MRI Using Sharable Information Among Images With Different Contrasts: Motion Compensation

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Introduction

Typical clinical MR examinations are composed of several sets of scans to acquire images with different contrasts, such as T1w (T1 weighted), T2w ((T1 weighted)) and proton density weighted imaging. Currently, the acquisition and reconstruction schemes of these images are independent of each other. In this abstract, it is shown that jointly optimizing the reconstructions of all different contrasts can be used for motion compensation. One specific example is presented using the data correlation among channels, which is sharable among images with different contrasts. Preliminary results with in-vivo data sets show that motion correction can be improved by sharing information among scans.

Theory

Conventional motion compensation techniques for rigid motion need to detect motion parameters, such as translation and rotation to correct the acquired data. Detection of these motion parameters requires some kind of navigators [1, 2], oversampling [3], or non-Cartesian trajectory [4]. These methods change the original clinical acquisition scheme. It is preferred that the motion artifacts can be compensated without modifying the routine clinical protocols. A clinical MR examination usually contains several sets of images with different contrasts. These images are scanned in the same system using the same RF coil of the same subject. Hence, there is a significant amount of redundant information among these images. One specific example of shared information is the data correlation among channels, which has been used in non-rigid motion compensation [5]. Fig.1 shows the flowchart of the example. The data correlation among channels is mainly determined by the coil sensitivity maps. Hence, the data correlation should be the same among these images with different contrasts if there is no motion. The shared data correlation can be calculated either using one set of data which is motion free, or acquired by a motion insensitive sequence, or using the average of the data correlation of all data sets. Using the shared data correlation, an extra synthetic data set can be calculated for each image contrast. The data consistency can then be checked to detect the motion corrupted *k*-space data using the *convolution difference* introduced in [5]. The criteria for using synthetic *k*-space data provided in Table 1 of Ref [5] can be used for data rejection. After rejecting the corrupted *k*-space data, the residual *k*-space data could have a random *k*-space coverage along phase encoding (PE) direction. Hence, one obvious choice for final reconstruction is self-calibrated multi-channel compressed sensing [6].

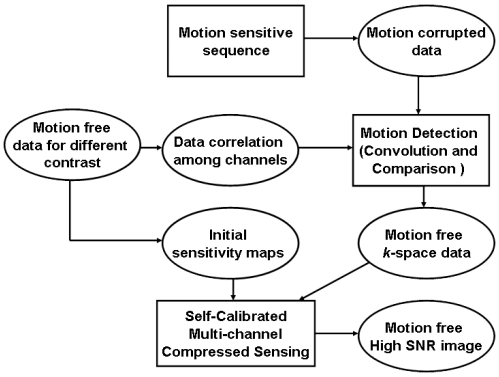

Figure 1. One example of the proposed method

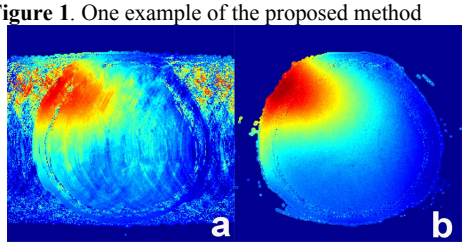

Figure 2. Comparison of self-calibrated sensitivity maps without (a) and with (b) shared information..

Methods As an example, a two-scan examination consisting of T1w and T2w contrasts with a gradient echo sequence was acquired on a Philips 1.5 T Achieva system with an 8-channel head coil. Four sets of axial images were acquired: motion free T1w images (Fig. 3a), motion free T2w images (Fig. 3b), T2w images with shaking head motion (Fig. 3c), and T2w images with nodding head motion (Fig. 3d). The motion free T1w images were used to calculate the data correlation among channels, as well as the initial sensitivity maps for the self-calibrated multi-channel compressed sensing.

Results Fig. 2 compares the sensitivity maps used for final reconstruction with and without shared information. Figs. 4e and 4f are the images after motion compensation using the information shared from the T1w image. For comparison, the results (Figs. 4c and 4d) using self-calibrated data correlation among channels and self-calibrated initial sensitivity maps are also presented.

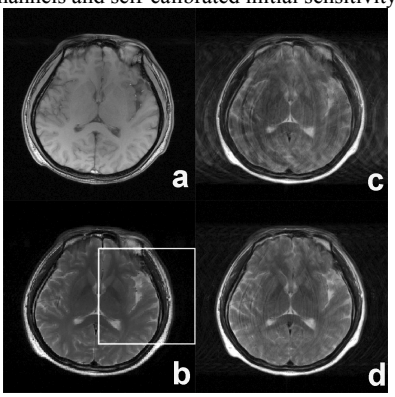

Figure 3. Four sets of acquired images. a) motion free T1w image, which was used to provide data correlation among channels and initial coil sensitivity maps. b) motion free T2w image, the reference image. c) and d) are T2w image corrupted by rotating and nodding respectively.

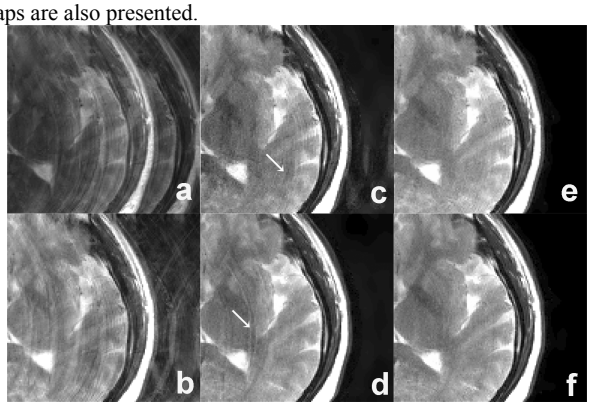

Figure 4. Comparison of images before (a and b) and after motion compensation without (c and d) and with (e and f) shared information among images with different contrasts. a), c), and e) are for rotating (Fig. 3c). b), d) and f) are for nodding (Fig. 3d). For better visibility, a zoomed in region (the white box in Fig. 3b) with brightened intensity is presented.

Discussions and Conclusion

From Fig. 4, it can be seen that using shared information as in the proposed method can dramatically reduce the motion artifact level (Figs 4a and 4e, Figs 4b and 4f) as compared to methods without shared information. There are two reasons for the better results. First, the data correlation among channels is more accurate if it is extracted from a set of motion-free data. The second reason is that a set of artifact free initial sensitivity maps can result in better self-calibrated sensitivity maps (Figs. 2a and 2b) for final reconstruction. This abstract shows the feasibility to use sharable information among images with different contrast for motion compensation. In this example, a set of motion free data was used to provide the shared information to correct for motion in other data sets. The average of data correlation and sensitivity maps from all scans in one exam, which are all potentially motion corrupted, can also be used to provide the shared information for motion compensation. Using this method, the motion artifacts can be compensated without modifying the routine clinical protocols.

References : [1] Kadah, Y.M., et al., MRM, 2004. 51: 403-407 [2] Fu, Z.W., et al., MRM, 1995. 34: 746-753. [3] Pipe, J.G., MRM., 1999. 42: 963 - 969 [4] Schaffter, T., et al., MRM, 1999. 41: 954-963. [5] Huang, F., et. al. MRM 2010;64(1):157-166 [6] Huang F., et. al. ISMRM. 2011; 28