Dynamic parallel MRI by generating sparse data: tracking temporal changes

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Introduction: TSENSE [1] and TGRAPPA [2] have been presented as useful techniques for dynamic parallel imaging. However, particularly at high acceleration factors, both approaches suffer from noise enhancement due to an increased geometry factor. Here, we present a novel approach to overcome this limitation by taking into account that dynamic changes occur in localized regions within the FOV. Therefore, parallel imaging reconstructions can be applied to sparse data generated by raw data subtraction from a composite data set. In that way, the geometry factor is decreased since fewer pixels fold on top of each other in the sparse images. The reconstructed subtraction image is then added to a composite image to obtain the final image. In particular, dynamic cardiac applications and CE angiography benefit from this approach.

Theory: The proposed method is based on a time-interleaved phase-encoding (PE) scheme as in TSENSE or TGRAPPA. Prior to all further processing, a fully Fourier-encoded composite data set (COMP) is required. COMP can be generated by summing over all time frames, for example. The reconstruction scheme for a single frame is illustrated in Fig 1. First, a subtraction data set (RAW,sub) is created by subtracting raw data of a single time-frame (RAW,frame) from corresponding k-space lines of the composite data set (RAW,comp). RAW,sub contains information about changes with respect to the composite data. For many dynamic applications, temporal changes occur in localized regions within the FOV. Compared to conventional parallel imaging, the number of signal-containing pixels folding on top of each other is reduced resulting in a reduced g-factor. In our approach, the aliased pixels are separated by GRAPPA using auto-calibration signal (ACS,sub) generated by assembling adjacent frames (ACS,frame) and subtraction from COMP (Fig1, top). ACS,sub contains information about the locations at which the temporal changes occur. The final reconstruction of a time frame is obtained by adding the reconstructed subtraction data (RECO,sub) to COMP.

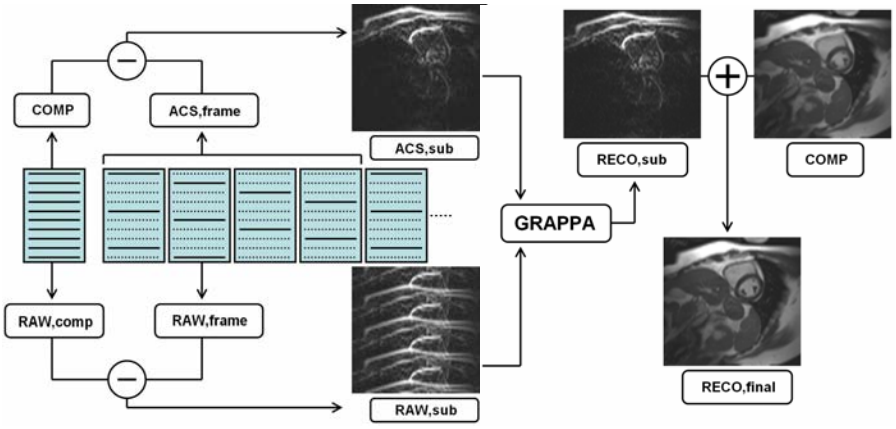

Fig 1: Reconstruction Scheme

Methods and Results: Fig 2 shows in-vivo results using 32-channel data from a full Fourier-encoded cardiac segmented cine experiment. A six-fold accelerated interleaved PE acquisition scheme was simulated and reconstructed with conventional TGRAPPA and the proposed method. Root mean-squared-error (RMSE) was calculated for ROIs in each frame showing the improved performance of the proposed method. Fig 3 demonstrates improved image quality as compared with conventional TGRAPPA for a free-breathing acquisition (R=4, corresponding to 25 fps) performed on a clinical 1.5 T scanner with an 8-channel cardiac array.

Discussion: We have presented a self-calibrated parallel MRI technique for dynamic applications using sparse data. Compared with standard parallel MRI, the SNR is enhanced due to a reduced g-factor. In contrast to other dynamic MRI approaches, no additional training data is required. Although there are similarities with HYPR [3], this technique works with Cartesian trajectories and could be extended for non-Cartesian trajectories. Since adjacent time frames are merged for obtaining the auto-calibration signal, there might be some implicit temporal filtering effects which are being investigated. Also, Instead of the time-interleaved acquisition, a variable-density PE scheme could be used.

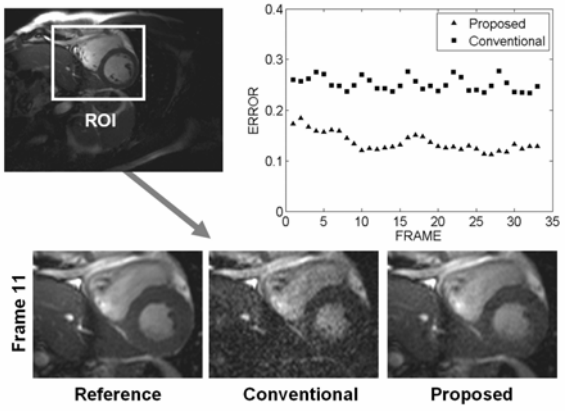

Fig 2: In vivo results (R=6, 32 channels)

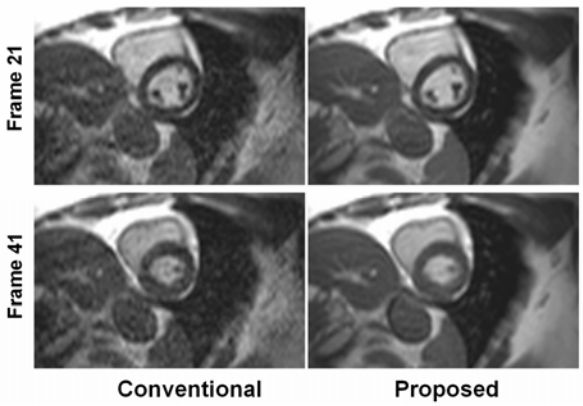

Fig 3: Free-breathing in-vivo results (R=4, 8 channels)

References:

[1] Kellman P, et al. MRM. 2001;45:846-52.

[2] Breuer FA, et al. MRM. 2005;53:981-5.

[3] Mistretta CA, et al. MRM. 2006;55:30-40.