Project: Super resolution using Deep learning

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Significance:

Science and medicine have been tremendously benefitted by Magnetic Resonance Imaging (MRI) for few decades due to its non-invasiveness and excellent soft-tissue contrast. But MRI is still an active area of research to be used as an intervention tool for real-time supervision of different physiological dynamics due to its inherently slow speed of image acquisition. Current state-of-the-art reconstruction techniques of accelerated dynamic MRI suffer from spatiotemporal tradeoff; a compromise between spatial and temporal resolution is evident in real-time imaging.

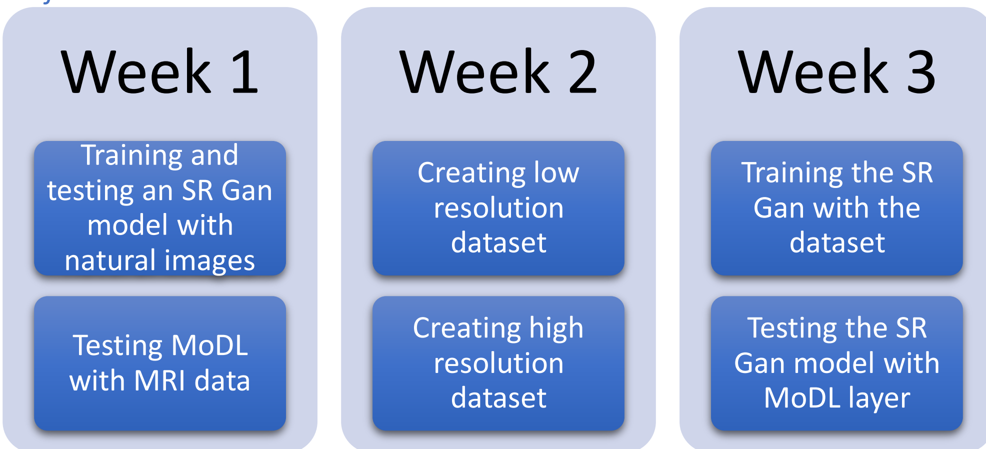
Super-resolution (SR), widely accepted in the computer vision community, has drawn attention of researchers and scientists in the field of natural-imaging, medical imaging, surveillance and security. SR refers to the technique of recovering high resolution images from the corresponding low-resolution images with high spatial-fidelity and finer details [1]. In the field of MRI, high-resolution images are always expensive due to large hardware setup. These images are also prone to motion artifacts due to lengthy data acquisition combined with subconscious or unconscious movement of the subjects onboard. SR in MRI aims at resolving these issues inherent to high-resolution MRI technology by shortening the scan times. The application of SR in the field of MRI is validated to be effective in recent times [2-4].

Background:

Earlier, super resolution was implemented by interpolation based statistical approaches for example, neighbor embedding and sparse coding techniques [5-7]. Recently, deep learning based super resolution have been widely practiced and have demonstrated significantly superior performance [8]. For example, Dong et al. implemented bicubic interpolation in SRCNN to upscale the LR image to the target size and applied a 3-layer CNN to produce the SR images by non-linear mapping [9]. Next, Shi et al. improves the computational complexity in ESPCN by extracting features from target sized images [10]. SRCNN3D have also been proposed recently to produce HR images using 3D CNN and patches of HR brain images [11]. Two significant limitations of the above-mentioned techniques are incapability to extract features of the various structures and requiring large datasets.

Later, Generative Adversarial Networks (GANs) have been applied to super-resolution. Ledig et al. were to first implement GANS for single-frame image super resolution, titled as SRGAN [12]. SRGAN feeds LR images to the generator to generate SR images; discriminator labels the SR images based on the HR images. Since then, several extensions of SRGAN have been applied to MR images. Performance of GANs is further enhanced by incorporating perceptual loss to make the SR images close to the HR images in terms of abstract features, texture details rather than based on SSIM and PSNR [13(28)].

Project timeline



Division of labor

Task	Subin	Wahid
Testing MoDL with MRI data		✖
Training and testing SR Gan model with natural images	✖	
Creating low resolution dataset		✖
Creating high resolution dataset	✖	
Training SR Gan with the dataset	✖	✖
Testing the SR Gan model with MoDL weights	✖	✖

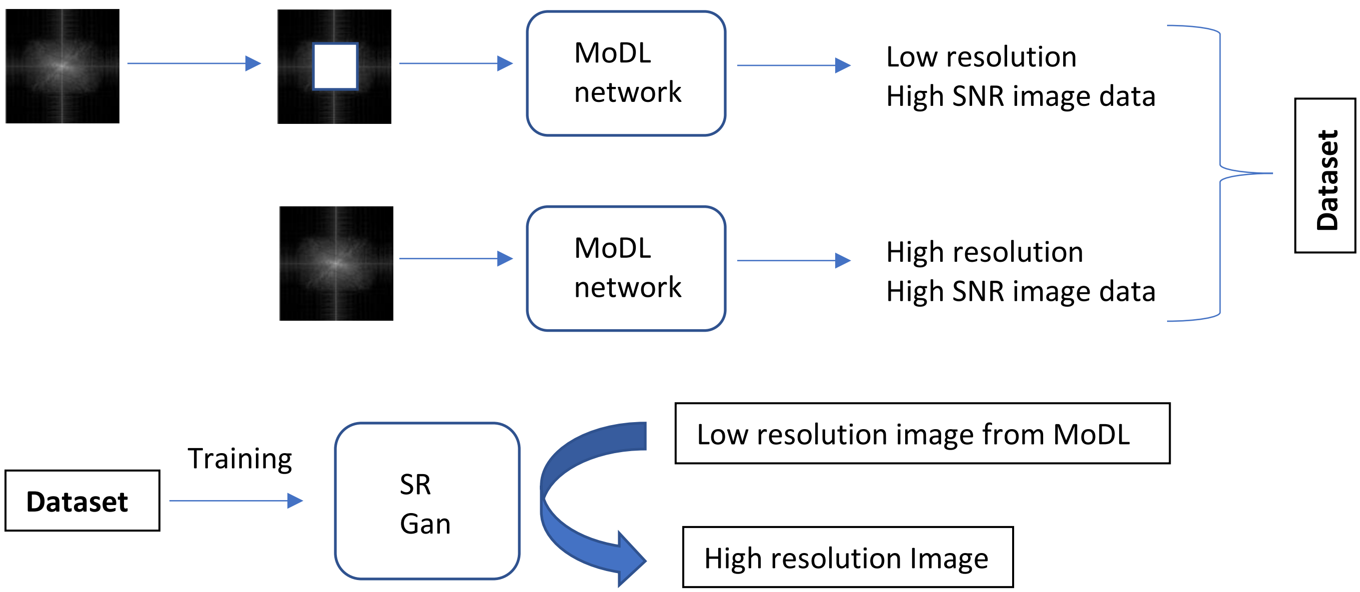
Anticipated challenges to overcome

There are two possible challenges in this project. First, Training and testing of the SR Gan model – This involve finding the right code set which will work for our specific problem and clear all the bugs and setting a suitable python environment for the same. The biggest challenge we could face during this phase is that there are any bugs which takes a long time to find and solve. That is one reason we anticipated almost a week to run both the neural networks properly. Second, is generating high SNR training data by training MoDL network with cropped and uncropped images. On using these images on the SR Gan, we are running on a hypothesis that the VGG loss will not create an issue but if it does then we will have to retrain a VGG network with MRI images and use that to create the SR Gan

Proposed solution

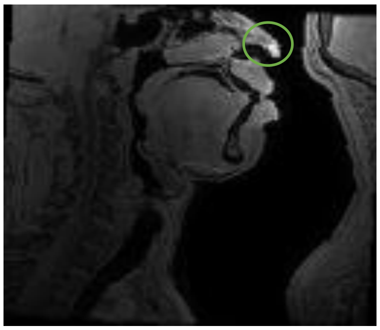
As explained above the problem involve generating a high-resolution image from a low-resolution image generated by density sampled cropping K-space with high SNR. For this problem the possible solution is to integrate the capabilities of both MoDL and SR Gan. To simulate a low-resolution MRI data, we crop the center region of a k-space. In the physical work applying a density sampling could accelerate the MRI acquisition. To simulate an accelerated MRI, we sample this cropped K-space with a density sampling pattern. This will further reduce the amount of information present in the K-space.

To reconstruct this K-space to image space with high SNR we use MoDL [14] network. This will generate the essential training dataset for the SR-Gan. With the generated training set we can train the SR-Gan to create high resolution MRI from low resolution density sampled MRI data. To generate the pairing high resolution images, we use the same MoDL network with an uncropped K-space and the same density spiral sampling patter. This solution has been presented as a figure below.



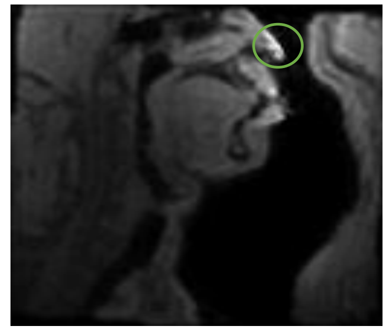
Phase 2

We have taken a close look at the results from phase one (figure given below). The network was able to do better performance compared to bilinear interpolation from MRI images. but there is some blurring happening in the output image. we suspected that blurring is caused by cropping in the K-space region.



Ground Truth

Low resolution input



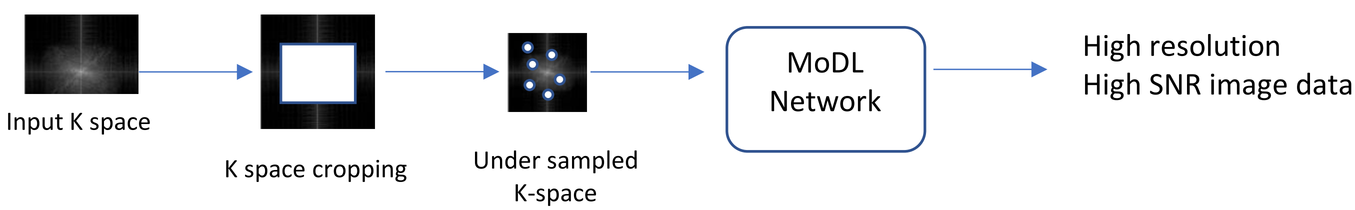
High resolution output

To test if the blurring is created due to throwing away the high-frequency components in k-space, we have revisited the experiment; where we have created the training input by downscaling the ground-truth in image domain instead of k-space. With this experiment we found that the blurring is still present in the network output. We suspect this is due to inappropriate learning of the network.

So, in Phase 2 we are planning to explore the following strategies for super resolution.

1) First, replacing the SRResnet with SRGAN to introduce unsupervised learning.
2) Alternatively, use the MoDL for doing both reconstruction and super resolution. Next, we will try to implement include additional unsupervised loss term with current pixelwise loss term if time permits [15].

with these directions for the phase two project here is how our network will look like if we go with using MoDL for both reconstruction and super resolution.



Reference

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