An efficient multi-resolution reconstruction scheme with motion compensation for 5D free-breathing whole-heart MRI

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Abstract. We propose a novel approach for the reconstruction of 3D isotropic free-breathing cardiac cine MRI with 100% data efficiency. The main components are a continuous 3D Golden radial k-space data acquisition, a robust groupwise cardio-respiratory motion estimation technique and a multi-resolution strategy introduced in a previously proposed compressed sensing reconstruction scheme. Initial results on simulated data show better reconstruction quality than the non-motion compensated counterpart and reduced reconstruction times with respect a single-resolution procedure for equivalent acceleration factors ranging 24.38 to 34.8.

1 Introduction

Cardiovascular diseases (CVDs) are the first cause of death with 17.5 million estimated deaths in 2012 (about 31% of all deceases in the world). As for detection and follow up of CVDs magnetic resonance imaging (MRI) has become the reference imaging modality in anatomic and functional heart studies due to its high contrast and spatiotemporal resolution.

However, MRI is a slow technique in terms of acquisition time and it is also highly sensitive to motion of the inspected structures. Specifically, motion induced by both the natural heart motion as well as patient breathing translate itself in artifacted images, a fact that constitutes one of the major challenges, still today, in cine cardiac MRI.

Cine MRI lets the practitioner visualize heart motion along the whole cardiac cycle, which, in turn, allows the physician to calculate descriptive parameters of both the function and the anatomy as well as to detect and diagnose contractility anomalies. In a conventional cine examination a set of bidimensional slices is obtained that cover the full cardiac volume (or, at least, the left ventricle). To mitigate the effect of motion in acquisition, current clinical practice either makes use of breath hold procedures or of navigators that trigger image acquisition intervals at certain positions of the diaphragm along the respiratory cycle; the two processes, however, are highly inefficient since a large fraction of the time spent by the patient within the magnet is not effective acquisition time. The final result is a set of 2D+t dynamic images whose spacing is typically several times higher than the intra-slice resolution (typically 8 mm interslice vs. 2 mm intraslice). This remarked anisotropy has an additional implication: due to the complex orientation of the heart in the interior of the thoracic cavity, a previous planification stage is mandatory in which the image planes orientation are carefully chosen to match the principal axes of the heart.

In order to speed up the acquisition procedure compressed sensing (CS) techniques have been proposed and they are now relatively mature. These techniques basically consists of drastically subsampling k-space and then resolve the reconstruction procedure by constrained optimization procedures based on the assumption that natural images are sparse in some transformed domain. Direct 3D approaches naturally avoid the problem of anisotropy mentioned above.

MRI sparse reconstruction, when it is applied to dynamic modalities, can benefit from the high redundancy level typically found along the temporal dimension of the image. As an example, in cine, intensity variations of a voxel in time will be mainly due to the motion of cardiac structures (ideally, if a material point is perfectly tracked intensity should be constant). Motion effects on the sparse representations have already been addressed in the literature [9, 6, 7, 1, 13, 15]. In the cited methods, the authors share the idea that a sparser representation can be obtained if the information about the motion present in the image is introduced in the sparsifying transform, enabling higher acceleration factors.

In order to increase the scan efficiency, several techniques have been proposed [12, 4, 3]; these techniques do not restrict data acquisition to certain respiratory states but data are continuously acquired following a radial trajectory in the k-space without respiratory gating. Cardiac and respiratory signals can be acquired simultaneously or estimated from the acquired data. These two signals are used to bin the data into several respiratory and cardiac states according to the breathing position and cardiac phase at which they were acquired. Images are then reconstructed imposing spatio-temporal smoothness constraints.

In this paper we show that better results can be obtained by incorporating motion estimation and compensation methods in the optimization procedure for 3D isotropic whole-heart free-breathing cine reconstruction. Motion is estimated by means of a groupwise nonrigid registration paradigm we have already used for the 2D case. For the 3D case computational load is much higher so we have resorted to a multiresolution procedure in which not both motion is estimated and images are reconstructed. Higher levels of the pyramid are then interpolated and serve as the starting point of the immediate lower level of the pyramid. Results indicate that this procedure better preserves edges and shows a better contrast than methods that do not incorporate this type of information in the reconstruction procedure.

2 Material & Methods

2.1 Compressed Sensing Reconstruction

The problem of MRI reconstruction under CS principle is defined as follows:

$$\underset{\mathbf{m}}{\operatorname{argmin}} \left\|\boldsymbol{\Phi}\mathbf{m}\right\|_{l1} \text{ s.t. } \left\|\mathbf{y}-\mathbf{E}\mathbf{m}\right\|_{l2}^{2} < \boldsymbol{\epsilon} \tag{1}$$

where $\mathbf{m}$ represents the image to reconstruct from the acquired undersampled k-t data ($\mathbf{y}$) and $\boldsymbol{\epsilon}$ indicates the noise level in the acquisition. $\boldsymbol{\Phi}$ is the sparsifying transform, which is typically chosen to be the temporal Fourier transform or the temporal total variation. The encoding operator $\mathbf{E}$ models the acquisition process by applying spatial Fourier transforms followed by the data undersampling strategy. Moreover, in multi-coil acquisitions, $\mathbf{E}$ also includes the multiplication by coil sensitivities [10]. Finally, the problem in Eq. (1) can be reformulated as follows:

$$\underset{\mathbf{m}}{\operatorname{argmin}} \frac{1}{2}\left\|\mathbf{y}-\mathbf{E}\mathbf{m}\right\|_{l2}^{2} + \lambda\left\|\boldsymbol{\Phi}\mathbf{m}\right\|_{l1} \tag{2}$$

where the parameter λ establishes a trade-off between data consistency and the sparsity of the solution.

2.2 Motion Compensated MRI Reconstruction

In CS with motion estimation and compensation (ME/MC), the operator $\boldsymbol{\Phi}$ is modified to include some knowledge about the specific motion of the structures being imaged. In particular, in groupwise (GW) CS [13], the authors propose a joint estimation and compensation of the motion in the whole image domain, and the optimization problem in Eq. (2) becomes

$$\underset{\mathbf{m}}{\operatorname{argmin}} \frac{1}{2}\left\|\mathbf{y}-\mathbf{E}\mathbf{m}\right\|_{l2}^{2} + \lambda\left\|\boldsymbol{\Phi}\mathcal{T}_{\Theta}\mathbf{m}\right\|_{l1} \tag{3}$$

where $\mathcal{T}_{\Theta}$ is the GW-MC operator, a set of spatial deformations defined by the parameters Θ, that performs a mapping between each temporal instant in the dynamic image and a common reference motion state. Note that the motion in $\mathbf{m}$ is unknown a priori. Therefore, firstly, it is necessary to perform a regular CS reconstruction by solving Eq. 2. Essentially, this motion estimation method consists on a GW registration method based on a B-spline deformation model with set of control points Θ. The registration metric is defined based on the variance of the intensity along time, and the control points that minimize its value are found as follows:

$$\underset{\Theta}{\operatorname{argmin}} \left\|\sum_{n=1}^{N}\left(\mathcal{T}_{\Theta,n}\mathbf{m}_{n} - \frac{1}{N}\sum_{k=1}^{N}\mathcal{T}_{\Theta,k}\mathbf{m}_{k}\right)\right\|^{2} + \mathcal{R}_{\Theta} \tag{4}$$

where $\mathcal{R}_{\Theta}$ is an additional regularization term that encourages local invertibility of the deformations [2].

2.3 eXtra-Dimensional (XD) MRI Reconstruction

A recently proposed approach for the reconstruction of free-breathing acquired data (XD-GRSAR) [5] is based on the continuous acquisition of k-space data following a 3D Golden Radial trajectory [8] (Figure 1.a). Data are then distributed in different respiratory and cardiac phases (double binning process, Fig. 1b), which results in a 5D domain (k_x, k_y, k_z, respiratory phase and cardiac phase). This division is made in accordance with the respiratory and cardiac motion signals, with the approximately same number of spokes in each temporal frame.

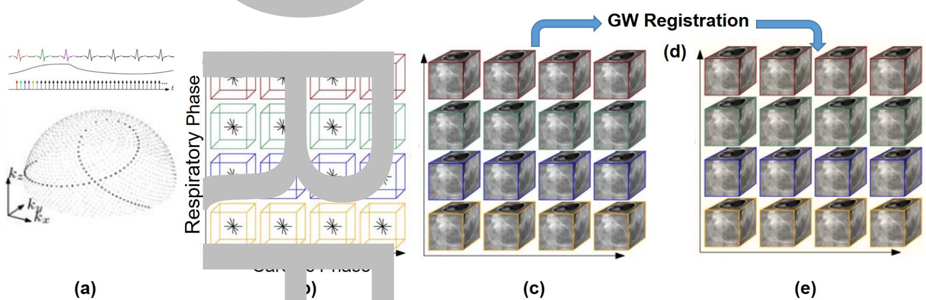

Fig. 1. Overview of the proposed reconstruction method: (a) data acquisition strategy: 3D golden radial sampling; (b) binned data: respiratory and cardiac phases; (c) initial CS reconstruction; (d) motion estimation by means of a GW registration method; (e) final MC-CS reconstruction.

The reconstruction is formulated as a CS problem in which sparsity along both temporal dimensions is simultaneously enforced:

$$\arg\min_{\mathbf{m}} \frac{1}{2}\left\|\mathbf{y}-\mathbf{E}\mathbf{m}\right\|_{l2}^2 + \lambda_c \left\|\boldsymbol{\nabla}_c\mathbf{m}\right\|_{l1} + \lambda_r \left\|\boldsymbol{\nabla}_r\mathbf{m}\right\|_{l1} \tag{5}$$

where $\boldsymbol{\nabla}_c$ and $\boldsymbol{\nabla}_r$ stand for the temporal differences along the cardiac and respiratory phases, respectively. As a result of the reconstruction, a set of 3D+t volumes is recovered, one for each respiratory state.

Since the data is divided into more motion states, less data is available for each of them, increasing the net acceleration factor consequently. Moreover, the size of the solution space is also increased, rising the computational cost.

2.4 Multi-Resolution Strategy for MC-XD MRI Reconstruction

In this work we propose to extend the XD scheme in two ways: 1) by introducing a MC approach in which both the cardiac and respiratory motions are considered during reconstruction and 2) by introducing a multi-resolution approach in which the nature of the radial k-space data acquisition is exploited. A description of the procedure follows.

Once the data has been sorted into a 5D space, an initial reconstruction is performed by solving Eq. [illegible] in which only the central portion of the k-space data is used (Fig. 2a-b). This solution corresponds to the XD-GRASP method [3, 5].

Once an initial reconstruction is available, a ME procedure is carried out. To this end we resort to the 3D extension of a group-wise registration algorithm, which provides robust motion estimation, both in and through-plane for the 3D case, previously proposed for the CS reconstruction of multi-slice 2D CINE MRI [13]. The estimation problem is summarized in Eq. 4.

The obtained results are finally used to perform a motion compensated reconstruction over the initial images (Fig. 1e), being possible to iterate over the last two steps to refine the results. The MC-XD reconstruction can be formulated as:

$$\underset{\mathbf{m}}{\operatorname{argmin}} \frac{1}{2} \|\mathbf{y} - \mathbf{E}\mathbf{m}\|_{l2}^2 + \lambda \left\|\boldsymbol{\nabla}_{c,r} \mathcal{T}_{\Theta}^{c,r} \mathbf{m}\right\|_{l1} \tag{6}$$

where $\mathcal{T}_{\Theta}^{c,r}$ is the MC operator that compensates both for cardiac and respiratory motions and $\boldsymbol{\nabla}_{c,r}$ calculates the gradient along both temporal dimensions.

Computational efficiency can be highly improved by means of the multiresolution algorithm proposed in this work, a graphical sketch of which is shown in Figure 2. In particular, we propose to perform the aforementioned process at minimal spatial resolution, that is, to obtain the initial reconstruction (XD-GRASP) at low resolution and to apply the motion estimation approach (3D GW registration) at this level. To this end we exploit the fact that, in radial trajectories, the central region of the k-space is sampled much more densely that the high frequency domain. In this situation, the resulting acceleration factor at the low resolution level is much lower than the original one, leading to a better posed reconstruction problem with lower computational demand.

Then, by means of an upscaling procedure, both initial images and deformation fields are interpolated to a higher resolution level and used as the starting point to perform the MC reconstruction in the following upper level.

2.5 Data and Experiments Description

The proposed strategy has been tested on synthetic data generated by a numerical phantom that provides detailed internal anatomy and realistic cardiorespiratory deformation models [11, 16]. A bSSFP acquisition was simulated in free-breathing with the following relevant parameters: TR/TE=3.0/1.5ms, flip angle=60°, field of view (FOV) of $(192\text{mm})^3$ with matrix size of 192^3 (voxel size = 1mm^3). The continuous acquisition of a total of 60.480 projections were simulated. Based on previous publications [5] this corresponds to a simulated acquisition time of approximately 7min. Respiratory and cardiac synchronization signal were provided by the numerical phantom and used to perform the double binning procedure described in Figure 1. The data was sorted into 4 respiratory states and 20 cardiac phases, leading to an average of 756 projections per reconstructed volume.

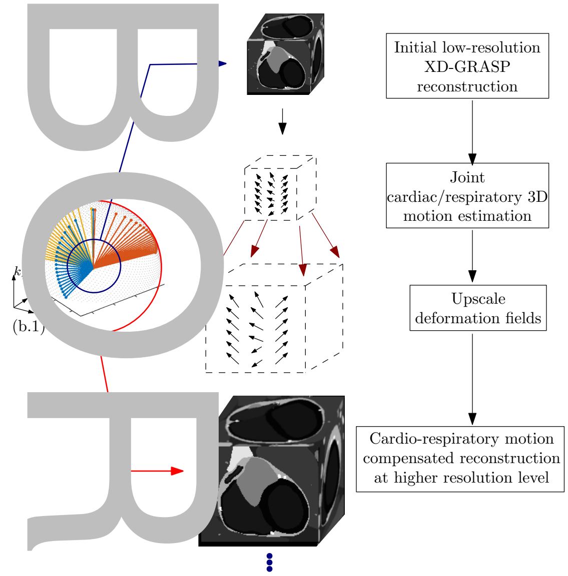

Fig. 2. Overview of the proposed multi-resolution scheme for MC-XD MRI reconstruction.

The reconstruction was carried out with the proposed method at an initial resolution of 4mm^3 and at a second level of 2mm^3 and with the original XD-GRASP approach at 2mm^3 for comparison purposes. A median filter of size 3^3 was applied to the final result to eliminate residual reconstructions artifacts. The equivalent acceleration factor (AF) was 6.08 for the low resolution level and 24.16 for the final level.

In order to validate the MC-XD approach on a real anatomy an isotropic 3D+t cardiac MR [illegible] has also been used to obtain MC-XD MRI reconstruction by using the general scheme in Fig. 1 (without the multiresolution strategy). Due to the nature of these animals, respiratory motion is not appreciated in MRI, so a spatiotemporal deformation was synthetically generated to simulate different respiratory positions. Relevant imaging parameters include: voxel size = 1 mm^3, field of view = 183 mm^3, temporal resolution = 43 ms. The acquisition of a total number of 12.831 spokes was simulated and data sorted as with the phantom data, leading to an AF of 34.8.

3 Results and Discussion

In Figure 3 the volumes reconstructed with XD-GRASP and the proposed method with MC are shown for the diastolic and systolic cardiac phases, for the four respiratory states in which the data was binned. A set of four short axis and one long axis slices were reformatted from the isotropic, unplanned volumes. In the images reconstructed with the proposed method, better contrast between blood pool and myocardium and sharped edges are recovered (green arrows).

However, high frequency artifacts can be appreciated in some areas in the results of the proposed method (red arrows). In these areas, the XD-GRASP reconstructions present strong blurring possibly due to residual *intrabin* motion than hinders the estimation of the cardio-respiratory motion. Similar artifacts have been previously reported for other MC related methods [13].

Figure 4 shows the obtained results for the swine MRI. XD-GRASP and MC reconstructions are presented for comparison. Better edge delineation, finer details and higher overall quality are appreciated in the case of images reconstructed with MC. The proposed method has shown to be robust against other acquisition artifacts not present in the synthetic data, such us flow effects, noise and system imperfections.

The reconstruction times for the synthetic data were 6.2min for the initial low-resolution step, 7.1min for the ME and 1.2hours for the final reconstruction. The same procedure directly applied to the final resolution level (not shown) took 23,6min for the initial step, [illegible].85min and 1.6hours for the MC reconstruction. Overall, the reconstruction time was 1.42hours for the multi-resolution scheme and 2.17hours for [illegible] leading to a reduction of 34%.

4 Conclusion

This paper proposes an efficient extension of the XD MRI reconstruction. On one hand, a ME/MC approach based on a groupwise temporal registration is introduced in the reconstruction procedure, which allows to obtain a better edge definition in the obtained results. The obtained results have been compared with the XD-GRASP solution to support this affirmation. In the ME stage, a new regularization term has been included in order to ensure diffeomorphic deformations. On the other hand, a multi-resolution procedure has been designed to significantly reduce the computational cost of the MC-XD reconstruction process with similar image quality after reconstruction. The tests have shown a reduction of 34% in the overall reconstruction time for the proposed approach. Future works will focus on the validation of these results and the inclusion of solutions to avoid the presence of reconstruction artifacts, as it is already proposed in [14].

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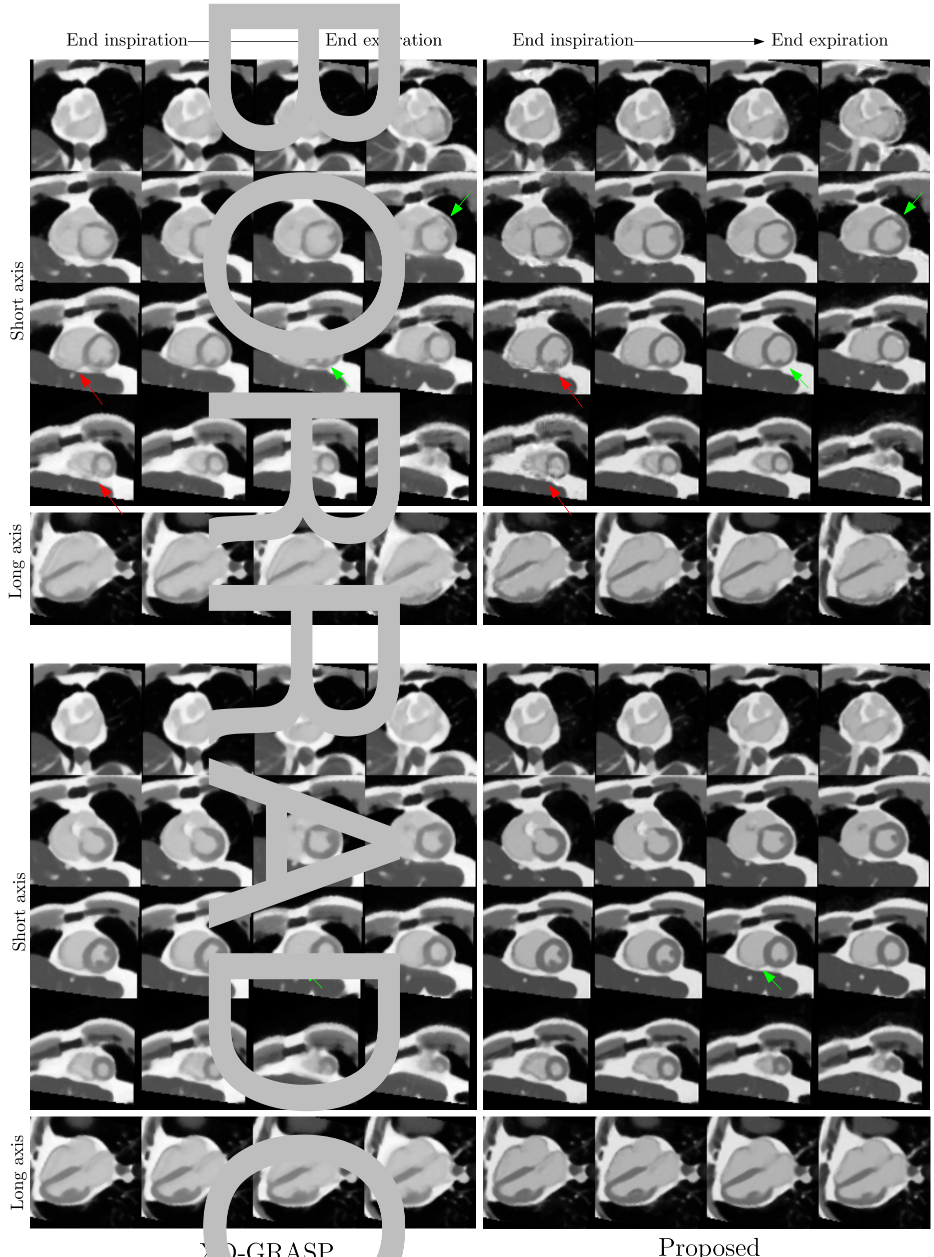

Fig. 3. Reconstructions of the XCAT phantom with XD-GRASP (left) and the proposed method with MC at diastole (top) and systole (bottom). Original volumes were reformatted to obtain four short axis slices covering the whole heart and one long axis slice. Data was binned in four respiratory states (from left to right for each reconstruction).

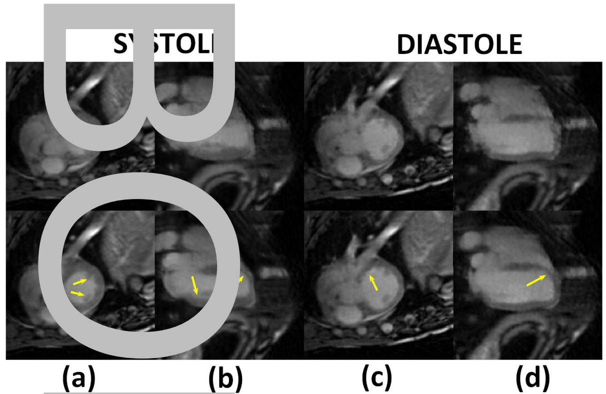

Fig. 4. MC reconstruction of pig MRI (general scheme Fig. 1) for 60,480 acquired spokes (2,880 golden-angle radial interleaves with 21 spokes each, leading to a mean AF = 34.8 per reconstructed volume). Short axis views (a, c) and long axis views (b, d) of the heart for both systolic (a, b) and diastolic (c, d) phases. Initial CS reconstruction (XD-GRASP) is shown in top images; whereas the bottom images show the corresponding proposed MC-XD reconstruction. Yellow arrows indicate areas where the improvement in the recovered details with MC can be observed.

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