A new framework for real-time MR imaging by using time and gradient sparsities

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Target audience Researchers on real time MR images with high spatial/ temporal resolution.

Purpose Real-time MR imaging has drawn great attention in clinical practice including medical diagnosis and therapy treatment monitoring. But there is always a tradeoff between temporal and spatial resolution: a highly under-sampled k-space data set is good for improving temporal resolution but at the cost of reducing spatial resolution and thus introducing artifacts which can be challenging for reconstruction. Since medical dynamic or 3D images are usually sparse in z-direction or t-direction after certain transformation, several methods have been proposed to reconstruct MR image using this nature of sparsity, like k-t FOCUSS[1] or 3D CS[2] However, k-t FOCUSS uses only temporal sparsity of images and is specially effective for dynamic process with periodic motion, while 3D CS utilizes the sparsity of the gradient of images. In this study, we propose a framework for high spatial/ temporal dynamic imaging reconstruction - combining k-t FOCUSS and 3D CS to improve quality of reconstructed images from highly under-sampled k-space by exploring sparsity of images in k-t domain and gradient in image domain. The results demonstrated that our method performs better than the existing methods in eliminating artifacts and keeping structure details.

Theory (1)K-t FOCUSS[1] explores sparsity of k-t domain by solving:

$$\min\|\Delta\rho\|,\ subject\ \|v - F\rho_0 - F\Delta\rho\| < \varepsilon$$

Where F denotes Fourier transform along y-direction and *t*-direction, v denotes undersampled k-space, $\rho_0 / \Delta\rho$ denotes prediction/residual encoding. Prediction encoding can be achieved by many kinds of methods as introduced in [1]. In this study, we use temporal average for prediction and therefore no full sampled reference frame is needed. Another consideration for k-t FOCUSS is that reconstruction has to be completed offline if we reconstruct all frames together, which is not practical for real-time dynamic imaging. A solution is to reconstruct certain number of images together as a batch when a new frame is to be reconstructed.

(2) A fast compressed sensing method using nonlinear filter (NFCS) is proposed in [2]. The basic assumption of NFCS is that the gradient along temporal direction for dynamic imaging or z-direction for 3D imaging is sparse. Reconstruction is completed by solving:

$$\min_{U\in C} F(U)\ subject\ to\ F_{sl}u_l = y_l,\ l = 1,2,\ldots,NF$$

Where u_l denotes the l^{th} frame of mage to be constructed, F_{s_l} denotes the Fourier transform and undersampling, and y_l denotes acquired k-space of l^{th} frame. By choosing a sparsity function of $F(U)=\|\nabla U\|$, NFCS explores the sparsity of gradient of dynamic/3D images. The minimization problem is solved by FISTA approach and the constrained total variation 3D filtering step solved with a median filter.

(3) A framework which combines k-t FOCUSS and NFCS for high spatial-temporal resolution dynamic imaging reconstruction is shown in Fig. 1. Firstly, reconstruct images with k-t FOCUSS to get recon1. Secondly, reconstruct recon2 using recon1 and undersampled k-space.

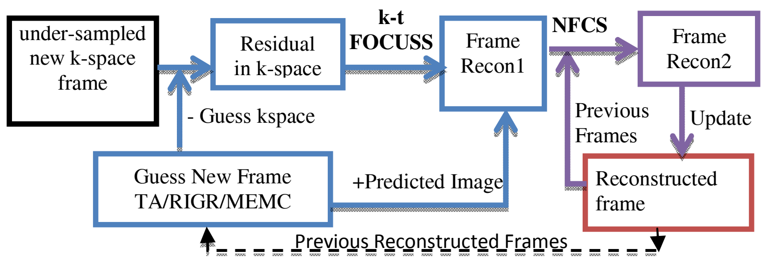

Fig. 1, Framework of proposed reconstruction method

Result and discussion: All data are acquired on a Philips 3T system with a 32-channel breast coil. Acquisition sequence was FFE, cardiac phase is 15, and matrix size is 512 x 154 x 15. K-space is fully sampled and retrospectively undersampled for simulations. The proposed method is compared with off-line k-t FOCUSS, batch k-t FOCUSS, as shown in Fig. 2. Off-line k-t FOCUSS eliminates most artifacts but also brings about structure sacrifice probably because using of temporal average for p rediction will make structure edges blur. Batch k-t FOCUSS also have such a problem and with fewer frames for online construction, results of batch k-t FOCUSS have more artifacts. Result of the proposed method shows less artifacts and better structure details. Because NFCS utilizes sparsity of gradient thus can avoid detail lose due to nonlinear changes in t-direction and compensate for edge diffusion caused by k-t FOCUSS, proposed method sufficiently explores sparsity of images both in k-t domain and in gradient of images to better reconstruction. Fig. 3 also demonstrates proposed method performs better reconstruction with the least total error.

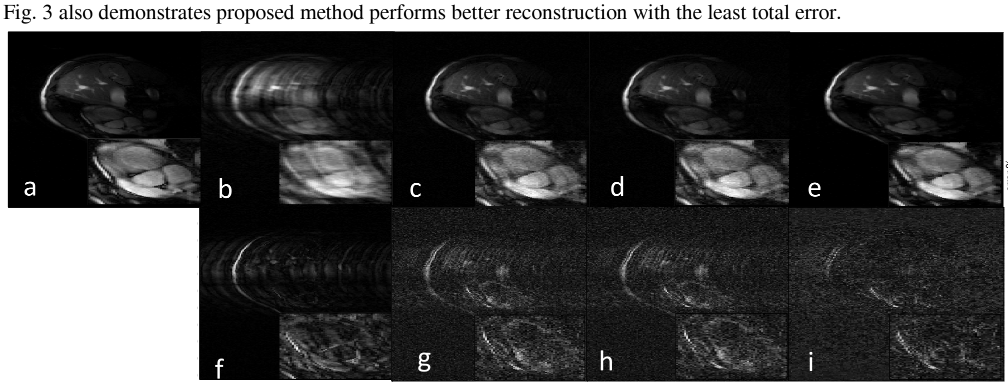

Fig. 2, Comparison of the proposed method with other existing methods at reduction factor of 4. a-e: reference image, images reconstructed from zero-padding, k-t FOCUSS, Batch k-t FOCUSS and NFCS+batch k-t FOCUSS; f-i: error map.

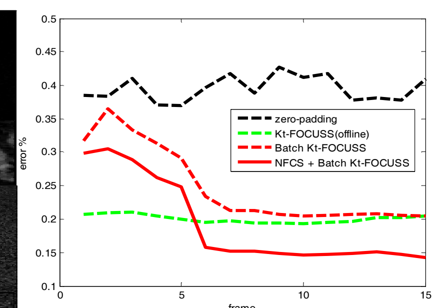

Fig. 3, RMSE of dynamic frames reconstructed from different methods, at reduction factor of 4

Conclusion The preliminary in-vivo results demonstrated that the proposed method can help improving spatial/ temporal resolution of dynamic MR images by eliminating artifacts and keeping structure details, thus can be used in more general dynamic imaging in adition to. In future work, using reconstructed frames for better prediction of next frame can be useful for improvement of image quality and more in-vivo experiments with different clinical applications can be carried out to further demonstrate the potential of the new framework.

References [1] Hong J, et al. MRM 2009; 61: 103-106 [2] Laura M, et al. IEEE Trans. Med. Imag. 2011; vol 30, no.5 [3] Wei L, et al. MRM 2010; 64:757-766