Accelerated Real time Cardiac CINE using Kernel PCA based Spatio-temporal Denoising

Muhammad Usman[1] and Claudia Prieto[1]

[1]*Division of Imaging Sciences and Biomedical Engineering, King's College London, London, United Kingdom*

Introduction: Standard Compressed Sensing (CS) techniques [1] require signal/image to be a linear combination of very few coefficients in a transform representation. For dynamic cardiac MRI, examples of commonly used linear transforms are Wavelets, finite differences, temporal Fourier Transform and Principal Component Analysis (PCA). Nonlinear data reduction techniques such as Kernel PCA (KPCA) [2] have the advantage over linear methods that these can detect nonlinearity or higher order moments within the given data set. By using appropriate nonlinear basis, complex features in the signal are expected to become separable that can be exploited for better signal classification or more compact representation of the signal. For MRI, this could be useful for a) better signal sparsity for CS and/or b) separation of signal content from artifacts in the undersampled reconstruction. Recently for retrospectively undersampled Cartesian cardiac CINE [3], compared to standard CS techniques, KPCA has been shown to more efficiently represent intra-frame spatial correlations for frame by frame reconstruction. In this work, we propose to accelerate real time dynamic cardiac CINE by exploiting both spatial and temporal denoising using kernel PCA. Prospective golden angle radial MR acquisitions, performed in 3 volunteers, demonstrate the feasibility of proposed framework for up to 8 fold accelerated real time CINE.

Theory: For a set of input signals $\mathbf{x}_1,\mathbf{x}_2,\ldots,\mathbf{x}_N$, Kernel PCA comprises three steps i) nonlinear mapping $\Phi(\mathbf{x}_i)$ of input signals into feature space, ii) linear PCA in feature space, and iii) mapping back into input space using first few principal components in feature space. The nonlinear mapping is implicitly performed by creating a kernel matrix **K,** whose entries are inner products obtained by using kernel functions $K(\mathbf{x}_1,\mathbf{x}_2)=\Phi(\mathbf{x}_1)^T\,\Phi(\mathbf{x}_2)$, such that $K(\mathbf{x}_1,\mathbf{x}_2)$ is symmetric and resulting kernel matrix **K** is positive-definite. Kernel functions such as polynomial ($K(\mathbf{x}_1,\mathbf{x}_2)=(c+\mathbf{x}_1^T\mathbf{x}_2)^d$, $c\geq 0$, $d\in N$) and Gaussian kernel functions ($K(\mathbf{x}_1,\mathbf{x}_2)=\exp(-\|\mathbf{x}_1-\mathbf{x}_2\|_2^2/2\sigma$, σ controls the degree of nonlinearity)) satisfy the above conditions. Linear PCA is performed on kernel matrix **K**, yielding principal components in feature space. Using first few principal components in feature space, back-mapping to input space is casted as a nonlinear optimization problem that can be solved using a fixed point iteration scheme [4].

Method: *a) Data Acquisition:* Free-breathing data are continuously acquired with golden angle radial trajectory [5] on three healthy volunteers on 1.5 T using b-SSFP acquisition (TR/TE=3/1.46 ms, matrix size: 160x160, FOV: 320x320 mm^2, scan time=10sec). Data are partitioned into a set of real time undersampled k-space frames (Fig.1a) by combining radial profiles such that the acceleration factor for each real time k-space frame was up to 8-fold. Set of aliased images are reconstructed from undersampled data via gridding (Fig.1b).

b) Spatio-temporal denoising using kernel PCA (Fig1c): Spatio-temporal denoising is performed on temporal sequence of aliased images using Kernel PCA. Kernel PCA is more effective if set of input signals is similar. For this purpose, spatial overlapping blocks are created from the aliased images. For each block, neighbour blocks in a search spatial window are identified that are most similar to current block (closest in l_2-norm distance). The input for Kernel PCA is formed by combining N temporal dynamics of each block together with N temporal dynamics of most similar blocks. Each block together with its temporal dynamics is denoised using Gaussian Kernel function. In our experiments, the size of blocks was set to 6x6 with 3 pixels overlapping between adjacent blocks. The number of PCs in feature space and σ were empirically set to 5 and 10 times the standard deviation of the pixels in input aliased blocks, respectively. For comparison with existing linear data reduction methods, linear PCA is performed on aliased set of images along the temporal direction with number of PCs set to 8 based on empirical denoising performance.

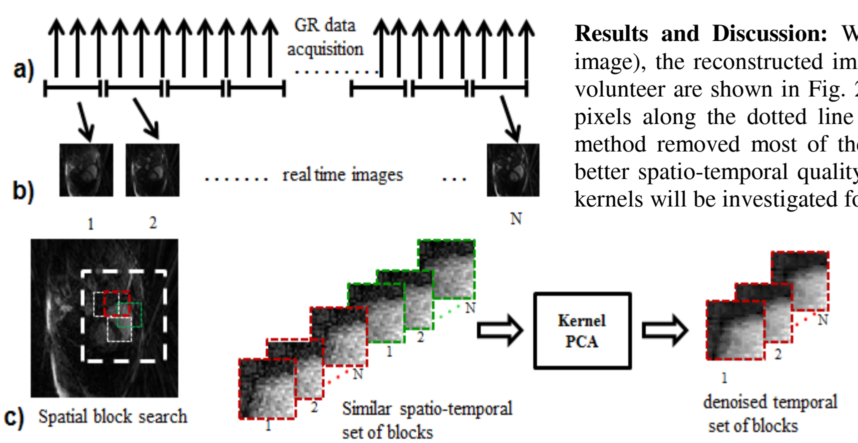

Fig1: Block diagram of proposed method: a) Data acquired with golden angle radial trajectory are partitioned into set of real time undersampled frames, b) aliased images are reconstructed from undersampled data via gridding, c) for each block in the first aliased frame, set of blocks are identified in a search window that are spatially similar to current block. Kernel PCA is applied on the temporal set of current (shown in red) and spatially similar blocks (shown in green) to get denoised image blocks.

Results and Discussion: With 8-fold acceleration (20 radial profiles per real time image), the reconstructed images in diastole (first row) and systole (second row) for a volunteer are shown in Fig. 2.The temporal evolution corresponding to the variation of pixels along the dotted line is also shown (third row). Kernel PCA based denoising method removed most of the aliasing artefacts in the gridded reconstruction and had better spatio-temporal quality than PCA based denoising. In future, choice of different kernels will be investigated for better image denoising and reconstruction.

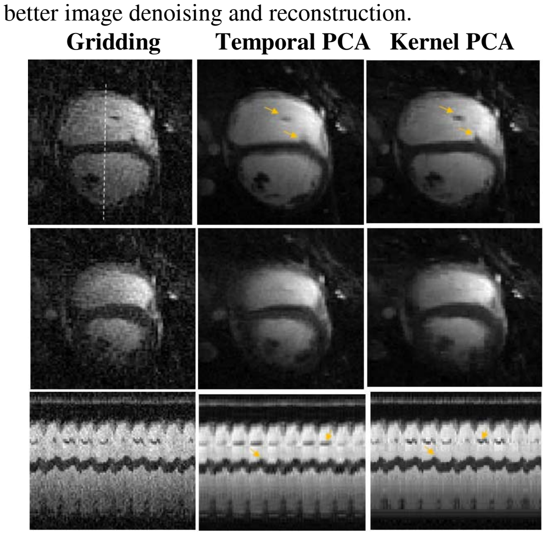

Fig 2: Left column: Gridded reconstruction from **8-fold** undersampled data, centre column: denoising results using temporal PCA, right column: denoising results using **spatio-temporal Kernel PCA**. Diastolic and systolic phases, and a temporal profile corresponding to variation of pixels along the dotted line are shown in each row.

References: [1] Candes et al, Proc. Int Congress Math. 2006 [2] Scholkopf et al, Neur Comp,1998 [3] Schmidt et al, ISMRM,2014 [4] Mika et al, Adv Neur Inf, 1998 [5] Winkelmann et al, TMI,2007