Deep-learning based super-resolution reconstruction for sub-millimeter 3D isotropic coronary MR angiography in less than a minute

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Purpose

3D whole-heart coronary magnetic resonance angiography (CMRA) has shown significant potential for diagnosis and characterization of coronary artery disease (CAD). A non-rigid motion compensated reconstruction and 2D respiratory image navigator has been recently proposed to enable free-breathing 0.9mm^3 CMRA in ~10min[1,2]. However, spatial resolution is still limited compared to coronary computed tomography angiography and scan time remains relatively long. To further accelerate the acquisition time, we propose in this work a deep-learning based super-resolution (SR) framework combined with non-rigid respiratory motion compensation. In this study, we analyse the possibility of an 8-fold increase in resolution of a low-resolution (LR)=1.2x4.8x4.8mm (FHxLRxAP) acquisition to a 0.6mm^3 target resolution in a cohort of 55 CMRA patients with suspected CAD. This reflects in an ~8x faster acquisition of <1min to reconstruct a high-resolution (HR) target of 0.6mm^3.

Methods

We propose a generative adversarial network which consists of three cascaded Enhanced Deep Residual Network for SR[3] generator and a trainable discriminator[4]. The EDSR is built up of 3 stages each performing a 2-fold upsampling in 8 consecutive residual blocks with 3x3 convolution filters of stride 1 and 64 kernels. The discriminator network is built as a convolutional neural network with dyadic kernel increase and alternating striding of 1 and 2. The input of the network is an LR CMRA whereas the output is the corresponding SR image (0.6mm^3). The network is trained in a supervised manner on 22600 axial pairs of HR and retrospectively downsampled LR images from 47 patients. Retrospectively simulating a 12.5% phase and slice resolution provides the LR training input (readout resolution was not affected). Testing is done on axial images from 5 patients with prospectively acquired LR of 1.2x4.8x4.8mm.In total, the network consists of ~2.4 million trainable parameters optimized under mean absolute error (MAE), structural similarity index (SSIM), adversarial and perceptual (VGG-16[5]) loss by an Adam optimizer (batch size=16, 60 epochs).

ECG-triggered 3D whole-heart Cartesian bSSFP CMRA was acquired under free-breathing in coronal orientation in patients with suspected CAD. Imaging parameters are stated in[2]. Data was acquired in ~7min with an isotropic resolution of 1.2mm^3 and reconstructed with a non-rigid PROST[2] to 0.6mm^3 serving as HR target. In 5 patients, prospectively subsampled data of LR=1.2x4.8x4.8mm resolution was acquired in <1min.

Results and Discussion

The low-resolution input, high-resolution target, commonly used bicubic interpolation and SR output of one prospectively downsampled test patients are shown in Fig.1. Qualitatively and quantitatively (NMSE, SSIM) SR showed significant improvement in edge sharpness and vessel delineation. The SR framework required ~110hrs for training but only 3s for inference.

In conclusion, the proposed SR framework has the potential to provide an 8-fold upsampling with comparable image quality than the high-resolution CMRA image reducing scan time to <1min.

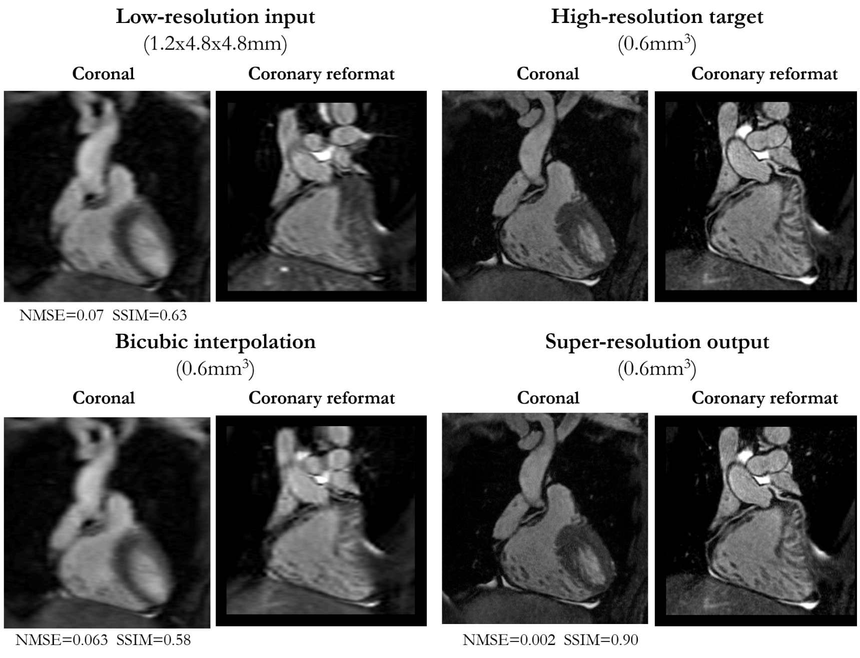

Fig. 1: Coronal and coronary reformat of low-resolution input/acquisition, high-resolution target, bicubic interpolation and super-resolution output in a patient with suspected CAD of a low-resolution acquisition in <1min. Metrics (normalized mean squared error, SSIM) state differences between images and high-resolution target.

References

1. Cruz et al. MRM 2017;77(5). 2. Bustin et al. JCMR 2020;22(1). 3. Lim et al. CVPR 2017. p136-44. 4. Ledig et al. CVPR 2017. p4681-90. 5. Russakovsky et al. IJCV 2015;115(3).