

Motion-Dependent L1 Minimization for Dynamic Cardiac MRI Reconstruction

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Introduction: Parallel imaging accelerates the acquisition by reducing the number of acquired frequencies. Cardiac Magnetic Resonance Imaging (CMRI) is a time-resolved imaging technology for non-invasive assessment of the function and structure of the cardiovascular system. In a SENSE-type reconstruction approach [1], the weighted 3D redundant Haar wavelets approach proposed in [2] has been proven effective in regularizing the target images to yield the desired spatial and temporal smoothness. However, strong spatial and temporal smoothness may eliminate the fine details of the heart such as valve leaflets. In this work, a new approach was proposed for dynamic cardiac MRI reconstruction by setting motion-dependent weights in the L_1 regularization. Experiments conducted on CMRI data demonstrate the effectiveness of the proposed approach in preserving fine details of the heart.

Methods: *Reconstruction Formulation:* Let x be a 3D (2D+t) tensor, where the first two dimensions correspond to the spatial directions and the third dimension denotes the temporal direction, and let x_t be the 2D image at time point t . Let s^c be the CSM for coil c , \odot the component-wise product between two matrices, $s^c \odot x_t$ the coil image of coil c at temporal phase t . Let Φ_t represent the acquisition operator at time t , and y_t^c the acquired k -space by coil c at time t . Let W^{3D} be the 3D redundant Haar wavelets, and λ^{3D} the tensor of weights applied on the wavelet coefficients of x . The optimization for the reconstruction can be written as:

$$\min_{x \frac{1}{2} \sum_{t=1}^T \sum_{c=1}^C \|y_t^c - \Phi_t(s^c \odot x_t)\|_2^2 + \|\lambda^{3D} \odot (W^{3D}x)\|_1. \quad (1)$$

Extract Motion Region: In the above optimization formulation, the tensor of weights λ^{3D} is assigned so that the high temporal frequencies were given a higher weight compared to the low temporal frequencies [2]. Higher temporal weights enforce stronger temporal correlation, which helps to overcome the aliasing caused by undersampling the data, but may also introduce blur in the motion. To deal with this problem, in addition to weighting the higher and lower temporal frequencies differently, we assign the relatively static spatial region with higher weights and the motion region with lower weights. The method we use to detect the motion region is as follows. Firstly, we do a regular reconstruction using Eq. (1). Secondly, we calculate for each pixel the standard deviation across time. Thirdly, we mark the pixels with temporal standard deviation above some threshold, and take these pixels as the motion region. Let \hat{x}_t be the reconstruction result from Eq. (1) at time point t , M be a 2D matrix of the same size as the 2D image and with entries 1 or 0 for each pixel to indicate whether the pixel is within the motion region or not, and $\epsilon > 0$ be a threshold. The formula for computing the motion region is:

$$M^{i,j} = I_\epsilon \left(\sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{x}_t^{i,j} - \frac{1}{T} \sum_{t=1}^T \hat{x}_t^{i,j})^2} \right), \quad (2)$$

where I_ϵ is an indicator function for inputs greater than threshold ϵ . With M , we construct a 3D tensor, denoted as M^{3D} , which has the same size as λ^{3D} .

Motion-Dependent L_1 minimization: After incorporating the idea in the previous step, the new weight $\hat{\lambda}^{3D}$ used to replace the original λ^{3D} inside the weighted L_1 penalization becomes:

$$\hat{\lambda}^{3D} = \lambda_1 \lambda^{3D} \odot M^{3D} + \lambda_2 \lambda^{3D} \odot (E^{3D} - M^{3D}), \quad (3)$$

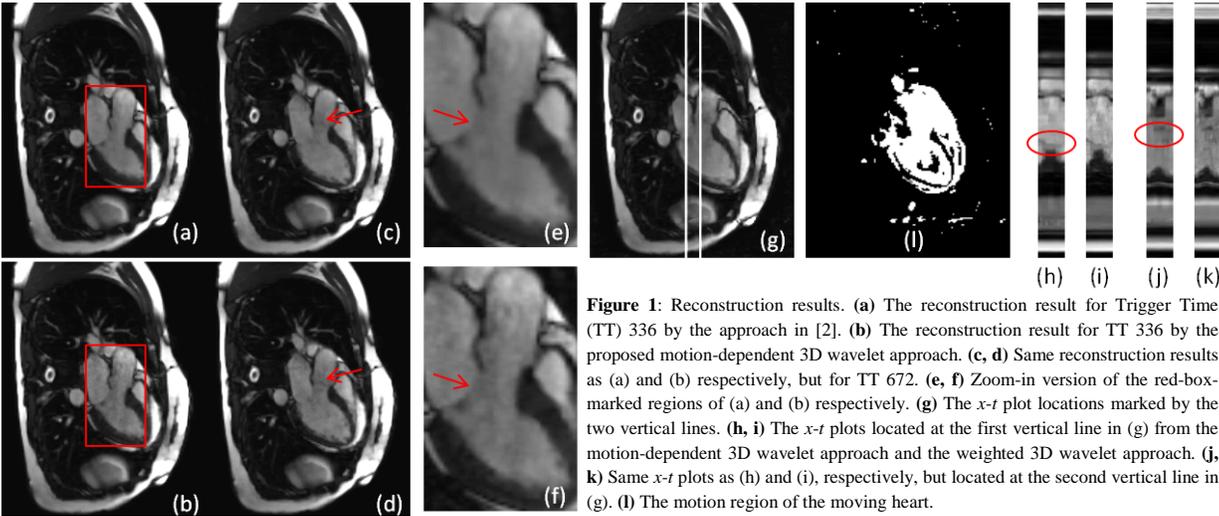


Figure 1: Reconstruction results. (a) The reconstruction result for Trigger Time (TT) 336 by the approach in [2]. (b) The reconstruction result for TT 336 by the proposed motion-dependent 3D wavelet approach. (c, d) Same reconstruction results as (a) and (b) respectively, but for TT 672. (e, f) Zoom-in version of the red-boxed regions of (a) and (b) respectively. (g) The x - t plot locations marked by the two vertical lines. (h, i) The x - t plots located at the first vertical line in (g) from the motion-dependent 3D wavelet approach and the weighted 3D wavelet approach. (j, k) Same x - t plots as (h) and (i), respectively, but located at the second vertical line in (g). (l) The motion region of the moving heart.

where E^{3D} is a 3D tensor with all entries equal to 1, and $\lambda_2 > \lambda_1 > 0$. The optimization problem (1) was solved using the approach specified in [2]. In addition, the Eigen-vector approach for CSM estimation [3, 4] was used to estimate the CSM s^c .

Data: The data was acquired in a healthy volunteer on a 1.5T clinical

MR scanner (MAGNETOM Aera, Siemens Healthcare, Erlangen, Germany). Imaging parameters included repetition time/echo time 48ms/1.6ms, field of view 192×144 mm², temporal resolution 42ms, flip angle 72°, band width per pixel 1085HZ, 19 temporal phases. For each temporal phase, 16 lines were acquired with 30 coil channels.

Results: The proposed motion-dependent 3D wavelet approach was compared to the weighted 3D redundant Haar wavelets approach proposed in [2]. The reconstruction results for Trigger Time (TT) 336 by both approaches are presented in Fig. 1 a) & b), respectively. The reconstruction results for TT 672 by both approaches are presented in Fig. 1 c) & d), respectively. Fig. 1 l) is the motion region of the images. By comparing Fig. 1 a) versus 1 c) and Fig. 1 b) versus 1 d), it can be observed that the motion-dependent 3D wavelet approach preserves more fine details inside the motion region of the heart. Fig. 1 e) and f) are the zoom-in versions of the boxed regions of Fig. 1 a) and c), respectively, to better compare the fine details. The x - t plots corresponding to the two vertical lines in Fig. 1 g) further verify the effectiveness of proposed approach, as the motion of the valve leaflet (marked by red circles) are less blurry. In summary, the proposed approach is effective in preserving fine details of the motion while keeping the same overall noise level within the entire FOV.

Discussion and Conclusion: We proposed a new approach for dynamic cardiac MRI reconstruction by setting motion-dependent weights in the L_1 regularization. The new approach prevents over-smoothing in both the spatial and temporal dimensions, thus preserving fine details of the heart which might be missing in the weighted 3D wavelet approach. Experiments on cardiac MRI data show higher spatial and temporal resolution within the selected motion region of the heart.

Disclaimer: The concepts and information presented in this paper are based on research and are not commercially available.

References: [1] K. P. Pruessmann, et al., Magn Reson Med, 42:952-962, 1999. [2] J. Liu et al., Proc Intl Soc Mag Reson Med, #4249, 2012. [3] M. Lustig et al., Proc Intl Soc Mag Reson Med, #479, 2010. [4] Liu et al., Technical Report, 2012.