BIM 241 2020 Fall Quarter

Course Project Report: T2 Shuffling Method

by

Denise Zhong, Henry Mai, Cheng Li

Instructor: Prof. Audrey Fan

12/15/2020

Department of Biomedical Engineering

University of California, Davis

T2 Shuffling Method Overview

Volumetric (three-dimensional [3D]) Fast spin echo (FSE) sequences are a common method for MR imaging due to its flexibility in acquiring multiple image contrasts within a reasonable scan time. However, the long echo trains attributed to FSE scans are subject to image blurring due to T2 decay. There is an inherent tradeoff between scan efficiency and image blurring due to T2 signal decay. Thus, previous works focus on reducing acquisition time through undersampling techniques such as compressed sensing. Additionally, pattern matching methods have been implemented to allow voxel-wise pairing of unknown signals to previously simulated signal evolutions. The T2 shuffling method proposed by Tamir et al. [1] combines compressed sensing techniques using randomized phase encode view ordering in k-space with subspace selection that models T2 decay. This novel acquisition and reconstruction method allows for the recovery of images at multiple T2 contrasts without significant blurring.

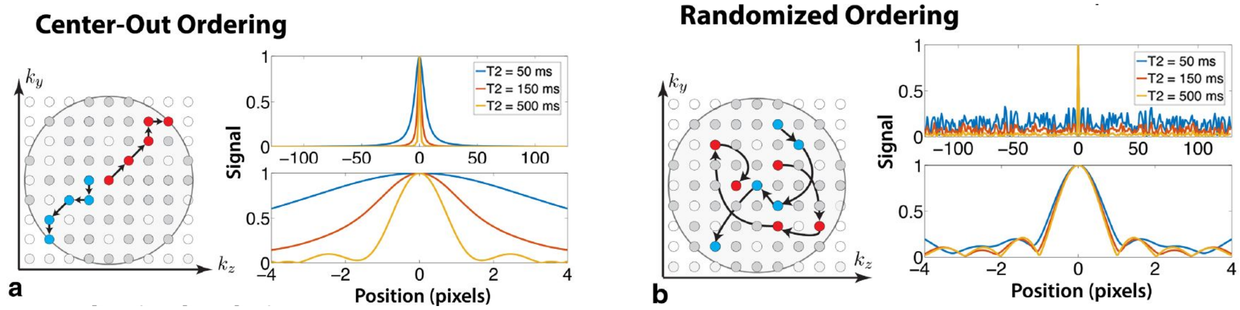
Theoretically, the observed signal is a product of proton density and a time-dependent signal evolution function. For a traditional 3D FSE scan, the time progression is ignored thereby reducing image contrast and contributing to blurring from T2 decay during acquisition. With the T2 shuffling procedure, the temporal aspect is handled by modeling signal evolutions with the Bloch equation and Extended Phase Graph algorithm. There is a low-rank orthonormal temporal basis ϕ suitable for matching the distribution of T1 and T2 parameters in tissue of interest. The basis can be described using $K = 4$ principal components and has been tested to have greater than 99% accuracy when representing the signal evolutions for the examined foot and knee images in the paper. For a traditional FSE scan, variable flip angles are imperative for reducing T2 signal decay and have a significant impact on the signal evolution. The orthonormal basis in the T2 shuffling model accounts for the temporal evolution, and so a specific variable flip angle train is not necessary to accommodate for signal decay. Instead, a particular SNR can be specified to design the flip angle train. Additionally, since each signal will be modeled temporally with this basis, the full evolution can be determined at any echo time. Thus, it is not necessary to acquire a specific TE to quantify the T1 and T2 parameters in the tissue. Hence, the voxels can in fact be represented by a linear subspace to reduce model error and preserve structure.

The signal evolutions for an ensemble of spins can be modeled by the product of the basis and the reconstruction coefficients α. The reconstruction problem then becomes dependent on the computation of α:

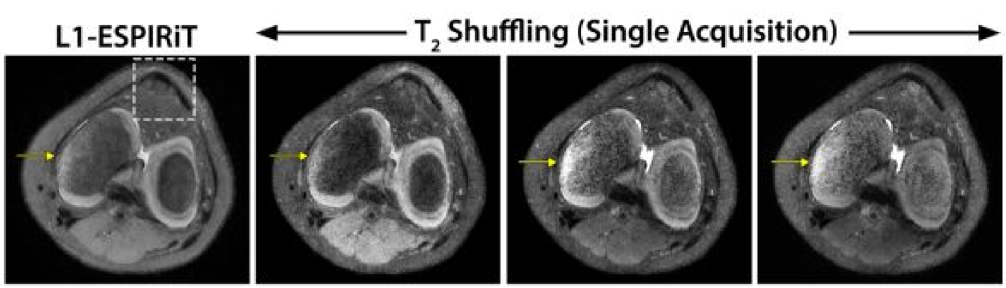
$$\min_{\boldsymbol{\alpha}} \frac{1}{2} ||\mathbf{y} - \mathbf{E}\boldsymbol{\Phi}_K \boldsymbol{\alpha}||_2^2 + \lambda \sum_{\mathbf{r}} ||R_{\mathbf{r}}(\boldsymbol{\alpha})||_*$$

The number of temporal basis coefficients determines the complexity of the optimization problem while the low-rank regularization portion of the function provides dimensional reduction by constraining local voxels to a smaller subspace. The true values in k-t space are represented by y and are determined by point-wise multiplication of coil sensitivity maps across the time series of images followed by a Fourier transformation and subsequent masking of acquired phase encodes.

For radial sampling, a common method of acquiring phase encodes is center-out view ordering. However, this manner of acquisition is ill-posed for the reconstruction problem due to coherent apo from signal decay. The sampling ordering differs from a traditional FSE scan by relying on randomized sampling in k-t space instead of a regular center-out ordering. Typically, low-frequency k-space values are acquired earlier during the echo train while high-frequency samples are acquired at later echo times. Due to the effects of T2 decay, periphery k-space data is largely filtered out resulting in coherent blurring of the image. The normalized point spread function which correlates to blurring has a non-negligible width which becomes increasingly significant for shorter T2 values. In comparison, the T2 shuffling method randomly selects phase encodes across the entire k-space, spreading artifacts incoherently and thereby resulting in a distinct, sharp peak in the point spread function. This corresponds to reduced image blurring even for species with lower T2 values. The cost of reduced blurring is the randomized distribution of incoherence across the reconstruction coefficients.



The T2 shuffling method was tested both on a 2D multi-echo sequence for a sagittal slice of a foot as well as a modified CUBE pulse sequence for a knee. The data was retrospectively undersampled using both center-out and randomly shuffled view ordering. The fully sampled data served as the standard for comparison. While the reconstruction from the center-out ordering had distinct blurring of important image features, the image acquired from randomized ordering remained sharp and retained the same level of quality as the original image. The more detailed structures within the image had been retained in the T2 shuffling method, demonstrating that denoising of potential incoherent artifacts was possible. Additionally, T2 shuffling allows for the recovery of the full time series and can provide different degrees of contrast from the same acquisition as demonstrated from the following in vivo scans of bone marrow edema:



The higher T2 value of the fluid is clearly highlighted in the virtual echo time images. Not only is the image quality preserved with the T2 shuffling method, but microstructures within the tissue are well-defined and can be viable for analyzing pathology in the clinical setting.

While traditional FSE scans must balance between scan time and image quality, T2 shuffling is able to acquire a series of sharp images without this time-resolution tradeoff. The reconstruction from sparse, undersampled data pairs well with the utilization of a low-rank temporal basis to model signal evolutions. Through a combination of compressed sensing, parametric modeling, and randomized masking techniques, T2 shuffling improves 3D FSE scans by simultaneously reducing image blurring while also allowing for the reconstruction of multicontrast images necessary for clinical examination.

Denise's project: Noise vs. bias tradeoff for sparser sampling patterns

This project focuses on modifying the sampling masks applied to an in vivo knee dataset and analyzing the noise vs. bias tradeoff in image reconstruction based on two key factors: the number of temporal coefficients (K) and the low rank regularization hyperparameter (λ). Further sparsity of the sampling masks corresponds to a decrease in number of phase encodes acquired at each echo time, effectively reducing the acquisition time. Thus, the main interest in this project was to determine whether image quality can be preserved with further undersampling of k-space data and what modification to the parameters must be made in comparison to the original data.

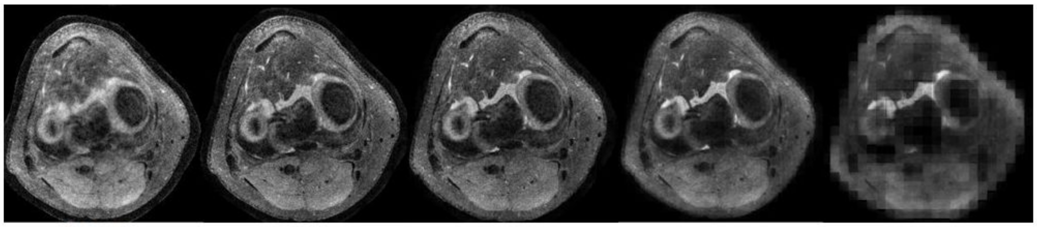
The initial reconstruction model implemented by the demo code contained 80 different randomly sampled masks corresponding to the sampled points in the k-space. Additionally, the reconstruction parameters were originally optimized at K = 4 and λ = 0.04. In order to first explore the tradeoff between bias and noise in the original dataset, I varied the values for one parameter while keeping the other constant and noted the changes to the reconstructed image. To quantify noise and bias, RMSE and SNR were evaluated for each reconstruction simulation. The reconstruction time was also noted to examine the optimization time costs. Without considering regularization by setting λ equal to zero, the following values were recorded:

For λ = 0

K	Model RMSE	Reconstruction time (min)	SNR
2	0.4456	21.70	7.61
3	0.3733	24.50	9.10
4	0.3388	26.42	10.69
5	0.3170	29.52	9.50
6	0.3082	35.28	9.01

As expected, the model error decreased as the number of temporal coefficients increased from 2 to 6. With increased complexity of the temporal basis, the model is able to better fit the original image. However, this may also pose an issue of overfitting as demonstrated by the decrease in SNR. Noise from the original image becomes increasingly amplified with a greater number of temporal coefficients past K = 4. Meanwhile, fewer temporal coefficients may not be sufficient to define the signal evolution and be subject to underfitting. The signal intensity may not be as sharp as before and different tissue types may appear more homogenous. Additionally, optimization of a higher rank matrix resulted in a notable increase to the reconstruction time. While this may not be significant for the reconstruction of a single knee, further attention is necessary when handling a larger dataset.

Then, by setting the number of temporal coefficients constant at K = 4, similar measurements were recorded for a range of different λ regularization values. Since the temporal basis complexity of the optimization remained constant, reconstruction time was not significant when changing the regularization weighting. The effect on image quality is demonstrated below:



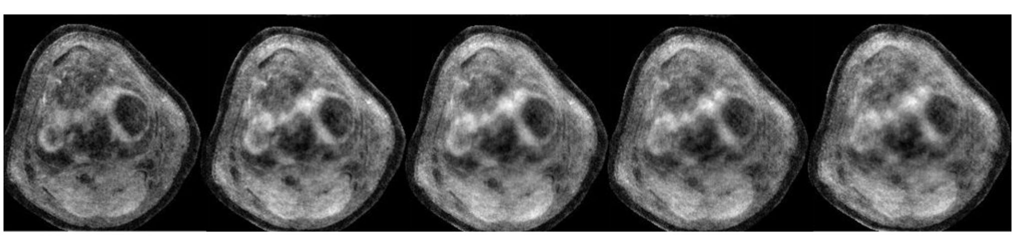
λ = 0 SNR = 10.69 | λ = 0.01 SNR = 11.57 | λ = 0.04 SNR = 12.75 | λ = 0.16 SNR = 13.46 | λ = 0.64 SNR = 11.58

Regularization reduces the complexity of the model by applying a constraint to local voxel groups. Thus, increasing the value of λ subsequently homogenizes the signal intensity values across neighboring voxels. This regularization portion of the reconstruction formula allows for better denoising while keeping the complexity of the temporal subspace. Using the original masks, the model RMSE increases with larger λ values while SNR increases going from $\lambda = 0$ to $\lambda = 0.16$. However, overregularization results in the loss of quality and important image features become increasingly blurred. Thus, a value λ must be selected which balances noise reduction with retention of image quality.

Following the preliminary analysis of K and λ, new masks were generated with increased sampling sparsity. Specifically, the new masks only contained half of the original positions in k-t space sampled while retaining the same manner of randomized T2 shuffling sampling, effectively reducing acquisition time by one half. Using the same parameter values for the original masks, $K = 4$ and $\lambda = 0.04$, results in a less defined reconstructed image compared to the original. With fewer points sampled in k-space, noise becomes further amplified and leads to an overall decrease to SNR. Similar to the original case, regularization was excluded and the effect of K was analyzed between the values of 2 to 6.

For λ = 0

K	Model RMSE	Reconstruction time (min)	SNR
2	1.4311	17.04	7.27
3	1.4001	17.55	7.62
4	1.3838	18.73	8.16
5	1.3748	21.02	7.84
6	1.3700	22.50	7.65



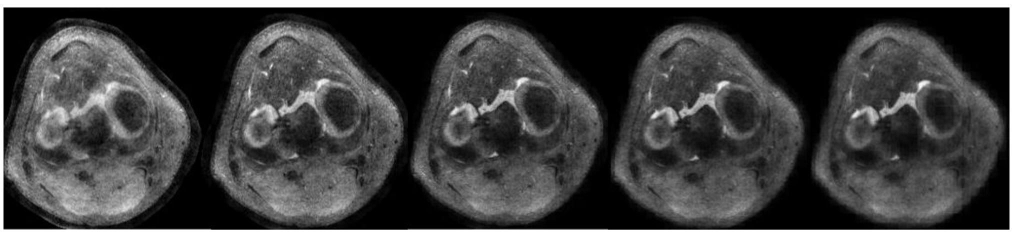
k = 2 | k = 3 | k = 4 | k = 5 | k = 6

While the overall image itself was considerably noisier, it is notable that features within the image remain differentiable despite having been significantly undersampled. As anticipated, the model RMSE is relatively higher since less k-space information is available. The overall SNR is reduced but not by a considerable amount. Many image features are still preserved in the undersampled case. Despite changing the sparsity of the sampling masks, the best number of temporal coefficients to represent the data remains consistent at about K = 4.

Using the most optimized K parameter value, a range of λ values were examined to determine what would result in the best image reconstruction. The results are shown below:

For K = 4

λ	Model RMSE	Reconstruction time (min)	SNR
0.04	1.3935	24.66	12.30
0.08	1.3996	26.80	12.43
0.12	1.4051	27.13	12.20
0.16	1.4112	27.17	11.17
0.20	1.4170	26.79	10.16



λ = 0.04 λ = 0.08 λ = 0.12 λ = 0.16 λ = 0.20

SNR increases significantly with regularization with little change to model RMSE, demonstrating how model complexity can be paired with low rank regularization for improved image quality. Instead of being most optimal at λ = 0.04, the SNR is highest at about double the parameter value at λ = 0.08. While altering the value of K did not improve the image reconstruction, changing the value of λ was significant. This observation is most likely due to the increased apparent noise in the limited k-space acquisition. The weighting of the low rank regularization consequently needs to be increased to accommodate for the noisier dataset.

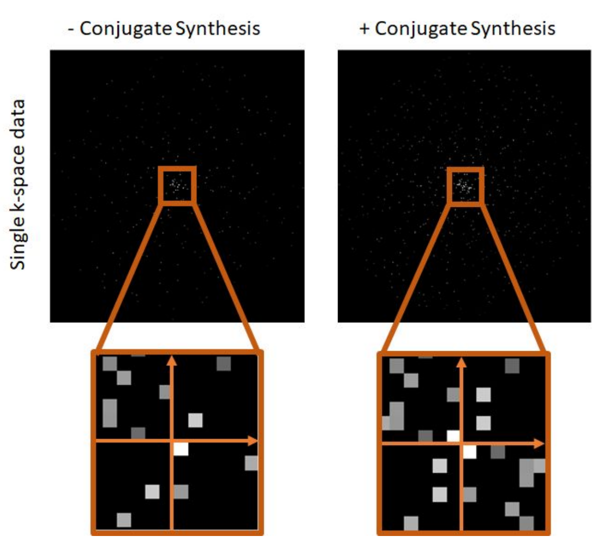
Based on the results from the sparser mask experiment, there is an inherent tradeoff between noise and bias when selecting for the number of temporal basis coefficients and the weighting of the low rank regularization. Increasing the value of K provides improved complexity of the signal evolution model but will also amplify noise in higher order models. To reduce the noise, the value of λ can be increased which forces similarity of signal evolutions between neighboring voxels and reduces model complexity. Overregularization will cause image blurring and loss of defined features. With more limited sampling in k-t space, image reconstructed is best performed with a larger λ but same K value in order to accommodate for amplified noise artifacts. However, due to time constraints, no other sampling masks were tested and number of iterations per ADMM optimization may not have been sufficient for generating the best reconstructed image with each pair of parameters. Additional different sparsity masks and more iterations per optimization should be tested to evaluate this relationship between undersampling and noise/bias tradeoffs.

Henry's project: Change in image quality with conjugate synthesis

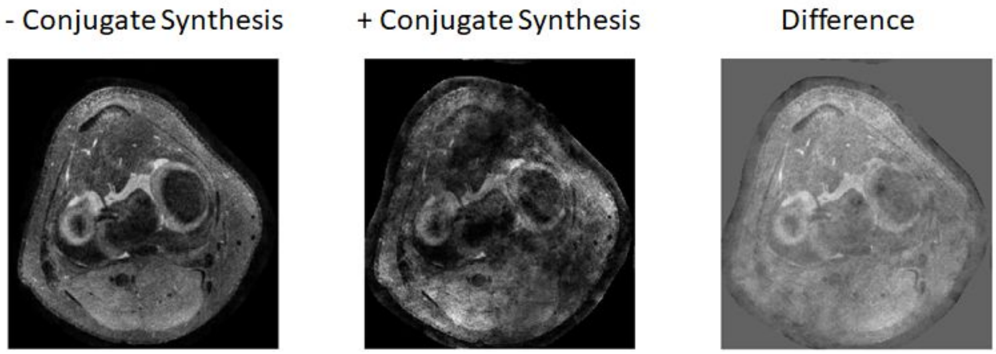
Based on our knowledge about the T2 Shuffling acquisition method, it randomly selects phase encodes across the k-space for every TE over the echo train. This method was then able to reduce blurring with its randomized sampling scheme and shorten the overall scan time. However, the number of phase encodes selected within a single TE is limited due to signal recovery in the longitudinal direction, leading to an inefficient amount of collected samples in k-space. As uncollected data in k-space could cause blurring from reconstruction, it is important to fill in the missing data. Recall from the partial k-space reconstruction methods, it does seem possible to synthesize the missing uncollected data. In this investigation, we will focus on the conjugate synthesis method specifically, and look at how it would contribute to image quality upon reconstruction.

Conjugate synthesis, by definition, synthesizes missing data at corresponding data points by conjugate symmetry. In general, the method requires phase correction before applying conjugate symmetry. However, in the case of data acquisition using the current T2 Shuffling approach where data is randomly spread across k-space, symmetric coverage in k-space has not been achieved for the purpose of phase correction. Therefore, phase correction will be skipped for the scope of this investigation. The potential workaround method to achieve phase correction will be discussed later in the report.

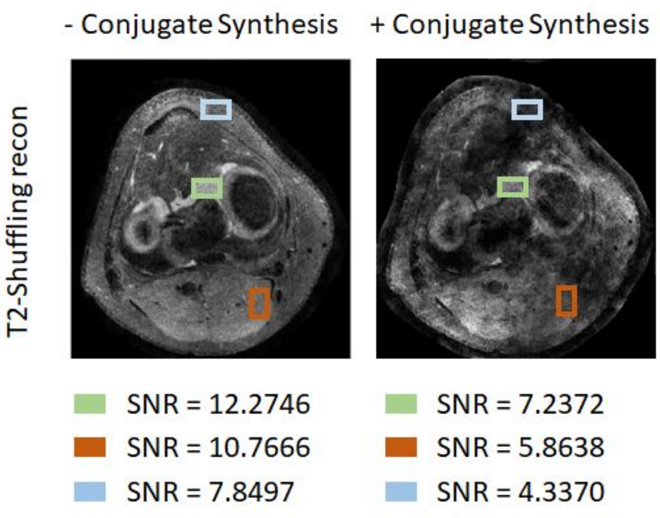
Using the in vivo knee data provided, modifications are made to the k-spaces for each sensitivity coil and at each echo time. Within the 260*240 k-space data matrix, column 120 and 121 are treated as the middle two phase encodes, and $k_x = 0$ is considered not collected. Conjugate symmetry is applied about the origin at ($k_x = 0$, $k_y = 0$). The following figure shows an example of how conjugate synthesis is performed in this investigation. To summarize, if data is missing at one of the two conjugate symmetric locations, data will be synthesized to fill in the missing spot. On the contrary if both conjugate symmetric locations are filled or both locations are missing data, no synthesis will be done at these two specific locations.



In T2 Shuffling reconstruction of the modified data, the sampling masks are also modified using the same conjugate synthesis algorithm. Reconstruction runs at the most optimal K value at K = 4, and at $\lambda = 0.04$ with and without conjugate synthesis. The reconstructed images under comparison are shown below:



The difference image is obtained by subtracting the second image (+ Conjugate Synthesis) from the first image (- Conjugate Synthesis). Overall, Conjugate-Synthesis-Aided reconstruction preserves the structure of the imaged knee, but it does seem to have more noticeable incoherent artifacts and reduction of contrast relative to the surroundings. Despite the increased incoherent artifacts and reduced contrast, the Conjugate-Synthesis-Aided reconstruction generates a much brighter contour at the outermost epithelial layer. The boundary separating body tissue and the external environment becomes more obvious as a result. To better quantify image quality, SNR measurements are collected at different regions of the knee images:



According to the SNR readings, Conjugate-Synthesis-Aided reconstruction in fact has lower SNRs compared to reconstruction in the original work. The significant decrease in SNRs can also be observed from the image as incoherent artifacts.

From the results, it seems that the current conjugate synthesis approach retains structural information and enhances reconstruction at boundaries but trades off contrast and SNR. Possible cause of the artifacts could be skipped phase correction step as mentioned earlier. In order to introduce phase correction to this proposed method in future work, the signal acquisition scheme will need to be altered in a way that the k-spaces have symmetric coverage. Adequate phase correction is expected to remove the unwanted artifacts.

In addition, by taking a closer look at the original k-space data, one may find duplicated data collection at conjugate symmetric locations. In fact, this could negatively affect the performance of the conjugate synthesis approach under a fixed scan time and sampling frequency. One would otherwise synthesize more data in k-space and reconstruct a sharper image by avoiding duplicated collection at conjugate symmetric locations. Potential solution to address the duplication issue is to limit the range of randomized sampling to only two adjacent quadrants in k-space, so that all collected data will be utilized fully to synthesize data for their corresponding conjugate symmetric locations.

Cheng's Investigation: T2 shuffling method with simple motion artifacts

Introduction

Artifacts from the motion of patients could be inevitable if the scan time of MRI is relatively long. Motion artifact is considered as one of the main challenges of MRI acquisition. Based on the compress sensing method with constrained subspace, the T2 shuffling approach is robust to artifacts due to the presence of B1 inhomogeneity, which has been quantitatively discussed in Fig. 5 of the paper by Dr. Tamir. However, motion artifacts could lead to degradation of the reconstruction since it causes model mismatch that makes the temporal subspace fail to model the signal formation. Here I will investigate the T2 shuffling method with several simple motion artifacts during the MR scan. The objective of this investigation is to explore how the motion artifacts affect the results of MR image reconstruction based on T2 shuffling method. To quantify the effects from motion artifacts, structural similarity (SSIM) index and peak signal-to-noise (PSNR) are used to calculate and compare the difference between the reconstructed images and the reference image without motion artifacts.

Method

Simple motion artifacts in real space or image space can lead to linear phase shifts in the k space domain. In other words, the simple motion artifacts can be represented by the phase shifts of the k space data. To simplify the question, we consider such linear phase shifts occur at phase encoding direction of the k space at some moment, and such phase shifts are applied to k space data of all sensitivity coils and each echo train. Here we focus on four types of phase shifts as shown in the following Figure 3-1. Figure 3-1 shows phase shift of the k space data when (a) the motion artifacts occur from the beginning to the middle of the MR scan; (b) the motion artifacts occur from the middle to the end of the MR scan; (c) the motion artifacts occur at the middle of the MR scan and disappear before the end of the MR scan; (d) the repeated motions during the MR scan.

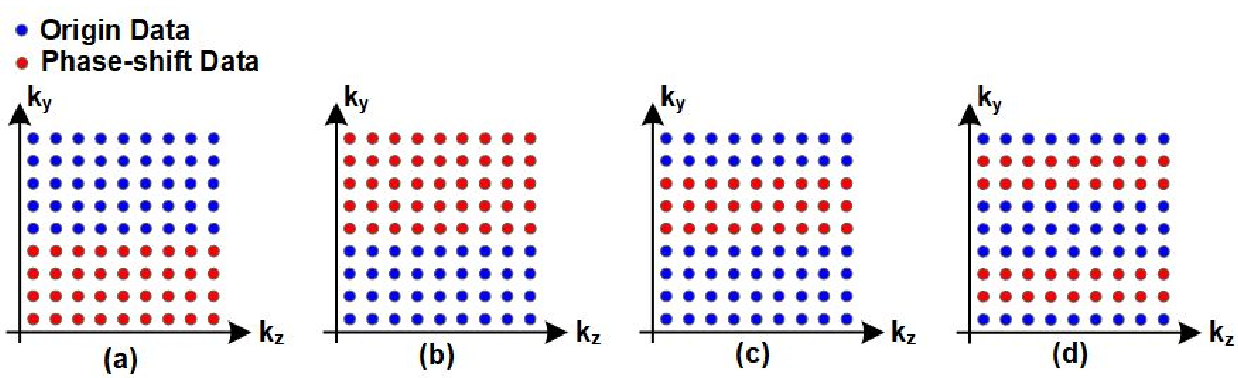


Figure 3-1 Four types of phase shifts in k space data

With consideration of the local image structure, image contrast and luminance, structural similarity index is commonly used as image quality metrics to compare the different images to the reference image. The reference image is generated by using the origin k-space vivo data without any artifacts, and the main reconstruction parameters are set to be λ = 0.04 and K=4. Based on this reference image, the SSIMs of the images with artifacts are calculated to evaluate the effects of the artifact on the T2 Shuffling method. In addition, Peak signal-to-noise ratio (PSNR) is also taken into consideration for the artifact evaluation.

Results and Discussion

First, we start the simulations with different phase shifts applied to the k space vivo data. To simplify the scenario, here we consider the case in Figure 3-1 (a) and the phase shifts are only applied to the first half of the k space data in phase encoding direction. Figure 3-2 shows the simulation results with different phase shifts applied. Table 3-I shows the simulated SSIM and PSNR of different phase shifts applied to the first half of the k space data. As shown in Figure 3-2, small phase shifts (< 30 degree) cause the blurring at the boundary between different tissues. When the phase shift due to the artifact is larger than 90 degree, major features of the image will be lost after reconstruction. The value of SSIM and PSNR also reflects the quality of the reconstructed image.

Table 3-I

Phase shifts / degree	SSIM	PSNR / dB
0	1	Infinity
10	0.7570	39.68
30	0.5861	31.23
60	0.4205	25.59
90	0.3244	22.57
120	0.2719	20.80
150	0.2484	19.83
180	0.2375	19.59

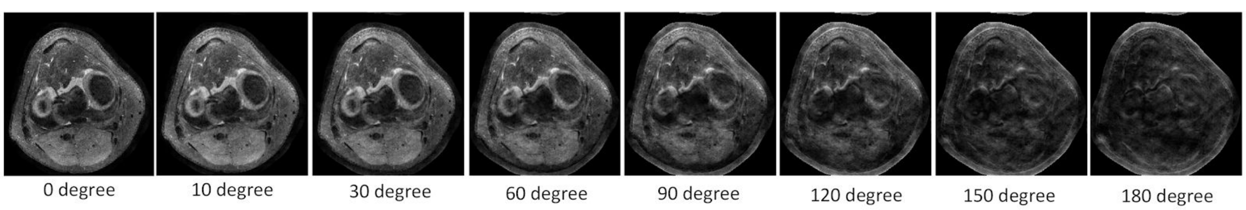


Figure 3-2

Then, to compare the difference between the scenarios of Figure 3-1(a) and Figure 3-1(b), we apply a fixed phase shift of 90 degree to the first half of the k space data (1st to 130th of the phase encoding line, total number of phase encoding line is 260) and the last half of the k space data (131th to 260th of the phase encoding line). The simulation results are shown in the following Figure 3-3. It shows that the reconstruction is more sensitive to the motion artifact during the last half phase encoding of the MR scans, which shows a smaller SSIM and PSNR compared to the other case with same phase shifts.

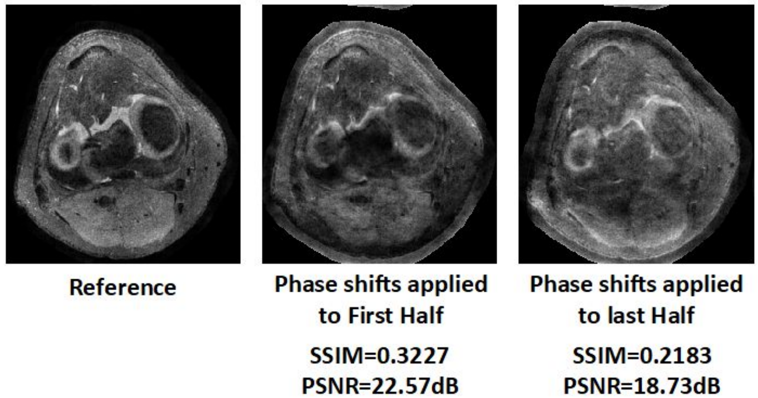


Figure 3-3

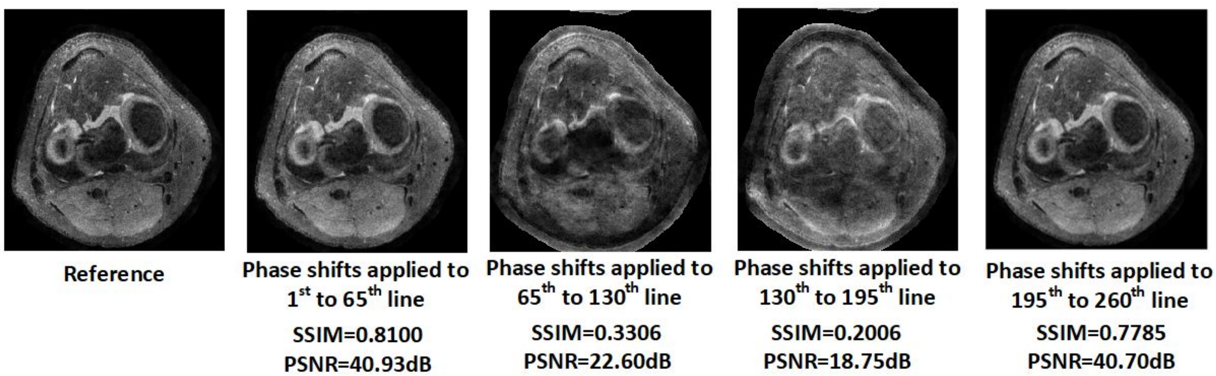


Figure 3-4

In addition, we apply the same phase shifts to different positions of the phase encoding line to simulate the motion artifacts of Figure 3-1(c). The results are shown in Figure 3-4. The reconstrued images with phase shifts applied to the first and last ¼ portion of the phase encoding time have higher SSIM and PSNR value compared with the other cases with phase shifts applied to the middle of MR scan. Hence, the motions at the beginning and last ¼ portion of the phase encoding time cause less blurring effect in the image reconstruction, while the motions at the middle of the phase encoding time lead to large model mismatch and cause significant degradation of the reconstruction.

To consider the scenario in Figure 3-1(d) where motions are repeated by twice during the MR scan, the phase shifts are applied to the two locations of the phase encoding line in k space. Figure 3-5 shows the simulation results with 90 degree phase shift applied from 26th to 78th and 130th to 156th line at the phase encoding direction. To make a comparison, we consider the case where the 90 degree phase shift is applied to the last half of the phase encoding line, since these two cases have the same motion time and include the critical information of the image reconstructure. The simulation shows that the SSIM value of the repeated motion case is smaller than the one motion case, but the PSNR value of the repeated motion case is a little bit higher than one motion case. This suggests that the reconstruction with the repeated motion could lose more image feature and cause more blurring at the edge of different tissue, but introduce the same level noise compared with the one motion case. Due to the time constraint, the effect of artifacts due to other specific patterned or repeated motions are not discussed here but could be explored in the future work.

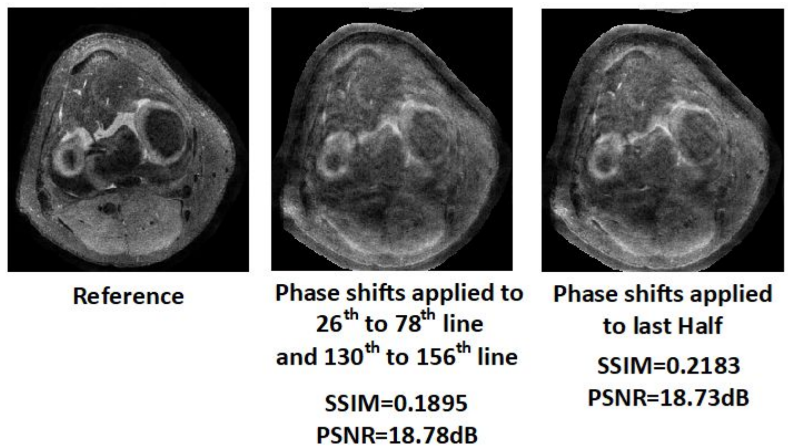


Figure 3-5

The above investigations of the motion artifacts are based on the demo codes of T2 shuffling method from Dr. Tamir. The reconstruction with motion artifacts could be improved if we can generate different bas data and masks that reduce the model mismatch due to the motion artifacts. In reality, motion artifacts could be more complicated and challenging for analysis, which can not be modeled as linear phase shifts. Hence, to reconstruct the image with complicated motion artifacts, extra information such as motion tracking would be needed.

To conclude, this investigation presents the results from T2 shuffling reconstruction with simple motion artifacts. The motion artifacts occurring from the middle to last portion of the phase encoding time could lead to large model mismatch between the temporal subspace and signal formation and thus significantly degrade the reconstruction.

Reference

[1] Tamir, J.I., Uecker, M., Chen, W., Lai, P., Alley, M.T., Vasanawala, S.S. and Lustig, M. (2017), T2 shuffling: Sharp, multicontrast, volumetric fast spin‐echo imaging. Magn. Reson. Med., 77: 180-195.

[2] Mugler JP 3rd. Optimized three-dimensional fast-spin-echo MRI. J Magn Reson Imaging. 2014 Apr;39(4):745-67. doi: 10.1002/jmri.24542. Epub 2014 Jan 8. PMID: 24399498.