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Joint Reconstruction Framework of Compressed Sensing and Nonlinear Parallel Imaging for Dynamic Cardiac Magnetic Resonance Imaging

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ABSTRACT

Compressed Sensing (CS) and parallel imaging are two promising techniques that accelerate the MRI acquisition process. Combining these two techniques is of great interest due to the complementary information used in each. In this study, we propose a new reconstruction framework for dynamic cardiac imaging that takes advantage of both CS-based dynamic imaging and one nonlinear parallel imaging technique. The method decouples the reconstruction process into two

sequential steps: use CS to reconstruct a series of aliased dynamic images from the highly undersampled k-space data; use nonlinear GRAPPA method, one nonlinear technique of parallel imaging, to reconstruct the original dynamic images from the k-space data that has been reconstructed by CS. The sampling scheme of the proposed method is designed to simultaneously satisfy the incoherent undersampling requirement for CS and the structured undersampling requirement for nonlinear parallel imaging. Four in vivo experiments of dynamic cardiac cine MRI were carried out with retrospective undersampling to evaluate the performance of the proposed method. Experiments show the proposed method of dynamic cardiac cine MRI is superior at reducing aliasing artifacts and preserving the spatial details and temporal variations, when compared with k-t FOCUSS and k-t FOCUSS with sensitivity encoding, using the same numbers of measurements. The proposed joint reconstruction framework effectively combines the CS method and one nonlinear technique of parallel imaging, and improves the image quality of dynamic cardiac cine MRI reconstruction when comparing to the state-of-the-art methods.

INDEX TERMS dynamic cardiac MRI, compressed sensing, parallel imaging, nonlinear GRAPPA

I. INTRODUCTION

Magnetic resonance imaging (MRI) is one of the most important medical imaging modalities that has been used in the diagnosis of cardiovascular diseases. Due to its excellent tissue contrast, MRI can effectively evaluate cardiac functions and vascular abnormalities. Currently, dynamic MRI has been applied in the applications of cardiac imaging through acquiring a time series of images at a high frame rate during cardiac motion. During dynamic cardiac MRI, measurements are taken in k-space at different time points. To obtain an artifact-free image series using conventional Fourier reconstruction, the Nyquist sampling requirement must be satisfied in both spatial and temporal directions.

Dynamic MRI, due to its low data acquisition speed, however, does not always meet this criterion, which causes aliasing artifacts or motion artifacts in Fourier reconstruction. The acquisition speed

is hence of primary importance for achieving high spatial-temporal resolution in dynamic MRI applications. By utilizing spatial and/or temporal correlations in dynamic cardiac image series, various strategies have been developed for reconstructing a high-quality image series from undersampled MRI data. It is possible to estimate missing data from undersampled measurements using these spatial and temporal correlations. Typical methods include RIGR [1], keyhole [2], view-sharing [3], UNFOLD [4], Partially Separable Function (PS) [5]-[7], Kalman filter [8], PARADIGM [9], k-t BLAST [10] and so on.

Two promising techniques for speeding up acquisition are parallel imaging and compressed sensing, which downsamples the k-space below the Nyquist rate. Parallel imaging [11]-[14] uses information from multiple coil signals to estimate the unacquired k-space data, such as the classical SENSE [12] and GRAPPA [13]. Theoretically, the maximum acceleration rate of parallel imaging can be up to the number of physical channels under ideal conditions. However, noise and imperfect coil geometry limits the achievement to the maximum acceleration in practice. Compressed sensing (CS) [15]-[17] exploits the sparseness of the signal in a certain domain as the prior constraint and recovers the accurately signal using nonlinear optimization algorithms. The success of applying CS to dynamic cardiac MRI greatly accelerates the acquisition process [18]-[26]. Such success is based on two important properties of the dynamic cardiac images: firstly, the dynamic cardiac images exhibits strong correlations between frames which guarantee the sparse representation of the sequence in a specific transform domain; secondly, the sampling pattern can be easily designed to satisfy the incoherence requirement of CS theory.

Combining these two strategies is of great interest due to the complementary information employed in these two techniques. Several researches [27]-[39] have been developed to combine parallel MRI (pMRI) and CS for static imaging. For instance, Sparse SENSE [27] and k-t SparseSENSE [25] incorporated the sensitivity information by replacing Fourier encoding by sensitivity encoding in the data consistency term; the low-rank method has been applied into dynamic Cardiac MRI applications [31][32]; the dictionary learning method for CS reconstruction has been applied in [33][34]; the E-SPiRiT method has been applied into Cardiac MRI applications [35]; Golden-angle radial sparse parallel MRI has been applied into dynamic volumetric MRI [36]; recently some deep learning

methods from the CS and pMRI frameworks have been introduced into Cardiac MRI applications [37]-[39]. However, research on how to combine the CS and pMRI frameworks into Cardiac MRI applications is still important. For example, because each approach has different sample needs, it is difficult to optimize the accelerations that can be achieved by a simple combination.

In this paper, we aim to develop a novel reconstruction framework that efficiently combines compressed sensing and non-linear parallel imaging technique to accelerate the dynamic cardiac imaging, extending results in our conference papers [40][41]. The proposed reconstruction framework divides the procedure into two parts. In the first phase, the highly undersampled k-space data is used to recreate a series of aliased dynamic cardiac images using a CS approach. The missing k-space data for the original image is reconstructed in the second stage using state-of-the-art nonlinear GRAPPA algorithm, [42]-[44], one nonlinear parallel imaging technique, which has not been investigated how to combine with CS to accelerate cardiac cine MRI. The sampling method for each step is thus designed independently, allowing for simultaneous satisfaction of the incoherent undersampling need for CS and the structured undersampling requirement for parallel imaging. In vivo human cardiac cine MR tests are used to evaluate the proposed method's performance. The proposed joint reconstruction framework can effectively combine the CS method and the nonlinear technique of parallel imaging, and improves the reconstructed image quality of dynamic cardiac MRI reconstruction when comparing to the state-of-the-art k-t FOCUSS methods.

II. THEORY AND METHOD

Since the sampling scheme of CS and parallel imaging exploit complementary redundancy information in MRI, it is of great interest to combine these two techniques so that higher reduction factor could be achieved. Motivated by this, the proposed framework decouples the reconstruction process into two sequential steps. In the data acquisition process, the k-t space is undersampled by taking a random subset of the already uniformly undersampled k-space data at each time point. Mathematically, let $\mathbf{M}_u$ represent the uniform undersampling operation, $\mathbf{M}_r$ represents the operation of taking a random subset in k-space. The data acquisition process can be expressed by:

$$\mathbf{d}_{u,r} = \mathbf{M}_r \mathbf{M}_u \mathbf{d}_{full} \quad (1)$$

where $\mathbf{d}_{u,r}$ is the acquired data, and $\mathbf{d}_{full}$ is the fully sampled reference data in k-t space. The uniform undersampling has a reduction factor of R_1 , and the random subset has a reduction factor of R_2 for the CS requirement. As a result, the total acceleration is $R_1 \times R_2$. For all time frames, additional auto calibration signals (ACS) are also acquired at the center k-space.

Based on the decoupled undersampling operations $\mathbf{M}_u$ and $\mathbf{M}_r$, the reconstruction is carried out in two sequential steps. The CS reconstruction framework is used in the first stage, with the goal of reconstructing a uniformly undersampled k-space by “inverting” the operation $\mathbf{M}_r$. Let the aliased image series to be reconstructed in the $(x-f)$ domain is represented by $\boldsymbol{\rho}_u$. The data consistency term is then given by

$$\mathbf{d}_{u,r} = \mathbf{F}\boldsymbol{\rho}_u \quad (2)$$

where $\mathbf{F}$ is the Fourier transform along both x and f directions. The reconstruction of the signal $\boldsymbol{\rho}_u$ in $x-f$ domain can be modeled as a truncated ℓ_1 minimization problem

$$\min_{\boldsymbol{\rho}_u} \|\boldsymbol{\rho}_u\|_1 \quad s. t. \quad \|\mathbf{d}_{u,r} - \mathbf{F}\boldsymbol{\rho}_u\|_2 \leq \varepsilon \quad (3)$$

Here we use the k-t FOCUSS [21] algorithm to reconstruct the aliased image sequence in the temporal-frequency $(x-f)$ domain, although other methods may also be applied.

The solution to Eq. (3) is computed by iteratively solving a reweighted ℓ_2 minimization problem defined as

$$\text{find } \boldsymbol{\rho}_u = \mathbf{W}\mathbf{q}$$

Such that $\mathbf{q}$ is the solution to

$$\min_{\mathbf{q}} \|\mathbf{q}\|_2 \quad s. t. \quad \|\mathbf{d}_{u,r} - \mathbf{F}\mathbf{W}\mathbf{q}\|_2 \leq \varepsilon \quad (4)$$

where $\mathbf{W}$ is a diagonal weighting matrix that is updated iteratively. Eq. (4) can be converted into an unconstrained optimization problem by introducing the Lagrangian multiplier λ ,

$$\min_{\mathbf{q}} \|\mathbf{d}_{u,r} - \mathbf{F}\mathbf{W}\mathbf{q}\|_2^2 + \lambda \|\mathbf{q}\|_2^2 \quad (5)$$

which has a closed-form solution

$$\mathbf{q} = \mathbf{W}^H \mathbf{F}^H (\mathbf{F} \mathbf{W} \mathbf{W}^H \mathbf{F}^H + \lambda \mathbf{I})^{-1} \mathbf{d} \quad (6)$$

Conjugate gradient is used to solve Eq. (6) to avoid the large matrix inversion. So the $x-f$ image is given by

$$\boldsymbol{\rho}_u = \mathbf{W}\mathbf{q} = \mathbf{W}\mathbf{W}^H\mathbf{F}^H(\mathbf{F}\mathbf{W}\mathbf{W}^H\mathbf{F}^H + \lambda\mathbf{I})^{-1}\mathbf{d} \quad (7)$$

Specifically, in the l -th iteration, the diagonal elements of the matrix $\mathbf{W}^{(l)}$ are the square root of the absolute value of the solution $\boldsymbol{\rho}_u^{(l-1)}$ from the previous iteration,

$$\mathbf{W}^{(l)} = \begin{pmatrix} |\boldsymbol{\rho}_1^{(l-1)}|^{0.5} & 0 & L & 0 \\ 0 & |\boldsymbol{\rho}_2^{(l-1)}|^{0.5} & L & 0 \\ M & M & O & M \\ 0 & 0 & L & |\boldsymbol{\rho}_n^{(l-1)}|^{0.5} \end{pmatrix}, \quad (8)$$

where $\boldsymbol{\rho}_n^{(l-1)}$ is the n th element of $\boldsymbol{\rho}_u^{(l-1)}$. The reconstructed $\boldsymbol{\rho}_u$ is then Fourier transformed along both spatial and temporal frequency directions to obtain the uniformly undersampled data in k-t space.

The missing k-space lines in the reconstructed uniformly undersampled data in k-t space are further reconstructed by parallel imaging techniques. To avoid the computation of sensitivity maps and minimize the error/noise amplification from the CS step, nonlinear GRAPPA is used, although other parallel imaging methods are applicable. The pre-acquired ACS lines are used to normalize the reconstructed k-space to correct any mismatch. Specifically, we assume the reconstructed and the acquired data differ by a scaling complex constant:

$$\mathbf{d}_{\text{recon}} = \beta \mathbf{d}_{\text{acq}} \quad (9)$$

where β is the scaling factor, so that each frame is scaled based on the k-space data from overlapping locations between reconstructed and acquired data.

Nonlinear GRAPPA [42]-[44] is then conducted after normalization. In nonlinear GRAPPA, the missing data is represented by a nonlinear combination of the acquired data. Here we apply a truncated second-order polynomial whose efficiency and effectiveness have been demonstrated in [42]-[44]. The missing k-space signal S_j in $\mathbf{d}_{\text{recon}}$ is obtained by

$$\begin{aligned}
S_j(k_y + r\Delta k_y, k_x) = & w_{j,r}^{(0)} \times I \\
& + \sum_{l=1}^L \sum_{b=B_l}^{B_2} \sum_{h=H_l}^{H_2} w_{j,r}^{(1)}(l, b, h) \times S_l(k_y + bR\Delta k_y, k_x + h\Delta k_x) \\
& + \sum_{l=1}^L \sum_{b=B_l}^{B_2} \sum_{h=H_l}^{H_2} w_{j,r}^{(2,0)}(l, b, h) \times S_l^2(k_y + bR\Delta k_y, k_x + h\Delta k_x) \\
& + \sum_{l=1}^L \sum_{b=B_l}^{B_2} \sum_{h=H_l}^{H_2-1} w_{j,r}^{(2,1)}(l, b, h) \times S_l(k_y + bR\Delta k_y, k_x + h\Delta k_x) \times \\
& \quad S_l(k_y + bR\Delta k_y, k_x + (h+1)\Delta k_x) \\
& + \sum_{l=1}^L \sum_{b=B_l}^{B_2} \sum_{h=H_l}^{H_2-2} w_{j,r}^{(2,2)}(l, b, h) \times S_l(k_y + bR\Delta k_y, k_x + h\Delta k_x) \times \\
& \quad S_l(k_y + bR\Delta k_y, k_x + (h+2)\Delta k_x),
\end{aligned} \tag{10}$$

where S_l represents the acquired k-space data, w is the coefficient set, R is the outer reduction factor, j is the target coil, l counts all coils, b and h transverse the acquired neighboring k-space data in k_y and k_x directions respectively, and k_x and k_y represent the coordinates along the frequency- and phase-encoding directions, respectively. The final image is obtained by combining images from all coils using root of sum-of-squares after the missing k-space data for all coils has been recovered. The proposed framework is demonstrated in FIGURE 1.

FIGURE 1. Reconstruction flowchart of the proposed method

Validation of the proposed method was performed on four sets of cardiac cine data from dynamic MRI, each covering a complete cardiac cycle. The imaging parameters are shown in TABLE 1.

Informed consent was obtained from all volunteers in accordance with the institutional review board policy. The fully sampled data were uniformly undersampled with a reduction factor of R_1 and furthermore randomly undersampled with a reduction factor of R_2 using a zero-mean random Gaussian distribution whose density tapers off toward the outer k -space retrospectively.

TABLE I

	Data 1	Data 2	Data 3	Data 4
<i>Scanner</i>	3T Siemens	3T Siemens	3T Siemens	3T Siemens
<i>Sequence</i>	SSFP	2D true FISP	SSFP	SSFP
<i>Flip Angle</i>	44	50	50	44
<i>Echo Time/Repetition time (ms)</i>	1.5/3.0	1.87/29.9	1.89/56.6	1.22/42.5
<i>Matrix Size</i>	$166 \times 130 \times$	$256 \times 216 \times$	$256 \times 224 \times$	$304 \times 165 \times$
<i>(FE $\times$ PE $\times$ Frame $\times$ Coil)</i>	15×5	20×4	14×4	26×12

DATA ACQUISITION PARAMETERS FOR IMAGING EXPERIMENTS

The proposed method, k-t FOCUSS [24] and k-t FOCUSS with sensitivity encoding [20] are used to reconstruct the desired image sequence. The code for k-t FOCUSS [24] was obtained from <http://bisp.kaist.ac.kr>. Same net reduction factor is used for all methods. For the reconstruction using k-t FOCUSS, images were reconstructed for each coil separately and then combined using square-root of sum-of-squares. The center k -space was fully sampled to estimate the low-resolution image for FOCUSS algorithm, to estimate the sensitivity map for k-t FOCUSS with sensitivity encoding and the Auto Calibration Data (ACS) for the proposed method. The net reduction factor R can be calculated as,

$$R = \frac{\text{number of phase encoding lines}}{\frac{\text{number of phase encoding lines}}{R_1 \times R_2} + \text{fully sampled center phase encoding lines}} \quad (11)$$

The image sequence reconstructed from the full k-t data were used as the reference for comparison. All image data in FIGURE 2 was zero-padded to display images with the correct ratio representing the original FOV, normalized, and displayed on the same scale. All the computations were carried out on a workstation with Intel i7-3770 3.40GHz CPU and 64GB RAM running MATLAB 2019a (Mathworks, Natick, MA).

FIGURE 2. A single frame reconstructed from the fully sampled data for all four datasets.

III. RESULTS

A. IMAGE QUALITY OF PROPOSED FRAMEWORK

FIGURE 3 shows the reconstruction result and the corresponding error images compare with the reference at the sixth frame of the first dataset. The difference images were scaled appropriately to highlight the differences between the reconstructions and the reference images. For the proposed method, the reduction factor is 2 for parallel imaging and 3 for CS. For k-t FOCUSS [24] and k-t FOCUSS with sensitivity encoding [20], the outer reduction factor is 6. The center 32 phase encoding lines are fully sampled as the ACS data and estimating the coil sensitivity, which makes the net reduction factor $R = 2.89$ for all methods. It is seen in FIGURE 3 that the reconstruction using k-t FOCUSS [24] presents serious aliasing artifacts along the undersampled phase encoding direction. By incorporating sensitivity encoding, the aliasing artifacts are suppressed but presents noise in both cardiac region and background as indicated as arrowheads. The advantage of proposed methods on suppressing aliasing and noise artifacts can be better appreciated in the difference images. FIGURE 4 shows the reconstruction result of the 16th frame of the second dataset at a net reduction $R = 4.11$. For the proposed method, acceleration combination is 4 for CS and 2 for Nonlinear GRAPPA [42]-[44].

Center 36 phase encoding lines are fully sampled. The results of data 2 lead to the same conclusion that the proposed method can suppress more aliasing

FIGURE 3. Reconstructions of the 6th frame of Data 1 using the proposed method (second column), k-t FOCUSS (third column) and k-t FOCUSS with sensitivity encoding (forth column). Center 32 phase encoding lines are fully sampled. For the proposed method, the acceleration combination is 3 for CS and 2 for Nonlinear GRAPPA. The net reduction factor is 2.89 for all methods. The red box indicates the ROI.

FIGURE 4. Reconstructions of the 16th frame of Data 2 using the proposed method (second column), k-t FOCUSS (third column) and k-t FOCUSS with sensitivity encoding (forth column). Center 36 phase encoding lines are fully sampled. For the proposed method, the acceleration combination is 4 for CS and 2 for Nonlinear GRAPPA. The net reduction factor is 4.11 for all methods.

artifacts and preserve more details than either k-t FOCUSS [21] or k-t FOCUSS with sensitivity encoding [17]. It's worth noting that although compare with k-t FOCUSS [24], add sensitivity encoding could significantly remove the aliasing artifacts; it also over-smoothed the image that causes the loss of details in the cardiac region indicated by the arrowheads. It is mainly due to the inaccurate estimation of the sensitivity map.

Here, to quantitatively evaluate the performance of the proposed method, the normalized mean-square error (NMSE) of the region of interest (ROI) between the reconstruction and the reference were calculated and plotted as a function of time in FIGURE 5. The NMSE is calculated by

$$NMSE(I_{ref}, I_{recon}) = \frac{\|I_{ref} - I_{recon}\|_2^2}{\|I_{ref}\|_2^2} \quad (12)$$

FIGURE 5. Frame-by-frame plots of NMSE in the ROI for the proposed method, k-t FOCUSS, and k-t FOCUSS with SENSE with net reduction factor $R = 2.89$ for the Data 1, $R = 4.11$ for the Data 2, $R = 4.14$ for

the Data 3, and $R=3.6$ for the Data 4. The blue solid lines are for the proposed method, green dotted lines for the k - t FOCUSS with SENSE, and black dashed lines for the k - t FOCUSS.

To further evaluate the performance of the proposed method in clinical diagnosis, the heart region with the most dynamic motion are considered as the region of interest and zoomed-in for comparison for all method in the third and fourth dataset. FIGURE 6 shows the reconstruction in the heart region comparison from different frames of the third dataset at a net reduction factor of 4.14. The acceleration combination of proposed method is 4 for CS and 3 for nonlinear GRAPPA [42]-[44]. The center 38 phase encoding lines are fully sampled. It can be seen that k - t FOCUSS [24] presents blurring on the image and lost details, while by incorporating sensitivity encoding reduces blurring but introduces noise-like artifacts. The proposed method evidently removes the blurring and the noise. FIGURE 7 shows the comparison between the proposed method with other three methods with Data 4. It suggested that the proposed method is superior at removing motion and aliasing artifact, especially at the cardiac region than the other three methods.

FIGURE 6. Region of interest of reference (first column), the proposed method (second column), k - t FOCUSS (third column) and k - t FOCUSS with SENSE (forth column) of data 3. Center 38 phase encoding lines are fully

sampled. For the proposed method, the acceleration combination is 4 for CS and 3 for Nonlinear GRAPPA. The net reduction factor is 4.14 for all methods.

It can be seen that the proposed method has a lower NMSE than the other two methods for all frames. The ability to capture the temporal variation is another important criterion to evaluate the performance of dynamic reconstruction methods. The temporal profiles of the second data with a net $R = 4.11$ and Data 4 with a net $R = 3.6$ are shown in FIGURE 8. It is seen that the k - t FOCUSS method [24] can smooth out the rapid temporal changes and k - t FOCUSS with sensitivity encoding [20] presents loss of contrast. In comparison, the proposed method preserves most of the temporal variations than other methods especially in regions indicated by arrowheads.

FIGURE 7. Reference (first column), the proposed method (second column), k - t FOCUSS (third column) and k - t FOCUSS with SENSE (forth column) of data 4. Center 32 phase encoding lines are fully sampled. For the proposed method, the acceleration combination is 6 for CS and 2 for Nonlinear GRAPPA. The net reduction factor is 3.6 for all methods.

B. CHOICE OF ACCELERATION FACTOR COMBINATION FOR CS AND PI

It has been proven that the error propagating property [28] is critical to the reconstruction quality and the proper choice of the acceleration combination of CS and PI can significantly affect the final result. FIGURE 9 shows the comparison of the reconstruction quality of Data 3 with different acceleration combinations for CS and PI at the same net reduction factors $R = 4$ (1×4 , 2×2 , 4×1) and $R = 12$ (2×6 , 3×4 , 4×3 , 6×2) with fixed 40 ACS lines. It can be seen that with a fixed number of ACS lines and outer reduction factor (ORF), a small R_1 will result in losing the de-noised power from CS and result in large error/noise amplification, especially at high ORF as shown in $R_1 \times R_2 = 2 \times 6$. While a small R_2 will result in more aliasing

FIGURE 8. The temporal profiles in x - t plane of the different reconstruction methods, the proposed method, k - t FOCUSS and k - t FOCUSS with SENSE, for the Data 2 with net reduction factor of 4.11 and data 4 with net reduction factor of 3.6 (bottom row).

artifacts (e.g. $R_1 \times R_2 = 6 \times 2$). When evenly distribute the acceleration factor, to avoid error propagation, it is better to keep the acceleration at CS step slightly higher than it at the PI step to avoid the amplification of the error. This conclusion can be better appreciated at the NMSE plot as shown in FIGURE 10.

FIGURE 9. The proposed method of the Data 3 with different combinations of reduction factors.

FIGURE 10. The NMSE plots of the proposed method reconstructions of the Data 3 with different combinations of reduction factors.

C. EFFECT ON NUMBER OF ACS LINES

It is very important to carefully choose the number of fully sampled ACS lines as it not only effects the performance of nonlinear GRAPPA [33] but also the key factor of the overall net reduction factor. FIGURE 11 shows the comparison of the reconstruction quality in terms of NMSE of the third dataset at a fixed net reduction factor of 4.14 with different combination of R_1 , R_2 and ACS lines. It can be seen that the best performance appears when the reduction factor of CS and PI are both low ($R_1 \times R_2 = 3 \times 2$ ACS = 28). However, when the reduction factor is high for PI, even with large number of ACS, the reconstruction quality will still be poor as $R_1 \times R_2 = 3 \times 6$ ACS = 48. When the reduction factor is evenly distributed and number of ACS lines is fairly large ($R_1 \times R_2 = 4 \times 3$ ACS = 38, $R_1 \times R_2 = 4 \times 4$ ACS = 46 and $R_1 \times R_2 = 5 \times 4$ ACS = 50), the result lies in the acceptable range compare with those has either high acceleration at CS or PI ($R_1 \times R_2 = 4 \times 6$ ACS = 50, $R_1 \times R_2 = 8 \times 3$ ACS = 52), although they have large number of ACS lines. This observation is consistent with that been discussed in the previous section. From what has been discussed above, we can get the conclusion that to get the best reconstruction result, the choice of number of ACS mainly depends on the acceleration factor on PI, when the accelerations for CS and PI are evenly distributed and keep CS slightly higher than PI if necessary.

FIGURE 11. The quality comparison of the proposed method in terms of NMSE of the Data 3 at a fixed net reduction factor of 4.14 with the different combinations of R_1 , R_2 and ACS lines.

IV. DISCUSSION

In this paper, we proposed a novel reconstruction framework that efficiently combines compressed sensing and parallel imaging for dynamic MRI reconstruction. Although both k-t FOCUSS and non-linear GRAPPA reconstruction algorithm used in this study was previously published state-of-art techniques. The novelty of this study is not concentrate on a single reconstruction algorithm, but the reconstruction flowchart that efficiently combines compressed sensing and parallel imaging to achieve higher acceleration with clinical-quality image. Although k-t FOCUSS and non-linear GRAPPA were used to evaluate the performance of the proposed framework, each component could easily be replaced by more advanced techniques, i.e. low-rank model [31][32], dictionary learning [33][34] for CS reconstruction; E-SPiRiT for the parallel imaging reconstruction [35]. Here, we demonstrate the application of the proposed method in cardiac cine imaging, the proposed framework is expected to be useful in other dynamic cardiac MRI applications, such as dynamic contrast-enhanced MRI [21][23] and dynamic MR angiography to accelerate the data acquisition process and improve the spatiotemporal resolution. This specific procedure should be application dependent to accommodate the unique characteristics of the signals in each application. For instance, in dynamic image series that is not periodic, the Fourier transform might not be the best choice to sparsifying the images, thus, in the CS step, the proposed k-t PCA [43] algorithm that uses Karhunen-Loeve transform or principal component analysis might have better ability to sparse the image thus provides a more accurate k-space reconstruction for the PI step.

There are many researches that attempt to combine CS and PI [20][25][28]. In [28], it uses a very similar framework but limited to the static images. When applying to dynamic MRI, the temporal information is not counted which could further reduce the amount of data required for reconstruction. Also the inaccurate estimation of the sensitivity information could degrade the image quality. In the methods mentioned in Ref. [20] and [25], the sensitivity encoding is incorporated into the Fourier encoding in the data consistency term and the algorithm represents the distributed compressed sensing framework by exploit the joint sparsity from all coils. However, such a simple combination is difficult

to maximize the accelerations that can be achieved by each individual method because each method has different sampling requirements. Particularly, at high accelerations, the methods mentioned in [20] and [25] will present the reconstruction artifacts such as spatiotemporal blurring, attenuation of low-contrast features and increase of noise. This is due to that the signal to reconstruct is not ideally sparse but only compressible. Under ideal case, when the signal is strictly sparse, CS will recover only the sparse signal coefficients and suppress the noise. However, in practice, the combined noise and pseudo noise level increases as the acceleration increases. Thus the low-valued coefficients such as high frequency components and low-contrast image features that are below the noise level will be suppressed. However, the proposed framework decouples the acceleration into two independent steps so that the acceleration at the CS step is limited to guarantee the accurate recovery of the signal. This explains why in FIGURE 4, the proposed framework could preserve the low contrast cardiac blood flow shadow region as indicated by the yellow arrow, and in FIGURE 8, the proposed framework preserves more temporal information than the method mentioned in Ref. [20] does. Additionally, employing nonlinear GRAPPA instead of SENSE may also help suppress noise and remove artifacts. Jung et al compared the performance of k-t SENSE and k-t GRAPPA applied to cardiac cine and phase-contrast images[46]. They observed that although both methods provide excellent image quality and temporal fidelity for different acceleration factors, k-t GRAPPA demonstrated less spatially varying noise than k-t SENSE. Meanwhile, nonlinear GRAPPA has shown to have superior noise suppression properties than traditional GRAPPA [42], thus may also be an important factor that contributing to the improved quality of reconstructed images. In addition, the sampling trajectory demonstrated in this study uses the combination of random sampling pattern over a uniform undersampling pattern in Cartesian manner. However, the proposed method could also be applied to non-Cartesian cases, i.e. radial or spiral subsampling, so that many more advanced techniques [35]-[38] based on compressed sensing and parallel imaging could be applied to achieve better performance. The evaluation of different combinations of those techniques will be studied in future.

The proposed method contains sequential steps. In the CS step, FOCUSS algorithm approximates the solution to the ℓ_1 minimization through iteratively reweighted ℓ_2 minimization. The computational complexity is exactly equivalent to that in k-t FOCUSS [24]. In the PI step, the nonlinear GRAPPA

[42] is about 2-5 times that of the conventional GRAPPA [13]. So overall the proposed method has a higher computational complexity than that of k-t FOCUSS [24] or k-t FOCUSS with SENSE [20] due to the nonlinear GRAPPA process. On our workstation that is mentioned before, the FOCUSS algorithm took about 19 seconds to reconstruct a series of $256 \times 224 \times 14 \times 4$ dynamic complex MR images and 304 seconds for the nonlinear GRAPPA to reconstruct the final image series. The total computation time is about 323 seconds of the proposed method comparing with 19 seconds that of k-t FOCUSS [24] and 33 seconds that of k-t FOCUSS with SENSE [20]. In addition to this, this study has limitations. First, the reconstruction techniques used in this study, i.e. k-t FOCUSS and nonlinear GRAPPA, were bit out of date. Some more recent or state-of-the-art method should be applied. This is warranted in future studies. Second, we only demonstrate our proposed framework on the current four datasets, the robust of the proposed framework definitely needs to be validated further on the more clinical and patients' data. But the current data are enough to prove the potential ability of the proposed method.

V. CONCLUSION

We proposed a novel joint framework to sufficiently combines compressed sensing technique with parallel imaging to accelerate dynamic MRI. The proposed method decouples the reconstruction process into two sequential steps: use the CS method to reconstruct a series of aliased dynamic images from the highly undersampled k-space data, and use the nonlinear GRAPPA method to missing k-space data for the original image. The in vivo experiments of cardiac cine imaging show that the proposed method can preserve more spatial details and temporal variations of dynamic cardiac images than the state-of-the-art dynamic imaging methods such as the classical k-t FOCUSS method either with or without sensitivity information.

DECLARATIONS

Ethics approval and consent to participate

This study was approved by the Shenzhen children's hospital. Informed consent was obtained from all volunteers in accordance with the institutional review board policy.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study available from the corresponding author upon request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Z.H and C.Z conducted the experiments and performed the computations. X.Z, L.K, and J.Y summarized the results and prepared the figures; X.W and J. L verified the analytical methods and helped to revise the manuscript. Y.Z conceived of the presented idea, drafted the main manuscript text, and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

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