

3D Cardiac MRI Cine Image Denoising

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Abstract—Breath-held segmented bSSFP cine imaging is clinical gold standard for analyzing cardiac function, but it uses ECG gating and requires breath-holds. Our group has developed a continuous-acquisition respiratory and cardiac self-gated cine sequence for free-breathing cardiac function acquisition using 3D stack of spiral gradient echo sequence to perform 3D cine evaluation of the left ventricle. However, iterative compressed sensing reconstruction of 3D spiral imaging is time-consuming and not clinically feasible. In this project, we develop high-resolution 3D cardiac cine imaging using rapid spiral acquisitions and deep learning-based imaging reconstruction to enable rapid online reconstruction.

Index Terms—CMR, UNet, 3D Imaging, Image reconstruction, CINE Imaging

1 INTRODUCTION

HEART failure (HF) occurs when the heart muscle cannot pump oxygen-rich blood to meet body's need, which results in frequent hospitalizations, low life quality, or high mortality rates [1]. Cardiovascular diseases (CAD), also known as ischemic heart disease, is a primary factor for HF, which is caused by atherosclerosis leading to insufficient blood supplement and potentially mortal ramifications like myocardial infarction. Numerous factors increase the risk of developing HF and CAD, including aging, family history, hypertension, diabetes, dyslipidemia, obesity, alcohol and tobacco use, stress and inactivity [2] [3]. Thus, early detection, proper treatment plan and lifestyle changes are crucial in decelerating disease progression and improving patient outcomes.

Our group has developed a continuous-acquisition respiratory and cardiac self-gated cine sequence for free-breathing cardiac function acquisition using 2D stack spiral acquisition [4]. However, the acquisition still takes 2-3 min to cover the left ventricle, and it would benefit from the SNR efficiency of 3D imaging. Thus, we develop a rapid 3D self-gated cine, using randomized stack of spiral gradient echo sequence to perform 3D cine evaluation of the left ventricle [5]. We have also developed iterative compressed sensing image reconstruction of 3D spiral imaging that can further reduce the spiral aliasing artifacts [5]. However, these advanced image reconstruction techniques rely on iterative algorithms such as conjugate gradient which is time-consuming and not clinically feasible.

In this project, we develop high-resolution 3D cardiac cine imaging using rapid spiral acquisitions and deep learning-based imaging reconstruction to enable rapid online reconstruction for cardiac cine imaging feasible.

2 RELATED WORK

For clinical feasibility, it's crucial to have a fast method for reconstructing images rather than relying on iterative non-Cartesian reconstruction techniques to make clinical

adoption smoother. Utilizing deep convolutional neural networks (CNNs) for cardiac magnetic resonance (CMR) image reconstruction not only enhances the speed of reconstruction and simplify parameters tuning but also ensures high-quality images.

Although recent progress in CMR image reconstruction has employed CNNs [6] [7] [8] [9] [10] [11] [12], the majority of these studies have focused on Cartesian imaging. Fan et al. [6]. and Hauptmann et al. [13] have showcased the use of 3D U-Net-based networks for reconstructing dynamic radial CMR images. Nonetheless, the use of deep learning for reconstructing CMR images from spiral imaging remains scarcely explored.

3 PROPOSED METHOD

Self-gating 3D stack of spiral gradient echo (GRE) cine imaging technique which can eliminate the need for ECG and breath-holding, which is often challenging for patients, especially those with respiratory impairments. Specifically, we aim to develop a 3D stack of spiral sampling strategy and robust image reconstruction method to minimize the scan time with desirable image quality.

3.1 Data Acquisition

11 patients were imaged on a 3T SIEMENS scanner (MAGNETOM Skyra; Siemens Healthineers, Erlangen, Germany). Imaging occurred 3 minutes after the injection of 0.15 mmol/kg of Clariscan or Gadovist. Stack of spiral gradient echo parameters are show in Table 1. Our stack-of-spiral sampling strategy consisted of a variable kz-density stack of dual density spirals rotated by the golden angle ($\theta = \frac{\sqrt{5}+1}{2}$). The kz-t sampling pattern is shown on the top panel of Figure 1(A). We acquired 5 partitions out of 10 total partitions. The first partition (shown in rectangles and black spirals) of each measurement is set to kz=0 and used as a self-gating navigator. The other sampled kz partition in each measurement are randomly picked from a Bates distribution [14]:

$$P(t, n) = -P_c + P_t \left\{ \frac{n}{2(n-1)!} \sum_{k=0}^n (-1)^k \binom{n}{k} (nt-k)^{n-1} \text{sgn}(nt-k) \right\}$$

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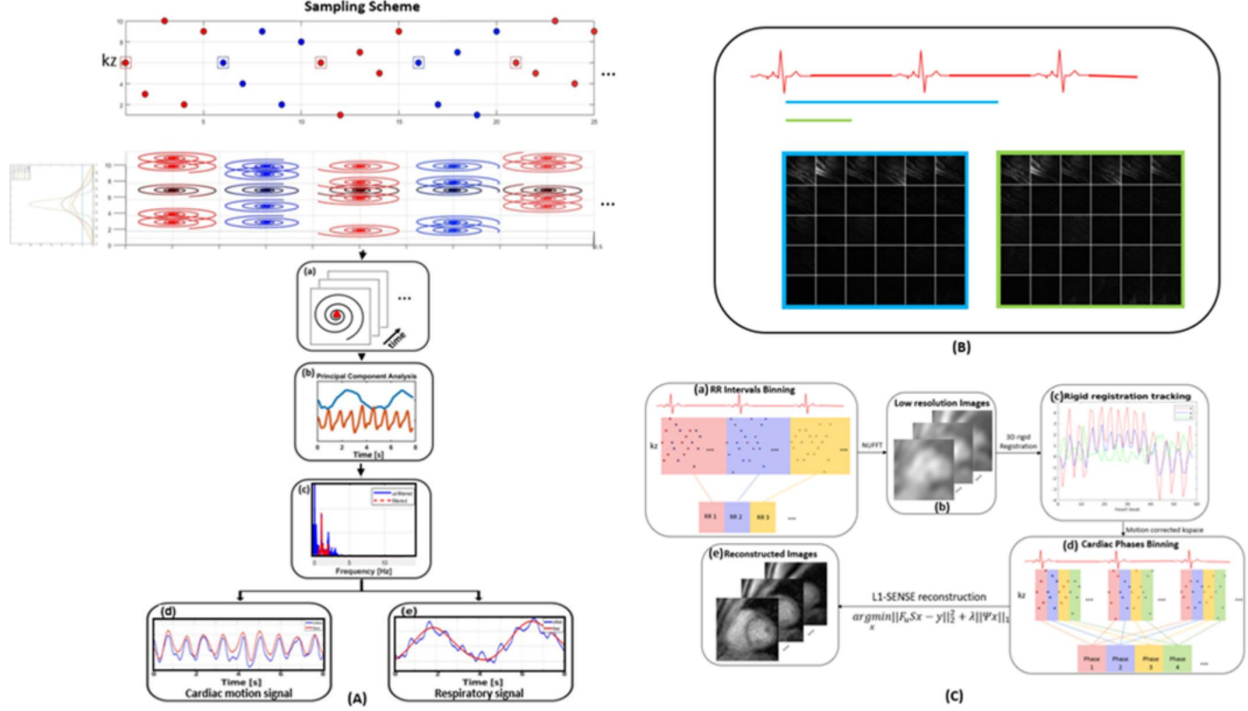


Fig. 1. (A) Sampling Scheme and cardiac self-gating (a) Self-gating signals were determined by center of k-space (b) PCA is performed to separate the cardiac and respiratory components (c) Frequency spectrum to find the cardiac (d) and respiratory (e) motion component (B) Automatic coil selection (C) Motion correction and Reconstruction (a) retrospective cardiac binning (b) Defined heart ROI and data were averaged over part of individual heartbeats. (c) 3D registration (d) Retrospective cardiac binning by groups of 3D k-space volume (e) Image reconstruction from motion corrected kspace [5]

where $P(t, n)$ is desired sampling partition index, P_t is fully-sampled partition number, P_c is central partition index, n is density factor, n is larger for more centralized distribution. To distribute the spirals across the partition we made sure that no kz partitions were repeated in each group, and we insured that there were equal numbers of spirals collected in each half of the kz plane.

3.2 Image Reconstruction for Reference Images

Reference images were reconstructed with a 3D iterative L1-SENSE-based reconstruction technique for 3D SPARCS imaging. The reconstruction pipeline for the reference images is shown in Figure 1. The automatic cardiac self-gating pipeline is shown in Figure 1(A): Self-gating cardiac signals were determined using the center point of the central partition each group of spiral partitions for all receiver coils. Principal component analysis was performed to separate the cardiac and respiratory components followed by frequency spectrum analysis to extract filtered cardiac and respiratory signals. Figure 1(B) shows the auto coil selection over whole 3D volume. Figure 1(C) shows the retrospective cardiac binning followed by rigid motion correction in k space and non-Cartesian spiral L1-SENSE reconstruction [15] [16] [17], which can be formulated as:

$$\arg \min_x \|F_u Sx - y\|_2^2 + \lambda \|\psi x\|_1$$

,where x is the dynamic image series to be reconstructed, S is the coil sensitivity maps estimated from the temporal

average image using a method described by Walsh et al [18], F_u is the inverse Fourier gridding operator that transforms the Cartesian image space to the spiral k-space operated by gnuNUFFT [17] (NVIDIA Tesla P100 GPU), y is the acquired spiral k-space data, ψ is the finite time difference a sparsifying basis, and λ balances between data consistency and sparsity.

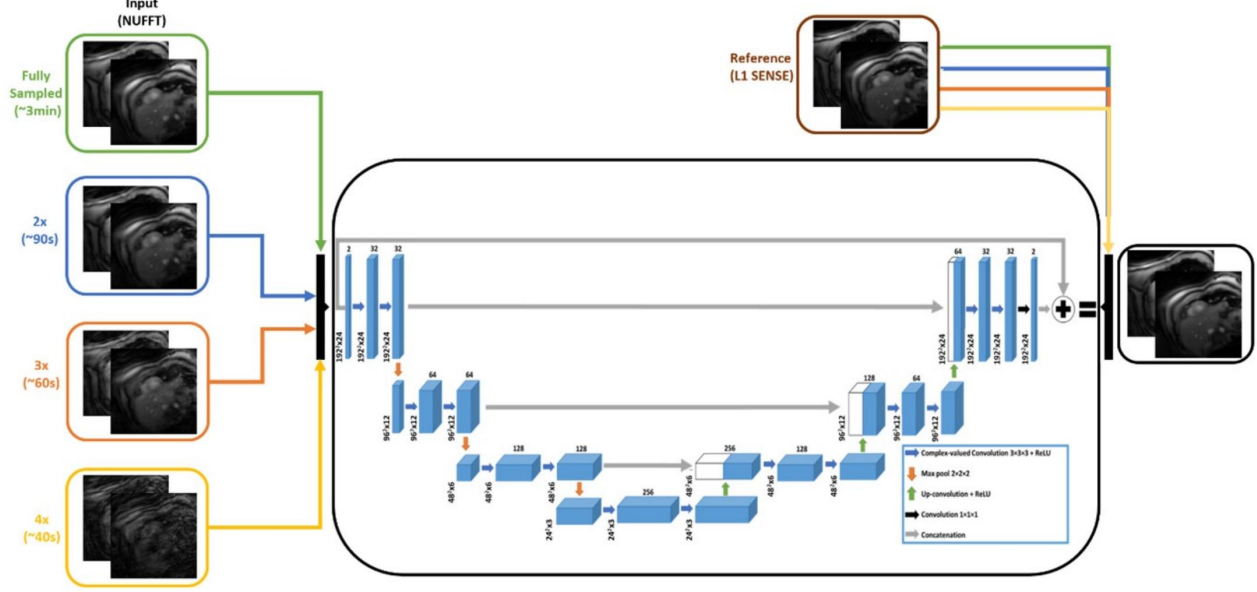
$$\lambda = tTV * M_0$$

was chosen as a tradeoff between image quality and temporal fidelity, where λ_0 was the maximal magnitude value of the NUFFT image series and tTV is temporal total variation factor. The objective function was solved using non-linear conjugate gradient algorithm with 30 iterations and takes 120 minutes to finish 10 slices and 25 cardiac phases reconstruction.

3.3 Proposed Image Reconstruction Network

3.3.1 Deep learning Reconstruction from 3D data

The proposed 3D U-Net image reconstruction framework [19] depicted in Figure 2 is characterized by three layers in depth ($D=3$) and starts off with 32 kernels ($K=32$). In the U-Net architecture, the quantity of kernels doubles at each subsequent layer as the depth increases. Our goal was to investigate how the depth (D) and the initial number of kernels (K) affect the network's ability to reconstruct images. By tuning the initial kernel count, the network gains enhanced capacity to learn the transformation from



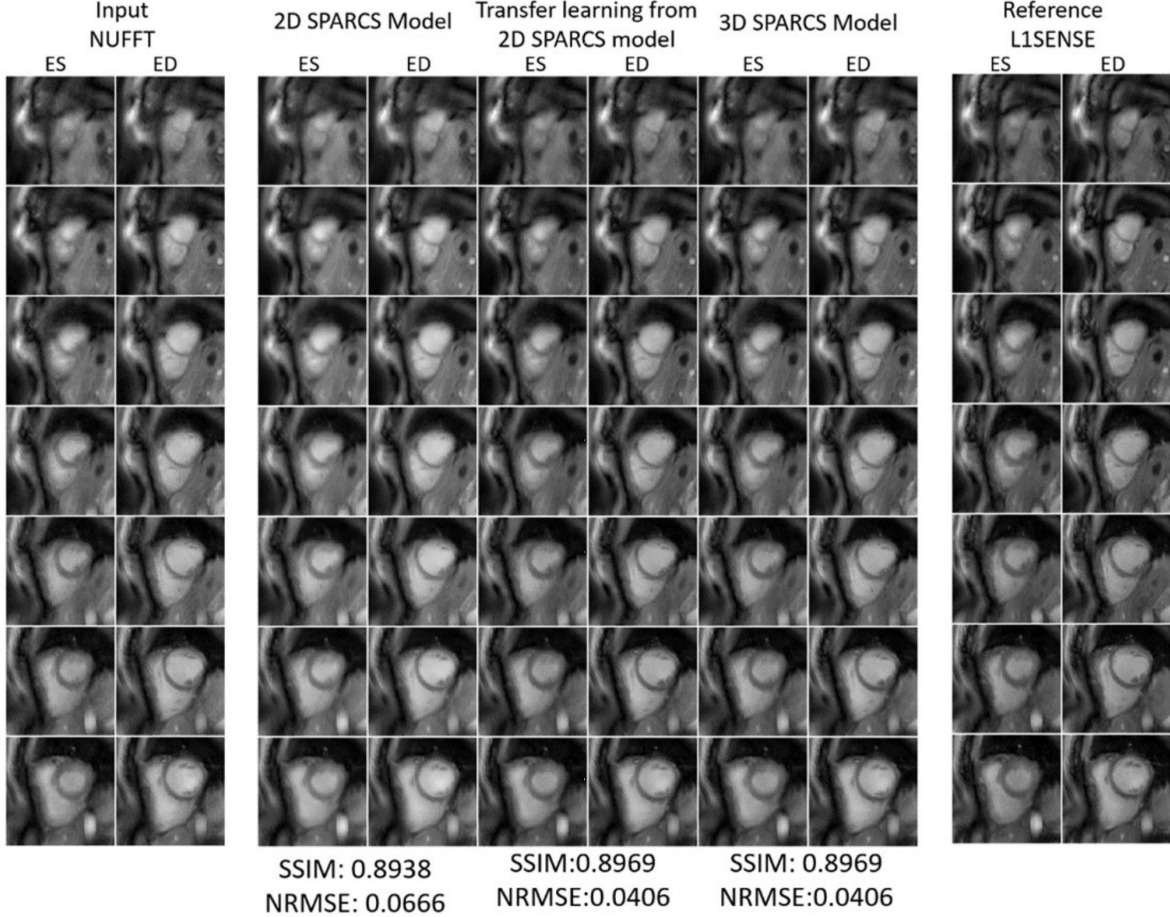


Fig. 3. End systolic and end diastolic images reconstructed by our proposed reconstruction techniques for whole heart coverage. All the proposed networks had an inference time of less than 1 second as compared to 120 minutes for the 3D-L1 SENSE reconstruction. With comparison of the image quality, SSIM, and NRMSE, transfer learning from 2D SPARCS model (DESIRE6 network trained with 2D SPARCS data) and 3D SPARCS model (DESIRE [19] network trained with slices of 3D SPARCS data) [19] have the same performance, and slightly perform better than 2D SPARCS model6. For training process, transfer learning from 2D SPARCS model converges after 50 epochs, while 3D SPARCS model converges after 150 epochs

and 4x, corresponding 90s, 60s and 45s acquisition time. The qualitative result reveals that conducting the acquisition over a span of 60 seconds strikes an ideal equilibrium, significantly boosting the quality of the images while concurrently reducing the time required for acquisition. This observation highlights the efficiency and effectiveness of our proposed reconstruction techniques in producing high-quality cardiac imaging, demonstrating their potential to streamline and enhance diagnostic processes.

5 CONCLUSION AND DISCUSSION

Our proposed deep learning-based imaging reconstruction technique for self-gated free-breathing 3D stack of spiral cardiac cine imaging can produce cine images with high temporal and spatial resolution with a 60s acquisition with a deep-learning inference time of less than 1s.

We anticipate that image quality could be further improved using the pre-trained DESIRE network followed by transfer-learning with fully sampled 3D SPARCS cine data.

5.1 Image quality metrics

For medical imaging, the evaluation process demands metrics capable of capturing image quality in a way that aligns closely with the requirements of clinical practice and the precision of diagnostic procedures. The Structural Similarity Index Measure (SSIM) and Normalized Root Mean Square Error (NRMSE), while popular for general image quality assessment, exhibit notable shortcomings in the context of medical image. These metrics are essentially broad in scope, lacking the specificity required to address the nuanced demands of clinical diagnostics. They do not accommodate particular clinical considerations, diagnostic objectives, or the intricate details of medical images, such as distinct pathological features or critical anatomical structures.

To bridge this gap, there is a compelling need to extend our evaluation to include clinical metrics that offer a direct measure of diagnostic relevance, such as quantifying the left ventricular ejection fraction (LVEF). The ejection fraction (EF) is calculated as follows:

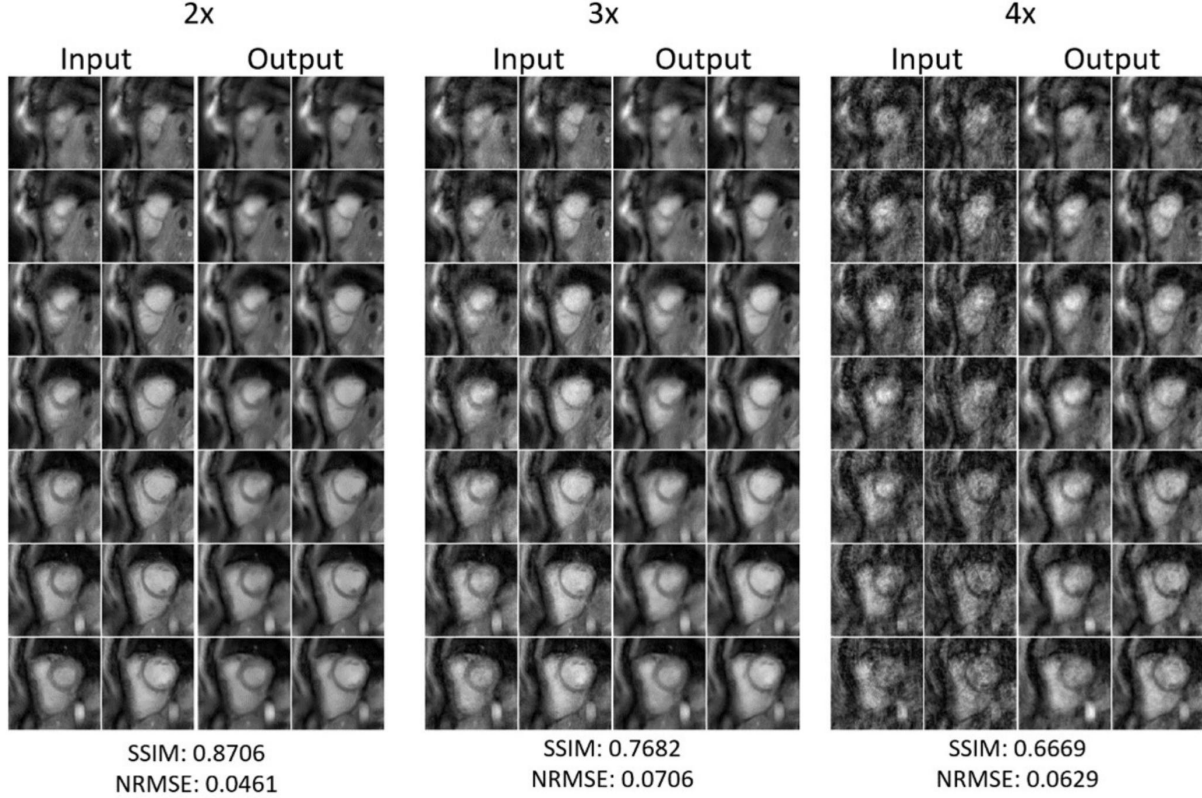


Fig. 4. DL reconstruction cine images from 3D SPARCS model for different retrospective under sampled rates. 2x corresponds 90s acquisition 3x corresponds 60s acquisition and 4x corresponds 40s acquisition.

$$EF(\%) = \frac{SV}{EDV} \times 100$$

where:

- EF = ejection fraction,
- SV = stroke volume,
- EDV = end-diastolic volume.

Comparing LVEF values with those obtained from established clinical gold-standard techniques can provide a more detailed and clinically relevant assessment of our imaging method's efficacy. The ejection fraction (EF), a critical parameter in cardiac diagnostics, serves as an example of how specific clinical measures can provide insights beyond those afforded by general image quality metrics. Such specific evaluations are indispensable for validating the practical utility and diagnostic accuracy of new medical imaging techniques, ensuring they meet the high standards required for clinical application.

5.2 Future work

We realized challenges and potential directions following the observation that our transfer learning approach tended to overfit after 50 epochs. This was evidenced by an increase in the loss for the validation dataset, a trend that is clearly illustrated in Figure 5. To address this issue, we are considering the implementation of early stopping mechanisms

or the possibility of fixing the weights of the initial layers of the network to allow for more refined fine-tuning of the model's later stages.

Furthermore, our research agenda includes exploring the potential of a 4D U-Net model, which represents an innovative approach to achieving reconstruction in both three-dimensional space and time. This model aims to enhance the accuracy and detail of cardiac imaging by incorporating temporal dynamics, thereby providing a more comprehensive understanding of cardiac function. The development and validation of a 3D+time reconstruction model could mark a significant advancement in medical imaging, offering more detailed and dynamic insights into cardiac health and potentially improving diagnostic and treatment outcomes.

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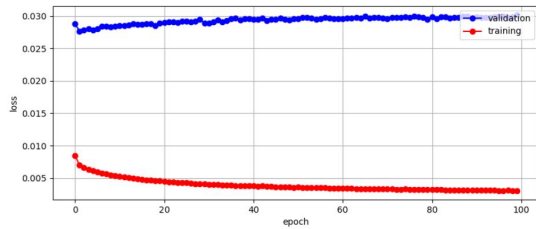


Fig. 5. Loss function for transfer learning from 2D SPARCS data

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