Compressive Manifold Learning Respiratory Self-Gated Liver MRI: Estimating the respiratory motion directly from undersampled k-space

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INTRODUCTION: Manifold learning (ML) allows the estimation of low-dimensional underlying signals from of a set of higher dimensional images by assuming they lie on an embedded low-dimensional non-linear manifold. In MRI, an image-based ML respiratory self-gating method was proposed [1] by extracting the low-dimensional respiratory signal from a set of free-breathing liver images (high-dimension). However, this approach estimates the respiratory signal from reconstructed fully sampled images and therefore is not applicable to undersampled MRI data or requires undersampled reconstructions. Recently the concept of compressive spectral clustering/compressive manifold learning (CML) has been introduced in signal processing theory [2]. CML combines compressed sensing (CS) with ML by learning the manifolds directly from a partial set of compressed measurements, provided that the sampling satisfies the Restricted Isometry Property (RIP). Here we propose to use the CML concept for respiratory self-gated MRI by extracting the respiratory signal directly from undersampled k-space data, without the need for undersampled reconstructions. Results for simulated free-breathing abdominal MR data, using a radial and random Cartesian sampling scheme, show that CML can accurately recover the respiratory signal from highly undersampled k-space data. Prospective free-breathing golden radial liver acquisitions, performed in 3 volunteers, further demonstrate the feasibility of applying CML directly to undersampled data for respiratory self-gating.

THEORY: ML techniques, such as Laplacian Eigenmaps (LE) [3], estimate a low-dimensional representation for data while preserving their higher dimensional structure. This is done by ensuring data points which are close in the high dimensional space remain close in the low dimensional embedding. This is achieved by minimizing a cost function based on weighted Euclidian distances. Considering a set of images $\mathbf{x_1}, \mathbf{x_2}, .., \mathbf{x_T}$ where each image $\mathbf{x_i}$ resides in a high N-dimensional space (N being number of voxels per image, T being the number of images), the cost function to be minimized is given by $\sum_{ij}\|\mathbf{s}_i - \mathbf{s}_j\|_2^2 W(\mathbf{x}_i, \mathbf{x}_j)$ where $\mathbf{s_1}, \mathbf{s_2}, .., \mathbf{s_T}$ are the corresponding points in a low K-dimensional space and $W(x_i,x_j) = \exp(-\|\mathbf{x}_i - \mathbf{x}_j\|_2^2/2\sigma)$, with σ a scaling parameter. In CS theory, a S-sparse signal/image $\mathbf{x}$ can be recovered from the undersampled data $\mathbf{y} = \boldsymbol{\phi}\mathbf{x}$, provided the measurement matrix $\boldsymbol{\phi}$ satisfies the RIP [4] given as: $(1-\delta)\,\|\mathbf{x}\|_2^2 \le \|\boldsymbol{\phi}\mathbf{x}\|_2^2 \le (1+\delta)\,\|\mathbf{x}\|_2^2$, for small δ. CML uses the fact that the RIP condition guarantees the preservation of the neighbourhood structure as high dimensional signals $\mathbf{x_i}$'s are projected onto the M-dimensional measurement space. For two S sparse signals $\mathbf{x_i}$ and $\mathbf{x_j}$, RIP implies that, $\|\mathbf{x}_i - \mathbf{x}_j\|_2^2 \approx \|\boldsymbol{\phi}\mathbf{x}_i - \boldsymbol{\phi}\mathbf{x}_j\|_2^2$ and thus the associated weights W will yield low dimensional embedding similar to the one obtained by manifold learning from the original images themselves. Since RIP holds for a randomly undersampled Fourier matrix, here we propose to apply CML directly to undersampled k-space data acquired with random or pseudo-random sampling trajectories. A comparison of the standard ML and CML frameworks for MRI is shown in Fig.1.

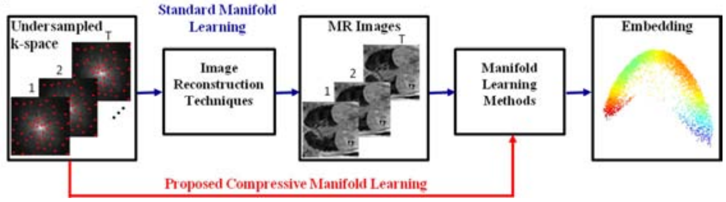

Fig.1: *Sequence of steps in standard manifold learning (ML) and proposed compressive manifold learning (CML) frameworks.*

EXPERIMENTS: ***a) Simulations:*** The accuracy of CML respiratory motion estimation was investigated for different retrospective sampling schemes (radial and random Cartesian) and undersampling factors. Free-breathing 2D liver MRI data was acquired on five healthy volunteers on a 1.5T scanner (Achieva, Philips Healthcare) using a b-SSFP acquisition (TR/TE=3/1.46 ms, matrix size: 336x336, FOV: 450mmx450mm). CML from just k-space centre and standard ML from the images were also computed for comparison. In addition, a pencil beam respiratory navigator signal (NAV) was obtained from the diaphragm for each volunteer.

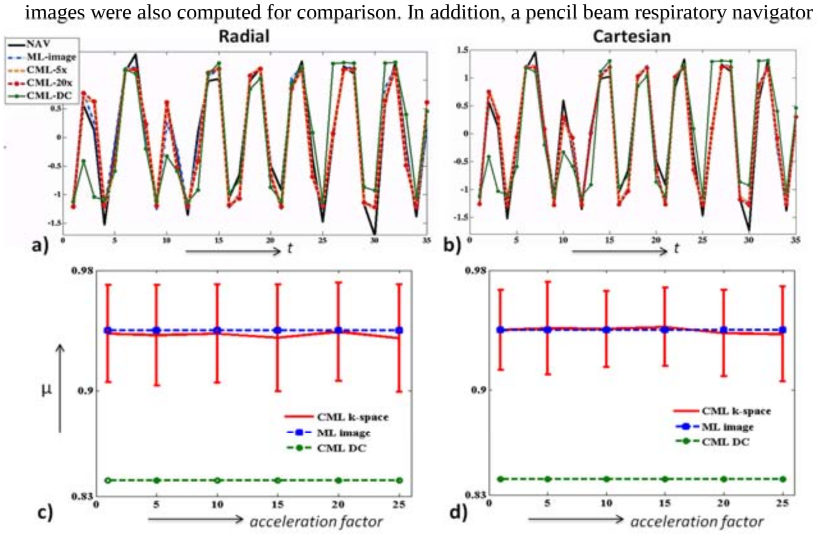

Fig.2: ***(a-b)*** *Comparison of respiratory signal obtained from diaphragmatic navigator (NAV, black curve) with those estimated with ML from fully sampled images (ML-image, blue curve), 5x and 20x undersampled k-space (CML, orange and red curves), and k-space centre only (CML-DC, green curve) for radial and random- Cartesian trajectories.* ***(c-d)*** *Cross correlation (μ) between NAV and CML as function of acceleration factor (values for ML-image and CML-DC are also shown).*

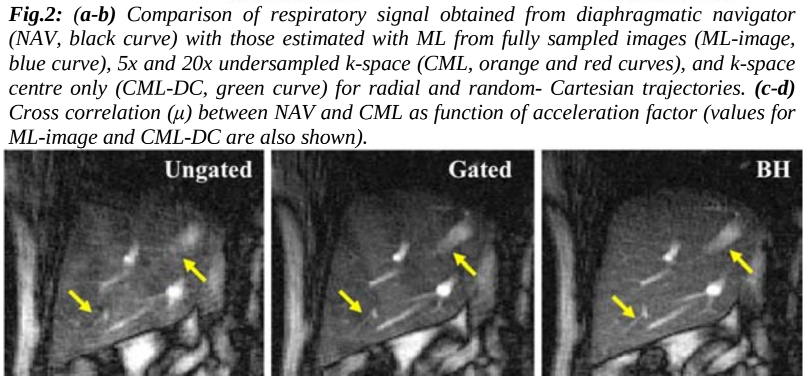

Fig.3: *Use of proposed Compressive Manifold Learning (CML) for respiratory gating of free breathing golden angle liver MRI.* ***Left:*** *Un-gated reconstruction,* ***centre:*** *CML gated reconstruction,* ***right:*** *breath-hold (BH) reconstruction.*

b) In-vivo Experiments: CML respiratory self-gating of the abdomen was performed using 2D golden angle radial [5] acquisition. Fully sampled free-breathing data was continuously acquired on three healthy volunteers on a 1.5T Philips scanner using b-SSFP acquisition (TR/TE=3/1.46 ms, matrix size: 160x160, FOV: 320mm x320 mm, scan time=20sec). Data was partitioned into a set of real time undersampled k-space frames by combining radial profiles such that the acceleration factor for each real time k-space frame was 5. A breath-hold (BH) acquisition with similar parameters was performed as gold standard.

RESULTS: ***a) Simulations:*** A comparison of respiratory signal obtained from CML and respiratory beam (NAV) is shown in Fig. 2a-b for radial and Cartesian acquisition. The respiratory signal estimated with CML showed high fidelity (>98% correlation) to the gold standard NAV signal even for very high acceleration factors (20-fold). Using only k-space centre for each real time frame (CML-DC), the respiratory signal cannot be accurately estimated. Mean values of cross correlation (μ) and associated standard deviations across all the volunteers, as a function of acceleration factor, for radial and random Cartesian trajectories are shown in Fig. 2c-d. CML technique achieved similar performance with both trajectories and mean cross correlation value for all volunteers was higher than 94%.
b) In-vivo Experiments: Respiratory gating results with CML are shown in Fig.3. Most of the blurring in the ungated reconstruction was removed with the CML gated approach. Reconstruction quality with the proposed method was comparable with the reconstruction from BH data.

CONCLUSIONS: The use of self-gating CML was demonstrated in free breathing abdominal MRI. Accuracy of the estimated respiratory signal was similar to that learned from the fully sampled images and highly correlated with the gold standard respiratory navigator. CML could be potentially extendable to the other applications where main interest is in the underlying global structure of a MR sequence, for example ECG-gated cardiac reconstructions.

REFERENCES: [1] Wachinger et al, MedIA, 2012, [2] Hunter et al, CORR 2010 [3] Belkin et al, MIT Press,2001, [4] Candes et al, Proc. Int Congress Math. 2006 [5] Winkelmann et al, IEEE TMI,2007.