Simultaneous Channel Compression and Noise Suppression in Parallel MRI

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INTRODUCTION:

To reduce the reconstruction complexity in parallel imaging, principal component analysis (PCA) has been used to compress large array coils [1-4] into a new set of fewer virtual channels. The denoising effect of such PCA-based channel reduction methods have also been briefly mentioned in Ref. [5], but no significant improvements have been reported. In this study, we investigate the noise suppression capability of software-based channel reduction methods. A kernel (nonlinear) PCA approach is proposed to achieve noise suppression and channel reductions simultaneously. Using GRAPPA [6] as the reconstruction method, we compare both the computation time and the reconstruction quality when PCA and proposed kernel PCA are employed for channel reduction.

THEORY AND METHOD:

When PCA is applied to channel reduction, the ACS data is used to obtain the transformation which is then applied to all acquired data to obtain a new set of data in the new coordinate system. Mathematically, the linear transformation W can be obtained by the eigen-decomposition of the covariance matrix of the ACS data: $\mathbf{A}^H\mathbf{A} = \mathbf{W}^H\mathbf{\Sigma}\mathbf{W}$, where $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_L]$ is composed of vector $\mathbf{a}_l$ formed from the ACS data of the l^{th} channel (L channels in total) after removing the mean, and $\mathbf{W}$ and $\mathbf{\Sigma}$ are matrices with eigenvectors and eigenvalues. For reduction, only the first few eigenvectors which correspond to the largest eigenvalues are kept to form the linear transformation $\mathbf{T}$. This transformation matrix is then applied to the acquired *k*-space data to obtain the orthogonal projections onto the principal components, which gives a new set of reduced virtual channels. To apply Kernel PCA (KPCA) [7] to channel reduction, we map the ACS data matrix $\mathbf{A}$ into a new feature space $\Phi(\mathbf{A})$ through a nonlinear transformation [8]. Linear PCA is then applied in the feature space. Specifically, for the covariance matrix $\Phi(\mathbf{A})^T\Phi(\mathbf{A})$, eigenvectors that correspond to the largest few eigenvalues are maintained in matrix $\mathbf{T}$, which will be used to project the data in feature space to another space with reduced number of virtual channels. We choose an inhomogeneous polynomial kernel for Φ mapping: $\kappa(\mathbf{a},\mathbf{b}) = (\gamma\mathbf{a}^T\mathbf{b} + r)^d$, where λ and r are scalars and d is the degree of the polynomial. For example, if d = 2, $\Phi(\mathbf{A})$ maps the original L-channel data $\mathbf{A}$ to $\Phi(\mathbf{A}) = [r^2, \sqrt{2\lambda r}\mathbf{a}_1, \ldots, \sqrt{2\lambda r}\mathbf{a}_L, \lambda\mathbf{a}_1^{(2)}, \ldots, \lambda\mathbf{a}_L^{(2)}, \sqrt{2}\lambda\mathbf{a}_1\Theta\mathbf{a}_2, \ldots, \sqrt{2}\lambda\mathbf{a}_i\Theta\mathbf{a}_j, \ldots, \sqrt{2}\lambda\mathbf{a}_{L-1}\Theta\mathbf{a}_L]^T$, where $\mathbf{a}_1$, $\mathbf{a}_2$, …, $\mathbf{a}_L$ are vectors representing different channels, superscript $^{(2)}$ means piecewise square, and Θ denotes piecewise multiplication. Since the target channel and source channel in GRAPPA are rather independent [4], different feature spaces can be used. We choose the original space for the target channel to avoid the complication of transforming data back from the feature space to the original space. The source channels are only used for estimation and thereby do not need to be transformed back to the original space. In this study, we choose the number of second-order terms to be three times of that of the first-order terms for constructing the source channels. Conventional GRAPPA reconstruction is then applied on the new dataset to reconstruct missing data in the transform domain. For optimal performance, we first find the maximum absolute value M_{2nd} of the second-order terms to be used for constructing the feature space. We then let λ_{source} take any value in the range between ($1/M_{2nd}$, $10/M_{2nd}$).

RESULTS AND DISCUSSION

A set of axial brain data was acquired on a Siemens 3T scanner (Siemens Trio, Erlangen, Germany) with a 32-channel head coil using a 2D gradient echo sequence (TE/TR = 2.29/100 ms, flip angle = 25, matrix size = 256 × 256, slice thickness = 3 mm, FOV = 24 cm^2). An ORF of 4 and the ACS of 48 were used with a net acceleration of 2.56. The numbers of target and sources channels are both 16, and λ_{source} is 1.23e-9. It is seen that the GRAPPA reconstruction using the proposed channel reduction method is able to suppress the spatially-varying noise in both conventional GRAPPA and PCA-reduced GRAPPA reconstructions. Furthermore, the proposed method also preserves the details of the image without blurring. The proposed KPCA-reduced GRAPPA takes almost the same time (863 seconds) as the PCA-reduced GRAPPA, which is only about 11% reconstruction time of the conventional GRAPPA without reduction (7771 seconds), but with better quality. A small region of interest was chosen to calculate the SNR of each reconstruction. The SNRs of reference, conventional GRAPPA, PCA and KPCA reduced GRAPPA reconstructions are 16.69dB, 14.86dB, 14.47dB and 15.42dB, respectively.

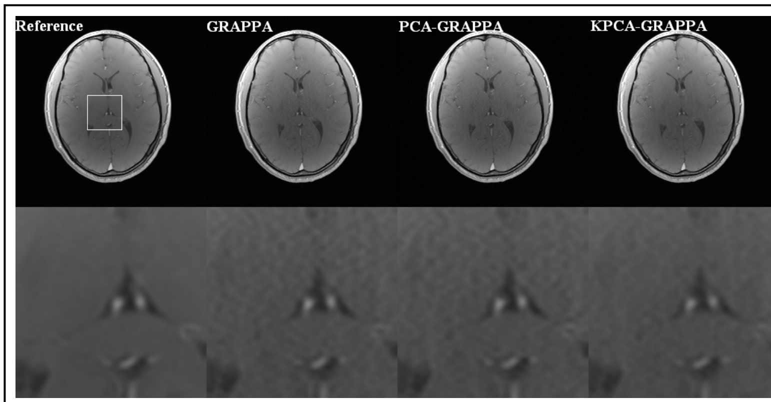

Figure1 Reconstructions using a set of 32-channel brain (axial) data.

CONCLUSION: We have presented a novel KPCA-based channel reduction method for parallel MRI. Experimental results demonstrate that the proposed KPCA-based channel reduction method is able to not only reduce the computational time, as the PCA-based method does, but also suppress noise in GRAPPA reconstruction.

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