Calibration-free manifold recovery for free breathing & ungated Cardiac MR Imaging

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Target Audience – This work caters to researchers and clinicians interested in the recovery of dynamic MR images from highly under-sampled k-space data.

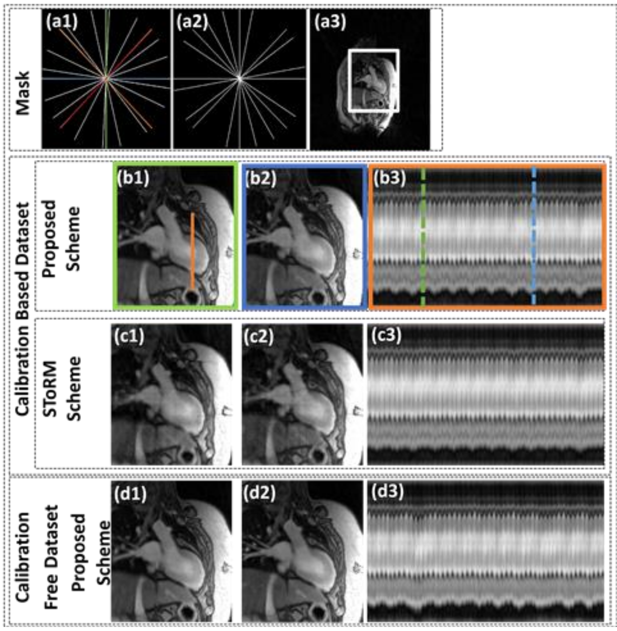

Fig1: Evaluation of the proposed calibration-free patch-based scheme on two radially downsampled free breathing ungated cardiac CINE MRI acquired from healthy subject. Both of the datasets are undersampled by retaining a subset of 10 spokes, one calibrated with 4 navigators and one calibrated-free; the sampling trajectories for one of the frames are shown in a(1-2) with colored lines indicating the fixed navigators. Two frames of each dataset are shown using the proposed and navigator-based STORM. The images are zoomed versions around the square box shown in (a3) and the time profiles in the last column are drown for the entire 1000 frames along the line shown in b(1). The chosen frames are depicted in their perspective colors in the time profiles. The proposed scheme gives comparable results to STORM with less motion artifacts without relying on any navigator signals.

Synopsis: A navigatorless scheme is introduced to recover free-breathing & ungated cardiac MRI data. The proposed algorithm is based on the idea that MR images in a free breathing and ungated dataset lie on a smooth and low-dimensional manifold. The earlier work in this direction relied on specially modified sequences with navigators to estimate the structure of the manifold. The manifold recovery from undersampled measurements is formulated as a regularized optimization problem, where the regularization penalty is the sum of robust distances between images in the times series. An alternating minimization strategy, which alternates between the estimation of the graph Laplacian matrix from the current image estimate, and the estimation of the images assuming the graph Laplacian matrix is introduced. We use homotopy continuation strategies to encourage the convergence of the algorithm to the global minimum of the cost function. The utility of the proposed scheme is demonstrated in the context of prospective free-breathing and ungated cardiac CINE MRI imaging with multichannel acquisitions.

Purpose: In the recent years, there has been significant interest in developing free breathing and ungated methods to acquire cardiac functional MRI data, which improve the compliance and comfort of several patient groups, including pediatric and obese subjects [1-2]. Many of the current methods either rely on self-gating, navigator signals, or physiological signals (ECG and respiratory bellows) to bin the k-space data into specific cardiac and respiratory phases, followed by a constrained reconstruction strategy of the binned data. The recent STORM framework [3] uses an alternate strategy of implicit motion-resolved reconstruction to recover the dynamic data with cardiac and respiratory motion without explicit binning. STORM exploits the property that the images in a free-breathing and ungated dataset are points on a smooth and low-dimensional manifold; the smoothness regularization of the images on the manifold assuming the graph Laplacian operator is used to recover the dataset from highly undersampled measurement. The graph Laplacian matrix is estimated from special navigator signals. While SToRM offers good reconstructions, the need for specialized radial navigator signals translates to low scanning efficiency; specifically, ~40% of the scan time is devoted to the acquisition of the navigator signals. Another challenge is that STORM is not capable of exploiting the spatial variations in the manifold structure. Since motion in different spatial regions of the image is different (e.g cardiac & respiratory motion), it is better to use different Laplacian matrices for different spatial regions. The main focus of this abstract is to introduce a generalized SToRM algorithm, which does not require navigators and can also account for the spatially varying manifold structure. The proposed framework has conceptual similarities to our recent patch-based PRICE formulation [4].

Methods: We formulate the proposed framework to recover the dynamic dataset F as the

$$\mathbf{F}^* = \arg\min_{\mathbf{F}} \|\mathcal{A}(\mathbf{F}) - \mathbf{B}\|_2^2 + \lambda_1 \sum_{i=1}^{N_f}\sum_{j=1}^{N_f}\sum_{\mathbf{r}} \varphi\left(\|\mathbf{P_r}(\mathbf{f}_i) - \mathbf{P_r}(\mathbf{f}_j)\|\right) + \lambda_2 \sum_{i=1}^{N_f} \||\nabla \mathbf{f}_i|\|_{\ell_1}$$

following unconstrained optimization problem:

The second term in the above expression is the proposed manifold smoothness penalty, while the last one is a standard spatial total variation penalty. A key difference of the proposed formulation from [3] is the use of image patches instead of image frames. Here, Pr(fi) is a patch extraction operator, which extracts a square shaped 2-D image patch of dimension (N+1)×(N+1), centered at the spatial location r from the ith frame in the dataset. The generalized formulation allows the manifold structure to vary depending on the spatial locations, which is more efficient than the approach in (3). Another difference is the use of unweighted robust distances between patches in the dataset, rather than the weighted quadratic distances used in (3). The distance metric φ is chosen as a saturating metric that penalizes the small distances heavily, while it saturates with larger distances. Specifically, we use the H1 metric, defined as in (5).

$$\varphi(t) = 1 - \exp\left(-t^2/2\sigma^2\right)$$

The modified formulation using the robust distance metric allows us to estimate the manifold structure from the undersampled data itself, thus eliminating the need for navigators. We use an iterative reweighted formulation introduced in [5] to majorize the second term. While alternating direction method of multipliers exists, the use of such methods along with nonconvex priors may suffer from local minima issues. By contrast, the monotonic convergence offered by the MM framework, along with efficient continuation strategies, can be combined to encourage the convergence of the algorithm to the global minimum of the cost function. The resulting minimization strategy alternates between the estimation of the manifold Laplacian, Matrix W, using the current dataset, and the estimation of the images assuming the manifold Laplacian as follows.

$$\{\mathbf{F}, \mathbf{Z}\} = \arg\min_{\mathbf{F},\mathbf{Z}} \|\mathcal{A}(\mathbf{F}) - \mathbf{B}\|_2^2 + \lambda_1 \|\mathbf{F}\mathbf{W}\|_2^2 + \lambda_2 \|\mathbf{Z}\|_{\ell_1} + \lambda_2\, \beta\, \|\mathbf{Z} - \mathbf{D}\mathbf{F}\|_2^2$$

Results: The proposed scheme is validated on four in-vivo cardiac CINE MRI with multi-channel acquisitions, only one shown here in the abstract. These are challenging cases since they are ungated, accelerated by a high undersampling factor,~ 56 fold, and there is considerable cardio-respiratory motion due to the free breathing mode. b(1-2) and c(1-2) of Fig 1 show the recon of the proposed scheme vs the state-of-the-art navigator-based STORM using a dataset set calibrated with 4 navigator signals as shown in a(1). d(1-2) show the recon of the proposed scheme using calibrated-free datasets with subsampling mask shown in a(2). The new framework provides comparable image quality to SToRM without the necessity for any calibration based trajectories. Also the time series motion and the time profiles b(3),c(3),d(3) show that SToRM reconstructions considerably exhibit flickering and streaking artifacts that are absent in the proposed scheme, supplementary document can be found here (https://www.dropbox.com/s/d9x46cs22404ec9/Final_Web.rar?dl=0). The ability of the proposed scheme to work without navigators makes it more flexible to be applied on data acquired from Cartesian or golden angle sampled sequences, which become available nowadays on clinical scanners.

Conclusion: The experiments demonstrate the potential of the proposed scheme in the recovery of ungated & free breathing dynamic MRI data with considerable motion and high undersampling factor without the need for any specially designed navigator or gating signals.

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