Compressed Sensing ASL Perfusion Imaging Using Adaptive Nonlinear Sparsifying Transforms

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INTRODUCTION:
In dynamic MRI using compressed sensing (CS), a number of linear transforms have been investigated to sparsify the dynamic image series, such as Fourier transform (1), finite difference (2), wavelet transforms (3), principle component analysis (4), and learned dictionaries (5). Among them, the data-driven transforms have gained popularity due to its ability to adapt to different types of temporal variations. Although adaptive, these transforms are restricted to a linear family and thereby have difficulty sparsely representing dynamic images with abrupt temporal variations as in perfusion imaging. By including a broader family of nonlinear transforms, rapid-changing dynamic images are expected to have a sparser representation. In this study, we propose a novel CS method that implicitly uses nonlinear transforms to sparsify the dynamic image series of interest. Specifically, the method first maps the acquired data in *k-t* space to a high-dimensional feature space via a nonlinear mapping, then conventional CS reconstruction is performed in the feature space, and finally the reconstruction is converted back to the original spatial-temporal domain. The proposed method is shown to be able to preserve well both the spatial and temporal information in arterial spin labeled (ASL) perfusion images.

THEORY AND METHODS:
Similar to most existing CS-based dynamic imaging method, a random subset of the full *k*-space data is taken in reduced acquisition. Different random patterns are used at different time. The central *k*-space is fully sampled at all times. Let matrix $\mathbf{K}$ denotes the acquired *k*-space data at all times where each column represent the *k*-space data at a certain time frame and each row represent the temporal variation for a particular *k*-space location. To sparsify the dynamic images along the temporal direction using nonlinear transforms, we exploit the concept of kernel methods (6) that are widely used in machine learning and recently used in parallel imaging (7). Specifically, a nonlinear mapping $\boldsymbol{\psi}(\cdot)$ is applied on each row of $\mathbf{K}$ so that the temporal data from the original time domain is mapped onto a new high-dimensional feature space. We use a second-order polynomial function for the nonlinear mapping $\boldsymbol{\psi}(\cdot)$. The acquired data mapped in the feature space is then expressed in the form of $\tilde{\boldsymbol{\psi}}(\mathbf{K}) = \left[\mathbf{k}_1, \ldots, \mathbf{k}_N, \lambda\mathbf{k}_1^{(2)}, \ldots, \lambda\mathbf{k}_N^{(2)}\right]$ [1], where $\mathbf{k}_i$ denotes the *i-th* column vector of matrix $\mathbf{K}=[\mathbf{k}_1 \ldots, \mathbf{k}_N]$, λ is a scalar, and the superscript $^{(2)}$ represents piecewise square. When all the data are mapped onto the feature space, conventional CS reconstruction is performed. Specifically, the image sequence $\boldsymbol{\rho}$ is reconstructed in the feature space using $\min_{\boldsymbol{\rho}} \left\|\mathbf{P}^H\boldsymbol{\rho}\right\|_1 \quad s.t \ \left\|\tilde{\boldsymbol{\psi}}(\mathbf{K}) - \mathbf{F}_u\boldsymbol{\rho}\right\|_2 \le \varepsilon$ [2], where $\mathbf{P}^H$ is the linear sparsifying transform in the feature space, $\boldsymbol{\rho}$ denotes the desired image sequence in the feature space, and $\mathbf{F}_u$ denotes the Fourier transform in the image domain with undersampling. It is worth noting that the Fourier-transform relationship still holds between the image and *k*-space data in the new feature space because the nonlinear mapping is performed in the temporal direction only. Non-linear conjugate gradient is used to solve this optimization problem. After the image sequence is obtained from Eq. [2], it needs to be converted from the feature space to the original space. Since the mapping $\tilde{\boldsymbol{\psi}}$ is highly non-linear, the conversion involves solving nonlinear equations. We find the dynamic images in the original space by solving the least square problem in *k*-space: $\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}} \left\|\tilde{\boldsymbol{\psi}}(\mathbf{FX}) - \mathbf{F}\boldsymbol{\rho}\right\|_2^2$ [3], where $\tilde{\mathbf{X}}$ is the final reconstructed image sequence in the original space, and $\mathbf{F}$ denotes the Fourier transform. To fully take advantage of the nonlinear sparsifying transform enabled by the proposed method, data-driven linear sparsifying transforms such as principle component analysis (PCA) or learned dictionary are preferred in the feature space. Here we use PCA where $\mathbf{P}$ in Eq. [2] is obtained from the principal components estimated using the low-resolution dynamic images reconstructed from the central *k*-space data.

RESULTS:
The performance of the proposed method was evaluated using two sets of ASL perfusion data, calf muscle data (TR/TE= 2.8/1.2ms, flip angle = 5^o, FOV = 160 x 112 mm^2, matrix = 112 x 100, 20 T1-weighted images) and myocardial data (TR/TE= 2.5/1.1ms, flip angle = 5^o, FOV = 320 x 200 mm^2, matrix = 160 x 90, total acquisition = 18 sec). The data were acquired in full *k-t* space and then undersampled retrospectively based on the designed random-undersampling pattern with a net reduction factor of 2 for the calf muscle data and 2.5 for myocardial data. Both the proposed method and the conventional PCA-based CS were used to reconstruct the image sequences from undersampled (*k*, *t*) data. In both methods, the fully sampled 18 auto-calibration data lines at the central *k*-space were used as the training data for the calf muscle data and 12 lines for the myocardial data. In Fig. 1, we compare the reconstructed calf muscle images at the 2nd time frame and the intensity vs. time curves at a single pixel of interest. It is seen that the image has serious aliasing artifacts in the PCA-based reconstruction because the linear transform cannot represent the rapid temporal variations sparsely. The proposed method is able to better suppress the aliasing artifacts. In Fig. 2, we compare the reconstructed myocardial images at 2nd frame and the intensity curves of blood and tissue in the ROI indicated by the red and orange circles. The intensity curves also suggest that the proposed method is superior to the PCA-based CS method in preserving kinetic information.

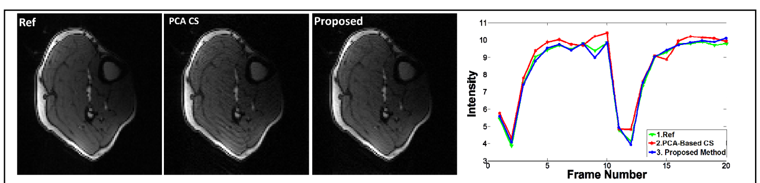

Fig.1. Comparison of calf muscle reconstructions and intensity variation curves

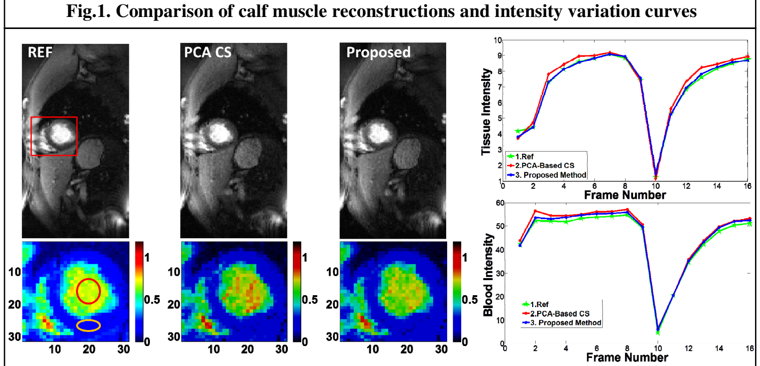

Fig.2 Comparison of myocardial reconstructions and intensity curves for blood and tissue ROIs

CONCLUSION:
A novel kernel-based CS approach is proposed to exploit the sparseness of dynamic image series using nonlinear transforms. The proposed method is able to adapt to the image series of interest in a nonlinear fashion and thus represent it more sparely. Results on ASL perfusion imaging experiments demonstrate that the proposed method is able to better preserve both the spatial details and the abrupt temporal variations than the conventional PCA-based CS method.

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