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TITLE PAGE

Optimization of Through-time Radial GRAPPA with Coil Compression and Weight Sharing

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ABSTRACT

Purpose: This work proposes PCA coil compression and weight sharing to reduce acquisition and reconstruction time of through-time radial GRAPPA.

Theory and Methods: Through-time radial GRAPPA enables ungated free-breathing motion-resolved cardiac imaging but requires a long calibration acquisition and GRAPPA weight calculation time. PCA coil compression reduces calibration data requirements and associated acquisition time, and weight sharing reduces the number of unique GRAPPA weight sets and associated weight computation time. In vivo cardiac data reconstructed with coil compression and weight sharing are compared to a gold standard to demonstrate improvement in calibration acquisition and reconstruction performance with minimal loss of image quality.

Results: Coil compression from 30 physical to 12 virtual coils (90% of signal variance) decreases requisite calibration data by 60%, reducing calibration acquisition time to 6.7s per slice from 31.5s per slice reported in original through-time radial GRAPPA work. Resulting images have small increase in RMSE. Reconstruction with a weight sharing factor of 8 results in 8-fold reduction in GRAPPA weight calculation time with a comparable RMSE to reconstructions with no weight sharing. Optimized parameters for coil compression and weight sharing applied to reconstructions enables images to be collected with a temporal resolution of 66ms/frame and spatial resolution of 2.34mm x 2.34mm while reducing calibration acquisition time from 34s to 6.7s, weight calculation time from 200s to 3s, and weight application time 18s to 5s.

Conclusion: Coil compression and weight sharing applied to through-time radial GRAPPA enables fast free-breathing ungated cardiac cine without compromising image quality.

Keywords: parallel imaging; channel compression; non-Cartesian; GRAPPA; cardiac imaging

INTRODUCTION

Cardiac cine MRI is a well-established dynamic imaging technique with high spatial and temporal resolution to assess both cardiac structure and physiological motion[1]. In clinical practice, cardiac cine is a precise and reproducible method for assessment of function and mass of both ventricles though the cardiac cycle. In comparison to other approaches to functional assessment of the heart, cardiac MR is non-invasive, does not use ionizing radiation, and provides superior soft tissue contrast with more possible imaging planes. For these reasons, cardiac cine is considered to be the gold standard for clinical assessment of cardiac function[2].

Despite the success of cardiac cine, patient pathologies can reduce the quality of acquired images. To eliminate motion artifacts, a long acquisition through multiple cardiac cycles is performed with retrospective ECG gating to obtain enough data to resolve motion during each cardiac phase. Due to the long acquisition time, multiple breath-holds are required to eliminate respiratory motion. However, cardiac dysrhythmia can reduce the accuracy of cardiac gating and introduce motion artifacts into acquired images and non-cooperative patients such as children or patients with dyspnea are unable to perform the long breath-holds required for high-quality cardiac cine. Thus, imaging failure due to motion artifacts is a challenge with cardiac cine.

Real-time cardiac imaging techniques have been proposed that do not require breath holds or ECG gating by using rapid data sampling and image reconstruction methods, such as parallel imaging and compressed sensing.[3–7] Non-Cartesian parallel imaging techniques have enabled free-breathing and ungated cardiac imaging with comparable image quality to conventional Cartesian cine[8,9]. Radial and spiral sampling trajectories oversample the signal-rich central region of k-space reducing their sensitivity to motion-related artifacts. In addition, undersampled non-Cartesian trajectories often produce less obtrusive aliasing artifacts than their Cartesian counterparts, enabling higher acceleration factors and, thus, improved temporal resolution to resolve motion. One such non-Cartesian parallel imaging-based approach for rapid cardiac imaging is through-time radial GRAPPA which has been previously deployed for real-time imaging[10–14] due to its low reconstruction latency (<1s).

However, through-time radial GRAPPA requires several fully sampled datasets to calibrate GRAPPA weights, resulting in lower acquisition efficiency. Reported implementations of through-time radial GRAPPA have typically required between 25s[10] to up to 150s[14] per slice for the collection of this calibration data, though calibration times have been reduced to 2.6s[8] by using large reconstruction segment sizes that may introduce blurring and artifacts that can degrade image quality. Longer GRAPPA calibration acquisition may be acceptable in interventional applications[10] where a single calibration scan can be used to reconstruct multiple accelerated acquisitions. In contrast, cardiac cine not only is acquired in a single acquisition, but also requires several slices for ventricular coverage, each slice requiring a new calibration scan. Thus, while capable of generating high-quality cardiac images, through-time radial GRAPPA is inefficient for cardiac cine imaging; reduction of the acquisition time for calibration data without loss of image quality could facilitate the deployment of through-time radial GRAPPA for functional cardiac imaging in the clinic[15].

In addition, growing multichannel receiver arrays and an increasing demand for higher resolution[16–19] place additional computational burden on through-time radial GRAPPA reconstructions. Previously reported real-time applications[10] have demonstrated reconstruction latencies of <1s only during application of the GRAPPA weights, as the calculation of GRAPPA weights are performed only once and do not contribute significantly to the overall reconstruction efficiency. However, compared to GRAPPA weight application, GRAPPA weight calculation is far more computationally intensive and is a major contributor to reconstruction latency for cardiac functional imaging.

Thus, the purpose of this work is to minimize calibration acquisition and GRAPPA weight computation time for through-time radial GRAPPA without impacting image quality. PCA coil compression and weight sharing are the two approaches explored in this work to meet this goal. As both calibration acquisition time and reconstruction latency scale with receiver array size, PCA coil compression can potentially reduce both calibration acquisition time and reconstruction latency while retaining the SNR and encoding benefits of a large array. In addition, reusing GRAPPA weights across small regions of k-space reduces the number of GRAPPA weights required and can thus

reduce the time spent on calculating the GRAPPA weights. Calibration acquisition time and GRAPPA weight calculation time is compared between previously reported through-time radial GRAPPA reconstructions and optimized reconstructions with coil compression and weight sharing. In addition, image RMSE of reconstructions with different settings are compared to determine if coil compression or weight sharing can be performed without loss of image quality.

METHODS

Theory

In radial GRAPPA, and many other non-Cartesian GRAPPA implementations, the relationship between the source and target points is different in different areas of k-space, and thus the GRAPPA kernel, and associated weights, also differs across k-space. As a result, a unique set of weights must be computed for each kernel geometry. In through-time radial GRAPPA, multiple fully sampled datasets are collected and used as calibration data. However, acquiring a sufficient number of kernel repetitions solely from repeated fully-sampled data results in a long acquisition time for the calibration data. The original work on through-time radial GRAPPA proposes a hybrid method which takes calibration data over a small (often 8x1) k-space segment to reduce the number of fully-sampled calibration frames which must be collected[12,14]. The lower bound of calibration frames needed to estimate the GRAPPA weights can be written as:

$$Calibration\ Frames > \frac{N_{kr}N_{kp}N_c}{N_{rseg}N_{pseg}} \quad (1)$$

where N_{rseg} and N_{pseg} are the k-space segment sizes used for calibration in the readout and phase encoding directions respectively.

PCA coil compression is a dimensionality reduction technique along the coil dimension that has been used to improve image SNR and reduce reconstruction time[16–19]. When applied to through-time GRAPPA, PCA coil compression also reduces the lower bound of calibration frames required to estimate the GRAPPA weights as shown in Equation 1. We hypothesize PCA coil compression will significantly reduce the number of calibration frames needed for through-time radial GRAPPA, thereby reducing

the acquisition time, which is a limiting factor in efficient implementation of radial GRAPPA in clinical practice.

In radial GRAPPA, the relationship between each target point and source point kernel in k-space is unique. However, computing a set of GRAPPA weights for each missing point in an undersampled radial dataset is a computationally intensive reconstruction step due to the need for repeated pseudoinverse operations. While every GRAPPA kernel in radial k-space is unique, kernels that are locally adjacent are geometrically similar, and the GRAPPA weights can be assumed to be approximately the same. Thus one weight set could be applied to reconstruct several adjacent target points, and the number of unique GRAPPA weights required for a complete reconstruction could be reduced, in turn reducing the GRAPPA weight computation time. The "weight sharing factor" is the number of target points reconstructed with a single GRAPPA weight set. Note that weight sharing is distinct from the use of k-space segments for calibration, where several kernel repetitions are collected over a region of k-space to estimate the GRAPPA weights.

Data Acquisition

In vivo cardiac data were collected from 15 healthy volunteers in an IRB approved study on a 1.5T Sola Siemens MRI scanner using a 30-channel body receiver array. A total of 400 frames of calibration data were collected during free-breathing with no ECG-gating in the short axis orientation using a radial bSSFP readout with the following imaging parameters: 128x128 matrix, 144 radial projections, 256 readout points per projection, TR/TE=2.94/1.48ms, 37^{o} flip angle, 8mm slice thickness, 300mm^2 FOV. Following the collection of calibration data, ten seconds of accelerated data were collected with a similar imaging protocol using acceleration factors of 4, 6, 9 and 12 (36, 24, 16, and 12 projections, respectively), resulting in temporal resolutions of 100ms/frame, 67ms/frame, 44ms/frame, and 36ms/frame respectively.

Gold Standard Reconstruction

A gold standard image for each acceleration factor was generated via through-time radial GRAPPA reconstruction of collected undersampled data using 400 calibration frames, no k-space segmentation for calibration (1x1 segment), and a 3x2

GRAPPA kernel (in read and projection directions respectively)[14]. Following through-time radial GRAPPA reconstruction, a non-uniform Fast Fourier Transform (NUFFT) from the MIRT toolbox[20] was performed and coils were combined using adaptive combination[21].

Impact of Coil Compression on Required Calibration Data

The radial k-space data, with 30 independent receiver channels, were projected onto a virtual coil subspace at each k-space location using a linear PCA coil compression algorithm[17,22,23]. The through-time radial GRAPPA reconstruction was performed using truncated subsets of the virtual coil space, from 30 virtual coils to 8 virtual coils, with 30 virtual coils accounting for 100% of the signal from the original data. Signal content of the compressed data is defined as the sum of the singular values of the virtual coil subset over the total sum of all singular values. Reconstructions were also performed at specific compression levels (95%, 90%, 80%), defined as the smallest number of virtual coils to needed exceed a signal content threshold. For our system, these compression levels corresponded to 16, 12, and 8 virtual coils.

Through-time radial GRAPPA reconstructions were performed with a 8 x 1 (read x projection) k-space segment size and 3x2 kernel size, as suggested in Seiberlich, et al.[14]. For each virtual coil subset, the number of calibration frames employed to generate GRAPPA weights was monotonically decreased from 80 to the lower bound described by equation 1. Any fewer frames would result in the GRAPPA calibration being underdetermined, where a unique solution for the weights cannot be calculated. In addition, reconstructions where the number of coils were insufficient to perform parallel imaging at a given acceleration factor were not considered.

Image quality of accelerated acquisitions was quantified by calculating the root mean squared error (RMSE) between grayscale normalized gold standard and reconstructed images in an ROI drawn around the heart.

Impact of GRAPPA Weight Sharing on Reconstruction Time and Quality

The through-time radial GRAPPA reconstruction algorithm was modified such that a single GRAPPA weight set was used to estimate multiple target points along the same radial projection. The extent of weight sharing was varied from no weight sharing (weight sharing factor of one, where each target point was associated with a unique

weight set) to weight sharing over 32 points (weight sharing factor of 32) for all acceleration factors. Reconstructions with weight sharing were performed with no coil compression and 80 calibration repetitions to assess image quality changes due to weight sharing independently of coil compression. Image quality was assessed by computing the RMSE between images reconstructed with weight sharing and previously described gold standard images.

Reconstruction with Coil Compression and Weight Sharing

A set of reconstruction parameters were chosen based on coil compression and weight sharing results that demonstrated improved calibration acquisition and reconstruction time performance with minimal image quality degradation. The parameters selected were 12 virtual coils, 16 calibration frames, and a weight sharing factor of 8. Reconstructions with the selected optimized parameters were performed at acquired acceleration factors and were compared to the gold standard reconstruction via RMSE.

Reconstruction Performance

All reconstructions were performed on a dual 12-core Intel Xeon Silver 4214 platform with 128GB of RAM. Reconstruction times for through-time radial GRAPPA with coil compression and weight sharing were normalized to the most computationally intensive reconstruction (no coil compression, no weight sharing, 80 calibration frames). Reconstruction times were subdivided into the three most computationally intensive tasks: Non-uniform fast Fourier transform (NUFFT), GRAPPA weight calculation, and GRAPPA weight application.

RESULTS

Figure 1 shows a heatmap of the RMSE values for reconstructions performed across the range of coil compression factors and calibration frames for a single subject at acceleration factor of 8. Going from right to left, decreasing the number of virtual coils (e.g. decreasing the signal content threshold) improves the RMSE for a given number of calibration frames. Going from top to bottom, decreasing the number of calibration frames worsens the image quality, with a sharp increase in RMSE as the GRAPPA weight equation approaches being exactly determined (as described in equation 1).

Representative images from the heatmap, together with the gold standard reconstruction (Figure 1a, 1x1 segment, 30 coils, 400 calibration frames), are also shown. Figure 1b shows a reconstruction with no coil compression (8x1 segment, 30 coils, 40 calibration frames). Figure 1c shows a reconstruction with coil compression to a 90% signal content threshold (8x1 segment, 12 coils, 16 calibration frames). Figure 1d shows a reconstruction with coil compression to an 80% signal content threshold (8x1 segment, 8 coils, 12 calibration frames). Compared to the gold standard, the reconstructed images have comparable image quality, with RMSE of 1.09% for the reconstruction with no coil compression, 1.24% for the reconstruction with coil compression toa 90% signal content threshold, and 1.32% for the reconstruction with coil compression to a 80% signal content threshold. In addition, the total acquisition time of the calibration data required to perform the reconstruction with coil compression is reduced from 17s to 4.2s per slice.

Diastolic images from a matrix of reconstructions at acceleration factors of 4,6,8 and 9 with weight sharing factors of 1, 8,16, and 32 are shown in Figure 2. All reconstructions are performed with no coil compression and 80 calibration frames. Reference images with no weight sharing are shown on the left and labeled with a weight sharing factor of 1. The RMSE of the reconstruction increases along with both acceleration factor and the weight sharing factor. All reconstructions with a weight sharing factor of 8 have similar RMSE to the reference. A weight sharing factor of 32 leads to artifacts and loss of image quality across all acceleration factors.

Figure 3 shows the radial GRAPPA reconstruction performance improvements associated with coil compression and weight sharing. With no coil compression, the reconstruction time was 237s. At a 95% coil compression level (16 coils), the reconstruction time is reduced to 104s. At a 90% coil compression level (12 coils), the reconstruction time is reduced to 68s. The primary contributor to these performance improvements is the reduction of weight calculation time. While weight sharing does not impact NUFFT or weight application performance, it does affect the weight calculation time, as shown in the bottom plot of Figure 3. A weight sharing factor of 8 reduces the time required to calculate the GRAPPA weights from 134s to 18s, an 86.6% reduction in weight computation time, independent of coil compression.

In figures 4 and 5, systolic and diastolic images are shown in three representative healthy subjects at acceleration factors of six and nine respectively (frame rates of 15 frames/s and 27.5 frames/s) and compared between optimized reconstructions with coil compression and weight sharing, and reconstructions without. The associated calibration data acquisition of optimized reconstructions was obtained retrospectively from the gold standard dataset and could be collected in 6.77s/slice compared to reconstructions with 80 calibration frames, where calibration data are acquired in 34s/slice. In addition, weight computation time for the optimized reconstructions was reduced from 201s to 3.1s per slice for an acceleration factor of 6, and 144s to 2.0s per slice for an acceleration factor of 9. Video timeseries of data shown in figures 4 and 5 is presented in Supporting Information Videos 1 and 2.

DISCUSSION

In this work, through-time radial GRAPPA, a real-time free-breathing ungated acquisition technique for functional cardiac MRI, is optimized for clinical application by reducing the calibration acquisition time and GRAPPA weight computation time. While prior work has optimized the radial GRAPPA weight application step to enable real-time imaging in an interventional setting[10], such optimizations do not address the calibration acquisition time and GRAPPA weight computation time. However, in functional cardiac MRI, the calibration acquisition and GRAPPA weight computation time are the primary sources of inefficiency: calibration requirements can increase scan time by a factor of 2 or more, and GRAPPA weight computation accounts for nearly 60% of the total reconstruction time. Indeed, the long acquisition time for calibration data has been a limiting factor when implementing through-time radial GRAPPA in a clinical setting. As proposed in Seiberlich et al[14], a through-time radial GRAPPA acquisition for a cardiac imaging application with 75 calibration frames would take 31.5s per slice solely for calibration, and would be inefficient in a clinical setting where 10-15 slices are required for whole heart coverage. In addition to long calibration acquisition times, long GRAPPA weight computation times are impractical for on-line implementation, as more than 20 minutes would be required to calculate the GRAPPA weights for a typical short-axis

stack, adversely affecting clinical workflow. To address these issues, an optimized acquisition and reconstruction (12 virtual coils, 16 calibration frames, and weight sharing factor of 8) is suggested, in which images can be generated with image quality comparable to the gold standard despite requiring only 6.7s of calibration data per slice. In addition, GRAPPA weight calculation times were reduced from 201s to 3.1s per slice for an acceleration factor of 6, and 144s to 2.0s per slice for an acceleration factor of 9. With the suggested optimization, the combined calibration acquisition and weight calculation steps may have a reduced impact on clinical workflow, especially as all data collection steps can be performed without ECG gating during free-breathing.

In this work, calibration frames were retrospectively reduced during reconstruction, but in practice, the number of calibration frames must be selected at the time of acquisition. This problem can be addressed by an a priori selection of the number of virtual coils to use in reconstruction at acquisition time. This selection creates a lower bound on the number of calibration frames required to perform GRAPPA, as shown in equation 1. For the experimental arrangement at our institution, coil compression to 12 virtual coils results in 90% of the information to be retained with little variability between subjects (see Supporting Information Figure 1). Correspondingly, the image reconstructed with weights generated using only 16 calibration frames and 12 virtual coils had an RMSE (1.24%) comparable to an uncompressed reconstruction with 80 calibration frames (1.09%).

It should be noted that coil compression reduces the total signal content used in reconstruction, but despite reduced signal, reconstruction with coil compression either has similar or better RMSE to a reconstruction with no compression but similar number of calibration frames. The effect of improved image quality with coil compression has been described in other work with Cartesian SENSE[23] and Cartesian GRAPPA[19] and is due to truncation of virtual coils with the lowest signal content which can be dominated by noise. Removal of these virtual coils prevents fitting to noise during GRAPPA weight estimation. The noise reduction performance due to coil compression is expected to depend on a variety of factors including the SNR of the imaging application, the size of the real multichannel array, and the geometry of the array. In addition, truncating too many virtual coils can result in pruning real signal instead of noise. For functional

cardiac imaging, the RMSE of through-time radial GRAPPA reconstructions with coil compression was reduced at all compression levels compared to an uncompressed reconstruction for a fixed number of calibration frames, as shown in figure 1, suggesting that the signal from a smaller number of virtual coils contains sufficient structural and contrast information for robust image reconstruction.

In comparison to many other techniques for rapid functional cardiac MRI, such as machine learning based parallel imaging approaches[24,25] or compressed sensing[26], non-Cartesian GRAPPA methods acquire images with sufficient temporal resolution to not require ECG-gating or breath holds. While compressed sensing approaches have the advantage of greatly reducing acquisition time, the non-linear reconstruction is not conducive to parallelization, impeding optimization of reconstruction performance[6,26,27]. Machine learning based approaches have excellent reconstruction speed but have not yet been shown to be generalizable. Thus, many newer cardiac MR approaches still require breath-holds or ECG-gating which are points of imaging failure in patients with dyspnea or arrhythmia. Non-Cartesian GRAPPA techniques are clinically robust to many pathologies[8] and the presented optimized strategy for through-time radial GRAPPA resolves long-standing issues with clinical implementation without compromising image quality. In addition, coil compression and weight sharing should be applicable to other though-time non-Cartesian GRAPPA implementations.

CONCLUSION

Through-time radial GRAPPA enables free-breathing ungated functional cardiac imaging with high temporal resolution. However, the initial formulation of through-time radial GRAPPA requires a time-consuming calibration acquisition and long weight computation times. In this work, these disadvantages are mitigated via coil compression and weight sharing. Coil compression to 12 virtual coils (90% compression factor) results in minimal impact on image quality across all tested acceleration factors. The associated reduction in requisite calibration data to 16 frames enables calibration acquisition time to be reduced from 31.5s to 6.7 seconds per slice and GRAPPA weight calculation time to be reduced by 63%. Weight sharing further reduces GRAPPA weight calculation time with minor impact on image RMSE at a weight sharing factor of eight.

Combined application of coil compression and weight sharing does not degrade image quality while retaining calibration and reconstruction benefits of each processing step and reducing GRAPPA weight calculation to <3s across all acceleration factors. This work demonstrates that coil compression and weight sharing can be used to reduce calibration acquisition time and reconstruction latency of through-time radial GRAPPA for functional cardiac imaging without compromising image quality.

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FIGURE CAPTIONS

Figure 1: Right: A representative heatmap indicating the log(RMSE) between the gold standard and reconstructions performed with a specific number of virtual coils and calibration frames for R=8. Left: The gold standard image for this heat map is shown as image A. Images B, C and D correspond to reconstructions from specific regions of the heatmap with similar RMSE and are reconstructed with coil compression to signal content of 100%, 90%, and 80% respectively. The acquisition time of the calibration data (T_{acq}) is shown in the bottom right of each image. The RMSE between the gold standard and each reconstruction is shown on the top right of each image.

Figure 2: Reconstructed images over a range of weight sharing factors and acceleration factors. Images were reconstructed with no coil compression and 80 calibration frames. The leftmost column of images was reconstructed with no weight sharing, equivalent to a weight sharing factor of one. The RMSE between the gold standard and reconstructed image is shown on the top left of each image.

Figure 3: (Top) A representative plot showing the total reconstruction time (purple) for reconstructions with varying numbers of virtual coils at an acceleration factor of 9. All reconstructions were performed with 80 calibration frames. The calculation time of the GRAPPA weights is shown in blue and the reconstruction time, where the weights are applied to reconstruct undersampled data, is shown in red. Time taken to perform radial gridding is shown in yellow. Other computational tasks, such as data transfer or IO overhead, are negligible compared to GRAPPA and NUFFT time. (Bottom) A representative plot showing the reduction in weight calculation time due to weight sharing at an acceleration factor of 9. Weight sharing does not impact NUFFT or weight application time.

Figure 4: Reconstructed images from diastole and systole from three healthy subjects at an acceleration factor of 6. Image RMSE are shown in the top left of each image. Optimized

reconstructions performed with 12 virtual coils, 16 calibration frames, and a weight sharing factor of 8 are compared to reconstructions performed with no coil compression, 80 calibration frames, and no weight sharing. In plane resolution is 2.34x2.34mm^2 and temporal resolution is 67ms/frame resulting in a 15 frame/s acquisition. The acquisition time for the calibration data used in the optimized reconstruction was 6.77s, average weight computation time was 3.13s and average weight application time was 4.1s. In contrast, reconstructions with no coil compression or weight sharing have a calibration acquisition time of 34s, average weight computation time of 201s, and average weight application time of 15.1s. Video timeseries of this data can be found in supplementary material as Supporting Information Video 1.

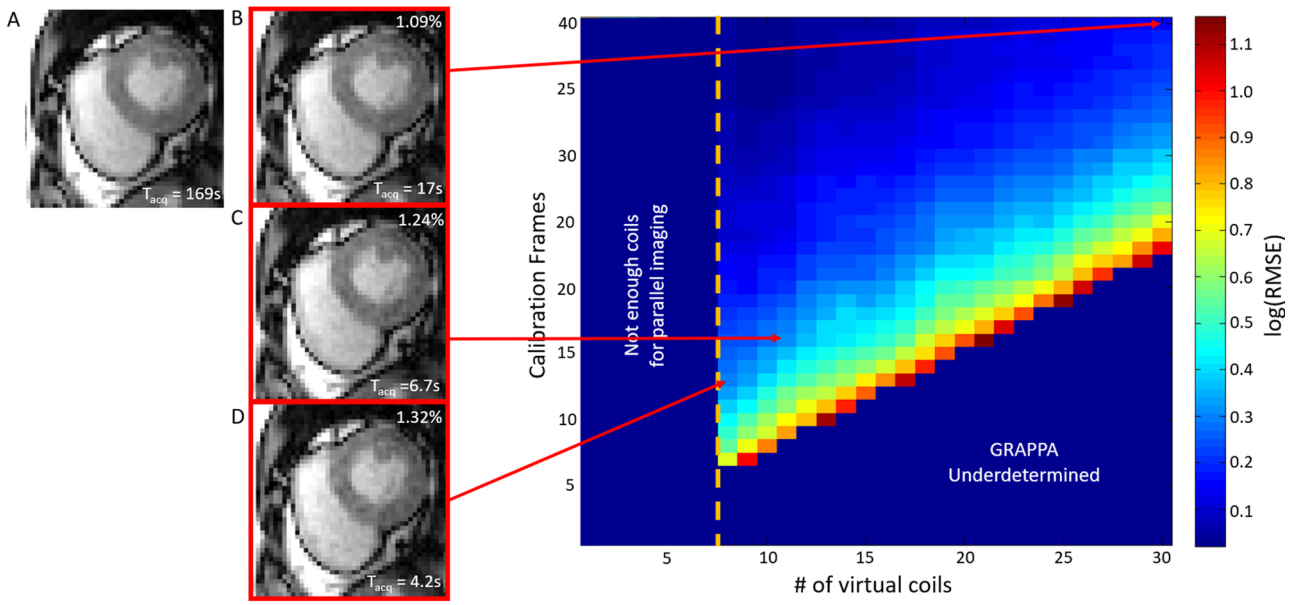
Figure 5: Reconstructed images from diastole and systole from three healthy subjects at an acceleration factor of 9. Image RMSE are shown in the top left of each image. Optimized reconstructions performed with 12 virtual coils, 16 calibration frames, and a weight sharing factor of 8 are compared to reconstructions performed with no coil compression, 80 calibration frames, and no weight sharing. In plane resolution is 2.34x2.34mm^2 and temporal resolution is 44ms/frame resulting in a 27.5 frame/s acquisition. The acquisition time for the calibration data used in the optimized reconstruction was 6.77s, average weight computation time was 2.0s and average weight application time was 4.9s. In contrast, reconstructions with no coil compression or weight sharing have a calibration acquisition time of 34s, average weight computation time of 144s, and average weight application time of 18.5s. Video timeseries of this figure can be found in supplementary material as Supporting Information Video 2.

Supporting Information Figure 1: Left: A series of boxplots indicating the signal content remaining after coil compression to a specific virtual coil count. Each boxplot represents information from N=15 healthy subjects. The median is shown as a white circle with a central blue dot, the interquartile range is shown as a thick blue box, and the minimum and maximum values are shown as whiskers extending from the interquartile range. Right: A series of boxplots indicating the number of virtual coils required to yield a specific signal content threshold. The median is shown as a red line, the interquartile range is shown as a blue box, and the minimum

and maximum are shown as whiskers extending from the interquartile range. Outliers beyond 1.5x the interquartile range are shown as red pluses.

Supporting Information Video 1: Reconstructed timeseries from three healthy subjects at an acceleration factor of 6. Optimized reconstructions performed with 12 virtual coils, 16 calibration frames, and a weight sharing factor of 8 are compared to reconstructions performed with no coil compression, 80 calibration frames, and no weight sharing. In plane resolution is 2.34x2.34mm^2 and temporal resolution is 67ms/frame resulting in a 15 frame/s acquisition. The acquisition time for the calibration data used in the optimized reconstruction was 6.77s, average weight computation time was 3.13s and average weight application time was 4.1s. In contrast, reconstructions with no coil compression or weight sharing have a calibration acquisition time of 34s, average weight computation time of 201s, and average weight application time of 15.1s.

Supporting Information Video 2: Reconstructed timeseries from three healthy subjects at an acceleration factor of 9. Optimized reconstructions performed with 12 virtual coils, 16 calibration frames, and a weight sharing factor of 8 are compared to reconstructions performed with no coil compression, 80 calibration frames, and no weight sharing. In plane resolution is 2.34x2.34mm^2 and temporal resolution is 44ms/frame resulting in a 27.5 frame/s acquisition. The acquisition time for the calibration data used in the optimized reconstruction was 6.77s, average weight computation time was 2.0s and average weight application time was 4.9s. In contrast, reconstructions with no coil compression or weight sharing have a calibration acquisition time of 34s, average weight computation time of 144s, and average weight application time of 18.5s.



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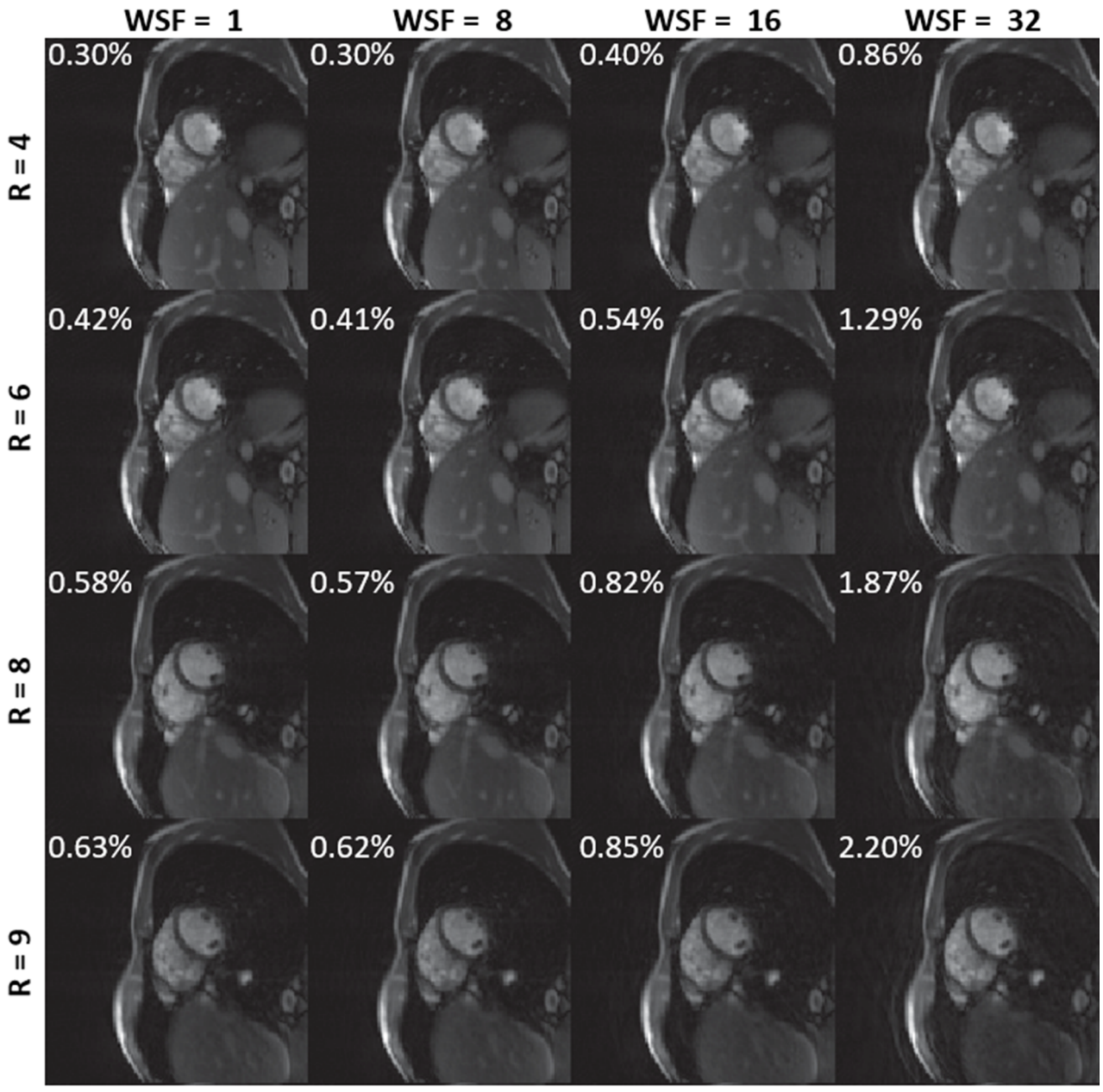

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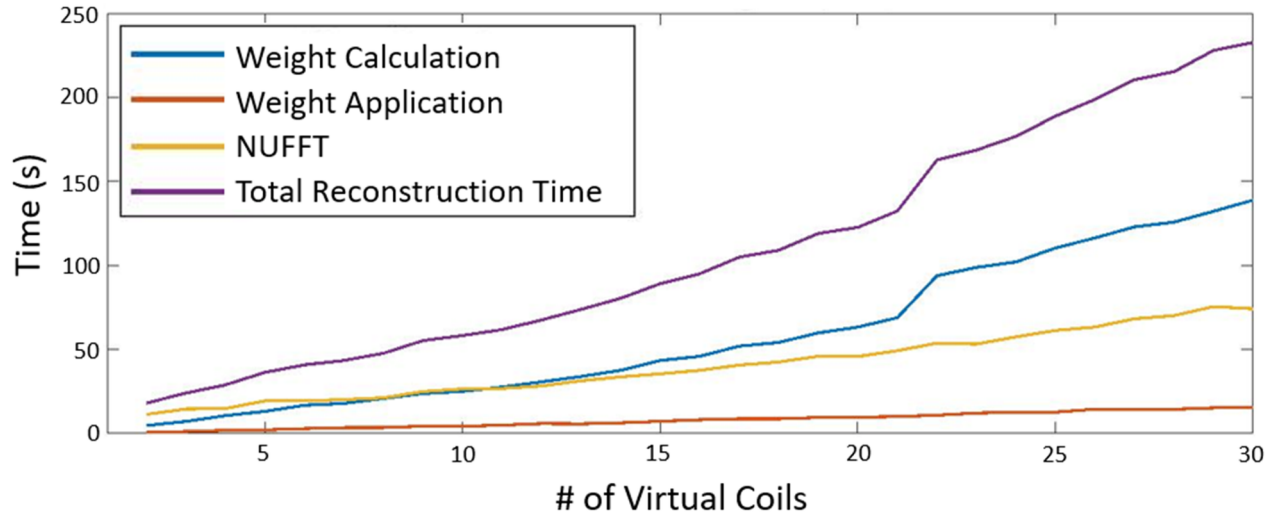

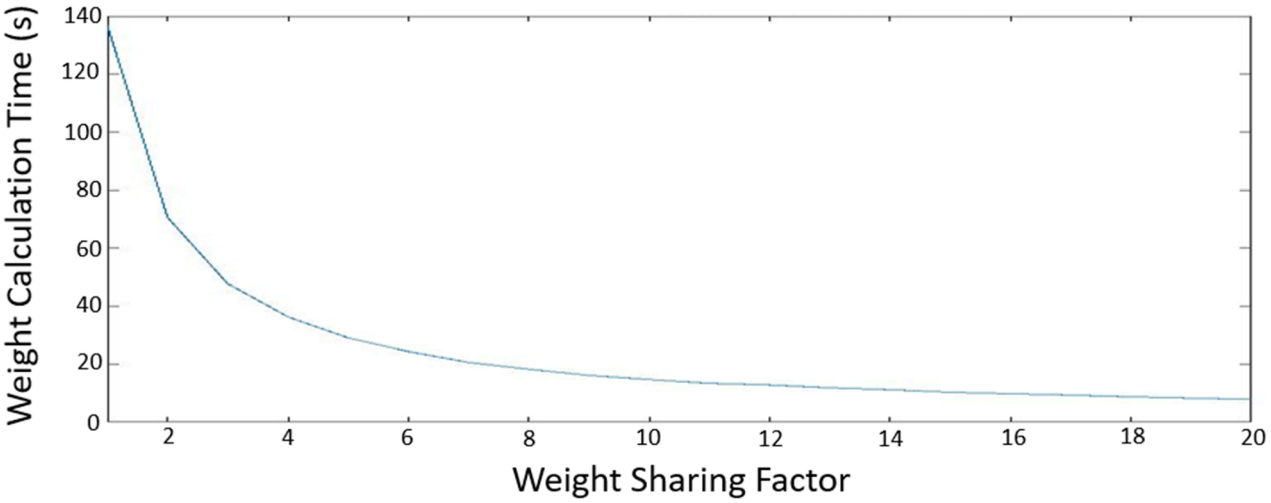

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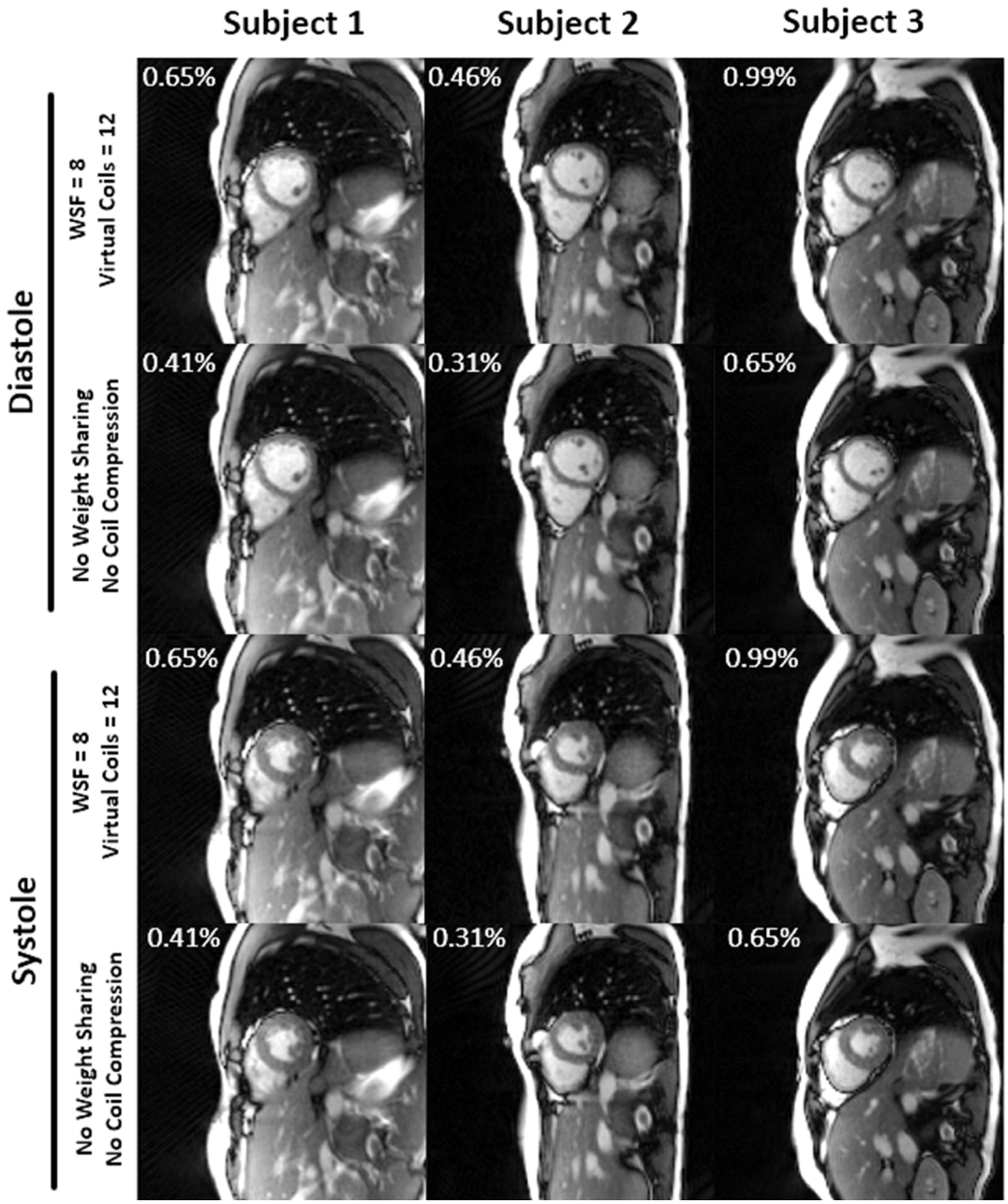

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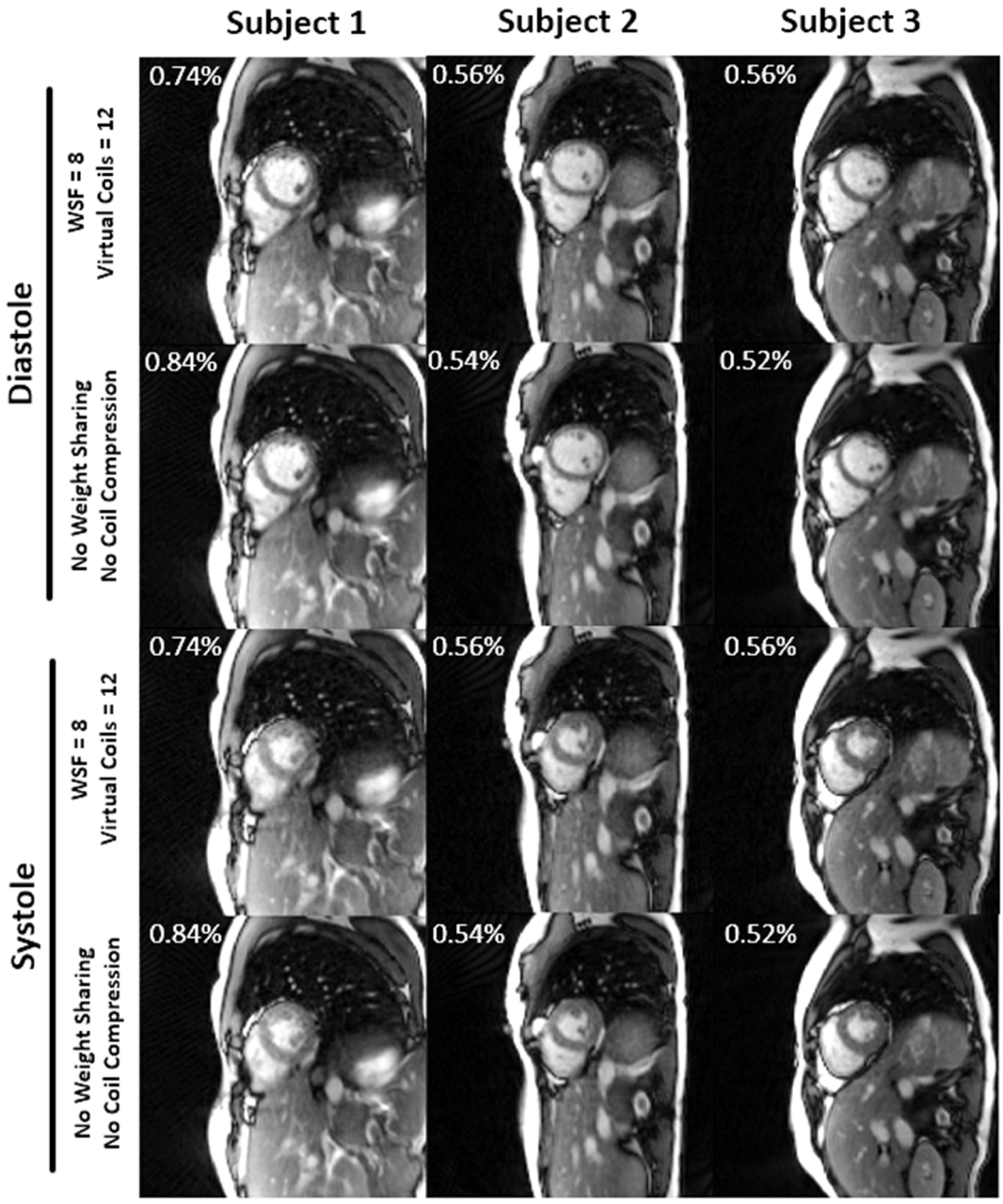

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