Dynamically Regularized TSENSE improves Image Quality in Parallel MRI

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Introduction: We propose improved image quality in TSENSE [1] by utilizing temporal signal correlations. In TSENSE, the coil sensitivity maps are derived from the data itself and full FOV information are available allowing the use of regularization techniques for SNR optimization [2]. However, at high acceleration factors the image quality is degraded due to an increased geometry factor leading to a spatially varying noise enhancement. An improved image quality is achieved by applying TSENSE only to the dynamic portion of the signal (i.e. subtracting the temporal average, also termed DC). In addition, temporal correlations from the dynamics are used for regularizing the solution. The a-priori temporal information required for regularization is obtained by additional TGRAPPA [3] reconstructions. TGRAPPA was chosen because it is robust in case of pre-folding and does not exhibit temporal filtering effects.

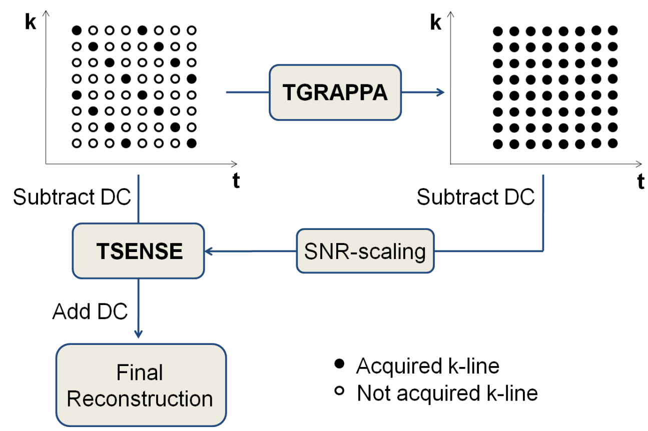

Figure 1: Reconstruction Scheme.

Theory and Methods: TSENSE offers the possibility to use full FOV prior information for SNR optimization on a pixel-by-pixel basis by regularization. To avoid degradation of the images, aliasing artifacts should ideally be suppressed below the noise level. Thus, after noise decorrelation and by incorporating a-priori SNR knowledge, a regularized SENSE inversion can be written [Equation 1]:

$$\boldsymbol{\rho}_{x,t} = \left[\mathbf{S}^H\mathbf{S} + \boldsymbol{\Lambda}\right]^{-1}\mathbf{S}^H \cdot \boldsymbol{\rho}_{x,t,alias} \quad \text{where} \quad \boldsymbol{\Lambda}(x,y) = \alpha\left[\mathrm{diag}(SNR(x,y))\right]^{-1}$$

The vectors $\rho_{x,t,alias}$ and $\rho_{x,t}$ contain aliased and true pixel values, respectively and $\mathbf{S}$ is the coil sensitivity matrix. The matrix $\boldsymbol{\Lambda}$ is the regularization matrix and α is a constant describing the degree of regularization (typically α<0.5 to avoid residual aliasing). SNR estimates required in Equation 1 are obtained by additional TGRAPPA reconstructions. Analogous to the SNR-units reconstruction [4], the resulting TGRAPPA images $\mathbf{p}_{GRAPPA}$ are scaled to yield SNR estimates:

$$SNR^{RSS}_{GRAPPA} = \sqrt{2\left(\mathbf{p}^H_{GRAPPA} \cdot \mathbf{p}_{GRAPPA}\right)} / g_{GRAPPA} \qquad \text{[Equation 2]}$$

Spatial noise enhancement g_{GRAPPA} are calculated as described in ref. [5]. Additionally, the DC is subtracted prior to SENSE to further improve the image quality. This approach is used in other dynamic parallel MRI methods [6,7] and makes use of the fact that the number of overlapping signal containing pixels is reduced [8]. The reconstruction scheme is summarized in Fig 1. Gated cardiac cine and free-breathing cardiac imaging was performed on clinical 1,5 T scanners using different accelerations.

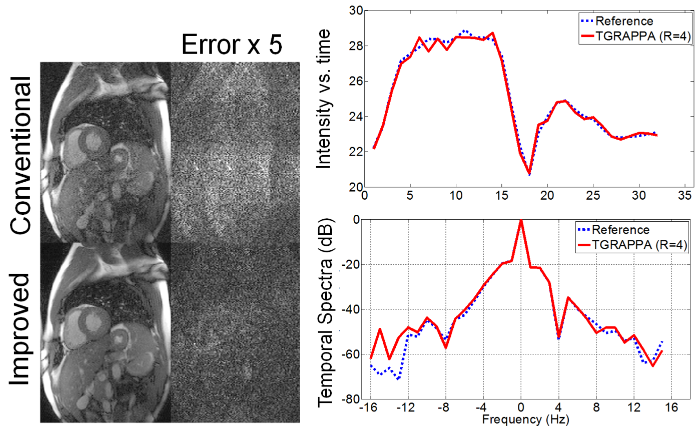

Figure 2: Simulated undersampling. Left: Image reconstructions (Rate=4, 12 channels). Right: Intensity curves (top) and temporal spectra (bottom) from a ROI (5x5 pixels) for TGRAPPA (Rate = 4, 32 channels) and fully encoded reference demonstrating the temporal fidelity of TGRAPPA.

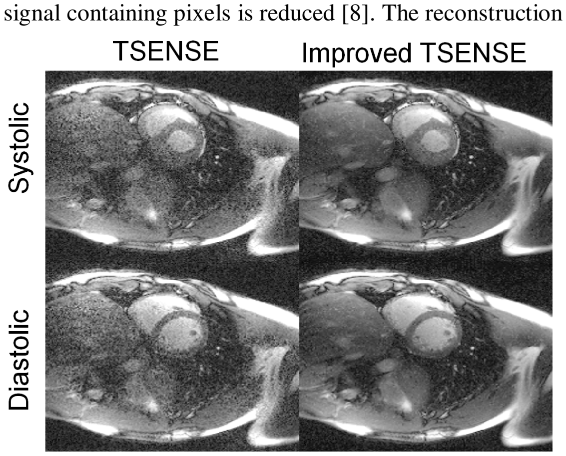

Figure 3: Results from an accelerated (Rate=6, 32 channels) gated cardiac cine MRI experiment.

Results and Discussion: Results using in-vivo data are presented in Fig 2 (simulated undersampling) and Fig 3 (accelerated acquisition). Compared to conventional TSENSE, noise is significantly reduced when using the proposed dynamic regularized reconstruction. No visible artifacts have been introduced when using a regularization constant α<0.5. The proposed method is similar to k-t-SENSE [6] except uses a single wideband temporal frequency bin. Auto-calibrating TGRAPPA has been shown to provide full temporal resolution without filtering (Fig 2, right) removing the need for separate training data. In summary, robust reconstructions with improved image quality can be obtained with dynamic regularized TSENSE.

References: **[1]** Kellman P, et al. *MRM* 2001;45(5):846. **[2]** Lin FH, et al. MRM 2005;54(2):343. **[3]** Breuer FA, et al. *MRM* 2005;53(4):981. **[4]** Kellman P, McVeigh ER. *MRM* 2005;54(6):1439. **[5]** Breuer FA, et al. *Proc ISMRM* 2008 (Toronto):10. **[6]** Tsao J, et al. *MRM* 2003; 50(5):1031. **[7]** Huang F, et al. *MRM* 2005;54(5):1172. **[8]** Malik S, et al. *MRM* 2006;56(4):811.