Analysis of MRI Data Compression Using Principal Component Analysis

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Introduction: MRI data size is becoming increasing larger as the number of receiver channels continues to increase. Several MR manufacturers have already begun to provide commercial systems with 32 or more channels. In addition, some newer imaging techniques, such as q-ball and dynamic spectroscopy imaging, requires much greater memory than conventional sequences. The data size for a single scan could be as large as several gigabytes, and this huge size makes data storage and transfer more difficult. Recently, the method of using principal component analysis (PCA) for data reduction has been proposed for several applications, including dynamic PET imaging [1] and multi-coil MRI [2]. In the current work, we propose applying PCA in k-space along the phase-encoding axis, and demonstrate that effective data compression can be achieved while maintaining high image quality.

Method: PCA is a simple, non-parametric method of extracting relevant information from data and reducing the number of dimensions. PCA is used to extract the variance-covariance structure in a data set through a set of linear combinations of the original data. PCA was implemented using the Singular Value Decomposition (SVD) in this work. Let matrix $\underline{K}$ represent a k-space data with data size $N_x \times N_y$. Singular value matrix $\underline{S}$ and orthogonal matrices $\underline{U} = [\vec{U}_1, \vec{U}_2, \vec{U}_3 ...... \vec{U}_{N_y}]$ and $\underline{V} = [\vec{V}_1, \vec{V}_2, \vec{V}_3 ...... \vec{V}_{N_y}]$ are produced using SVD. The newly formed k-space using only the first N_{com} main components becomes $\underline{K}_{PCA} = \sum_{i=1}^{N_{com}} \vec{U}_i S_i \vec{V}_i$. The new image $\underline{I}_{PCA}$ then becomes:

$$\underline{I}_{PCA} = FT^{-1}(\underline{K}_{PCA}) = \sum_{i=1}^{N_{com}} FT^{-1}(\vec{U}_i) S_i FT^{-1}(\vec{V}_i) = \sum_{i=1}^{N_{com}} \vec{u}_i S_i \vec{v}_i = \sum_{i=1}^{N_{com}} \vec{u}_{si} \vec{v}_i \quad (1)$$

where $\vec{u}_{si}$, $\vec{v}_i$ are $N_x \times 1$ vectors. Therefore, the new image could be represented by N_{com} $\vec{u}_{si}$ and N_{com} $\vec{v}_i$ vectors. The data size for a transformed image is then $2N_{com} \times N_x$ instead of the original $N_x \times N_y$. For N_s images (e.g. number of slices, coils, or images in a dynamic series), the new data size reduces to $N_{com}(1+N_s)N_x$. The compression ratio (CR) will then range from $N_y/2N_{com}$ for one slice to approximately N_y/N_{com} when N_s is large. For example, the CR will be between 2.56 and 5.12 for $N_y=256$, $N_{com} = 50$.

In this work, different data sets were first rearranged to form a data matrix in k-space with the size $[N_x, N_y \times N_s]$, and then the matrix manipulated using the proposed PCA method. The normalized root-mean-square (NRMS) errors were calculated for each case to quantify the effect of compression.

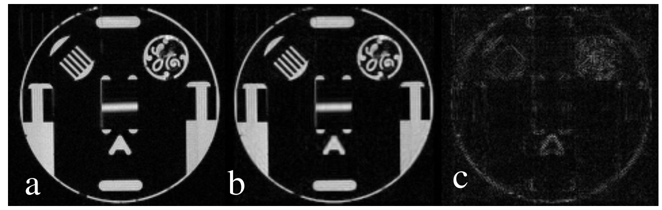

Fig 1 Comparison between the original (a) and PCA_{50} (b) images using first 50 components. The difference images for two slices are shown in (c).

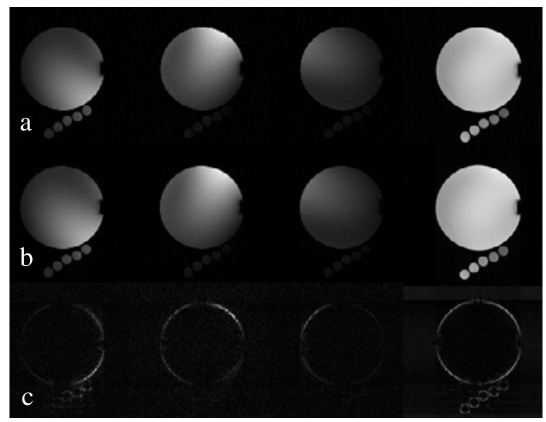

Fig 2 Three images from three different channels (out of 8) are shown in each row. (a) Original; (b) PCA processed. The Sum of Square (SoS) images are shown on right, and the differences in the bottom row.

Results and Discussion: Figure 1 shows the results from a 3D data set. The CR was 4.8 for the $N_x \times N_y \times N_z = 256 \times 256 \times 16$ data set when using the only first 50 components. **Figure 2** shows the results of several images from an 8-channel data set. CR was 4.55 for the $N_x \times N_y \times N_c = 256 \times 256 \times 8$ data set. In the above results, the image quality was maintained when a conservative number of the principal components (50) was used. Higher CR can be achieved by using fewer components without substantially sacrificing the image quality. PCA processed data using only 30 components for a 2D image is shown in **Fig. 3a** (CR=4.27). For comparison, a PCA image processed in the image domain using the same number of components, and a partial k-space image that uses the same amount of data and zerofilled in the outer k-space region are shown in **Fig. 3b** and **3c**. The NRMS errors for **Fig. 3a-3c** are 0.176, 0.176 and 1.078, respectively. The proposed method achieved the equivalent image quality to that in image domain. The image quality using PCA in k-space is significantly better than that of partial k-space image.

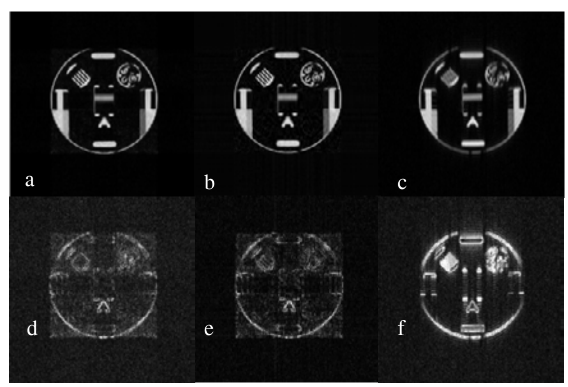

Fig 3 a. PCA image using the first 30 main components in k-space, b. PCA image using the first 30 main components in image space, c. Partial k-space image which uses the same amount of data as a; d, e, f are the corresponding difference images from the original uncompressed data set. Each row are in the same scale.

Conclusion: MRI data size is becoming larger with increasing number of receiver channels, and the problem is exacerbated in applications requiring multiple series of images. Our preliminary results demonstrate data compression using PCA in k-space is effective, and compression ratios of about 5 achieved without significant loss in image quality.

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References:

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[2] Huang F., et al. Proc. 2005 IEEE, Engineering in Medicine and Biology.