HYPRIT: Generalized HYPR Reconstruction by Iterative Estimation

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Introduction: The **H**ighl**Y** constrained back-**PR**ojection (**HYPR**) algorithm was recently proposed for reconstruction of time varying images with sparse spatial signal distribution acquired with radial trajectories [1]. HYPR uses an anatomical average image to assist in restoring individual time frames from vastly undersampled data. The average, or composite image, is typically obtained using a sliding window reconstruction of interleaved time frames. The temporal fidelity of HYPR may be further improved correcting HYPR images with data residuals [2]. In this work, we propose a generalized method for the utilization of composite images for constrained reconstruction of vastly undersampled data. As HYPR, the new technique, **HYPRIT** (generalized **HYPR** by Iterative es**T**imation) uses *a priori* information from the composite images. In addition, HYPRIT is applicable to arbitrary trajectories, and its temporal resolution may be further enhanced with parallel MRI and temporal filtering.

Theory: The MR signal **s** may be represented as the result of applying a projection operator **P** to the image function **f**: $\mathbf{s}=\mathbf{Pf}$. Depending on the representation basis, **P** may be the encoding matrix [3] or the Radon transform matrix, and **s** is a stacked column vector of *k*-space or Radon space data from one or more receivers, respectively. We assume that the image from the current time frame may be created by multiplicative correction of the mask image represented as diagonal matrix **C**. The mask image may be taken as any function of the composite image. We incorporate the composite image model into the formulation as follows: $\mathbf{s}=\mathbf{PCw}$, where $\mathbf{w}=\mathbf{C}^{-1}\mathbf{f}$ is the weighting image. The weighing image is estimated by back-projecting the data vector into image space. One way is to apply the pseudoinverse: $\mathbf{w}=(\mathbf{PC})^{\dagger}\mathbf{s}$. For non-Cartesian trajectories, however, this is infeasible in most cases. Instead, we choose to iteratively estimate **w** from a system of the normal equations $\left(\mathbf{C}^{H}\mathbf{P}^{H}\mathbf{PC}+\lambda^{2}\mathbf{M}^{H}\mathbf{M}\right)\mathbf{w}=\left(\mathbf{C}^{H}\mathbf{P}^{H}\right)\mathbf{s}$, where λ and **M** are the optional regularization parameter and the regularizing matrix, respectively. The final image is obtained as $\mathbf{f}=\mathbf{Cw}$.

Methods: The HYPRIT system was solved using Conjugate Gradients with gridding approximation of the discrete Fourier transform [4]. **M** was chosen as the identity matrix and lambda was set to the Frobenius norm of the composite image matrix [5]. 2D MIP of PC VIPR volume (Fig. 1a,b) was corrupted by 5% noise, and used in simulation studies (spiral trajectory, 7 interleaves, 400 points per interleave, acceleration of 25 compared to Cartesian case). The real data were obtained from a CE MRA thigh exam of a volunteer. Imaging parameters included: 312 data points in readout (fractional echo of 512), 16 projections per time frame (interleave), radial undersampling factor = 50, TR/TE = 5.2/1.1 ms, frame rate = 2.2 s. The composite image was created from 16 time frames.

Results: Fig. 1 shows the results of digital phantom reconstruction and Fig. 2 shows images from real scan.

Discussion: Both simulated and in-vivo data studies showed that HYPRIT may be a valuable tool for improving temporal resolution of dynamic studies (Fig. 2). Enhancing constrained reconstruction with parallel MRI improves image quality in terms of image resolution and residual artifacts (Fig. 1). Additional acceleration factors from parallel MRI may have potential impact when higher temporal fidelity is required (for example, cranial AVMs). HYPRIT is directly applicable to any non-Cartesian trajectory such as spiral (Fig.1) and radial (Fig. 2).

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References: [1] Mistretta CA, et al. MRM, 55:30-40 (2006). [2] Griswold M, et al. MRA Workshop, Basel, Switzerland, September 2006. [3] Pruessmann et al. MRM, 42:952-962 (1999). [4] Pruessmann et al. MRM, 46:638-651 (2001). [5] Bydder M, private communication.

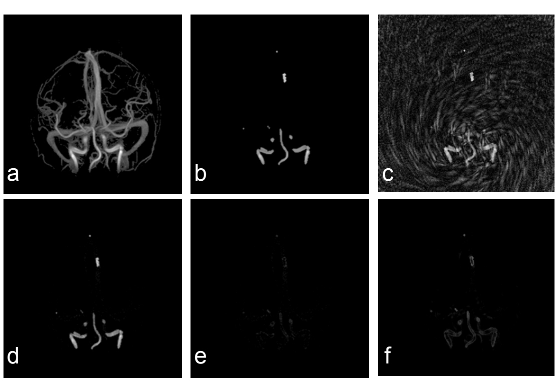

Figure 1. Simulated studies. **a,b,c:** Composite, reference and reduced data images. **d:** HYPRIT with parallel MRI. **e,f:** image errors of (*d*) and single channel HYPRIT.

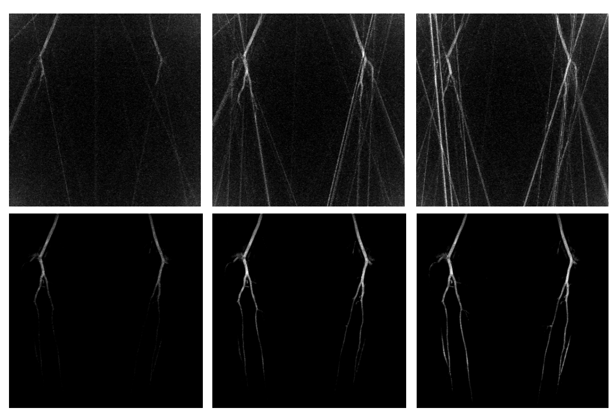

Figure 2. Real data study. **Top row:** MIPs of reduced data (6 slices). **Bottom row:** Corresponding MIPs of HYPRIT images.