Dynamic Contrast-Enhanced Three-Dimensional Lung Imaging Acceleration Using k-t PCA

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Introduction

Three-dimensional imaging with high temporal resolution is desirable for dynamic contrast-enhanced (DCE) MRI to assess lung perfusion for its higher SNR and broader slice coverage over the multi-slice 2D approach. While feasibilities of accelerating 2D DCE lung imaging using k-t BLAST were demonstrated in recent studies [1], the acceleration of 3D DCE lung imaging remains a challenging task with performance assessments constrained to parallel MRI [2-3]. This work demonstrates that k-t PCA, shown to improve the reconstruction fidelity of accelerated MR cardiac images [4] and other applications [5-6], could accelerate 3D DCE lung imaging under single-coil modality.

Theory and Methods

k-t PCA is a decomposition technique in which the unaliased signal ρ is represented as a set of temporal basis functions (B) and their corresponding spatial weightings [eq.(1)]. A set of fully-sampled low-resolution training data are acquired to derive B by performing PCA, based on which the spatial weightings can be calculated using eq.(2), where M_x^2 is the signal covariance matrix and E is the signal encoding matrix. Since PCA reorders eigenvalues in a sequential manner, it is possible to selectively prioritize a constrained amount of spatial weighting, reformulating the under-sampled (hence underdetermined) data into an overdetermined reconstruction using eq.(2).

$$\rho(x,f) = \mathrm{w}(x)\mathrm{B}(f) \quad (1)$$

$$\mathbf{w}_x = \mathbf{M}_x^2\mathbf{E}^H(\mathbf{E}\mathbf{M}_x^2\mathbf{E}^H + \lambda\mathbf{I})^+\mathbf{P}_{alias,x} \quad (2)$$

This method was applied to DCE lung images, which were obtained by using gradient-echo with TR/TE=4/1.26 ms, with 16 1cm-slices. The images were reconstructed using 2- to 5-fold undersampling with optimized sampling pattern in 3D [7], including 21 fully-sampled k-spaces as training profiles and the principal component (PC). The number of PCs was varied from 10 to 40 to assess its effects on image reconstruction. ROIs were manually selected from aorta and parenchyma at locations with fluctuant time-intensity dynamics for evaluation of the effectiveness under potentially extreme condition.

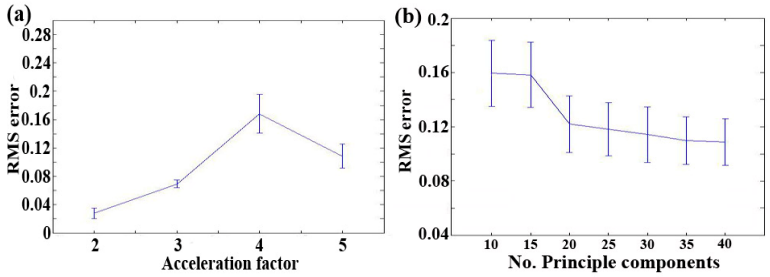

Fig. 1 Average RMS errors of k-t PCA vs. (a) acceleration factor and (b) numbers of principal component (R=5). Error bars showed the standard deviations for all slices. The number of training profile was fixed at 21.

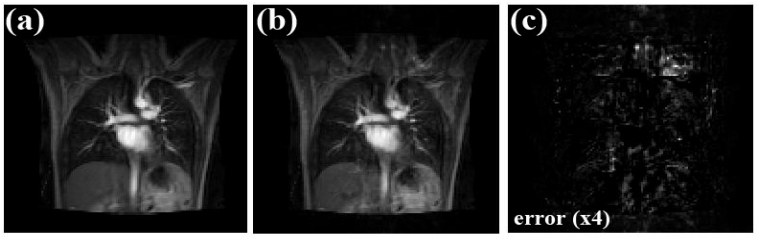

Fig. 2 (a) The 8th slice was selected to show the results of full-sampled data, and (b) reconstruction images using reduction factor of 5. (c) The differences between the original data and the reconstruction images with 4 times magnification of the signal intensity.

Results and Discussion

Fig. 1(a) shows the root-mean-square (RMS) error of the reconstructed images using different acceleration factors (R). The RMS error is less than 3% when R=2 and gradually increases to 11% in R=5. Meanwhile, the standard deviations of RMS errors between different slices also become larger, while the abrupt increment at R=4 could be attributed to smaller minimal main-lobe separation as indicated in previous studies [7]. Fig. 1(b) plots the relationship between the RMS error and the number of PC. The RMS errors are close to 16% when PC number was less than 15, from which the error drops significantly and gradually converges thereafter. While both the amount and proportion of PC required seem to be higher than that suggested by its 2D dynamic cardiac counterpart [4], this may be reasonable because of the higher complexity of dynamics from the branching pulmonary vasculature. Fig.2 shows the full-sampled image and the reconstructed image from one slice of the 3D image-set, where most regions in lung and heart are successfully reconstructed. Fig. 3 depicts the time-intensity curves of the full sampled and reconstructed images in aorta, left and right parenchyma. Although the time-intensity curves of accelerated dataset show consistent tendency with that from the full-sampled image, the peak of bolus passage slightly deviates from the original together with mild temporal blurring. While the initial overshooting (arrows) resembles those reported in k-t BLAST and k-t SENSE owing to temporal discontinuity [8], undershooting is comparatively milder near the end of time series. Last but not the least, the additional spatial-encoding along the z-direction adds extra flexibility to sampling pattern manipulation comparing with multi-slice 2D imaging, which enables larger minimal main-lobe separation distance (d_{min}) [7] therefore lowering the potential level of aliasing.

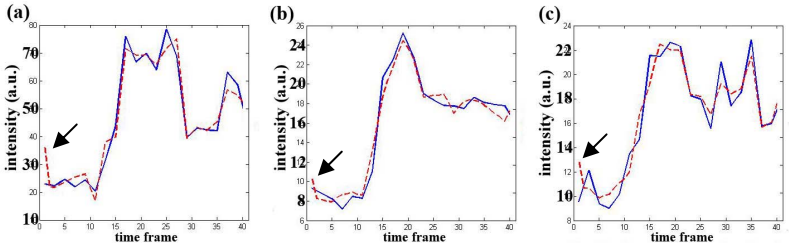

Fig. 3 The time intensity curves plotted from full-sampled data (blue) and reconstructive images (red) from (a) aorta, (b) left lung and (c) right lung. ROIs were selected on the same slice shown in Fig.2 with R=3.

Conclusion

In this work we show preliminary results of the consistency of reconstruction images and time-intensity curve between full-sampled and 3D k-t PCA accelerated DCE lung images. The results suggest possibility for single-coil three-dimensional imaging acceleration.

References

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