Reducing MRI Motion Blur with U-Net

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Abstract

Motion blur can hinder the ability to analyze and draw significant medical conclusions from MRI images. As motion blur cannot always be prevented, techniques to remove motion artifacts are crucial to patient well being. By adapting U-Net and adding a layer to blind-deconvolve blur, deep learning can be explored as a technique to de-blur MRI images. With computationally-limited training, the architecture trained well and showed potential for use as a method of MRI de-blurring. Quantitative and qualitative analysis show that using a custom loss function could provide for much stronger de-blurred image prediction.

1 Introduction

As a consequence of patients moving during MRI acquisition, motion blur presents as artifacts of streaking or general blurring that are amplified by longer exposure times [1]. Patient motion can often be involuntary, so post-processing to de-blur MRI scans is necessary to accurately analyze images.

1.1 Deconvolution process

"Deconvolution" pertains to the concept of undoing filtering that worsens an image. A transposed convolution, somewhat misleadingly also known as a deconvolution, accomplishes this task by performing a convolution to upsample an input to output an image that contains spatial dimensions that match the original image. Transfer convolutions can be used to correct the low pass filtering done in motion blurring. Without knowledge of the size of the blur, a "blind deconvolution," can be done using a somewhat arbitrary guess for dimensions. Blur size can also be estimated through point spread function analysis to perform a more curated convolution.

1.2 Dataset

The RealNoiseMRI Grand Challenge intended for contestants to create accurate images by reconstructing motion-degraded MRI k-space data. The data set from the challenge used for this project included hundreds of 3D knee MRI's in k-space. Only non-degraded data was used.

1.3 Goal

U-Net, a convolutional network that is made up of symmetrical downsampling and upsampling layers, is popular for biomedical image segmentation [2]. The project intends to add a blind convolution layer to the front of U-Net and to modify the number of input/output channels to adapt U-Net for MRI motion de-blurring. In doing so, the process will require first constructing image slices from k-space, and then simulating random motion blur on the images through convolution.

2 Related work

Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee published research last revised in 2018 about a convolutional network for de-blurring using a multi-scale loss function [3]. The research focuses on removing blur that can be less easily estimated - instead of uniform or linear kernels, they seek to resolve more complex types of motion blur.

Jile Jiao, Jun Sun, and Naoi Satoshi's 2017 paper proposes a two-stage debluring convolutional neural network to handle focal blur and real motion blur without need for precise blur estimation [4]. In their architecture, the model focuses on predicting subspaces of the blurred image, and then selecting a blur kernel for each. The research found that the subspace technique was effective with subsets of images.

3 Methods

3.1 Data setup

The data, provided in the .h5 file type, was first read and converted from k-space to image space to reconstruct images. For each MRI, there were 30 to 40 2D slices from the 3D construction. To maximize robustness and minimize the computational expense of training with the data, a random slice was selected from each MRI. After reconstruction, each 640 x 368 pixel image was resized to 512 x 256 since U-Net requires dimensions divisible by 32 to allow for sampling. Then, to simulate motion blur, a low-pass filter randomly sized between 5 and 10 pixels was convolved with each image in a randomized direction. The blurred images were used as inputs and the un-blurred original images served as paired outputs for training.

3.2 Model architecture

Since the images were in grey scale, the input size to the network included the 512 x 256 image with a single gray channel. As the goal was to output a blur-reduced version of the image, the output mirrored the input. The transposed convolution layer needed to output a 512 x 256 single-channel image to undisturb the input dimensions. As such, the layer included a single filter to maintain output dimensionality, and a kernel of size 10 x 10 to serve as a blind deconvolution that would match the upper limit of simulated blur 1.

After the transposed convolution layer, the model followed a Tensorflow implementation of U-Net written by Pavel Yakubovskiy using resnet34 as a backbone and Adam as an optimizer [5]. Mean-squared error was used for training to allow for a direct comparison of pixels in the original and model generated images.

4 Results

As seen in the figure, training and validation loss both converged toward zero during the ten epochs 2. The training loss was always slightly lower than the validation loss, indicating mild underfitting. The test loss averaged to 0.00126, a similar value to the validation loss in the last epoch as expected.

The example image from the test set allows for a qualitative representation of results 3. The generated image appears dark, making it difficult to assess differences well. Overall, generated images appeared to have less streaking than blurred images. However, features of the MRI such as tendons or other anatomical "line"-like parts were sometimes removed by the network (perhaps confused with a streaking artifact). This confusion is demonstrated in the example images. The reconstruction shown, when compared with the original image, had a peak signal-to-noise ratio (PSNR) of 31.09 dB. This PSNR is relatively low compared to what would be desired, and is likely dropped greatly due to the darkness of the image.

5 Discussion

Overall, the model trained well given the limited data set size and computational power. With respect to mean squared error, the error rates were extremely close to zero. However, mean squared error is

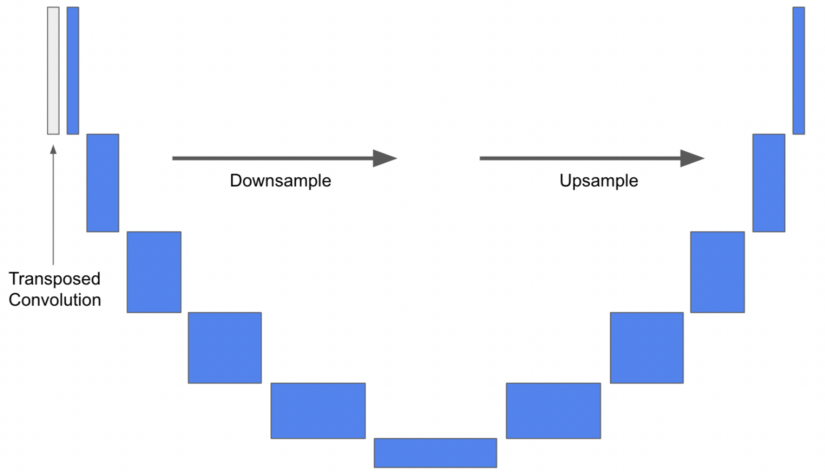

Figure 1: Modified U-net architecture used for de-blurring

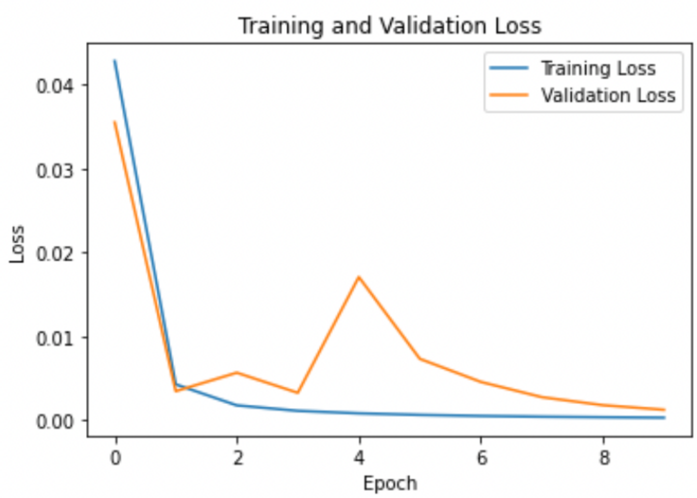

Figure 2: Training and validation loss from modified U-Net for de-blurring

only one measurement - for a more dynamic network, a more customized loss function could be more effective. Mean squared error values all pixels equally, so in MRI images that are composed of so much black, the similarity in the black can be over represented and cause the higher frequency parts of the image to be damped. A better loss function might account for this and give more weighting to similarity in edges. The transposed convolution layer was helpful for achieving a lower mean squared error. By removing some streaking artifacts a the start of the architecture, the images were better set up to be resolved.

Looking at the examples of images where in many cases, the generated output was too dark, signals that post-processing could be helpful to improving the model. For example, adding layers at the end of the network to high-pass filter or brighten the images could strengthen the architecture. Due to time and computational limitations, heavy experimentation of this was not viable, but this could be useful to explore in the future.

Overall, the project shows that a modified U-Net has potential to train well to get rid of motion artifacts in MRI 2D images. However, lots of trial and error and curated research would need to go into identifying an optimal loss function and pre and post processing technique to allow for the model

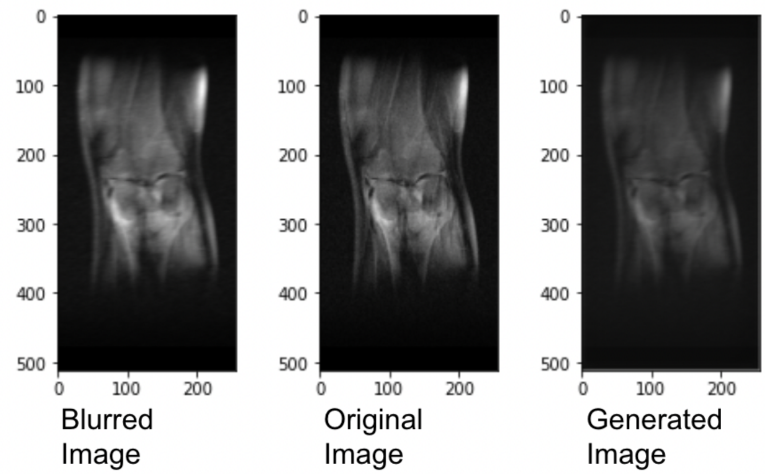

Figure 3: Example from test run of input, output, and predicted image

to be reliable and consistent. Additionally and as expected, access to more computational power would allow for stronger training using a larger data set.

References

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