# Image Denoising using Deep Residual Blocks with Fourier Transform

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## 1 Motivation:

In recent years, images have become an essential medium for humans to obtain information. Noise is inevitably mixed during acquisition, compression, and transmission due to the influence of the environment, transmission channel, and other factors, resulting in distortion and loss of image information. This interferes with the human understanding of the original picture and subsequent image processing applications. Thus, Image Denoising, which removes noise from an input image while maintaining high-frequency details, is critical in the image processing pipeline and computer vision tasks. So far, researchers have proposed various strategies for reducing noise, ranging from classic filtering to neural networks. However, few have investigated adding Fourier transforms into inner network structures for image-denoising tasks. This study aims to propose an innovative denoising method combining transform domain and neural networks based on previous image processing research.

## 2 Related Work:

Image denoising has been studied extensively, and there are many techniques with both advantages and disadvantages. The existing developed methods are mainly traditional filtering algorithms and deep-learning-based methods. Traditional algorithms like Spatial Domain Filtering and Transform Domain Filtering generally target noise that can be easily removed, and the computational cost is relatively moderate. Nevertheless, Spatial Filtering blurs and reduces image sharpness. Some Transform Domain Filtering methods are time-consuming and rely on the behavior of the filter function and cut-off frequency (Fan et al., 2019).

Because of its advantages, such as significant feature learning capability, deep-learning-based convolutional neural networks (CNN) and their evolutions have gained popularity as computer computational power has grown. According to recent research, complex-valued CNN (CVCNN), which builds on the basic CNN with complex number operations, offers another promising deep-learning method for image denoising (Quan et al., 2021). Since the Fourier transform can turn an image into a complex domain, researchers have shown that if the noisy images are processed via the Fourier transform before being employed in CVCNN, most of the time, this model outperforms the previous depth learning methods (Pham et al., 2021). Combining the Fourier transform and CNNs also improves tools for other image-processing tasks. Recently, a method adding Fourier transforms to inner network structures to investigate image deblurring got good PSNR and SSIM scores, demonstrating the field's potential and inspiring this proposal (Mao et al., 2021).

## 3 Project Overview:

A central part of deblurring is to properly handle the image noise. Joshi et al., 2009. argue that denoising can be considered a subproblem of deblurring, and deconvolution methods can be used purely for denoising by considering the blurring kernel to be a delta function. With that in mind, we plan to leverage the Res FFT-Conv Block of Mao et al., 2021, an architecture that was proven to be effective in integrating high- and low-frequency discrepancies, as an attempt to explore its potential for image denoising. We intend to build both residual blocks as proposed in Figure 1 below and use the blocks to construct our model. The BSD300 dataset will be preprocessed with different noise levels and used in training. To measure how our model performs, we plan to compare it with other state-of-the-art denoising methods (e.g. BM3D, DnCNN, UNet). The models will be evaluated on the BSD68 dataset. We expect to show that our model with the proposed residual blocks outperforms other methods by quantitatively evaluating the PSNR and qualitatively observing the images. If time permits, we will also try to put this residual block into the CVCNN to further study the potential of this residual block combined with Fourier transform and convolution.

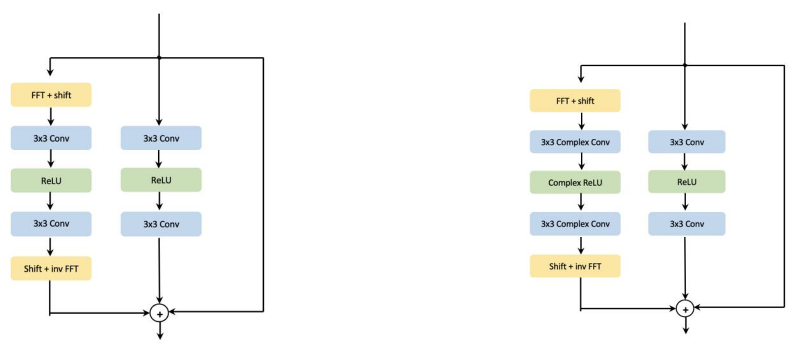


Figure 1: The proposed residual block. The left block uses real-valued convolution and activation layers; the right block uses complex-valued convolution and activation layers.

## 4 Milestones, Timeline & Goals:

- **Nov 16:** Project proposal due. Deeply study relevant research, build the framework.
- **Nov 16 - Nov 24:** Prepare datasets and the preprocessing. Build the residual blocks and networks. Train and compare different CNN models. Expect higher PSNRs.
- **Nov 24 - Dec 1:** Continue the training and testing. Test the CVCNNs if time permits.
- **Dec 1 - Dec 8:** Wrap up the results and possible optimizations and complete the final report, code, and poster.
- **Dec 8:** Project report & code due. Have the in-person project poster + demo session.

# References


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