A Deep Learning Framework for Image Super-Resolution for Late Gadolinium Enhanced Cardiac MRI

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Abstract

Cardiac magnetic resonance imaging (MRI) provides 3D images with high-resolution in-plane information, however, they are known to have low through-plane resolution due to the trade-off between resolution, image acquisition time and signal-to-noise ratio. This results in anisotropic 3D images which could lead to difficulty in diagnosis, especially in late gadolinium enhanced (LGE) cardiac MRI which is the reference imaging modality for locating the extent of fibrosis in various cardiovascular diseases like myocardial infarction and atrial fibrillation. To address this issue, we propose a self-supervised deep learning-based approach to enhance the through-plane resolution of the LGE MRI images. We train a convolutional neural network (CNN) model on randomly extracted patches of short-axis LGE MRI images and this trained CNN model is used to leverage the information learnt from the high-resolution in-plane data to improve the through-plane resolution. We conducted experiments on LGE MRI dataset made available through the 2018 *atrial segmentation challenge. Our proposed method achieved a mean peak signal-to-noise-ratio (PSNR) of* 36.99 *and* 35.92 *and a mean structural similarity index measure (SSIM) of* 0.9 *and* 0.84 *on training the CNN model using low-resolution images downsampled by a scale factor of* 2 *and* 4*, respectively.*

1. Introduction

Cardiac MRI is the current gold standard to assess cardiac function and diagnose various cardiovascular diseases. They provide dynamic 3D images of the heart with high-resolution in-plane information. In clinical cardiac MRI, due to the limitations of the maximal breath-hold time achievable by the patient, high-resolution 2D stacks of images are typically acquired resulting in anisotropic 3D volumes of the heart. Therefore, these 3D volumes usually have low through-plane resolution (i.e., slice thickness). For example, in a typical LGE cardiac MRI, which is widely used to assess the myocardium viability in post-infarct patient, study the extent of fibrosis in the atria of patients with atrial fibrillation [1], etc., has a high in-plane resolution of 1 to 1.5 mm, but a low through-plane resolution of 5 to 10 mm [2]. The anisotropic 3D cardiac MRI images results in low-resolution representation of the cardiac anatomy, which may impose challenge in cardiac image visualization, analysis and diagnosis [3]. This issue cannot be resolved through interpolation, as it results in artifacts such as blurring and loss of information. To address this limitation, researchers have proposed a number of super-resolution methods, wherein they computationally enhance the resolution of an image.

In recent years, deep neural networks-based image super-resolution algorithms have gained increased popularity for enhancing the resolution of MRI images, especially in neuroimaging [4–6]. The deep learning-based super-resolution techniques have also been successfully applied to cine cardiac MRI images [7]. Steeden et al. [8] demonstrated the potential of a 3D residual U-Net architecture for super-resolution using synthetic whole heart, balanced steady state free precession images. However, it is hard to obtain real world high-resolution isotropic images for training such supervised models. Sander et al. [9] proposed an unsupervised deep learning-based approach to enhance the resolution of anisotropic cardiac MRI images. The authors use the latent space interpolation ability of the autoencoders to increase the through-plane resolution of the images. Here, large variations in anatomy between adjacent slices affects the performance of the method. Bustin et al. [2] presented a novel technique to reconstruct 3D LGE cardiac MRI images using a 3D self-similarity framework. However, limited efforts have been made to explore deep neural networks-based super-resolution methods to improve the resolution of LGE cardiac MRI images.

In this work, we propose a self-supervised deep learning framework to compute super-resolution LGE cardiac MRI images. Inspired by Zhao et al. [6], this method leverages the information learnt from the high-resolution in-plane data to improve the through-plane resolution, eliminating

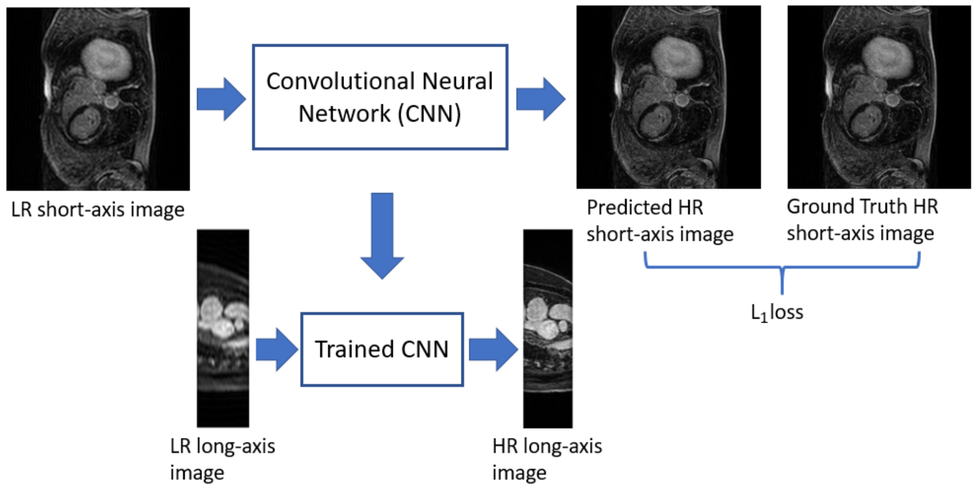


Figure 1: Self-supervised deep learning framework to improve though-plane resolution in LGE cardiac MRI

the need for external training data. We assess the performance of the proposed method on the 2018 atrial segmentation challenge dataset [10].

2. Methodology

2.1. Data

We used the 2018 atrial segmentation challenge dataset [10], consisting of 154 3D LGE MRI volumes from 60 subjects with atrial fibrillation, acquired using either a 1.5 Tesla Avanto or a 3.0 Tesla Verio scanner. The dataset features isotropic voxel spacing of 0.625x0.625x0.625 mm^3 with spatial dimensions of 576x576x88 or 640x640x88 voxels. We use zero-padding to obtain uniform spatial dimensions of 640x640x88 voxels.

2.2. Self Supervised Super-Resolution

In order to generate low-resolution data for training, we first blur the images in the x-axis to obtain low-resolution in-plane images. This is done by Fourier downsampling to simulate data acquisition process in MRI and to ensure no high frequency information on the u-axis in the Fourier domain. Now, we have the low-resolution in-plane data and their corresponding high-resolution in-plane data to train the CNN. This CNN model will be trained to learn the mapping between the low-resolution and the high-resolution data. We also repeat the Fourier downsampling process in z-axis to obtain low-resolution through-plane data. This low-resolution through-plane data is used as the test dataset for our experiments.

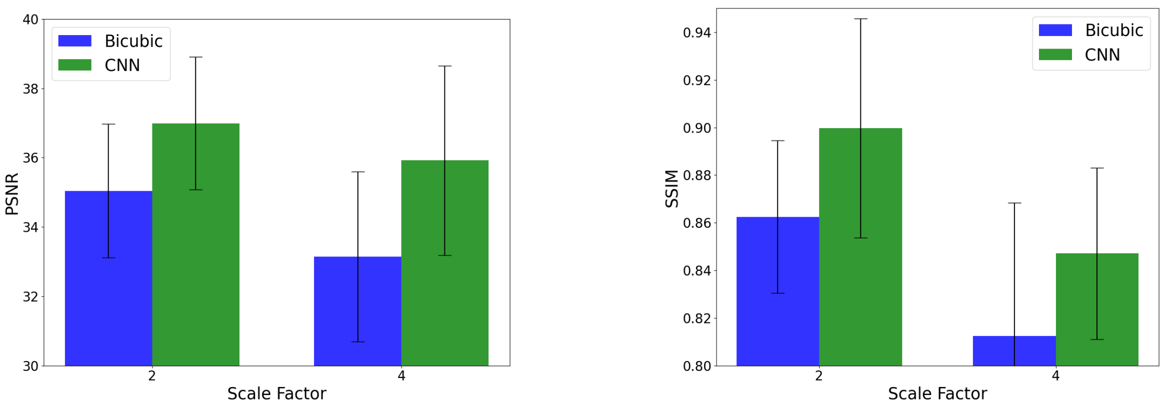
To train the CNN model, we first extract patches of dimensions 640x88 pixels from the low-resolution short-axis images in both horizontal and vertical directions. These low-resolution patches are input to a 2D CNN, an encoder-decoder network with skip connections (U-Net [11]). The output of the CNN and the corresponding high-resolution patch is used to compute a L_1 loss function to backpropagate the CNN, thereby, learning the mapping from low-resolution in-plane data to high-resolution in-plane data. This mapping is subsequently applied to long-axis images to improve the through-plane resolution (Fig. 1).

In our experiments, we split the total 154 LGE MRI dataset to 100 for training and 54 for testing in a 3-fold cross-validation strategy. The networks are trained using the Adam optimizer with a learning rate of 10^{-4} and a gamma decay of 0.99 every alternate epoch for fine-tuning, a batch size of 20 patches, for 50 epochs on a machine equipped with NVIDIA RTX 2080 Ti GPU with 11GB of memory.

3. Results

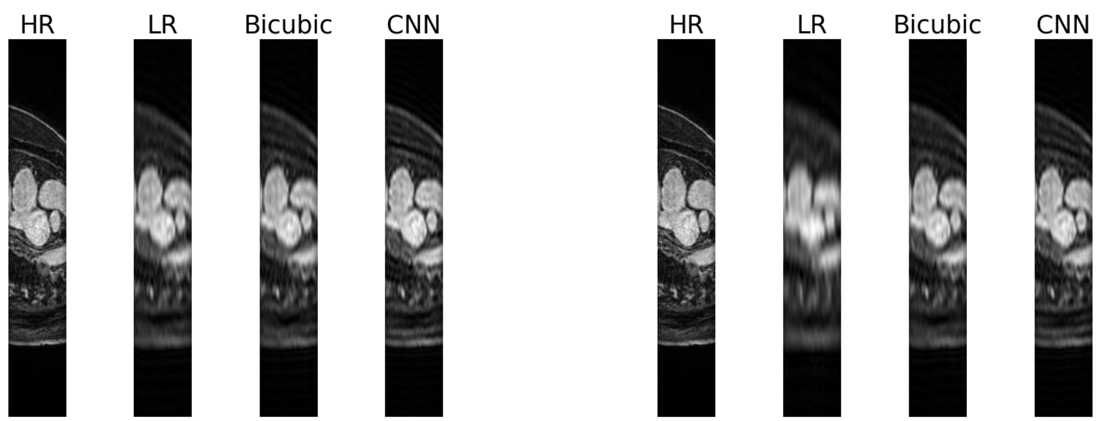
Table 1: Mean (std-dev) peak signal-to-noise-ratio (PSNR) and structural similarity index measure (SSIM) achieved using bicubic interpolation and our proposed CNN framework for downsampling scale factor of 2 and 4, respectively. The best evaluation metrics achieved are labeled in **bold**. Statistically significant differences were evaluated using the Student t-test and are reported using * $p < 0.005$.

Methods	Scale Factor: 2		Scale Factor: 4	
	PSNR	SSIM	PSNR	SSIM
Bicubic Interpolation	35.04 (1.93)	0.86 (0.03)	33.14 (2.45)	0.81 (0.05)
CNN	**36.99 (1.91)***	**0.90 (0.04)***	**35.92 (2.73)***	**0.84 (0.03)***



(a) (b)

Figure 2: Comparison of (a) mean PSNR and (b) mean SSIM values achieved by bicubic interpolation and the proposed CNN framework



(a) (b)

Figure 3: Long axis views of LGE cardiac MRI with ground-truth high-resolution (HR), (a) low-resolution (LR) with downsampling scale factor 2 (PSNR: 27.34, SSIM: 0.61), the LR image upsampled by bicubic interpolation (PSNR: 29.93, SSIM: 0.73) and the super-resolution image from CNN model (PSNR: 32.43, SSIM: 0.81), and (a) low-resolution (LR) with downsampling scale factor 4 (PSNR: 23.42, SSIM: 0.48), the LR image upsampled by bicubic interpolation (PSNR: 28.38, SSIM: 0.69) and the super-resolution image from CNN model (PSNR: 31.04, SSIM: 0.79)

To evaluate our results, we compute the mean PSNR and mean SSIM between the super-resolution long-axis images obtained from the proposed method and the ground truth high-resolution long-axis images. We then compare the computed PSNR and SSIM with the results obtained by bicubic interpolation.

Table 1 shows a comparison of the mean PSNR and mean SSIM between our proposed method and the bicubic interpolation for low-resolution images simulated by a downsampling scale factor of 2 and 4. We achieved a mean PSNR of 36.99 and 35.92 using our trained CNN model on images downsampled by a scale factor of 2 and 4, respectively, compared to 35.04 and 33.14, respectively, using bicubic interpolation alone. Similarly, we achieved a mean SSIM of 0.9 and 0.84 using our trained CNN model on images downsampled by a scale factor of 2 and 4, respectively, compared to 0.86 and 0.81, respectively, using bicubic interpolation alone (Fig. 2). We show an example of the improved through-plane resolution for low-resolution images simulated by a downsampling scale factor of 2 and

4 in Fig. 3a and Fig. 3b, resprectively.

4. Discussion

Here, we presented a CNN-based super-resolution framework to improve the through-plane resolution of LGE cardiac MRI images without the need for external training data to train the network. The CNN model is trained to learn the mapping of simulated short-axis low-resolution patches to their corresponding ground truth short-axis high-resolution patches. This information learnt from the in-plane data is used to improve the through-plane resolution. Our experiments show significantly improved PSNR and SSIM compared to the results obtained from bicubic interpolation. Lastly, the resulting super-resolution images featured less blurring and information loss than the bicubic interpolated images.

In light of the improved through-plane resolution achieved by the self-supervised deep learning framework in LGE MRI, further investigation into these methods, such as, incorporating the state-of-the-art enhanced deep super-resolution network (EDSN) [12] into the framework and including image similarity metrics (e.g. SSIM) in the loss function is warranted. We will be investigating the effect of the super-resolution LGE MRI images on downstream segmentation of left atrial cavity, to visualize it for clinical usage.

As part of our future work, we will be extending this super-resolution approach to 4D cine cardiac MRI images and investigate its effects on cardiac motion estimation. We will also study the effect of both, the super-resolution LGE cardiac MRI images and the super-resolution cine cardiac MRI images for multi-modal 3D registration.

5. Conclusion

This paper shows that the proposed self-supervised CNN-based super-resolution framework can be used to improve the through-plane resolution of LGE cardiac MRI images.

Acknowledgments

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