Acceleration of Perfusion MRI using Adaptive Artificial Sparsity

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Target audience: Researchers who are interested in accelerating perfusion MRI.

Purpose: In previous study of imaging acceleration methods [1, 2, 3], effort has been addressed to achieve better image reconstruction by predicting static part of dynamic images through temporal average or standard deviation evaluation. Subtraction of static part strengthens the sparsity of dynamic images thus result in better reconstruction [2]. However, these previous artificial sparsity (AS) methods [1, 2, 3] cannot be successfully applied for perfusion imaging because the intensities of images change a lot along time. But, artificial sparsity methods still have great potential for perfusion imaging because images in perfusion share almost the same structure. In this study, we proposed an adaptive artificial sparsity method specific for perfusion imaging. This method was validated with black blood vessel wall DCE MRI.

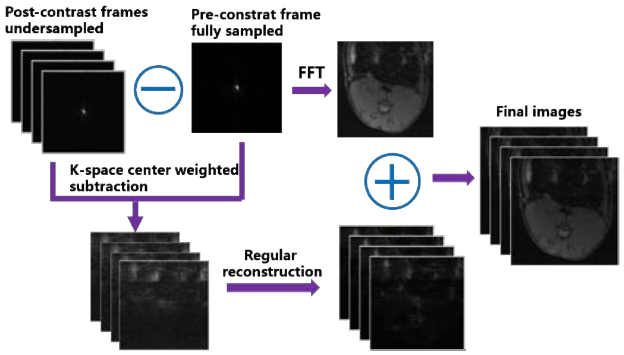

Fig. 1, flowchart of adaptive artificial sparsity reconstruction

Methods and materials:

Theory: The reconstruction is divided into 3 steps (Fig.1). 1). intensity change estimation: because temporal resolution of pre-contrast images is not as demanding as those after contrast injection, the first pre-contrast image is fully sampled, while subsequent images are under-sampled with a fully-sampled k-space centre. Considering the main difference between frames during DCE imaging are intensity variation, the subsequent images can be predicted with weighted pre-contrast frame. The Weightings are determined by calculating relative power in k-space centre for all subsequent frames, since k-space centre determines the contrast and most energy. After k-space centre weighted subtraction, the under-sampled k-space is separated into two parts: prediction and residual k-space. 2). Residual reconstruction. The residual k-space is corresponding to aliased but sparse images. Regular reconstruction methods, including k-t GRAPPA [4], k-t PCA [5] and k-t SLR [6], are applied on the residual k-space to resolve the aliasing. 3). Final reconstruction. Final reconstruction is obtained by adding Fourier reconstruction of the prediction and the reconstructed residual together.

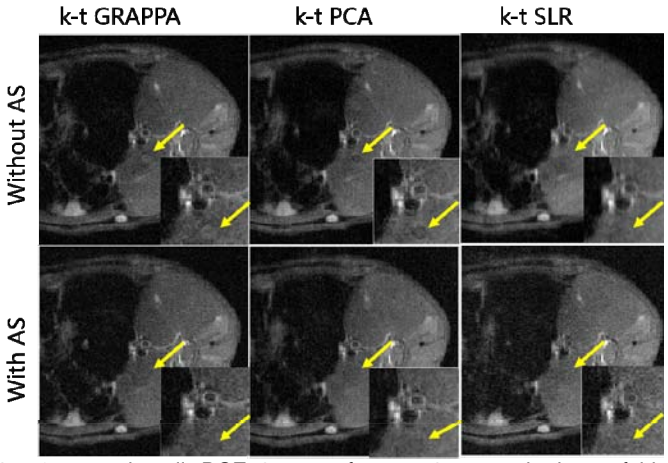

Fig. 2, vessel wall DCE images from various methods, 5 fold undersampling. Arrows indicate unresolved aliasing which presented in common reconstruction but not in adaptive artificial sparsity

Data acquisition: Vessel wall DCE imaging datasets were acquired with a standard atherosclerosis animal mode [7]. Atherosclerotic aortas of 10 male mature New Zealand white rabbits were imaged on a clinical 3.0T MRI scanner (Philips), with an 8-coil human knee coil and a QIR-based DCE sequence [8] (only black blood images were used). Other imaging parameters are FOV=80*80mm, in-plane resolution = 0.5mm and temporal resolution = 8s. All datasets were fully sampled and under-sampled retrospectively.

Data Analysis: The reference-region based Patlak model [7] was used to calculate K^{trans} for each artery according to a standard image processing protocol [ref here]. Correlation coefficient was used to evaluate the agreement of the generated parameters between the reference images and the reconstructed images by three k-t based methods with/without adaptive artificial sparsity.

Table 1: correlation coefficients of K^{trans} estimated from accelerated reconstructions and fully sampled reference DCE images

method	netR	Correlation coefficient	
		Without adaptive-AS	With adaptive-AS
k-t GRAPPA	3.3	0.906**	0.906**
	5.5	0.423	0.899**
k-t PCA	3.3	0.904**	0.920**
	5.5	0.724*	0.794**
k-t SLR	3	0.918**	0.960**
	5	0.808**	0.838**

netR: net reduction factor

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Results: The reconstructed images with adaptive artificial sparsity showed fewer artifacts for all tested reconstruction methods (Fig. 2), indicating that aliasing can be better resolved because of the strengthened sparsity. With adaptive artificial sparsity, the correlation coefficients of K^{trans} estimated from images reconstructed by all tested k-t methods and the reference images were higher than those without adaptive artificial sparsity, especially when the acceleration factor was high (Table 1).

Discussion and conclusion: In this study, an adaptive artificial sparsity method for perfusion MR imaging acceleration was proposed. Adaptive subtraction resulted in sparser residual k-space, and further improved performances of all tested reconstruction algorithms. The proposed framework is easy to implement and is potential to be applied to other temporal acceleration reconstruction method and other applications.

References

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