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Wavelet-space Correlation Imaging for High-speed MRI without Motion Monitoring or Data Segmentation

Yu Li, Hui Wang, Jean Tkach, David Roach, Jason Woods, and Charles Dumoulin

Abstract

Purpose—This study aims to 1) develop a new high-speed MRI approach by implementing correlation imaging in wavelet-space, and 2) demonstrate the ability of wavelet-space correlation imaging to image human anatomy with involuntary or physiological motion.

Methods—Correlation imaging is a high-speed MRI framework in which image reconstruction relies on quantification of data correlation. The presented work integrates correlation imaging with a wavelet transform technique developed originally in the field of signal and image processing. This provides a new high-speed MRI approach to motion-free data collection without motion monitoring or data segmentation. The new approach, called “wavelet-space correlation imaging”, is investigated in brain imaging with involuntary motion and chest imaging with free-breathing.

Results—Wavelet-space correlation imaging can exceed the speed limit of conventional parallel imaging methods. Using this approach with high acceleration factors (6 for brain MRI, 16 for cardiac MRI and 8 for lung MRI), motion-free images can be generated in static brain MRI with involuntary motion and nonsegmented dynamic cardiac/lung MRI with free-breathing.

Conclusion—Wavelet-space correlation imaging enables high-speed MRI in the presence of involuntary motion or physiological dynamics without motion monitoring or data segmentation.

Keywords

Correlation imaging; Data correlation function; High-speed MRI

Introduction

Magnetic resonance imaging (MRI) is a powerful tool for clinical diagnosis and therapeutic guidance. However, the clinical potential of MRI is challenged by motion (1–8). Artifacts introduced by involuntary patient motion are common when imaging static anatomy. To reduce artifacts, patients are instructed to remain stationary during image acquisition (1). Restraint and/or sedation may also be necessary in the pediatric population (9). Motion can be monitored using external devices, e.g., optical devices/field detectors (10–13), and/or imaging navigators integrated into pulse sequences (6,14–19). With monitoring information, motion may be corrected prospectively and/or retrospectively (1,10,20–26). Motion prevention and monitoring both have limitations. For example, motion prevention is only

partially effective in uncooperative patients (1) and sedation may introduce medical risk (27,28). Motion monitoring techniques typically increase imaging time, introduce additional hardware cost and can be uncomfortable to patients (1,6,8,17,27–29).

MRI has been used to image physiological dynamics such as cardiac and respiratory motion. These applications frequently suffer from low temporal resolution. To overcome this challenge, data segmentation is routinely used for cardiac and pulmonary imaging. This technique segments k-space data into several groups that are collected across different physiological cycles. The segmented k-space data are then sorted to form full k-space data based upon ECG/respiration tracking information or internal navigator sequences (4,6–8,30,31). The drawback of data segmentation is apparent: Non-periodic physiological motion cannot be observed. This reduces the fidelity and reliability of MRI in clinical examination.

It is therefore desirable to perform an MRI scan without motion monitoring or data segmentation. This is particularly required in pediatric imaging since pediatric patients are uncooperative and most strategies suitable for adults (e.g. breath holding) are ineffective. An ideal solution would be to use high-speed MRI techniques that permit data to be collected faster than typical motion. Currently, there exist four types of high-speed imaging techniques: partial Fourier imaging, parallel imaging, compressed sensing and data sharing methods. Partial Fourier imaging provides an acceleration factor of ~ 2 by reconstructing images from approximately half k-space (32,33). Parallel imaging uses multi-channel coil sensitivity to reconstruct images from undersampled data (34–37). Compressed sensing relies on data sparsity and non-uniform sampling (38–40). Data-sharing methods can accelerate dynamic imaging by sharing static information along time (41–53). In clinical MRI, two parallel imaging techniques, SENSE (35) and GRAPPA (36) are primarily used. They have successfully transformed clinical MRI by providing an acceleration factor > 2 for many applications. In dynamic imaging, SENSE and GRAPPA can be implemented synergistically with data sharing methods. Two clinical standards are k-t SENSE/BLAST (54,55) and k-t GRAPPA (56).

Because clinical MRI relies on conventional parallel MRI techniques (SENSE and GRAPPA), its speed is limited by the inherent signal to noise ratio (SNR) and the coil sensitivity encoding ability (35,57), which are both related to the physical configuration of a coil array. With this limitation, static MRI cannot use an acceleration factor higher than the number of coil elements in the phase-encoding direction (35). As a result, motion-free images cannot be generated in the event of involuntary movement. In dynamic imaging, k-t SENSE/BLAST or k-t GRAPPA may be run beyond the coil-number limitation because of data sharing (54,56). However, they are not sufficient for imaging fast physiological motion without data segmentation, e.g., cardiac imaging that requires a data collection rate of < 100 milliseconds per time frame. Recently, several new techniques have been developed. By controlling aliasing patterns, CAIPIRINHA (58,59) and acceleration apportionment (60) can overcome the coil-number limitation in multi-slice 2D or 3D imaging. In addition, a few non-linear image reconstruction algorithms have been used to image physiological motion in real-time or free breathing (20,61–63). These efforts have shown the potential to overcome the current motion challenge using high-speed imaging techniques.

The work presented herein is a technical effort to seek a new high-speed MRI approach that offers the potential to image static and dynamic anatomy without motion monitoring or data segmentation. It is expected that this approach will meet the following two clinical needs: First, the implementation complexity should be affordable for clinical translation. For simplicity, a linear image reconstruction algorithm with a uniform undersampling trajectory will be used. Second, the developed technique should offer the potential for real-time dynamic imaging that can provide immediate feedback during clinical examination. This implies that k-t SENSE and several compressed sensing techniques cannot be used because they need all the collected time frames for image reconstruction (20,54,62,64). For this reason, a k-t space image reconstruction algorithm is used.

The presented approach uses the framework of correlation imaging developed in our previous work (65). Correlation imaging is based on parallel imaging and may be implemented in k- or image-space. Its basic k-space implementation estimates missing data samples directly from collected samples. In contrast to other k-space methods such as GRAPPA and SPIRiT that implicitly use data correlation to make this estimate, correlation imaging explicitly estimates correlation functions that can be used to resolve reconstruction operators. This introduces a direct relationship between MRI speed and k-space data correlation, providing an approach to accelerating MRI by improving the quantification and the utilization of correlation functions. Herein, we introduce a wavelet transform technique developed originally in the field of signal and image processing. By implementing correlation imaging in wavelet space, more information can be translated into image reconstruction through the estimation and utilization of correlation functions than with conventional techniques. This gives an imaging speed gain that offers the potential to overcome the motion challenge in clinical MRI.

Methods

Review of Correlation Imaging

Correlation imaging (65) requires the estimation of correlation functions. A correlation function between two data acquisition channels is defined as:

$$c_{ij}(\mathbf{k}) = \text{mean} \left\{ d_i(\mathbf{k}') d_j^*(\mathbf{k}' + \mathbf{k}) \right\}_{\text{over } \mathbf{k}'}, \quad (1)$$

where i and j are channel indexes ranged from 1 to N , $\mathbf{k}$ and $\mathbf{k}'$ are multi-dimensional k-space or k-t space position vectors, and $\{d_i(\mathbf{k}), i=1, 2, \dots, N\}$ represents N -channel imaging data with full Fourier encoding. The previous work (65) demonstrates that image reconstruction operators for accelerated MRI with uniform undersampling satisfy the following linear equations:

$$R \sum_{i=1}^N \sum_{\mathbf{k}'=-\mathbf{L}}^{\mathbf{L}} c_{ij}(\mathbf{k}' - \mathbf{k}) t_s(\mathbf{k}' - \mathbf{k}) u_i(\mathbf{k}') = c_{mj}(-\mathbf{k}) \text{ for } j=1, 2, \dots, N \text{ and } -\mathbf{L} < \mathbf{k} < \mathbf{L}, \quad (2)$$

where R is the reduction or undersampling factor in MRI acceleration, $t_s(\mathbf{k})$ is the undersampling trajectory, $\{u_i(\mathbf{k}), i=1, 2, \dots, N\}$ represents a set of linear reconstruction

operators for a channel m ($m=1, \dots, 2, \dots, N$) and these reconstruction operators are finite-length filters that have a size of $2\mathbf{L}+1$. Accordingly, if correlation functions can be estimated from fully-sampled center $\mathbf{k}$ -space data, i.e., auto-calibration signals (ACS), a set of reconstruction operators may be resolved. An estimate of fully-sampled data for channel m is then given by:

$$\hat{d}_m(k) = \sum_{i=1}^N \sum_{\mathbf{k}'=-\mathbf{L}}^{\mathbf{L}} a_i(\mathbf{k}-\mathbf{k}') u_i(\mathbf{k}'), \quad (3)$$

where $\{a_i(\mathbf{k}), i=1, 2, \dots, N\}$ represents uniformly undersampled N -channel data.

Wavelet-space correlation imaging

The present work enhances correlation imaging by introducing a wavelet transform technique that has been widely used in the field of signal and image processing (66). The new approach is called “wavelet-space correlation imaging”. This approach includes three steps (Figure 1): 1) Wavelet transform of ACS and undersampled data, 2) Image reconstruction of the wavelet transform of fully-sampled data using correlation imaging, and 3) Inverse wavelet transform of the reconstructed wavelet-space data. Here the wavelet transform uses a set of wavelet decomposition filters to decompose the original data into multiple sets of wavelet-space data. The inverse wavelet transform is performed by passing the reconstructed wavelet-space data through a set of wavelet reconstruction filters and then summing them together. Since wavelet decomposition and reconstruction are lossless, the overall performance of image reconstruction is dependent solely on correlation imaging in wavelet-space.

In wavelet-space, correlation imaging is performed multiple times. Each wavelet-space correlation imaging aims to reconstruct a set of data resulting from filtering the fully-sampled data with a decomposition filter using the wavelet-space data generated by the same decomposition filter in wavelet transform. The wavelet-spaced data generated from ACS are used to estimate correlation functions and those from undersampled data are for reconstruction. Following the same procedure as in the previous work (65), the following equations may be generated for resolving the reconstruction operators $\{u_j^n(\mathbf{k}) j=1, 2, \dots, N\}$ associated with a wavelet decomposition filter $w_n(\mathbf{k})$:

$$R \sum_{i=1}^N \sum_{\mathbf{k}'=-\mathbf{L}}^{\mathbf{L}} \sum_{\mathbf{k}''=-(2\mathbf{L}'+1)}^{2\mathbf{L}'+1} c_{ij}(\mathbf{k}-\mathbf{k}'-\mathbf{k}'') t_s(\mathbf{k}-\mathbf{k}'-\mathbf{k}'') c_{w_n}(\mathbf{k}'') u_i^n(\mathbf{k}') = \sum_{\mathbf{k}'=-(2\mathbf{L}'+1)}^{2\mathbf{L}'+1} c_{mj}(\mathbf{k}-\mathbf{k}') c_{w_n}(\mathbf{k}'), \quad (4)$$

where

$$c_{w_n}(\mathbf{k}) = \frac{1}{2\mathbf{L}'+1} \sum_{\mathbf{k}'=-\mathbf{L}'}^{\mathbf{L}'} w_n(\mathbf{k}') w_n^*(\mathbf{k}'+\mathbf{k}), \text{ for } n=1, 2, \dots, M; \mathbf{k}=-(2\mathbf{L}'+1), -2\mathbf{L}', \dots, 2\mathbf{L}', 2\mathbf{L}'+1 \quad (5)$$

are correlation functions of wavelet decomposition filters, M is the total number of decomposition filters, $2\mathbf{L}+1$ is the size of reconstruction operators (finite-length filters) and

$2L'+1$ is the size of wavelet decomposition filters. An estimate of the data $\hat{d}_m^n(\mathbf{k})$ resulting from filtering the fully-sampled data with $w_n(\mathbf{k})$ is given by:

$$\hat{d}_m^n(k) = \sum_{i=1}^N \sum_{\mathbf{k}'=-L}^L \sum_{\mathbf{k}''=-L'}^{L'} a_i(\mathbf{k}-\mathbf{k}'-\mathbf{k}'') w_n(\mathbf{k}'') u_i^n(\mathbf{k}'). \quad (6)$$

The inverse wavelet transform of $\{\hat{d}_m^n(\mathbf{k}), n=1,2,\dots,M\}$ gives the final reconstruction of $\hat{d}_m(\mathbf{k})$ for channel m . In wavelet transform, decomposition filters are band-limited (66), i.e., every filter passes signals within a part of FOV. This FOV reduction will bring several benefits as shown below.

Role of wavelet transform in the estimation of correlation functions from ACS

Correlation imaging requires the estimation of correlation functions of the target data to be reconstructed. In this work, our target is the outer k-space data as center k-space can be known from ACS. In basic correlation imaging (65), correlation functions are estimated directly from center k-space (ACS). An experimental finding is that correlation functions calculated from center k-space using Eq. (1) are different than those from outer k-space. As a result, the previous work (65) cannot give a good approximate to the correlation functions of outer k-space. This estimation bias was found to be a limiting factor in basic correlation imaging. In the presented work, correlation functions are estimated from the wavelet transform of ACS. It is found that the difference of wavelet-space correlation functions calculated from center and outer k-space is smaller than that of k-space correlation functions. This can be understood as follows.

Mathematically, correlation functions provide the coefficients for Eq. (2) in basic correlation imaging. An estimation bias may introduce errors in matrix operation for resolving reconstruction operators. Similarly in wavelet-space correlation imaging, wavelet-space correlation functions provide the coefficients for Eq. (4). These coefficients (wavelet-space correlation functions) are:

$$[c_{ij}(\mathbf{k})]_{\text{wavelet}} = \sum_{\mathbf{k}'=-(2L'+1)}^{2L'+1} [c_{ij}(\mathbf{k}-\mathbf{k}')]_{\text{k-space}} c_{w_n}(\mathbf{k}'), \quad (7)$$

where $[c_{ij}(\mathbf{k})]_{\text{k-space}}$ is either a k-space correlation function (right side of Eq. 2) or an undersampled k-space correlation function (left side of Eq. 2), i.e.,

$$[c_{ij}(\mathbf{k})]_{\text{k-space}} = c_{ij}(\mathbf{k}) \quad \text{or} \quad [c_{ij}(\mathbf{k})]_{\text{k-space}} = c_{ij}(\mathbf{k}) t_s(\mathbf{k}). \quad (8)$$

If a wavelet-space correlation function is calculated from center k-space (i.e., ACS), its difference from the ideal one (calculated from outer k-space) is given by:

$$\left[c_{ij}^{ACS}(\mathbf{k}) - c_{ij}^{\text{outer k-space}}(\mathbf{k}) \right]_{\text{wavelet}} = \sum_{\mathbf{k}' = -(2L'+1)}^{2L'+1} \left[c_{ij}^{ACS}(\mathbf{k}-\mathbf{k}') - c_{ij}^{\text{outer k-space}}(\mathbf{k}-\mathbf{k}') \right]_{\text{k-space}} c_{wn}(\mathbf{k}'). \quad (9)$$

In image-space, this convolution becomes the multiplication of the difference of k-space correlation functions and the power spectrum of the decomposition filter. Since wavelet-decomposition filters are FOV-limited, i.e., each have a power of 1 in a part of FOV and ~ 0 in the other regions, Eq. (9) implies that the wavelet transform may reduce the difference of correlation functions calculated from ACS and outer k-space. This reduction is statistically meaningful as the correlation function is defined in the sense of mean (Eq. 1). Therefore, we expect that the estimation bias of correlation functions be smaller in wavelet-space than in k-space. This will improve image reconstruction in correlation imaging.

It should be noted that what we expect from wavelet transform is not a reduction in the difference of $c_{ij}^{ACS}(\mathbf{k})$ and $c_{ij}^{\text{outer k-space}}(\mathbf{k})$ over all $\mathbf{k}$ values. Typically, correlation imaging reconstruction operators are finite-length filters that have a small size (The presented work empirically uses $L = 2$). This implies that only the correlation functions for small $|\mathbf{k}|$ values, i.e., in the proximity of the k-space origin, play roles in the formation of Eq. (4). Therefore it is sufficient if the wavelet transform can reduce the bias in the estimation of correlation functions for small $|\mathbf{k}|$ values. Figure 2 illustrates an example that gives the calculated correlation functions in the proximity of the k-space origin using 1D data generated from a digital Shepp-Logan phantom. As shown in Figure 2(c), the correlation functions calculated from ACS are closer to those from outer k-space data in wavelet-space than in k-space. This improvement can be more clearly seen from the calculated differences of correlation functions in Figure 2(d).

Role of wavelet transform in the reconstruction of missing data

Image reconstruction in k-space relies on data correlation between different sampling positions. Figure 3(a) illustrates how data correlation is utilized differently in k- and wavelet-space. Like GRAPPA, our previous work performs image reconstruction by the convolution of reconstruction operators with undersampled k-space data (Figure 3a, left side). This reconstruction utilizes data correlation only between missing and collected samples (solid-line arrows, left side in Figure 3a) because missing samples make no contribution to the convolution. If the undersampling factor increases, missing samples may be positioned further away from those collected ones. Due to decreased data correlation with distance, image reconstruction quality may be reduced. Typically, this manifests as an increase of noise amplification with the undersampling factor.

In the presented work, wavelet-space reconstruction (Eq. 6) is performed by the convolution of reconstruction operators with the wavelet transform of undersampled k-space data (Figure 3a, right side). Since FOV reduction may introduce k-space data correlation, the convolution of undersampled data with a decomposition filter can introduce data filling at the sampling positions where data are missing. This allows for the utilization of data correlation between nearest sampling positions in reconstruction (solid-line arrows, right side in Figure 3a).

Since wavelet decomposition and reconstruction filters are designed with a power gain of 1, noise amplification in image reconstruction is dependent on wavelet-space reconstruction operators generated from data correlation. The use of data correlation between nearest neighbors gives a noise amplification level close to that of k-space reconstruction with a low undersampling factor. Therefore, we expect to achieve a reduction in noise amplification over our previous work when a high undersampling factor (>4) is used.

Figure 3(b) illustrates the noise reduction we should expect from wavelet transform using a Shepp-Logan phantom image in Figure 2(a). The reconstruction operators are calculated from a set of simulated 8-channel images. It can be seen that wavelet-space correlation imaging with a high undersampling factor (>4) generates noise amplification comparable to that of k-space correlation imaging with a low undersampling factor (<4).

In vivo MRI experiments

Human imaging data were acquired from a Philips Achieva 3.0 Tesla MRI scanner in compliance with the regulations of the institution's human ethics committee. To investigate whether wavelet-space correlation imaging provides a sufficient speed for motion-free imaging, the following studies were conducted:

1) Simulation using fully-sampled imaging data—Axial brain images were collected with full Fourier encoding using an 8-channel head coil array and a T1-weighted 2D gradient-echo pulse sequence (FOV=230×230 mm, matrix=232×232, phase-encoding direction=anterior-posterior, TR/TE=136/4 ms, flip angle=30°, number of slices=16, slice thickness=4 mm, slice gap=0 mm). Imaging acceleration was simulated by manual undersampling. The reference images were reconstructed from fully-sampled data. GRAPPA, SENSE, basic correlation imaging, and SPIRiT (35–37,65) were used as reference approaches. Wavelet-space correlation imaging was investigated without and with simulated motion.

2) In vivo brain imaging with involuntary motion—A brain imaging experiment was conducted using an 8-channel head coil array and a multi-slice T1 enhanced ultrafast gradient-echo sequence (FOV=240×240 mm, matrix=240×240, TR/TE=9.5/4.6 ms, TFE factor=60, phase-encoding direction=anterior-posterior, number of slices=16, slice thickness=4 mm, slice gap=0 mm, flip angle=8°, number of averages=1). The subject was instructed to nod the head once every ~2 seconds during the scan. Three sets of data were acquired sequentially with different undersampling factors. These undersampling factors were adjusted such that the data acquisition rate increases by a factor of ~2 with the scan number. The first was fully sampled with a data acquisition rate of ~2.3 seconds per slice. The second was undersampled by a factor of 2 with a data acquisition rate of ~1.3 seconds per slice. The third was undersampled by a factor of 6 with a data acquisition rate of ~570 milliseconds per slice. The second and the third sets of data include 24 ACS lines. Wavelet-space correlation imaging was compared with GRAPPA, SENSE, basic correlation imaging and SPIRiT (35–37,65).

3). In vivo free-breathing cardiac imaging—A cardiac imaging experiment was conducted using a 32-channel cardiac coil array. Segmented breath-holding cardiac CINE data were collected for references using a single-slice 2D ECG-gated bSSFP sequence (FOV=320×320 mm, matrix=160×160, TR/TE=2.3/1.2 ms, TFE factor=20, flip angle=30°, scan time=8 s, number of cardiac phases=30). The ECG signal was used to resort segmented k-space data. Free-breathing cardiac CINE data were collected without ECG or respiration monitoring using a single-slice 2D bSSFP sequence (FOV=320×320 mm, matrix=160×160, TR/TE=2.1/1.1 ms, flip angle=25°, acceleration factor=16, number of ACS lines=7, scan time=2 s), resulting in an acquisition rate of 37 milliseconds per time frame (~30 phases per cardiac cycle). Wavelet-space correlation imaging was compared with k-t SENSE, k-t GRAPPA and basic correlation imaging (54,56,65).

4). In vivo free-breathing pulmonary imaging—A lung imaging experiment was conducted using a 32-channel cardiac coil array. Coronal imaging data were collected using an ultrafast gradient-echo sequence (FOV=480×376 mm, matrix=240×184, TR/TE=2.4/1.2 ms, flip angle=10°, phase-encoding direction=left-right). The same sequence was run twice. In the first run, static images were collected at functional residual capacity (FRC) and FRC +tidal volume during breath hold. These images were used as references. In the second run, ~20 second long dynamic imaging data were collected at a rate of 96 milliseconds per time frame during free-breathing. This acquisition used 9 ACS lines and an acceleration factor of 8. Wavelet-space correlation imaging was compared with k-t SENSE and k-t GRAPPA and basic correlation imaging (54,56,65).

Algorithm implementation and performance characterization

Image reconstruction was performed in k-space or k-t space. Algorithms, including wavelet filter generation, matrix inverse and circular convolution, were implemented in MATLAB® (MathWorks Inc., Natick, MA). In static imaging, 1D wavelet transform (8 decomposition filters) was applied in the phase-encoding direction. In dynamic imaging, 2D wavelet transform (2×8 decomposition filters) was applied in the phase-encoding and time directions. Wavelet decomposition and reconstruction filters were generated from Daubechies wavelet of order 8 (66). In imaging acceleration, a reduction factor R is defined as the undersampling factor used in outer k-space. The actual imaging acceleration rate is lower than R because ACS data are collected. The reconstruction performance was characterized using an error image defined as the difference image between the reconstructed and reference images. Quantitative evaluation was given by the RSS error defined as the square Root of the Sum of Squares (RSS) of the error image. In the presented results, this error is normalized with respect to the reference image, i.e., the RSS error gives the ratio of the RSS of the error image to that of the reference image in percentage.

Results

Simulation using fully-sampled imaging data

Wavelet-space correlation imaging was investigated in the context of SENSE, GRAPPA, basic correlation imaging and SPIRiT (Figure 4). A series of undersampling factors ranging from 2 to 12 were used with 12, 24 and 48 ACS lines. Figure 4(a) shows how RSS errors

increase with the undersampling factor R in different approaches. From these plots, a critical undersampling factor ($R=4$) can be seen in GRAPPA, SENSE and basic correlation imaging: The RSS errors increase significantly (~ 2 times) faster with R when $R>4$ than those when $R \leq 4$. In comparison, SPIRiT and wavelet-space correlation imaging give lower RSS errors. They increase with the undersampling factor in a consistently linear fashion. No critical undersampling factor can be found. From the reconstructed images shown in Figure 4(b), SPIRiT and wavelet-space correlation imaging give lower noise and artifacts than the other approaches. This difference is more significant when $R>4$ than that when $R \leq 4$.

Wavelet-space correlation imaging was also investigated by introducing simulated motion. The simulation assumed that data acquisition within every TR experienced a translational movement at a constant speed and in a direction that varied randomly from TR to TR. Motion-corrupted data were generated by multiplying every phase-encoding line with a motion-induced phase shift. We simulated 4 different motion speeds: 0.01 voxels/TR, 0.015 voxels/TR, 0.02 voxels/TR and 0.025 voxels/TR. Figure 5(a) shows the RSS error plots using 12, 24 and 48 ACS lines. It can be seen that RSS errors first decrease and then increase with the undersampling factor. The descending phase indicates that data acquisition is slower than motion (low undersampling). Since motion-related errors dominate reconstruction, imaging acceleration may improve image quality. Once data acquisition is faster than motion, undersampling dominates reconstruction performance and the error plots show the same ascending pattern as those without motion (Figure 4a). By examining every reconstructed image, we found that image quality can be degraded either by motion ghosting (Figure 5b, left) or by noise and aliasing (Figure 5b middle). It was also found that the simulated experiments with acceptable image quality (Figure 5b right) are located in a specific region of Figure 5(a) (marked as Region A). These experiments in Region A have a motion-induced displacement (motion speed $\times$ number of TRs in data collection) less than 1 voxel over the duration of data acquisition. Based on human brain and chest imaging data collected in our laboratory, we assume that involuntary head motion has a speed of ~ 1 mm/second and cardiac motion has a speed of 20–50 mm/second. With these assumptions, wavelet-space correlation imaging will require a data acquisition rate of ~ 1 second per slice for 1 mm resolution brain imaging and that of 30–100 milliseconds per time frame for 2 mm resolution cardiac/pulmonary dynamic imaging. These estimated data acquisition rates based on simulation have been used as references for the other studies in the presented work.

In vivo brain imaging with involuntary motion

Figure 6 shows the image reconstruction results. It is found that motion primarily affects image reconstruction in the first 2 experiments with data acquisition time >1 second per slice. Motion-related ghost artifacts can be seen. In the third experiment with a data acquisition rate of ~ 570 milliseconds per slice, SPIRiT and wavelet-space correlation imaging generate images without visible motion-related ghost artifacts. This indicates that data are collected faster than motion. However, GRAPPA, SENSE and basic correlation imaging still perform poorly, indicating they suffer from high undersampling. In this experiment, wavelet-space correlation imaging is slightly better than SPIRiT which gives a few more undersampling-related artifacts (arrows in Figure 6).

In vivo free-breathing cardiac imaging

Figure 7 gives the cardiac images generated from in vivo data collected with an undersampling factor of 16. As compared to segmented imaging with breath-holding, k-t SENSE, k-t GRAPPA and basic correlation imaging generate significant artifacts and blurs (Figures 7a and 7b). These cause the loss of dynamic information in temporal motion trajectories (Figure 7c). In contrast, wavelet-space correlation imaging preserves blood-induced T1 contrast (Figures 7a and 7b) and dynamic information (Figure 7c) well, demonstrating it is sufficient for free-breathing cardiac imaging without ECG/respiration monitoring or data segmentation. It should be noted that segmented imaging and wavelet-space correlation imaging results have minor differences in diastolic/systolic images and temporal trajectories, most likely reflecting a difference in heart positions during breath holding and free-breathing.

In-vivo free-breathing pulmonary imaging

Figure 8 shows the pulmonary images generated from in vivo data collected with an undersampling factor of 8. As compared to static images collected with breath-holding, k-t SENSE, k-t GRAPPA, basic correlation imaging and wavelet-space correlation imaging all generate images without significant artifacts or noise at the end of inspiration and expiration phases (Figures 8a and 8b). However, temporal resolution is compromised considerably in k-t SENSE, k-t GRAPPA and basic correlation imaging. This introduces visible ghost artifacts associated with respiration in inspiration-phase images (arrows in Figure 8a) and the loss of dynamic information in temporal motion trajectories (Figure 8c). In contrast, wavelet-space correlation imaging gives artifact-free images (Figure 8a) and preserves dynamic information well (Figure 8c).

Discussion

Benefits of FOV reduction in k-space wavelet transform

FOV reduction in wavelet transform may improve the estimation of correlation functions and reduce noise amplification in image reconstruction. These benefits may be understood from a different perspective. Unlike conventional methods that estimate full-FOV imaging data directly, wavelet-space image reconstruction estimates k-space data from an image-space region smaller than the FOV. The data outside of this region are removed using a decomposition filter before image reconstruction (as illustrated in Figure 9). From this perspective, wavelet-space correlation imaging performs region-by-region reconstruction. Since aliasing and noise amplification vary spatially in image space, region-by-region reconstruction can improve image quality using reconstruction operators optimized differently in different regions. The image quality gain we found in the present work agrees well with that of a previous study that optimizes image reconstruction regionally using an image-space window approach (67).

Benefits of frequency bandwidth reduction in temporal wavelet transform

In the presented dynamic imaging studies, 2D wavelet transform is applied in the phase-encoding and time directions. The reduction in frequency bandwidth along the time direction

is not beneficial to the estimation of correlation functions because ACS data are collected over all the time frames. However, analogous to FOV reduction in k-space imaging, temporal wavelet transform permits image reconstruction to be optimized for a narrow temporal frequency bandwidth associated with a wavelet decomposition filter. Since physiological (cardiac or respiratory) motion is band-limited, motion aliasing is different in different temporal frequency bands. Wavelet-space correlation imaging can use reconstruction operators optimized differently in those temporal frequency bands with and without motion. This facilitates the removal of motion aliasing along time, thereby providing better performance than those methods that use a single set of reconstruction operators to reconstruct data from all of the temporal frequency bands.

Utilization of k-space data correlation in reference to SPIRiT

Wavelet-space correlation imaging can utilize data correlation between nearest neighboring k-space samples in image reconstruction (Figure 3a). This advantage is also offered by nonlinear k-space methods such as SPIRiT. The gain of SPIRiT over conventional linear reconstruction has been demonstrated in a previous work (37) and was observed in the presented experiments (Figures 4 and 6). Due to the need for iterative reconstruction, SPIRiT requires reconstruction operators to be self-convergent (37). Since this condition is not met in wavelet-space correlation imaging, SPIRiT may generate more accurate reconstruction. However, wavelet-space correlation imaging is a linear approach with lower algorithm complexity. Future clinical translation will benefit from its manageable computation cost and straightforward implementation.

Gain in imaging acceleration

In the presented work, the coil array for brain imaging has 8 elements uniformly positioned around the head. This configuration gives 4 different elements in the phase-encoding direction and the maximal acceleration factor for conventional parallel imaging is 4. This accounts for the finding of a critical undersampling factor in SENSE, GRAPPA and basic correlation imaging (Figure 4a). In contrast, wavelet-space correlation imaging can use an undersampling factor of >4 (Figures 4–6), demonstrating its ability to overcome the parallel imaging acceleration limit imposed by coil configuration.

The coil array for cardiac and pulmonary imaging has two paddles positioned anteriorly and posteriorly. Each paddle has 4×4 planar elements. This configuration gives at most 4 different elements in the phase-encoding direction and the maximal parallel imaging acceleration factor is also 4. With an additional gain from temporal data sharing in dynamic imaging, k-t SENSE, k-t GRAPPA or basic correlation imaging may exceed this limit (>4). However, these techniques are not fast enough to collect motion-free data in free-breathing cardiac and pulmonary imaging (Figures 7 and 8). In contrast, wavelet-space correlation imaging can image cardiac and respiratory motion without data segmentation using an acceleration factor of 16 or 8 as demonstrated in the presented experiments. This gain over conventional k-t imaging methods should be attributed to its ability to overcome the inherent parallel imaging acceleration limit.

Real-time imaging ability

Wavelet-space may be considered as filtered k-t space in dynamic imaging. The presented work performs wavelet decomposition and reconstruction by k-t space convolution with finite-length wavelet filters (temporal length=8 in current implementation). This may introduce a temporal delay of 8 time frames. In addition, there is a temporal delay from the temporal convolution with wavelet-space reconstruction operators (4 time frames). In total, the temporal delay in the presented work is ~500 milliseconds for cardiac imaging and ~1.2 seconds for pulmonary imaging. Since this will not introduce a considerable delay in providing clinical feedbacks when imaging a patient, the presented approach can meet our needs for real-time imaging. In the presented work, real-time imaging was not implemented because raw data were not available in real-time with the clinical scanner configuration. We are working on scanner reconfiguration with the MRI manufacturer.

Computation cost

Wavelet-space correlation imaging requires different reconstruction operators for every wavelet decomposition filter. In comparison to linear k-space methods (e.g., GRAPPA), however, its computation cost is increased by a factor less than the number of wavelet filters. This is because wavelet-space reconstruction operators have a kernel size smaller than that used in k-space (Figure 3). Using MATLAB on a workstation with 2.80 GHz Intel Xeon CPU and 32 GB memory, the reconstruction time for a 240×240 2D image is ~300 milliseconds. This is about three times higher than GRAPPA, SENSE and basic correlation imaging (80–110 milliseconds for the same image). However, it is significantly lower than non-linear methods that can give imaging performance comparable to the presented approach. For example, SPIRiT needs ~12 seconds for reconstructing the same 240×240 image in our experiments.

Future work

The presented work aims to show the potential of wavelet-space correlation imaging to overcome the motion challenge in clinical imaging. The algorithm implementation was intended to demonstrate the feasibility for translation into clinical practice. This implementation uses Daubechies wavelet of order 8, 8 decomposition filters for 1D wavelet transform and 2×8 decomposition filters for 2D wavelet transform. More effort is needed for optimizing these wavelet parameters. The authors believe that this optimization may vary with imaging anatomy and applications. A large-scale study will be needed for future clinical translation.

Summary

This study investigated the feasibility of motion-free MRI using wavelet-space correlation imaging without motion monitoring or data segmentation. It demonstrated that wavelet-space correlation imaging can exceed the speed limit of conventional parallel imaging methods. By collecting data faster than motion, motion-free MRI can be performed without motion monitoring or data segmentation in static and dynamic imaging. The approach presented here uses linear algorithms and uniform sampling, making clinical translation straightforward. Since wavelet-space correlation imaging can be run in k-t space, it offers

the potential of real-time dynamic imaging for clinical examination. Future work will address how to optimize reconstruction parameters and reduce computation cost.

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Figure 1.

Wavelet-space correlation imaging model: Collected data are first transformed into wavelet-space by filtering. Correlation imaging is then used to reconstruct the wavelet transform of fully-sampled data from that of undersampled data. The final images are generated by inverse wavelet transform. Here, N is the channel number, M is the number of wavelet decomposition/reconstruction filters, $\{w_i(\mathbf{k}), i=1,2,\dots,M\}$ are wavelet decomposition filters and $\{r_i(\mathbf{k}), i=1,2,\dots,M\}$ are wavelet reconstruction filters.

Figure 2.

Comparison of correlation functions calculated from center and outer k-space. (a) 1D image generated from Shepp-Logan phantom. (b) Center and outer k-space data of 1D image: Data are normalized with respect to the maximal magnitude in each plot. (c) Magnitude of correlation functions in the proximity of the k-space origin ($|k| < 6$): The k-space correlation functions are calculated from center and outer k-space data. The wavelet-space correlation functions are calculated from the wavelet transform of center and outer k-space data. Wavelet transform is performed with 2 decomposition filters (w_1 and w_2) generated from Daubechies wavelet of order 8. Data are normalized with respect to the average magnitude in each plot. (d) Difference of correlation functions calculated from center and outer k-space in (c): This difference is smaller in wavelet-space (dashed and solid lines) than in k-space (dotted lines). Before the calculation of the difference, each correlation function is normalized with respect its own average magnitude for removing the bias caused by power difference.

Figure 3.

Role of wavelet transform in the reconstruction of missing data. (a) Illustration of convolution relationship in k-space and wavelet-space reconstruction: In k-space (left), a target sample is estimated by the convolution of partial k-space and reconstruction operators (shaded area). The estimate relies on data correlation between missing and collected samples (solid-line arrows). In wavelet space (right), data filling introduced by wavelet transform converts partial k-space into full k-space. The estimate of a sample may use reconstruction operators (shaded area) arising from data correlation between nearest neighbors (solid-line arrows). (b) Noise amplification in k- and wavelet-space reconstruction: Reconstruction operators are resolved from images simulated by multiplying Shepp-Logan phantom (Figure 2a) and an 8-channel coil sensitivity profile. Amplified noise is calculated by the convolution of reconstruction operators with simulated white noise. The noise power gain is the average power ratio of the amplified noise to the input white noise. As a result of the use of data correlation between nearest neighbors, wavelet-space reconstruction gives lower noise amplification than k-space reconstruction.

Figure 4.

Simulation of imaging acceleration without motion using fully sampled brain imaging data.

(a) RSS error plots for GRAPPA, SENSE, basic correlation imaging, SPIRiT and wavelet-space correlation imaging with different ACS lines. (b) Reconstruction using GRAPPA, SENSE, basic correlation imaging, SPIRiT and wavelet-space correlation imaging with 24 ACS lines and undersampling factors $R=2, 4, 6, 8, 10$ and 12 . Reference image is reconstructed from fully-sampled data. Here “correlation” represents basic correlation imaging and “wavelet” represents wavelet-space correlation imaging.

Figure 5.

Simulation of imaging acceleration with motion using fully-sampled brain imaging data. (a) RSS error plots using wavelet-space correlation imaging with data corrupted by motion at 4 different speeds: 0.01 voxels/TR, 0.015 voxels/TR, 0.02 voxels/TR and 0.025 voxels/TR.

Motion is assumed to be translational within every TR. It has a constant speed, but a direction that varies randomly from TR to TR. These RSS plots were generated with 12, 24 and 48 ACS lines. (b) Typical examples of reconstruction with motion ghosting (left), noise and aliasing artifacts (middle) and acceptable image quality (right). The undersampling factors in these examples are 2 (left), 9 (middle) and 4 (right). The motion speeds are 0.015 voxels/TR (left), 0.025 voxels/TR (middle), and 0.01 voxels/TR (right). All the examples use 24 ACS lines. The image with acceptable quality is found in Region A of the plots (a). This region has a motion-induced image shift of 1 voxels over the time of data collection.

Figure 6.

In vivo brain imaging studies with involuntary motion. (a) Images reconstructed from fully sampled data (data acquisition time ~2.3 seconds), data collected with an undersampling factor of 2 (data acquisition time ~1.2 seconds), and data collected with an undersampling factor of 6 (data acquisition time ~570 milliseconds). (b) Zoomed images of the regions denoted by the dashed-line rectangular windows of (a). Here “correlation” represents basic correlation imaging and “wavelet” represents wavelet-space correlation imaging.

Figure 7. In vivo free-breathing cardiac imaging. (a) Reconstructed images at the end of systolic phase. (b) Reconstructed images at the end of diastolic phase. (c) Reconstructed time trajectories of the dashed lines in (a). Here “correlation” represents basic correlation imaging and “wavelet” represents wavelet-space correlation imaging.

Figure 8.

In vivo free-breathing pulmonary imaging. (a) Reconstructed images at the end of inspiration phase. (b) Reconstructed images at the end of expiration phase. (c) Reconstructed time trajectories of the dashed lines in (a). Here “correlation” represents basic correlation imaging and “wavelet” represents wavelet-space correlation imaging.

Figure 9.

Wavelet transform of k-space data generates multiple sets of wavelet-space data with reduced FOV. In this example, wavelet decomposition uses two decomposition filters (w_1 and w_2) generated from Daubechies wavelet of order 8. A 1D wavelet transform is applied in the phase-encoding direction. The brain imaging k-space data are from the simulation study shown in Figure 4.