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Real-time cardiac MRI with radial acquisition and k-space variant reduced-FOV reconstruction

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Abstract

This work aims to demonstrate that radial acquisition with k-space variant reduced-FOV reconstruction can enable real-time cardiac MRI with an affordable computation cost. Due to non-uniform sampling, radial imaging requires k-space variant reconstruction for optimal performance. By converting radial parallel imaging reconstruction into the estimation of correlation functions with a previously-developed correlation imaging framework, Cartesian k-space may be reconstructed point-wisely based on parallel imaging relationship between every Cartesian datum and its neighboring radial samples. Furthermore, reduced-FOV correlation functions may be used to calculate a subset of Cartesian k-space data for image reconstruction within a small region of interest, making it possible to run real-time cardiac MRI with an affordable computation cost. In a stress cardiac test where the subject is imaged during biking with a heart rate of > 100 bpm, this k-space variant reduced-FOV reconstruction is demonstrated in reference to several radial imaging techniques including gridding, GROG and SPIRiT. It is found that the k-space variant reconstruction outperforms gridding, GROG and SPIRiT in real-time imaging. The computation cost of reduced-FOV reconstruction is ~2 times higher than that of GROG. The presented work provides a practical solution to real-time cardiac MRI with radial acquisition and k-space variant reduced-FOV reconstruction in clinical settings.

Keywords

Correlation imaging; Correlation function; High-speed MRI; Parallel imaging; Real-time imaging

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1. Introduction

Magnetic resonance imaging (MRI) intrinsically has a low data acquisition speed. This poses a challenge for cardiac MRI where heartbeats and respiration may introduce motion [1, 2]. Currently, cardiac MRI relies primarily on data segmentation that divides the k-space into small segments with each collected in different cardiac cycles, assuming motion variance is minor from one cardiac cycle to another [3, 4]. By sorting data segments collected at different times in post-processing, a whole set of k-space data may be generated to perform retrospective reconstruction. This method requires breath holding for reduced motion and electrocardiogram (ECG) synchronization for data sorting. Image quality may be poor if a patient does not cooperate or has arrhythmias [2]. In addition, it is impossible to examine cardiovascular and respiratory coupling with breath holding. For these reasons, real-time cardiac MRI with free breathing is desirable in clinical practice.

Radial imaging has a potential for real-time cardiac MRI owing to its low motion sensitivity and high sampling efficiency [5–8]. With non-uniform sampling, however, radial imaging requires k-space variant reconstruction that needs a long computation time for optimal performance. To improve clinical throughput, most existing reconstruction techniques, e.g., gridding and GRAPPA operator gridding (GROG), trade performance for faster computation with k-space invariant algorithms [5, 6, 8–14]. Due to insufficient image quality, these techniques have found limited applications in real-time cardiac MRI. Recent research has led to several advanced radial reconstruction techniques including SPIRiT and compressed sensing [15–20]. However, algorithm complexity has prevented them from being widely used in clinical settings where high-performance computers are often not available. In addition, a number of k-t space reconstruction techniques have been developed, e.g., k-t SENSE, k-t GRAPPA, and through-time GRAPPA [21–25]. These techniques may reduce artifacts by taking advantage of data sharing along the temporal dimension. In many clinical applications, however, temporal data sharing may cause a certain loss in temporal resolution, making it difficult to track fast physiological motion in real-time cardiac MRI.

The work presented here is to develop a k-space variant radial reconstruction technique with affordable computation cost for real-time cardiac MRI in clinical settings. To that end, a correlation imaging framework is introduced to convert parallel imaging reconstruction into the estimation of correlation functions [26–28]. This allows for the calculation of every Cartesian datum directly from the linear combination of its neighboring radial samples in a k-space variant fashion. In addition, reduced-field of view (FOV) reconstruction is used to minimize the number of Cartesian samples required to be calculated, providing a clinically translatable approach to real-time imaging with an affordable computation cost. This study demonstrates the feasibility of real-time cardiac MRI with radial acquisition and k-space variant reduced-FOV reconstruction. It is found that the new technique may image fast and non-periodic cardiac motion with a temporal resolution of ~40 ms and a spatial resolution below 2 mm in a stress cardiac test that requires the subject be imaged during biking with a heart rate of > 100 beats per minute (bpm).

2. Methods

2.1. Parallel imaging relationship between Cartesian and radial samples

Parallel imaging (e.g. GRAPPA) indicates that every k-space datum may be represented as the linear combination of its neighboring samples. The linear weights are dependent on relative positions of this datum and its neighboring samples. Since radial samples are non-uniform, radial parallel imaging reconstruction requires point-wisely different linear weights. As illustrated in Fig. 1, the estimation of a Cartesian datum from its neighboring radial samples may be written as:

$$\hat{d}_m(\mathbf{k}_c) = \sum_{i=1}^N \sum_{\mathbf{k}_r \in \mathbf{k}_c \text{ neighbors}} d_i(\mathbf{k}_r) u_{mi}(\mathbf{k}_c, \mathbf{k}_r) \quad (1)$$

where i and m are channel indices ranging from 1 to N , $\mathbf{k}_c$ is a Cartesian position vector, $\mathbf{k}_r$ is a radial position vector, $\hat{d}_m(\mathbf{k}_c)$ is an estimate of the real Cartesian sample $d_m(\mathbf{k}_c)$, $d_i(\mathbf{k}_r)$ is a collected radial sample close to $\mathbf{k}_c$, and $u_{mi}(\mathbf{k}_c, \mathbf{k}_r)$ represents the parallel imaging linear weights for estimating $d_m(\mathbf{k}_c)$ from its neighbors $d_i(\mathbf{k}_r)$'s. These linear weights may be used to estimate all the data located at Cartesian grids from samples at $\mathbf{k}_r + \mathbf{k}_c$ (i.e., $\mathbf{k}_{r1} + \mathbf{k}_c$, $\mathbf{k}_{r2} + \mathbf{k}_c$, $\mathbf{k}_{r3} + \mathbf{k}_c$ and $\mathbf{k}_{r4} + \mathbf{k}_c$ in Fig. 1), where $\mathbf{k}_c$ is an arbitrary Cartesian shift in reference to $\mathbf{k}_c$. Then an error function for this virtual linear shift-invariant system may be defined as:

$$\begin{aligned} \varepsilon &= \sum_{\text{All } \Delta \mathbf{k}_c} |d_m(\mathbf{k}_c + \Delta \mathbf{k}_c) - \hat{d}_m(\mathbf{k}_c + \Delta \mathbf{k}_c)|^2 \\ &= \sum_{\text{All } \Delta \mathbf{k}_c} \left| d_m(\mathbf{k}_c + \Delta \mathbf{k}_c) - \sum_{i=1}^N \sum_{\mathbf{k}_r \in \mathbf{k}_c \text{ neighbors}} d_i(\mathbf{k}_r + \Delta \mathbf{k}_c) u_{mi}(\mathbf{k}_c, \mathbf{k}_r) \right|^2. \end{aligned} \quad (2)$$

By following the same procedures as in previous works on correlation imaging [26–28], i.e., by letting the partial derivative of the above equation with respect to the linear weights be zero, a set of linear equations may be generated to resolve the linear weights $u_{mi}(\mathbf{k}_c, \mathbf{k}_r)$ for estimating a single Cartesian datum $d_m(\mathbf{k}_c)$ as below:

$$\sum_{i=1}^N \sum_{\mathbf{k}_r \in \mathbf{k}_c \text{ neighbors}} c_{ij}(\mathbf{k}'_r - \mathbf{k}_r) u_{mi}(\mathbf{k}_c, \mathbf{k}_r) = c_{mj}(\mathbf{k}'_r - \mathbf{k}_c) \quad (3)$$

for all channel index $j = 1, 2, \dots, N$, and radial positions $\mathbf{k}'_r \in \mathbf{k}_c \text{ neighbors}$.

Here the equation coefficients are correlation functions given by:

$$c_{ij}(\mathbf{k}) = \sum_{all \mathbf{k}'} d_i(\mathbf{k}' + \mathbf{k}) d_j^*(\mathbf{k}'), \quad (4)$$

where $*$ is the conjugate operation, $\mathbf{k}$ and $\mathbf{k}'$ are k-space position vectors, and the N-channel data $\{d_i(\mathbf{k}), i = 1, 2, \dots, N\}$ should meet the Nyquist sampling criterion. It should be noted that Eq. (3) defines a linear system that may be used to resolve point-wisely different linear weights for reconstructing Cartesian k-space if correlation functions are available. The following section will address how to estimate correlation functions based on Eq. (4).

2.2. Estimation of correlation functions

As illustrated by the flowchart in Fig. 2 (left-side), Cartesian data may be generated from the oversampled radial samples in central k-space with gridding. These data meet the Nyquist sampling criterion and may be used to estimate correlation functions at a Cartesian grid with Eq. (4), as in previous works on correlation imaging [26–28]. In Fig. 2, the estimated correlation functions are shown in image space for better visualization. This image-space representation is calculated by applying inverse Fourier transform to Eq. (4). As derived in a previous work [27], the inverse Fourier transform of a correlation function gives image magnitude information and image phase differences between acquisition channels.

The estimated Cartesian correlation functions may be further used to interpolate those non-Cartesian correlation functions required for forming Eq. (3) based on the Nyquist theorem, i.e., by utilizing Whittaker-Shannon interpolation below:

$$c_{ij}(\mathbf{k}) = \sum_{All \mathbf{k}_c} c_{ij}(\mathbf{k}_c) \text{sinc}(\mathbf{k} - \mathbf{k}_c), \quad (5)$$

where $\mathbf{k}$ is an arbitrary k-space position vector, *sinc* denotes the normalized sine cardinal function for interpolation, and $c_{ij}(\mathbf{k}_c)$ represents the correlation functions at Cartesian grids estimated from radial samples. It should be noted that both $\mathbf{k}_r'$ and $\mathbf{k}_r$ are in a small distance to $\mathbf{k}_c$ in Eq. (3) (within $\mathbf{k}_c$ neighborhood) and as such only those correlation functions for small $|\mathbf{k}|$'s (central k-space) need to be calculated with Eq. (5). For this reason, the correlation functions calculated for Fig. 2 give low-resolution images transformed from central k-space data.

2.3. Reduced-FOV reconstruction

The clinical interest of cardiac MRI is heart anatomy that covers a small part of the FOV. It is beneficial to reconstruct reduced-FOV images with a lower Nyquist sampling rate, which allows for the calculation of fewer k-space samples and thus reduces the computation cost. To that end, the real data $d_m(\mathbf{k}_c)$ in Eq. (2) should arise from a reduced-FOV image with zeroes outside of the region of interest. The resultant linear equations (Eq. (3)) then have reduced-FOV correlation functions on the right side. As illustrated by the flowchart in Fig. 2 (right-side), the reduced-FOV correlation functions may be calculated by multiplying a window function in image space with the full-FOV Cartesian correlation functions estimated

from central k-space data. The size of image-space window function should cover the heart anatomy for clinical examination. The use of reduced-FOV correlation functions leads to a set of linear weights for generating a reduced-FOV image (Fig. 2 right side, in reference to left-side full-FOV). The reduced-FOV reconstruction needs the calculation of only a subset of Cartesian k-space data and the computation cost is thus lower.

2.4. MRI experiments

Human imaging data were acquired in compliance with the regulations of the institution's human ethics committee. The following studies were conducted on a 1.5 T clinical MRI scanner (SIEMENS MAGNETOM Avanto, 32 channel, whole-body horizontal 60 cm bore):

1. 2D retrospective cine imaging: A set of 2D radial cine images was collected with breath-holding using balanced steady-state precession sequence (segmented, FOV 250 mm, 130 views, 1.7 mm spatial resolution, slice thickness 8 mm, TR/TE 4.6/2.3 ms, flip angle 65°).
2. 2D real-time imaging: A stress cardiac test was performed with the subject first scanned when resting with a heart rate of ~60 bpm and then when biking with a heart rate of ~110 bpm. Real-time cardiac data were collected with free-breathing (FOV 300 mm, 220 time frames, 16 views per time frame, 1.7 mm spatial resolution, slice thickness 8 mm, TR/TE 2.5/1.3 ms, flip angle 50°). This gave a temporal resolution of 40 ms. The stress test was performed inside the magnet bore with an MR-compatible exercise bicycle (Lode B.V., Groningen, the Netherlands) mounted on the scanner table. During the exercise, the biking resistance was adjusted to keep the subject's heart rate to be consistently around 110 bpm.

All images were reconstructed offline in MATLAB (Natick, MA) using retrospective breath-holding cine and real-time free-breathing imaging data. The breath-holding cine data were used in a simulation study on k-space variant reconstruction in reference to gridding, GROG and SPIRiT. In simulation, images were reconstructed using different methods with different numbers of views extracted from the total 130 views for comparison. The real-time free-breathing imaging data were used to investigate how k-space variant reconstruction performs with respect to gridding, GROG, SPIRiT and through-time GRAPPA in real-time cardiac MRI. In real-time imaging experiments, each time frame was reconstructed from the collected 16 views, providing a temporal resolution of 40 ms. Only reduced-FOV images were generated with k-space variant reconstruction for manageable computation times. In each reconstruction, the central k-space radial data were used to estimate correlation functions and the estimated correlation functions were used to calculate point-wisely different linear weights for reconstructing the whole k-space (Fig. 2). Here gridding is the current standard on clinical MRI scanners. GROG represents a category of linear parallel imaging techniques with a low computation cost. SPIRiT is an iterative non-linear technique with a high computation cost. Through-time GRAPPA represents a group of k-t space techniques. Therefore, these experiments give a comprehensive evaluation on k-space variant reconstruction.

3. Results

3.1. Experiments with retrospective cine imaging data

Fig. 3 shows the comparison of different reconstruction methods in a simulation study with different view numbers from the retrospective cine radial data. It can be seen that, with sufficient radial data (65 or 130 views), all the methods generate adequate image quality. With a small number of views (22 or 33 views), non-linear methods (k-space variant reconstruction and SPIRiT) are better than linear methods (gridding and GROG). Gridding images are impaired by the appearance of streaking artifacts, whereas GROG images are blurry, which leads to the loss of small details. Like SPIRiT, both two k-space variant reconstruction methods produce images that have no major artifacts or blurring and retain small details. However, full-FOV reconstruction needs a long computation time while reduced-FOV reconstruction gives a computation cost comparable to that of GROG.

3.2. Free-breathing real-time cardiac imaging during a stress test

Fig. 4 shows a few reconstructed images at the end of systolic and diastolic phases during the resting and biking states. It can be seen that k-space variant reconstruction, SPIRiT and through-time GRAPPA generate single-phase images with comparable quality. They all outperform other methods: GROG suffers from image blurs, providing a low spatial resolution. Gridding suffers from streaking artifacts, generating noisy images.

Fig. 5 shows the temporal trajectories of those reconstructed images in Fig. 4 during a time course of ~10 s. From those trajectories along the dashed lines of Fig. 4, it can be seen that SPIRiT and gridding look noisy due to streaking artifacts, and GROG and through-time GRAPPA show blurs (Fig. 5 left and central columns). Both blurs and streaking may reduce temporal resolution. During the resting state when heart motion is slow, this seems not problematic and all the methods can track temporal changes well (Fig. 5 left column). However, during the biking state when heart motion is fast, k-space variant reconstruction gives better temporal resolution than the other methods (Fig. 5 central column). This gain can be more clearly seen from the temporal changes of a single voxel (Fig. 5 right plots): k-space variant reconstruction gives clear intensity changes associated with fast heartbeats over the entire time-course while the others cannot.

4. Discussion

4.1. A mathematical view

This work provides a mathematical solution to calculating a Cartesian datum from non-uniformly collected k-space samples with parallel imaging. In early studies on GRAPPA, it has been demonstrated that neighboring multi-channel k-space data have linear parallel imaging relationship (linear weights). In Cartesian imaging, it is straightforward to calculate this relationship with undersampled and fully-sampled data generated from the calibration data. In radial imaging where sampling is k-space variant and not at Cartesian grids, however, it is difficult to generate undersampled data with different sampling patterns around every Cartesian grid from a single set of calibration data. Correlation imaging provides an approach to addressing this issue: by converting parallel imaging reconstruction

into the estimation of correlation functions [26–28], the calculation of k-space variant parallel imaging relationship (linear weights) relies only on the estimation of a few correlation functions not at Cartesian grids. The presented work demonstrates that this estimation can be made with Whittaker-Shannon interpolation from those correlation functions at Cartesian grids. It should be mentioned that Whittaker-Shannon interpolation is similar to gridding. The direct gridding of radial data may lead to considerable errors in outer k-space where the Nyquist criterion cannot be met. In contrast, since correlation imaging requires only central k-space correlation functions (at small $|\mathbf{k}|$'s in Eq. (3)), the Nyquist criterion is always met.

4.2. Comparison to gridding, GROG, SPIRiT and through-time GRAPPA

Gridding (Eq. (5)) arises from Whittaker-Shannon interpolation with an assumption that the data meet the Nyquist sampling criterion. As a result, when data are undersampled, aliasing artifacts are produced which give rise to significant streaking artifacts in the image. In comparison, k-space variant reconstruction gives a parallel imaging estimate of Cartesian data from radial samples, providing an approach to suppressing streaking artifacts that gridding cannot address.

GROG is a GRAPPA-based linear approach to suppressing streaking artifacts in non-Cartesian parallel imaging. GROG needs calibration data to calculate base weights, which represents the parallel imaging relationship between two nearest neighboring data samples at Cartesian grids. The parallel imaging relationship between two arbitrary samples can be calculated as the base weights to a power equal to the distance of those two samples. In outer k-space where samples are distant, a high power is required to reconstruct those missing samples from collected radial samples. As a result, if the base weights have a power gain > 1 , noise amplification may be considerable. In real-time imaging with a low sampling density in outer k-space, it is necessary to use base weights with a power gain < 1 for reconstruction stability and robustness. A disadvantage is that this suppresses both noise and signals in outer k-space, manifesting as image blurs in GROG reconstruction (Figs. 4 and 5). In comparison, k-space variant reconstruction is not as sensitive to noise enhancement as GROG because the parallel imaging relationship for every datum is calculated independently from a set of linear equations generated by Eq. (3).

SPIRiT is a non-linear technique that employs the data constraint imposed by the parallel imaging relationship between neighboring samples. This constraint is calibrated from central k-space, but applied to outer k-space. SPIRiT uses an iterative algorithm, making it sensitive to calibration errors. In real-time cardiac imaging, there exist systematic calibration errors because outer k-space data are more sensitive to heart motion than central k-space data. As a result, streaking artifacts may be considerable with fast motion, as shown in reconstructed images during the biking state (Figs. 4 and 5). Compared with SPIRiT, k-space variant reconstruction is non-iterative and less sensitive to calibration errors.

Through-time GRAPPA calibrates GRAPPA operators for image reconstruction from undersampled radial data using high spatial resolution data collected at different times with a low temporal resolution. This calibration gives excellent GRAPPA reconstruction robustness with a certain loss in temporal accuracy of motion. As a result, the reconstruction gives high-

quality single-phase images with a low temporal resolution (Figs. 4 and 5). Compared with through-time GRAPPA, k-space variant reconstruction can provide better temporal resolution for real-time cardiac MRI when heart rate is high.

4.3. Reduced-FOV reconstruction

The reduced-FOV image is equal to the multiplication of a full-FOV image and a window function with zeroes outside of the region of interest. In k-space, this image-space multiplication becomes a filtering operation (k-space convolution), i.e., every k-space datum may be calculated as the linear combination of its neighbors. Therefore, the resolved linear weights for reduced-FOV reconstruction are the combination of parallel imaging relationship and the filtering operation (image-space window function). In principle, the k-space filter for reduced-FOV operation may be long (infinite for an ideal rectangular window). With parallel imaging, the filter may be shortened in a manner similar to transmit-SENSE [29, 30]. As a result, it is possible to generate every Cartesian datum from only a few neighboring radial samples in reduced-FOV reconstruction. A disadvantage here is that the region of interest must be known for the determination of image-space window function (Fig. 2 right-side), which may be estimated from the low-resolution images generated from central k-space radial data.

5. Conclusion

The k-space variant reduced-FOV reconstruction offers the potential for imaging real-time cardiac motion with an affordable computation cost in clinical applications.

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Fig. 1.

Illustration of parallel imaging reconstruction of an unknown Cartesian datum at $\mathbf{k}_c$ from the linear combination of radial samples at $\mathbf{k}_r \in \{\mathbf{k}_{r1}, \mathbf{k}_{r2}, \mathbf{k}_{r3}, \mathbf{k}_{r4}\}$ in $\mathbf{k}_c$ neighborhood: The sum of square error function (Eq. (2)) may be defined for $\mathbf{k}_c$ in a shift-invariant k-space virtually sampled around every Cartesian grid with the same pattern as $\mathbf{k}_r$'s in $\mathbf{k}_c$ neighborhood. By minimizing this error function, a set of linear equations (Eq. (3)) may be formed to resolve the linear weights for reconstructing the datum at $\mathbf{k}_c$. As non-uniform sampling introduces k-space variant parallel imaging relationship between Cartesian data and radial samples, the linear weights for Cartesian k-space reconstruction are point-wisely different.

Fig. 2.

Flowchart of k-space variant reconstruction: Correlation functions at Cartesian grids may be estimated with Eq. (4) from central k-space Cartesian data generated from radial samples with gridding. Since these correlation functions meet the Nyquist criterion, Whittaker-Shannon interpolation may be used to estimate those correlation functions at arbitrary positions required for forming Eq. (3). Reduced-FOV correlation functions can be generated by multiplying full-FOV correlation functions with a window function in image-space. Eq. (3) for reduced-FOV reconstruction needs both full- and reduced-FOV correlation functions.

Fig. 3.

Reconstructed single-phase images using gridding, GROG, SPIRiT, k-space variant full-FOV, and k-space variant reduced-FOV methods with different numbers of views from the breath-holding retrospective cine data: With sufficient radial data (65 or 130 views), all the methods give adequate image quality. With a small number of views (22 or 33 views), gridding shows considerable streaking artifacts and GROG shows image blurs. Non-linear methods (SPIRiT and k-space variant reconstruction) give better performance. The computation cost of k-space variant reduced-FOV reconstruction is ~2 times higher than that of GROG, but it is lower than that of SPIRiT and k-space variant full-FOV reconstruction.

Fig. 4.

Reconstructed images at the end of systolic and diastolic phases with gridding, GROG, SPIRiT, through-time GRAPPA and k-space variant reduced-FOV methods from free-breathing real-time cardiac imaging data during the resting and biking states in a stress test: Gridding shows strong streaking artifacts. GROG images are considerably blurred. SPIRiT, through-time GRAPPA and k-space variant reduced-FOV reconstruction are comparable. They all outperform gridding and GROG. Some streaking artifacts can be observed in SPIRiT images.

Fig. 5.

Real-time temporal trajectories along the dashed lines and at the "*" voxels in Fig. 4 during a time course of ~10 s: During the resting state when heart rate is slow (~60 bpm), all the methods can track the heart motion well (left column). During the biking state when heart rate is fast (~110 bpm), k-space variant reduced-FOV reconstruction shows better temporal resolution than the others (central column). With a fast heart rate, it is found that k-space variant reconstruction can track heartbeats well while the other methods, gridding, GROG, SPIRiT and through-time GRAPPA cannot be due to either image blurs or streaking artifacts (right plots).