Free-breathing abdominal MRI improved by repeated k-t-subsampling and artifact-minimization (ReKAM)

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(Received 31 May 2017; revised 2 November 2017; accepted for publication 3 November 2017; published 7 December 2017)

Purpose: We report an approach, termed Repeated k-t-subsampling and artifact-minimization (ReKAM), for removing motion artifacts in free-breathing abdominal MRI. The method is particularly valuable for challenging patients who may not hold their breath for a long time or have irregular respiratory rate.

Methods: The ReKAM framework comprises one acquisition module and two reconstruction modules. A fast MRI sequence is used to repeatedly acquire multiple sets of k-t space data. Motion artifacts are then minimized by two reconstruction modules: (a) a bootstrapping module in k-t-space is used to identify a low-artifact image; (b) a constrained reconstruction module that integrates projection onto convex set (POCS) and multiplexed sensitivity encoding (MUSE), termed POCSMUSE, is applied to further remove residual artifact. The ReKAM framework is compatible with different pulse sequences, and generally applicable to irregular data sampling patterns in k-space. Free-breathing fast spin-echo MRI data, acquired from healthy volunteers and patients, were used to evaluate the developed ReKAM method.

Results: Experimental results show that the ReKAM technique can produce high-quality free-breathing images with the artifact levels comparable to that of breath-holding MRI.

Conclusion: The ReKAM framework improves the quality of free-breathing abdominal MRI data, and is compatible with various MRI pulse sequences. © 2017 American Association of Physicists in Medicine [https://doi.org/10.1002/mp.12674]

Key words: free-breathing abdominal imaging, motion artifact correction, multiplexed sensitivity encoding, projection onto convex set

1. INTRODUCTION

Because MRI is highly susceptible to motion-induced artifacts, it has been challenging to generate high-quality MRI data in the presence of patients' continual and unpredicted motion. Therefore, existing abdominal MR imaging protocols largely rely on either breath holding or respiratory gating to reduce motion-related artifacts. However, the respiration-gated acquisition has low scan efficiency, particularly in subjects with irregular respiratory rates. Breath held techniques are more efficient but may not be feasible for seriously ill patients.

Free-breathing MRI is a preferred protocol for abdominal imaging, particularly in challenging patients who may be unable to hold their breath for an extended period of time or who have irregular respiratory rates. Several approaches have been developed to reduce motion-related artifacts in free-breathing abdominal MRI data using information derived from either navigator echoes^{1–3} or the oversampled central k-space data (e.g., PROPELLER).^{4,5} However, it may be difficult to use navigator signals, which are typically of low spatial resolution and provide only unidimensional localization, to effectively remove artifacts resulting from nonlinear motion. To address this concern, a series of methods have been reported recently to better model the nonlinear deformation due to respiration and improve the image quality of free-breathing abdominal MRI.^{6–8} Respiratory-triggered imaging triggers MRI acquisition at a specific respiratory phase, achieving high data consistency for the first slice. However, artifacts may not be removed for other slices when the respiratory frequency changes during scans.¹² Recently, parallel imaging and compressed sensing have been applied to free-breathing imaging.^{13–15} These techniques enable motion artifact reduction of highly accelerated MRI scans, and are particularly valuable for abdominal MRI.

Here, we report an alternative strategy for enhancing the quality of free-breathing abdominal MRI data. The new method, termed Repeated k-t-subsampling and artifact-minimization (ReKAM), is capable of effectively reducing motion-related artifacts during free-breathing abdominal MRI scans without relying on navigator echoes or mathematically modeling the image deformation. The ReKAM method can be generally applied to existing abdominal MRI protocols to obtain various clinically useful image contrasts.

2. MATERIALS AND METHODS

The developed ReKAM method comprises one acquisition and two reconstruction modules. A fast imaging pulse sequence (e.g., echo-planar imaging (EPI), fast spin-echo (FSE) imaging, or gradient-echo and spin-echo imaging (GRASE)⁹) is used to repeatedly acquire multiple sets of k-t-space data regardless of the subject position. After repeated k-t-sampling, artifact-minimization is achieved by subsequently applying two reconstruction modules. First, multiple images are reconstructed from the acquired data using all possible k-t-data grouping patterns (i.e.,

bootstrapping in k-t-space), and the highest quality images corresponding to one or multiple subject positions are identified from all the reconstructed images using an automatic procedure. Second, a constrained reconstruction algorithm that integrates the projection onto convex set (POCS)-based parallel imaging¹⁰ and multiplexed sensitivity encoding (MUSE),¹¹ termed POCSMUSE,¹² is applied to further minimize residual motion-induced aliasing artifacts. Figure 1 schematically illustrates the procedure of eliminating motion artifacts using a 4-shot interleaved MRI pulse sequence (e.g., 4-shot FSE or 4-shot EPI) with a phased array receiving coil as an example. Note that the developed strategy can generally be applied to various pulse sequences with different numbers of echo train length and segments, as described below.

2.A. Acquisition module: repeated k-t-sampling

The representation of the data acquisition module is shown in Fig. 1(a), where the solid and empty circles represent sampled and unsampled ky lines, respectively, and the circles with the same color (e.g., red) correspond to approximately the same subject position while the position changes continually during scans. As illustrated in Fig. 1(b), if the position information corresponding to every time point is known, then k-t-data corresponding to a particular position can be grouped to form an image with little motion artifact [e.g., red k-space data points in Fig. 1(b)].

2.B. Reconstruction module 1: bootstrapping in k-t-space

Practically, the patterns of intrascan motion are unknown and unpredictable. Therefore, in the bootstrapping-based reconstruction module [shown in Fig. 1(c)], a brute-force search strategy is used to identify images with the lowest artifact level using the following steps. First, the acquired k-t-space subsampled data are regrouped using all possible data grouping patterns (i.e., bootstrapping in k-t space), producing a series of candidate images. Second, the background artifact level of each candidate image is measured from a predefined background ROIs with the L2-norm method. The image with the lowest background artifact level can then be identified.

If the number of repetitions (i.e., the number of fully sampled k-space) is large, then in theory the bootstrapping module can group the k-space data corresponding to the identical subject position and produce a high-quality and artifact-free image. However, it is impractical to acquire data with a large number of repetitions during clinical scans. With a moderate number of repetitions (e.g., four repetitions), although the k-t-bootstrapping procedure can identify images with a lower artifact level, some amount of motion-induced aliasing artifact may still be present due to subtle inconsistencies between the segments of k-t-space data. Therefore, in the POCSMUSE module [Fig. 1(d)], a constrained reconstruction algorithm is applied to further reduce these artifacts (see the section on

FIG. 1. A schematic diagram of the ReKAM technique: (a) Multiple k-space datasets are acquired with a fast MRI pulse sequence (e.g., multishot FSE; multishot EPI). (b) Motion-related artifacts can be largely reduced by appropriately regrouping the k-t-space data, but requires knowledge of subject position during each data segment. (c) A bootstrapping procedure in k-t-space can be used to produce images based on all possible combinations of k-t-space data segments, and an image with the lowest motion artifact level can be selected without *a priori* knowledge of subject position. (d) The POCSMUSE constrained reconstruction algorithm is then applied to further reduce residual motion-related artifacts. [Color figure can be viewed at wileyonlinelibrary.com]

Reconstruction module 2). The reconstruction of all images generated by the bootstrapping procedure is time consuming, particularly for large numbers of repetitions. The computation cost can be significantly reduced by performing the bootstrapping reconstruction module on only the central portion of the k-space data (e.g., 64×64 samples). Once the correct k-t-data regrouping pattern is identified, the k-space data of the original matrix size (e.g., 256×256) can be recombined accordingly, and then undergo the subsequent POCSMUSE reconstruction module. Other approaches for reducing the bootstrapping computation cost will be described in the Section 4.

2.C. Reconstruction module 2: POCSMUSE

The POCSMUSE-based constrained reconstruction method¹² can be used to further suppress residual artifacts in images produced by reconstruction module 1 (i.e., k-t-bootstrapping). The POCSMUSE-based constrained reconstruction framework is schematically illustrated in Fig. 2. In short, in the iterative POCSMUSE module, an initial guess image is multiplied with the sensitivity profiles, and projected with the k-space data from the reconstruction module 1. The projected images are complex averaged, and used to update the guess image in the subsequence iterations. The full mathematical description and implementation can be found in the original publication by Chu et al.¹²

This POCSMUSE-based constrained reconstruction¹² has several strengths. First, the POCSMUSE method can be applied to segmented MRI with a number of segments greater than the number of coils. Second, the POCSMUSE framework is generally applicable to irregular data sampling in k-space. Third, the POCSMUSE framework is compatible with most existing imaging pulse sequences.

2.D. Human MRI experiments: healthy subjects

The developed free-breathing ReKAM technique was evaluated with human MRI scans using a 3 Tesla system (MR750, General Electric, Waukesha WI, USA) equipped with an 8-channel receiver coil. Data were acquired from seven volunteers using a FSE sequence with the following parameters: TR = 3750 ms, TE = 100 ms, axial-plane slice thickness = 8 mm, number of slices = 7, 9 or 14, FOV = 40 cm $\times$ 32 cm or 40 cm $\times$ 40 cm, echo train length (ETL) = 16, and in-plane matrix size = 320 $\times$ 206 or 256 $\times$ 256. The numbers of segments were 14 and 16 for the 320 $\times$ 206 and 256 $\times$ 256 datasets, respectively. Note that these segmented FSE k-space data were not regularly sampled. An irregular k-space sampling scheme was chosen by the manufacturer-provided FSE sequence, for achieving both high scan efficiency and optimal point spread function. The Cartesian ky sampling orders for all the FSE segments are shown in Table I, and the k-space trajectories for segments #1 and #2 are schematically illustrated in Fig. 3. We would like to point out that the k-space ordering does not change randomly after choosing a set of scan parameters and hardware configuration on an MRI scanner.

Five repetitions of full k-space free-breathing FSE data were acquired from each volunteer to evaluate the performance of the ReKAM method. The scan time of free-breathing FSE was 262.5 s for five repetitions of 320 $\times$ 206 data, and 300 sec for five repetitions of 256 $\times$ 256 data.

An additional set of FSE data was acquired while the subjects attempted to hold their breath (52.5 s for the 320 $\times$ 206 dataset; 60 s for the 256 $\times$ 256 dataset) as a comparison. While the long scan time for breath-holding sequences was not considered clinically feasible, these

FIG. 2. A schematic diagram of the POCSMUSE reconstruction.

experiments were performed to match the parameters and coverage with the free-breathing scans.

The image reconstruction and analysis are described below:

1. Five sets of free-breathing FSE data were processed with the following procedures. First, the bootstrapping procedure was used to identify an image with the lowest artifact level in background ROIs (indicated by rectangles in Fig. 4). Specifically, we performed the bootstrapping module using (a) the full 256×256 k-space data (long computation time), (b) only the central 64×64 portion of the k-space data (medium computation time), and (c) the full 256×256 k-space data after rejecting 50% of the data time points that obviously corresponded to different respiratory phases based on belly belt-based estimation (low computation time). It should be noted that in option (b) the final images were still reconstructed from the full k-space
2. In each case, the optimal k-t-data regrouping strategy was identified based on the lowest L2 norm of signals in a background ROI, and the full k-space data were recombined accordingly to produce an image with low artifact level. Second, the re-combined k-space dataset underwent the POCSMUSE reconstruction module to further reduce residual artifacts. Specifically, the initial guess of the source image (i.e., in Fig. 2) was a two-dimensional (2D) matrix of all zeros, and the convergence threshold was 0.01.
3. Free-breathing and breath-holding images were reconstructed using a sum-of-square approach from 8-channel coil data.
4. We quantitatively evaluated the performance of ReKAM by measuring the ghost-to-signal ratio (GSR) of uncorrected free-breathing images, breath-

TABLE I. List of the k_y lines obtained from each FSE segment for MRI studies on healthy subjects, corresponding to echo-train length (ETL) of 14 and 16.

Segment index	Ky lines obtained for each segment			
	ETL = 14		ETL = 16	
1	1,8,15,...,78,	197,204	1,9,17,...,97,	233,241,249
2	2,9,16,...,72,	191,198,205	2,10,18,...,98,	234,242,250
3	3,10,17,...,73,	192,199,206	3,11,19,...,99,	235,243,251
4	4,11,18,...,74,	193,200	4,12,20,...,100	236,244,252
5	5,12,19,...,75,	194,201	5,13,21,...,93,	229,237,245,253
6	6,13,20,...,76,	195,202	6,14,22,...,94	230,238,246,254
7	7,14,21,...,77,	196,203	7,15,23,...,95	231,239,247,255
8	—	79,86,93,...,184	8,16,24,...,96	232,240,248,256
9	—	80,87,94,...,185	—	101,109,117,...,221
10	—	81,88,95,...,186	—	102,110,118,...,222
11	—	82,89,96,...,187	—	103,111,119,...,223
12	—	83,90,97,...,188	—	104,112,120,...,224
13	—	84,91,98,...,189	—	105,113,121,...,225
14	—	85,92,99,...,190	—	106,114,122,...,226
15	—	—	—	107,115,123,...,227
16	—	—	—	108,116,124,...,228

FIG. 3. The k-space sampling trajectory for FSE segment #1 and #2 for ky-line acquisition order shown in Table I. The solid lines represent the sampled ky-lines and the dotted lines represent the unsampled ky lines. [Color figure can be viewed at wileyonlinelibrary.com]

holding images, and ReKAM-produced free-breathing images. Specifically, the ghost artifact level was measured from the background ROIs shown in Fig. 4, and the parent signal level was measured from regions with lower intensity variation [indicated by the ROIs selected with red rectangles in Fig. 4(a)]. To further evaluate the effectiveness of the POCSMUSE module in reducing artifacts, the GSR of free-breathing images produced by only k-t bootstrapping module (i.e., without POCSMUSE module) were measured, respectively. We then examined the GSR pairwise by performing a Mann–Whitney U test on the GSR values of the image sets from seven subjects.

5. To quantitatively assess the performance of POCSMUSE in reducing involuntary motion, we applied the POCSMUSE method to breath-holding MRI data, in which the artifacts were mainly resulting from involuntary and nonperiodic motion.
6. The signal-to-noise ratio (SNR) in uncorrected free-breathing images, breath-holding images, and ReKAM-produced free-breathing images were estimated and compared. Specifically, the SNR value was estimated by the ratio of the mean signal intensity to the standard deviation of signals within manually chosen ROIs [indicated by the red rectangles in Fig. 4(a)]. We then examined the SNR pairwise by performing a Mann–Whitney U test on the SNR values of the image sets from seven subjects.
7. To further quantify the SNR penalty directly associated with the POCSMUSE module, the POCSMUSE algorithm was applied to a single breath-holding FSE dataset, and the estimated SNR values in images before and after applying the POCSMUSE algorithm were compared.
8. To assess the diagnostic image quality of ReKAM, a board-certified abdominal radiologist with 12 yr of experience interpreting abdominal MRI reviewed the three sets of images in random order (i.e., uncorrected free-breathing images, breath-holding images, and ReKAM-produced free-breathing images), blinded to reconstruction algorithms. The radiologist assigned a motion artifact score to each image set based on the scale shown in Fig. 8. We then compared motion scores pairwise between reconstruction algorithms using the Mann–Whitney U test.
9. To further investigate the dependence of ReKAM-produced image quality on the number of repeated scans,

FIG. 4. Images of three selected slices acquired from a subject: (a) Uncorrected free-breathing data have significant motion-related artifacts (with $\text{GSR} > 11\%$); (b) Breath-holding data have higher image quality and lower artifact level (with $\text{GSR} < 9\%$); (c): Free-breathing data reconstructed by the ReKAM method have high quality and the lowest artifact level (with $\text{GSR} < 6.5\%$). [Color figure can be viewed at wileyonlinelibrary.com]

we applied the ReKAM reconstruction framework to subsets of the acquired data (i.e., n out of five repetitions; with $2 \leq n \leq 5$). For a fixed number of subsets, we evaluated the ReKAM performance, in terms of the GSR, using all possible combinations. For example, for two repeated scans, we evaluated the ReKAM performance using 10 (i.e., C_2^5) different ways of selecting two of five acquired datasets.

10. The k-t-bootstrapping module was implemented with C++, and the POCSMUSE module was implemented with Matlab. Image reconstruction and data analyses were performed in a Linux computer equipped with an Intel Xeon CPU (2.53 GHz) and 20 GB memory.

2.E. Human MRI experiments: patient subjects

The developed free-breathing ReKAM technique was evaluated with patient MRI scans using a GE Healthcare HDxt 1.5 Tesla system equipped with an 8-channel receiver coil. Four patients were recruited to this study: Patients #1 and #4

had diabetes and liver fibrosis; patients #2 and #3 had pulmonary hypertension and subclinical reduced right heart ejection fraction. Data were acquired using a FSE sequence with the following parameters: $\text{TR} = 3750$ ms, $\text{TE} = 100$ ms, axial-plane slice thickness = 8 mm, number of slices = 14, $\text{FOV} = 40 \text{ cm} \times 40 \text{ cm}$, $\text{ETL} = 16$, and in-plane matrix size = 256×256 . The Cartesian ky line scan orders for all the FSE segments are shown in Table II (chosen automatically by the manufacturer-provided FSE sequence).

Five repetitions of full k-space free-breathing FSE data were acquired from each patient. The total scan time of free-breathing FSE was 300 s for 5 repetitions of 256×256 data. An additional set of breath-holding FSE data was acquired as a comparison. The experiments were performed to match the parameters and coverage with the free-breathing scans, and the scan time was 60 s for a 256×256 dataset. The respiratory signals were recorded from the patients.

The image reconstruction (i.e., the k-t bootstrapping and POCSMUSE methods) was described in the previous subsection on MRI with healthy subjects. Free-breathing and breath-holding images were reconstructed using a sum-of-

TABLE II. List of the k_y lines obtained from each FSE segment for MRI studies with patients.

Segment index	Ky lines obtained for each segment	
	ETL = 16	
1	–	85,93,101,...,205
2	–	86,94,102,...,206
3	–	87,95,103,...,207
4	–	88,96,104,...,208
5	–	89,97,105,...,209
6	–	90,98,106,...,210
7	–	91,99,107,...,211
8	–	92,100,108,...,212
9	5,13,21,...,77,	213,221,229,...,253
10	6,14,22,...,78,	214,222,230,...,254
11	7,15,23,...,79,	215,223,231,...,255
12	8,16,24,...,80,	216,224,232,...,256
13	1,9,17,...,81	217,225,233,...,249
14	2,10,18,...,82	218,226,234,...,250
15	3,11,19,...,83	219,227,235,...,251
16	4,12,20,...,84	220,228,236,...,252

square approach from an 8-channel coil data. The GSR and SNR of images were calculated to assess the performance of the ReKAM method.

2.F. A digital phantom study with extended cardiac-torso (XCAT) phantom

The ReKAM method was also evaluated with an XCAT digital phantom, which had realistic T2-weighted MRI contrast and a tumor.¹⁶ Four-dimensional (4D) volumetric datasets were produced based on breathing patterns (of 55 s) measured from a patient.

The 4-shot 2D FSE k-space data were calculated from the 4D XCAT phantom with the following scan parameters: TR = 3600 ms, TE = 60 ms, number of axial slice = 50, and ETL = 16. Ky line acquisition order shown in Table II was used in this numerical study. A sequential slice acquisition order (with the first slice placed on the superior slice of XCAT phantom) was used in producing realistic simulation data. Images reconstructed with (a) 2D Fourier transform and (b) the ReKAM method were compared (in terms of the artifact level).

3. RESULTS

3.A. Human MRI experiments: healthy subjects

Reconstructed images of three selected slices from one of the healthy subjects (subject 4) are shown in Fig. 4. Free-breathing and breath-holding images reconstructed with the 2D Fourier transform and no artifact correction are shown in Figs. 4(a) and 4(b), respectively. As expected, the free-

breathing images [Fig. 4(a)] are corrupted by motion artifacts. Additionally, although the motion-related artifacts are greatly reduced by breath-holding, the acquired images are still affected by minor residual artifacts [arrows in Fig. 4(b)]. The artifacts likely result from involuntary movement of organs and the subjects' inability to sustain the long breath hold. Figure 4(c) shows high-quality images reconstructed from the acquired free-breathing data (five runs) using the ReKAM technique. The artifact level and anatomic resolvability in ReKAM-produced images are visually comparable to the breath-holding images. We would like to point out that the same k-space regrouping scheme was identified by three bootstrapping approaches (i.e., bootstrapping of 256×256 full k-space data; bootstrapping of 64×64 central k-space data; bootstrapping of 256×256 k-space data after rejecting 50% of irrelevant data). Therefore, the final images reconstructed from these three approaches are identical.

The mean GSR value of all slices in the reconstructed images was measured from each subject. The mean GSR values of (a) uncorrected free-breathing images, (b) breath-holding images, (c) breath-holding images processed with only the POCSMUSE module, (d) free-breathing images processed with only the k-t-bootstrapping module, and (e) ReKAM-reconstructed free-breathing images (i.e., processed with both k-t-bootstrapping and POCSMUSE modules) are shown in Fig. 5. The Mann–Whitney U test shows that ReKAM method was significantly better than free-breathing method (P -value = 0.0050) and breath-holding method (P -value = 0.0104); breath-holding method was not significantly different from free-breathing method (P -value = 0.5222). These data show that the developed ReKAM method can consistently and reliably suppress the artifacts in images, demonstrating the effectiveness of the ReKAM technique.

The experimental results suggest that (a) the POCSMUSE is capable of reducing artifacts that result from involuntary motion, and (b) the residual artifacts in bootstrapping produced images can be further reduced with POCSMUSE.

The estimated SNR values of the reconstructed images were also measured from each subject. The mean SNR values of (a) uncorrected free-breathing images, (b) breath-holding images, and (c) ReKAM-reconstructed free-breathing images shown in Fig. 6. The Mann–Whitney U test shows that ReKAM method was not significantly different from the free-breathing method (P -value = 1) and breath-holding method (P -value = 0.7949); breath-holding method was not significantly different from free-breathing method (P -value = 0.7949). These measures show that ReKAM technique can produce images without significant SNR penalties.

In order to quantify the potential SNR penalty directly associated with the POCSMUSE module, we compared the SNR values in breath-holding images with and without applying the POCSMUSE-based constrained reconstruction. The SNR values are shown in Fig. 7. These data suggest that the POCSMUSE-constrained reconstruction does not introduce significant SNR penalty.

FIG. 5. The mean GSR values of (a) uncorrected free-breathing images (the first bar, shown in blue, for each subject), (b) breath-holding images (the second bar, shown in green, for each subject), (c) breath-holding images produced by the POCSMUSE module (the third bar, shown in orange, for each subject), (d) free-breathing images produced by the k-t-bootstrapping module (the fourth bar, shown in red, for each subject), and (e) free-breathing images produced by ReKAM (the fifth bar, shown in purple, for each subject) for seven healthy subjects. [Color figure can be viewed at wileyonlinelibrary.com]

FIG. 6. The mean SNR values of (a) uncorrected free-breathing images (the first bar, shown in blue, for each subject), (b) breath-holding images (the second bar, shown in green, for each subject), and (c) free-breathing images produced by ReKAM (the third bar, shown in red, for each subject) from seven subjects. [Color figure can be viewed at wileyonlinelibrary.com]

FIG. 7. The mean SNR values of breath-holding images processed without (the first bar, shown in blue, for each subject) and with POCSMUSE (the second bar, shown in green, for each subject) from seven subjects. [Color figure can be viewed at wileyonlinelibrary.com]

In Fig. 8, we report the score of visual assessments of (a) uncorrected free-breathing images, (b) breath-holding images, and (c) ReKAM-reconstructed free-breathing images from a radiologist. The Mann–Whitney U test shows that ReKAM method was significantly better than free-breathing method (P -value = 0.0251); ReKAM method was not significantly different from the breath-holding method (P -value = 0.3077); breath-holding method was not significantly different from free-breathing method (P -value = 0.6101). The results show that the ReKAM method can provide diagnostic image quality comparable to that of

breath-holding methods, and can provide better quality than free-breathing method.

In Fig. 9, we report the dependence of the ReKAM performance (in terms of the GSR in a selected slice) on the number of repeated scans. For FSE imaging with our chosen parameters, a low GSR value can be achieved with four repeated scans, and ReKAM performance does not improve by further increasing the number of repeated scans to 5.

Figure 9 illustrates the ReKAM computational time for three data processing pipelines: (a) applying both k-t-bootstrap and POCSMUSE modules to full 256×256 k-

FIG. 8. The score of visual assessments from a radiologist: (a) uncorrected free-breathing images (the first bar, shown in blue, for each subject), (b) breath-holding images (the second bar, shown in green, for each subject), and (c) free-breathing images produced by ReKAM (the third bar, shown in red, for each subject) from seven subjects. [Color figure can be viewed at wileyonlinelibrary.com]

FIG. 9. The mean and standard deviation of GSR in ReKAM-produced images corresponding to different numbers of data repetition. The computational time of the ReKAM method are reported for (a) bootstrapping based on the full 256×256 k-space data, (b) bootstrapping based on the central 64×64 k-space data, and (c) bootstrapping based on full 256×256 k-space data after rejecting 50% of the data time points.

space data, (b) applying k-t-bootstrapping module to central 64×64 k-space data, followed by POCSMUSE module to full 256×256 k-space data, and c) applying k-t-bootstrapping module to full 256×256 k-space data for 50% of time points (based on belly belt-provided information), followed by POCSMUSE module to full 256×256 k-space data. The reconstruction time can be reduced if the k-t-bootstrapping module is applied to (a) central k-space data instead of full k-space data (e.g., 16.5 min instead of 4.4 h for four repeated scans) and (b) k-space data from 50% time points instead of all time points (e.g., 1.3 s instead of 4.4 h for four repeated scans).

3.B. Human MRI experiments: patient subjects

Data of a selected axial slice from four patient scans are shown in Fig. 10. Free-breathing and breath-holding images (reconstructed with 2D Fourier transform) are shown in Figs. 10(a) and 10(b), respectively. Fig. 10(c) shows ReKAM-produced free-breathing images, which have significantly reduced motion-related artifact as compared with images shown in Figs. 10(a) and 10(b). Figure 11 shows the respiratory signals recorded from patient #1 during the free-breathing acquisition (five runs; 300 s). Other patients also had irregular respiratory patterns (data not shown). The

FIG. 10. Images of a selected axial-slice acquired from four patients: (a) Uncorrected free-breathing data and (b) breath-holding data have significant motion-related artifacts; (c): Free-breathing data reconstructed by the ReKAM method have noticeably reduced artifact.

FIG. 11. The respiratory signals recorded from patient #1 during the free-breathing acquisition period, showing the irregular respiratory patterns. [Color figure can be viewed at wileyonlinelibrary.com]

results show that the ReKAM method can produce high-quality free-breathing MRI data in patients with irregular breathing patterns.

The mean GSR values of the reconstructed images were measured from each patient, as shown in Fig. 12. The Mann–Whitney U test shows that ReKAM-produced data have significantly lower GSR than free-breathing data (P -value = 0.0050) and breath-holding data (P -value = 0.0050).

FIG. 12. The mean GSR values of (a) uncorrected free-breathing images (the first bar, shown in blue, for each patient), (b) breath-holding images (the second bar, shown in green, for each patient), and (c) free-breathing images produced by ReKAM (the third bar, shown in yellow, for each subject) from four patients. [Color figure can be viewed at wileyonlinelibrary.com]

The mean SNR values of the reconstructed images were also measured from patients, as shown in Fig. 13. The Mann–Whitney U test shows that (a) the SNR of ReKAM-produced images is not significantly different from that of free-breathing images (P -value = 1) and breath-holding data (P -value = 0.8101); (b) the SNR of breath-holding data is not significantly different from that of free-breathing data (P -value = 0.7893).

3.C. A digital phantom study with extended cardiac-torso (XCAT) phantom

The XCAT phantom images of a selected slice (that include a tumor) obtained with different reconstruction procedures are shown in Fig. 14. It can be seen that free-breathing data [Fig. 14(a)] are corrupted by motion artifacts. The ReKAM method produces an image [Fig. 14(c)] with its quality comparable to that of the gold standard [Fig. 14(b)]. The mean GSR values of all slices is 0.2132 in uncorrected free-breathing data, and 0.0301 in ReKAM-reconstructed free-breathing images.

4. DISCUSSION AND CONCLUSION

The developed ReKAM method has several strengths. First, since the ReKAM method is compatible with different MRI pulse sequences, requiring no or little sequence modification, it may be used as a core technique to reliably enable abdominal MRI with different clinically required contrasts. Second, the POCSMUSE module included in the ReKAM pipeline is a very general mathematical framework, capable of reconstructing images from k-space data sampled with irregular trajectory. Third, the reported ReKAM method can produce high-quality abdominal MRI data without requiring the subjects to hold their breath or relying on respiratory gating, and is thus expected to be particularly useful for challenging subjects (e.g., seriously ill patients, children). Furthermore, the artifacts resulting from involuntary motion of organs may not be suppressed with either respiratory gating or breath

FIG. 13. The mean SNR values of (a) uncorrected free-breathing images (the first bar, shown in blue, for each patient), (b) breath-holding images (the second bar, shown in green, for each patient), and (c) free-breathing images produced by ReKAM (the third bar, shown in yellow, for each subject) measured from four patients. [Color figure can be viewed at wileyonlinelibrary.com]

FIG. 14. XCAT phantom data of a selected slice: (a) Uncorrected free-breathing data and (b) gold-standard image, and (c) free-breathing image reconstructed by the ReKAM method.

holding [e.g., indicated by an arrow in Fig. 4(b)], and may be better removed with the ReKAM method [e.g., Fig. 4(c)].

As illustrated by our experimental results, respiratory motion-related artifacts can be reduced through k-t-data bootstrapping and POCSMUSE, without relying on navigator echoes or non-MRI measurement (e.g., belly belt). It is worth noting that if the navigator echoes or any non-MRI measurement of respiratory cycles are available, they are compatible with the ReKAM method and can be used to reduce the computational cost of the k-t-data bootstrapping. For example, even with a rough belly belt-based estimation of the respiratory cycles, one may easily exclude 50% of the data (corresponding to different respiratory phases) from the k-t-data bootstrapping, and the computation time for our four-repetition bootstrapping can be reduced from 4.4 h to 1.3 s [Fig. 9]. Alternatively, the ReKAM computation time can also be largely reduced by utilizing parallel computation on multiple CPU or general purpose GPU.

In our bootstrapping module, an image with the lowest background artifact level is identified based on the artifact level in background ROIs [Fig. 1(c)]. This approach works well and reliably for data obtained with the segmented k-space sampling scheme (e.g., multishot segmented EPI; multishot FSE), where the intrascan motion results in ghosting artifacts.

On the other hand, the intrascan subject motion during the sequential k-space sampling scheme, for example, in conventional T1-weighted spoiled gradient recalled (SPGR) imaging, results in blurring artifacts rather than ghosting artifacts. Since the blurring artifacts may not be easily detected with a background ROI-based measurement, such an acquisition could be modified from sequential sampling (e.g., 1, 2, 3... 256) to segmented sampling (e.g., 1, 5, 9... 253, 2, 6, 10...) so that the developed ReKAM framework can be directly applied to free-breathing T1-weighted SPGR imaging.

It is convenient to use the data from each FSE segment as a unit for performing k-t-data regrouping [e.g., Figs. 1(a) and 1(b)]. For example, in our 16-shot FSE imaging studies (Table I), 16 k_y lines acquired in each FSE segment were treated as a unit when performing k-t-data regrouping. However, it is not necessary for the k-t-data regrouping scheme used in Reconstruction Module 1 to match the segmented k-space sampling scheme used in data acquisition. For example, if there is significant intrasegment motion within each FSE segment (e.g., due to very high respiratory rates), one can further decompose those 16 k_y lines acquired in our 16-shot FSE scans into two bootstrapping units (with the 1st to 8th k_y lines as the first unit, and the 9th to 16th k_y lines as the second unit) or even more units when performing the

k-t-bootstrapping, to better suppress motion-related artifacts, at the cost of greater computation time.

Our developed bootstrapping and k-data regrouping procedures are designed to reduce artifacts that result from pseudo-periodic motion of breathing. However, the involuntary and nonperiodic motion may not be effectively addressed with bootstrapping and k-data regrouping. Therefore, the POCS-MUSE method needs to be incorporated to further reduce residual artifacts, which may result from involuntary motion, after the bootstrapping and k-space data regrouping. Our experimental data demonstrate that the developed ReKAM method (including bootstrapping, k-data regrouping and POCSMUSE) can effectively reduce artifacts due to both respiratory motion and involuntary motion.

The ReKAM method neither relies on a specific motion model nor makes an assumption that breathing frequency is constant. Therefore, ReKAM is capable of reducing artifacts in data obtained from patients with irregular breathing patterns (see Figs. 10 and 11). As a postprocessing algorithm, the ReKAM method is expected to be compatible with different pulse sequences and k-space sampling trajectories (e.g., radial-sampling, PROPELLER⁴).

The current study has the following limitations. First, data in different slices of ReKAM-produced images may correspond to different respiratory phases, which may potentially lead to inaccurate volumetric measurement of internal organs or pathology. Second, the data acquisition time of ReKAM protocol is longer than that of breath-holding MRI. Therefore, a direct comparison of ReKAM image quality and breath-holding MRI quality may not be the optimal study design. Third, with our current implementation, the time-consuming ReKAM reconstruction is performed offline and does not immediately provide results.

Although the developed ReKAM method has only been applied to free-breathing abdominal MRI, it should be useful for several other applications. For example, for neuroimaging of Parkinson's patients with continual head tremors, one may acquire a series of sagittal-plane images (where the head tremor is an in-plane pseudo-periodic motion) and then use the ReKAM modules to remove motion-related artifacts.

In conclusion, the ReKAM framework enables high-quality, free-breathing abdominal MRI and is compatible with various MRI pulse sequences. The developed k-t-data bootstrapping and POCSMUSE reconstruction modules can be generally applied to remove motion artifacts in k-space data obtained with different pulse sequences. We expect that the ReKAM technique should prove valuable for clinical imaging of patients who may not hold their breath for an extended period of time or have irregular respiratory rates.

ACKNOWLEDGMENTS

This research is supported by NIH Grant R21 EB018419 (USA), and MOST 104-2221-E-002-209-MY3 (The Ministry of Science and Technology, Taiwan).

CONFLICTS OF INTEREST

Dr. Nan-Kuei Chen has a disclosed financial interest in Duke University that had no involvement in the work reported here. Specifically, the MUSE algorithm (PCT/US2013/048252; US Patent Application No. 13/928,757) invented by Dr. Nan-kuei Chen and owned by Duke University was licensed by Magtron Inc. (Jiangyin, China) and GE Healthcare (Waukesha, USA). The terms of this arrangement have been properly disclosed to the University of Arizona and reviewed by the Institutional Review Committee in accordance with its conflict of interest policies.

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