Comparison of k-space based parallel imaging approaches for reducing non-rigid motion induced ghosting

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Introduction: Non-rigid motion such as coughing and swallowing give rise to ghosting artifacts that often severely impact image quality, especially in the spine. Radial, PROPELLER [1] and other self-navigated sampling trajectories can minimize these artifacts, but clinical applications are still dominated by Cartesian imaging. Recently there has been a lot of interest to utilize the additional information from multiple coils by parallel imaging (PI) based techniques for elimination of motion-induced ghosting [2-5]. Barring exceptions such as SMASH navigators [3], most of these works can be applied to non-rigid motion. Iterative SENSE [6] based techniques have been presented where motion is modeled as a change in coil sensitivity [4]. A-priori information has also been used to improve motion detection in a combined SENSE with projection onto convex sets approach [7]. However, this paper focuses on non-rigid motion correction in k-space using data driven parallel imaging. In an early work, Bydder et al proposed motion detection in k-space by comparing PI reconstructed copies of subsets of the original corrupt data. He proposed rejection of the corrupt data followed by resynthesis by PI methods. Recently, Huang et al proposed a computationally inexpensive method, COCOA [5], where a single synthetic data, created from acquired data using a GRAPPA [8] like operation, is used to both detect and replace motion-corrupted data-points. In this work, we analyze the differences between these 2 motion correction techniques through simulations and *invivo* scans that were compromised by non-rigid motion-induced ghosting. In Bydder et al's work [2] mentioned above, the authors used SENSE for initial reconstruction and SMASH for synthesis of discarded data. In this paper, we will use ARC [9] for all parallel imaging operations and also use motion detection to improve self-calibration.

Theory and Methods: The underlying assumption in most PI motion correction techniques is that motion affects the consistency of local k-space. Since parallel imaging relies on k-space consistency, motion would compromise PI reconstruction. We implemented a similar approach to COCOA, where the synthetic dataset was generated by self-calibrated ARC from the acquired data. Corrupt data points were identified based on distance from the synthetic estimate and replaced with the synthetic data. In the method based on Bydder et al's work [2], we detected corrupt data by comparing between PI reconstructed datasets from 2-3 undersampled subsets of the acquired data. The same calibration was used for reconstruction of all the subsets. We used the motion detection results to discard corrupt data points and to also choose a relatively motion-free low frequency k-space data for calibration. The discarded data points were then synthesized by ARC, using the above-mentioned calibration data. We will be referring to these 2 motion correction methods outlined above as Convolution Combination (CC) and Rejection Resynthesis (RR) respectively.

Swallowing was simulated in a Shepp Logan phantom by vertical translation of the small white circle (Figure 1) and flow artifact was simulated by periodic change in intensity of the white circle. Simulated coil profiles were used, and studies were conducted for interleaved as well as single echo acquisitions. The cervical spine was imaged in 2 volunteers after informed consent on a 1.5 Tesla GE HDx system, using a 4 channel neck receiver array and 2D fast spin echo (FSE) sequence with TR/TE=5500/109 ms, 3 NEX, acquisition matrix: 384x256, echo-train length=18, FOV/slice thickness= 240/2.5mm. The volunteers were asked to cough and swallow deeply multiple times during the study. The 2 motion correction approaches described above were then applied to correct these datasets.

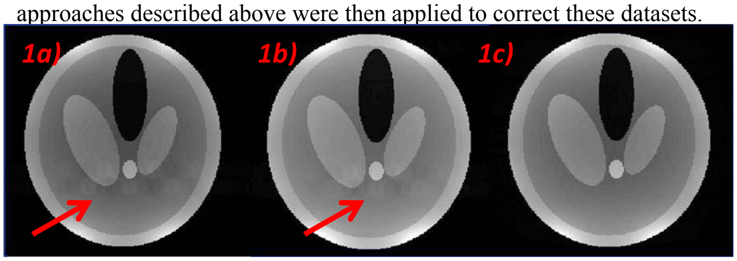

***Figure 1**. 1a shows a phantom image with simulated swallowing artifact. 1b) and 1c are the images after correction by methods CC and RR respectively.*

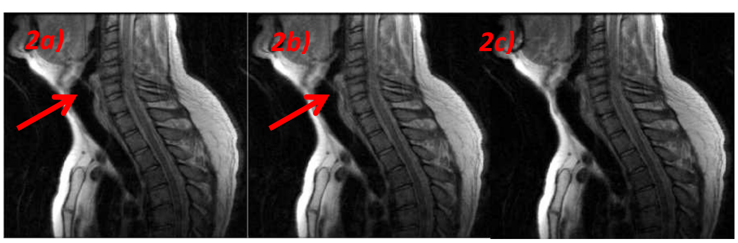

***Figure 2:** 2a) is a ghosted C-Spine image. 2b) and 2c) are the images after correction by CC and RR methods respectively.*

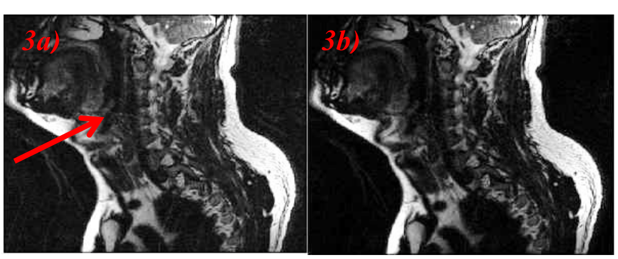

***Figure 3**. 3a) is a ghosted C- spine image 3b) is a combined image of the PI reconstructions from 2 undersampled subsets of the acquired corrupt data.*

Results and Discussion: In simulation studies same data-points were identified as corrupt by both CC and RR. Figure 1 shows images for the simulated swallowing artifact. There were some residual ghosting in CC corrected images (Figure 1b) while ghosting was completely eliminated in the RR method. This is probably because in method CC, synthesized data contains combinations of the corrupted data points. However, discarding of corrupt data in the RR method comes with an SNR penalty.

In the *in vivo* case, there were some differences in corrupt data point identification between the 2 methods. Differences between the synthetic data and acquired data in CC might arise from motion, as well as from multiple other factors such as low coil sensitivity in some regions of the image. In contrast, differences between PI reconstructed copies of undersampled subsets of the corrupt data where the same calibration data is shared between the reconstructions, is more likely to be dominated by motion-induced k-space inconsistencies. This might explain some differences in motion detection between the 2 methods. Figure 2 shows images from an *invivo* spine scan. The original dataset had severe ghosting artifacts (Fig. 2a). RR method (Fig 2c) performed slightly better than CC (Fig. 2b) in reducing ghosting, though there were some residual artifacts in both image sets. On further examination of the datasets, it was found that the reconstruction step of choosing a less motion-impacted calibration in RR had a favorable impact on the reconstructed image quality. Combination of PI images reconstructed from subsets of the original corrupt data, also had much lower ghosting levels (Fig. 3b) compared to the original image (Fig. 3a). Future work will include exploring strategies for optimally combining these subset images to reduce ghosting artifact and associating PI methods with other measures such as signal moment to improve motion detection.

Reference: 1 Pipe JG et al, MRM 42: 963-969, 1999 2. Bydder M et al, MRM 47:677-686, 2002 3. Bydder M et al, MRM 49:493-500, 2003 4. Atkinson D et al, MRM 52: 825-830, 2004 5. Huang F et al, MRM 64: 157-166, 2010 6. Pruessman KP et al, MRM 42:952-962, 1999 7. Samsonov AA et al, MRM 63:1104-1110, 2010 8. Griswold MA et al, MRM 47: 1202-1210, 2002 9. Beatty PJ et al, ISMRM 2007 # 1749