



Original contribution

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

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ARTICLE INFO

Keywords:

Correlation imaging

Correlation function

High-speed MRI

Parallel imaging

Real-time imaging

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.

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

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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 $\mathbf{k}_r + \Delta\mathbf{k}_c$ (i.e., $\mathbf{k}_{r1} + \Delta\mathbf{k}_c$, $\mathbf{k}_{r2} + \Delta\mathbf{k}_c$, $\mathbf{k}_{r3} + \Delta\mathbf{k}_c$ and $\mathbf{k}_{r4} + \Delta\mathbf{k}_c$ in Fig. 1), where $\Delta\mathbf{k}_c$ 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:

$$\begin{aligned} \sum_{i=1}^N \sum_{\mathbf{k}_r \in \mathbf{k}_c \text{ neighbors}} c_{ij}(\mathbf{k}_r' - \mathbf{k}_r) u_{mi}(\mathbf{k}_c, \mathbf{k}_r) &= c_{mj}(\mathbf{k}_r' - \mathbf{k}_c), \\ \text{for all channel index } j &= 1, 2, \dots, N, \text{ and radial positions } \mathbf{k}_r' \\ &\in \mathbf{k}_c \text{ neighbors}. \end{aligned} \quad (3)$$

Here the equation coefficients are correlation functions given by:

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

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

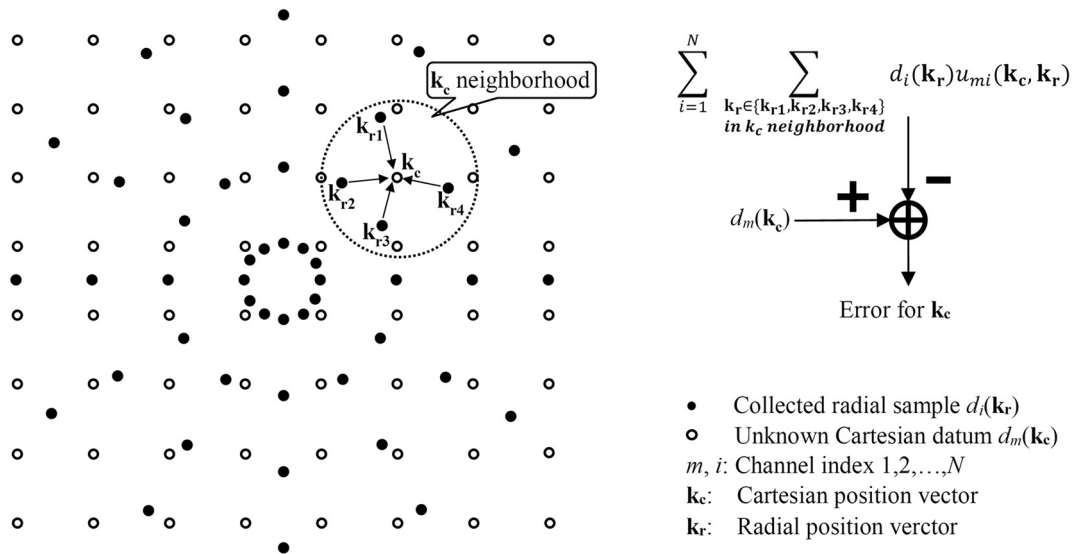


Fig. 1. Illustration of parallel imaging reconstruction of an unknown Cartesian datum at $\mathbf{k}_c$ from the linear combination of radial samples at $\mathbf{k}_r \in \{\mathbf{k}_{r1}, \mathbf{k}_{r2}, \mathbf{k}_{r3}, \mathbf{k}_{r4}\}$ in $\mathbf{k}_c$ neighborhood: The sum of square error function (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.

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