Dynamic cardiac MRI reconstruction with weighted redundant Haar wavelets

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Introduction: Cardiac Magnetic Resonance Imaging (CMRI) is a time-resolved imaging technology for non-invasive assessment of the function and structure of the cardiovascular system. High temporal resolution is often desired in CMRI. Parallel imaging enables the reconstruction with a reduced the number of acquired frequencies, hence accelerating the acquisition. The radial sampling scheme has many favorable intrinsic properties with respect to the demands of dynamic MRI [1, 2]. For the SENSE-type reconstruction [3], the Haar wavelets have proven effective in regularizing the target image to yield the desired spatial smoothness [4]. In this work, a new approach was proposed for dynamic cardiac MRI reconstruction by applying an L_1 regularization based on the weighted 3D redundant Haar wavelet. In the proposed approach, the dynamic images were treated as a 3D tensor, and the weighted 3D wavelets were imposed for incorporating the smoothness in both spatial and temporal directions. Experiments conducted on a CMRI data with only 15 spokes for each temporal phase demonstrated the effectiveness of the proposed approach.

Methods: *Data Fidelity*: Let x_t be the 2D image at time point t and x their concatenation into a 3D (2D+t) tensor, where the first two dimensions correspond to the spatial directions and the third dimension denotes the temporal direction. 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. The data fidelity term can be written as:

$$f(x) = \tfrac{1}{2} \sum_{t=1}^{T} \sum_{c=1}^{C} ||y_t^c - \Phi_t(s^c \odot x_t)||_2^2. \qquad (1)$$

Weighted 3D Redundant Wavelets: A L_1 penalization of the redundant Haar wavelet coefficients of each 2D image, denoted by $||W^{2D}x_t||_1$, can help including a piecewise constant prior, and such regularization has been widely used for MRI reconstruction. However, this is only a spatial penalization which does not take into account the temporal similarity between two consecutive images. For this sake, the 3D wavelets were used on the 2D+t data. In addition, since the acquisitions of temporal images are independent from each other, the high frequency temporal coefficients were more strongly penalized. Let W^{3D} be the 3D wavelets, and λ^{3D} the tensor of weights applied on the wavelet coefficients of x. The employed penalty is:

$$p(x) = ||\lambda^{3D} \odot (W^{3D}x)||_1, \qquad (2)$$

where the high temporal frequencies were given a higher weights compared to the temporal low frequencies.

Optimization: In our proposed 3D wavelet approach, the dynamic images x were obtained by:

$$\min_x f(x) + p(x)\,. \qquad (3)$$

In optimizing (3), the operator Φ was implemented by Fessler's NUFFT [5], and the problem was solved by the Nesterov type algorithm proposed in [6]. To efficiently solve the proximal operator associated with the non-smooth penalty term $p(x)$, the Dykstra-type algorithm [7] was used. In addition, Walsh's CSM estimation [8] was used to estimate the CSM s^c.

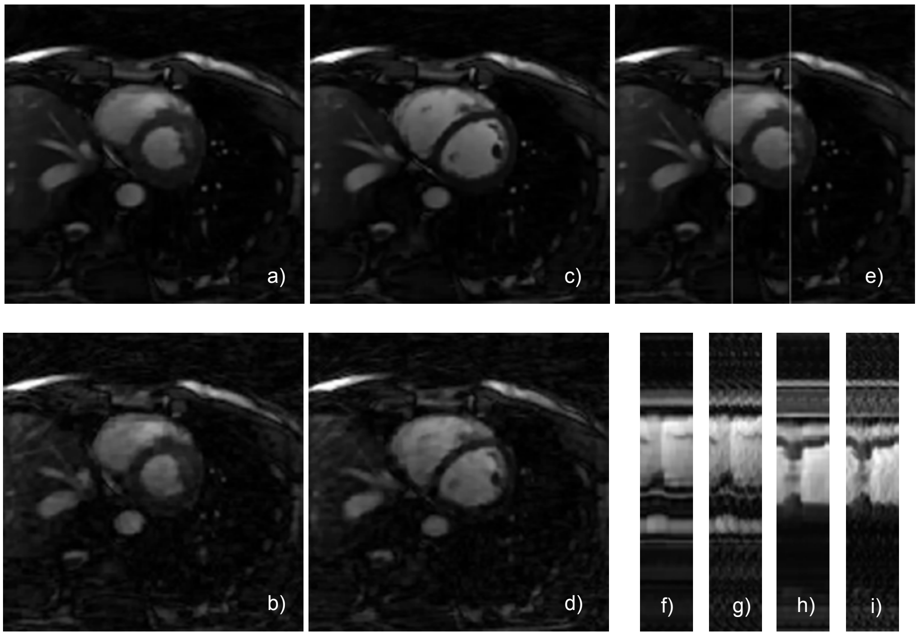

Fig. 1 Reconstruction results: a, c, f & h; 2D wavelet: b, d, g & i; temporal phase 8: a, b; temporal phase 16: c & d; *x-t* plot of the first vertical line in e: f & g; and *x-t* plot of the second vertical line in e: h & i.

Data: The data was acquired in healthy volunteer on a 1.5T clinical MR scanner (MAGNETOM Aera System, Siemens Healthcare, Erlangen, Germany). Imaging parameters include repetition time/echo time 48ms/1.6ms, field of view 256×256 mm^2, temporal resolution 48ms, flip angle 90°, band width per pixel 627 HZ, 22 temporal phases. The total acquisition time for this data set is about 1 second. For each temporal phase, 15 spokes of 256 samples were acquired by 30 coil channels.

Results: The proposed 3D wavelet approach was compared to the 2D wavelet approach, where redundant Haar was only applied to 2D image for spatial smoothness.

The reconstruction results for temporal phase 8 and 16 are presented in Fig. 1 a) & b), and Fig. 1 c) & d), respectively. It can be observed that, although the 2D wavelet approach achieves reasonably good result, the streaking artifacts can be observed and obvious noise is present in Fig. 1 b) & d). On the contrary, the proposed 3D wavelet approach achieves visually excellent reconstruction results, as shown in Fig. 1 a) & c). The *x-t* plots corresponding to the two vertical lines in Fig. 1 e) further verify the effectiveness of 3D wavelet. In summary, the proposed approach is able to effectively suppress the noise and meanwhile keep fine details.

Discussion and Conclusion: In this work, it was demonstrated that the L_1 regularization based on weighted 3D wavelets can be used for dynamic cardiac MRI reconstruction. Promising reconstructions were achieved for severely under-sampled data with little artifact and noise. Results on several other cardiac MRI data acquired using the same pulse sequence exhibit similar results as shown in Fig. 1.

References:

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