Optimized Combination of Parallel MRI and Sliding Window Reconstruction for Accelerated Time Resolved Radial MRI

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Introduction: For a long time, sliding window (SW) gridding reconstruction has been an efficient way to reconstruct undersampled interleaved radial MRI data in time-resolved imaging [1] and quantitative applications [2]. Temporal SW filters which widen as function of spatial frequency reduce streaking artifacts due to undersampling, but also reduce temporal resolution/quantification accuracy at higher spatial frequencies. Alternatively, parallel MRI (pMRI) may be used to mitigate the undersampling artifacts and improve temporal footprint/accuracy. However, the actual undersampling factors within the sets of interleaved radial data may significantly exceed the reduction factors possible with modern pMRI systems, which typically results in significant noise amplification/resolution loss. It was demonstrated that combination of parallel MRI and SW may significantly improve image quality in undersampled Cartesian imaging (k-t GRAPPA [3]). However, the combination of SW and pMRI reconstruction for radial imaging is not straightforward due to computational complexity associated with reconstruction of non-Cartesian k-space data and lack of related methodological developments. In this research, we propose a method to combine k-space based parallel MRI with sliding window reconstruction for radial trajectories. The new method, k-t PARS, is based on PARS approach proposed for pMRI reconstruction of non-Cartesian MRI data [4-6].

Theory and Methods: Let us assume that ratios of neighboring time frames are slowly varying functions, or, in other words, temporal changes may be represented as multiplicative low spatial frequency modulation. Under such assumption, temporal changes may act in the same way that coil sensitivities do in regular pMRI. Low resolution images from the fully sampled k-space center of radial interleaves may be used to create a set of virtual coil sensitivities for all time frames. These virtual coils contain both coil sensitivity information and temporal encoding function. The inclusion of the virtual coil sensitivities into the encoding matrix *E* may provide an additional regularization effect. The strength of the regularization effect will depend on the level of linear independency of such modulations in respect to physical coil sensitivities. The level of inaccuracies due to the sup-optimal mixing of temporal information will depend on the level of higher spatial frequency content of the temporal changes. To implement the idea, we chose the k-space based reconstruction framework of modified PARS for radial trajectories [4]. The k-space based approach is less sensitive to errors modeling errors then the image based techniques such as errors caused by low resolution representation of coil sensitivities. The diagram of the proposed k-t PARS reconstruction for a given coil image is shown in Fig 1. First, a temporally averaged baseline is subtracted from the data. Next, temporal filtering is done to select data for each time frame, which is then used to construct PARS matrix. To accelerate calculations, PARS coefficients are interpolated between few reference points [5]. The reconstructed coil images are combined using standard square-root-of-sum of squares combination.

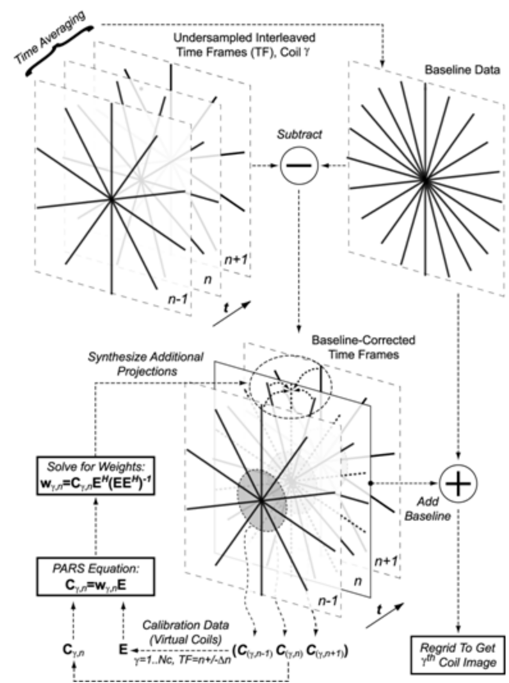

Figure 1. Diagram of the proposed method.

Results: We applied k-t PARS to simulated CE MRA data (2D radial, 8 realistic waveforms simulating contrast arrival dynamics in arteries and veins, 20 time frames, 20 projections/frame, 4 coils, noise added, image size 256x256). The sliding window spanned 5 time frames. The reconstruction of a single time frame is shown in Fig. 2. Additionally, the utility of the proposed technique was evaluated on radial cardiac perfusion data simulated from a Cartesian acquisition (Fig. 3). The method shows significant improvement of image quality when compared to pMRI alone.

Discussion: Our results demonstrate that k-t PARS promises to provide a robust combination of pMRI with SW reconstruction for highly undersampled non-Cartesian trajectories. k-t PARS approach regularizes pMRI reconstruction using information from neighbouring time frames, similar to k-t GRAPPA [4]. However, unlike k-t GRAPPA, our method is applicable to arbitrary trajectories, and may be viewed as its generalization. It may be shown that the method performs accurately under assumption that temporal changes are represented by fully sampled k-space central area. In one limit, when no changes occur from time point to time point as detected by the low resolution estimates, the method will be equivalent to least squares combination of interleaved time frames using regular PARS [6]. In the other limit, when temporal changes are not captured at all by low resolution footprints, the reconstruction will approach that of sliding window reconstruction, with additional benefit of parallel MRI. k-t PARS formulation also allows for inclusion of additional information into estimation through weighting terms to further enhance/deemphasize temporal behavior according to prior knowledge. It is interesting that many constrained reconstruction methods such HYPR LR [7] and RIGR [8] are also based on the assumption that changes between reference and target images are described by a multiplicative function with low spatial frequency content. These methods modulate the reference image by estimated temporal changes in the image space. The proposed method employs linear estimation framework to learn correlations between time frames for optimized reconstruction. The future work will concentrate on comparison of k-t PARS with the existing techniques.

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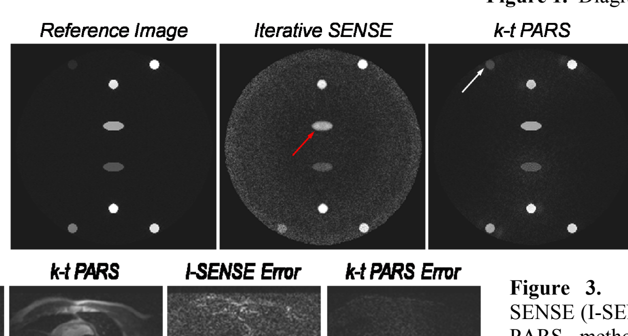

Figure 2. Simulated data studies. SENSE leads to significant noise amplification and blurring (red arrow) due to inability to cope with a large reduction factor (20). k-t PARS improves SNR and resolution.

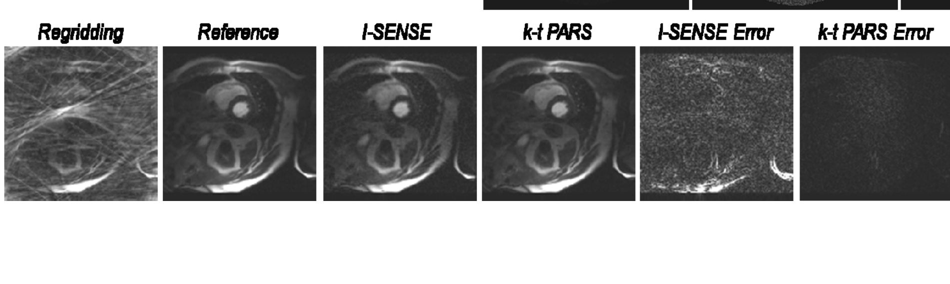

Figure 3. Comparison of iterative SENSE (I-SENSE) and the proposed k-t PARS method on cardiac perfusion data. Error images are magnified by a factor of 5. k-t PARS provides improved resolution and SNR.