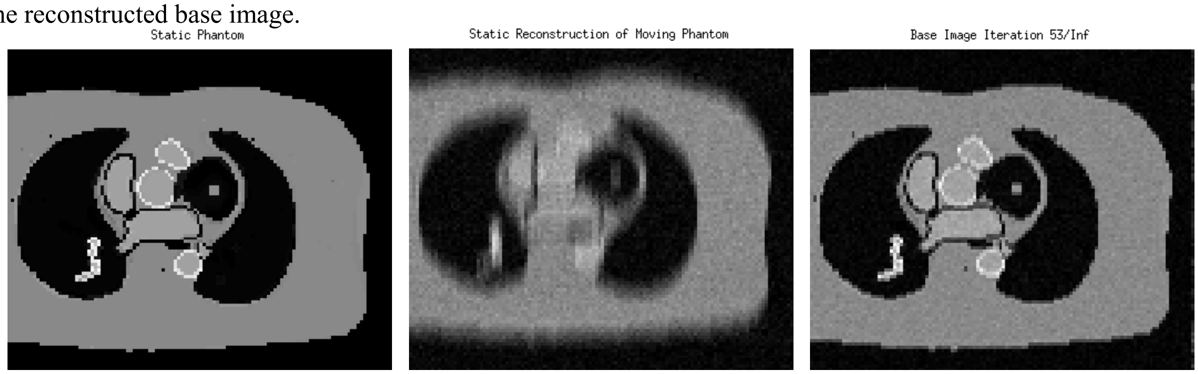
To eliminate motion artifacts, we seek to understand motion by modeling and estimating a four-dimensional image $I(t,x)$. Our method extends the method of Hinkle et al. [1] developed for CT to complex-valued MRI data. First the data acquisition process and noise in the data are modeled. For MRI, the data acquisition is described by the Fourier transform and complex Gaussian noise. The four-dimensional image is modeled as a single three-dimensional image I_0 undergoing a time-indexed deformation $h(t,x)$. Anatomy at any time t is represented by a three-dimensional image $I(t,x) = I_0 \circ h(t,x)$. The motion is modeled as a flow along smooth velocity fields. In this model the time derivative of the deformation is given by $\frac{dh(t,x)}{dt} = v\big(t, h(t,x)\big)$. Given time indexed velocity fields, the deformation is recovered by Euler integration of the differential equation. In order to enforce smoothness and other tissue properties a Sobolev norm is used on the velocity fields. The norm used in this work is $\|v\|_V^2 = \int \|Lv(t,x)\|^2 dxdt$, where $Lv = -\alpha\nabla^2 v + \beta\nabla\nabla \cdot \mathrm{v} + \gamma \mathrm{v}$. This norm plays the part of a prior distribution in the MAP formulation. Combining this prior with the data log-likelihood under the Gaussian noise model the posterior log-likelihood becomes:

$$L(I_0, v|d_i) = -\|v\|_V^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\int \|F\{I_0 \circ h(t_i,\cdot)\}(\omega) - d_i(\omega)\|_{\mathbb{C}}^2 d\omega.$$

This posterior log-likelihood is maximized via an alternating gradient descent algorithm in which the base image and velocity fields are estimated jointly. At each step of this iterative algorithm, the velocity fields are first updated by descending along the gradient of the posterior log-likelihood. The image is then updated in turn.

Results

A realistic 3D phantom was created from a late gadolinium enhancement (LGE) acquisition of a post-ablation patient [2,3] acquired on a Siemens Verio 3T scanner. Resolution was 1.25x1.25x2.5mm and 40 slices were acquired. 19 different structures were manually segmented and assigned different T1 values. The inversion time was chosen to null myocardial signal. k-space measurements were simulated as 40 phase encodes per heartbeat. Each set of 40 phase encodes was subjected to a deformation simulating breathing motion and Gaussian noise of SNR 13 was added. A static reconstruction was performed by averaging the recorded values at each point in k-space (Shown in the middle panel). The above described MAP reconstruction was also performed on the same data. Axial slices of the static phantom, static reconstruction of moving phantom, and MAP reconstruction of moving phantom are shown in the figure below. Notice the improvement in image quality. In particular, the MAP reconstruction accommodates the motion and improves the reconstructed base image.



References

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