

Real Image Denoising with Feature Attention Applied to Real Fluorescence Microscopy Images

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Abstract—The use of visually high-quality images is crucial for computer vision applications, which can be a challenge when the acquired images contain a significant amount of noise. Deep convolutional neural networks tackle this issue well with synthetic noise, where the amount of noise expected is spatially invariant. However, real photographs contain different levels of variance due to factors like lighting or ISO settings.

Although denoising algorithms exist, model-based algorithms fail to properly denoise variant noise levels and are computationally expensive to run, while learning-based models that are trained on the noisy and denoised versions of the image in large quantities deliver better results but are limited to a set amount of noise.

An ideal solution to the issue would be to have a single, flexible, and efficient model that could be used with spatially variant (real) and invariant (artificial) noise. RIDNet proposes a general solution, which raises the question of how much this model can be adapted and applied to specific areas. One of these areas is Real Fluorescence Microscopy Images.

I. INTRODUCTION

IMAGE denoising is an important step in image processing. When a picture is taken, noise is introduced due to the device or to the conditions. Real life conditions have the added problem of adding spatially variant noise. Hence, it is necessary to remove this noise, which is denoising. Currently, there are two types of denoising algorithms: model-based and learning-based. The model-based algorithms are computationally expensive and have difficulty with suppressing spatially variant noise.

Our work will be based on the paper *Real Image Denoising with Feature Attention* [1]. The paper explains the implementation of a single-stage real image denoising network called RIDNet. RIDNet is implemented in three parts, feature extraction, feature learning residual on residual and reconstruction.

II. RIDNET SINCE PUBLICATION

RIDNet has been used as a base of different applications, even in applications where the context is not images. For example, in the paper *Channel Estimation Using RIDNet Assisted OMP for Hybrid-Field THz Massive MIMO Systems* [2], RIDNet is used for channel estimation, which in turn is used to generate high-gain beams. These beams can then be used to enhance the quality of the Terahertz band. Overall, RIDNet has found its use as the denoising algorithm of choice to build upon.

III. ARCHITECTURE

Consider that the noise image is x and that the denoised image is y . To extract the initial features, the noisy image

is sent through one convolutional layer: $f_0 = M_e(x)$, where $M_e()$ is the convolution. Then, f_0 is passed to the learning residual on residual module.

The learning residual on residual module is composed of 4 cascading enhancement attention modules (EAM). An EAM begins with a merge-and-run unit. This unit has input features branched and passed through 2 dilated convolutions. Then they are concatenated and passed through another convolution. To learn the features, the preceding result goes through a residual block of the two convolutions. Then for speed, they are compressed by going through an enhanced residual block (ERB) of 3 convolutional layers. The last layer of the ERB is a 1×1 kernel, which flattens the features. Then, this is sent through global average pooling to determine the statistics of the whole image. This process would result in $f_1 = M_{fl}(f_0)$, where f_1 represents the learned features.

After these 4 EAM, f_1 is reconstructed through one convolutional layer. Depending on the input, it can either output 3 or 1 feature maps.

IV. FLUORESCENCE MICROSCOPY DENOISING (FMD) DATASET

The alternative dataset we found is the fluorescent microscopic denoising (FMD) dataset, from the paper *A Poisson-Gaussian Denoising Dataset with Real Fluorescence Microscopy Images* [3]. The dataset contains 12,000 real fluorescent microscopy images. These images were taken using different microscopes on diverse biological samples. The ground truth of these photos was determined by taking the average of the images.

Due to the weakness of the signal of fluorescence, the pictures are noisier than normal. This alternative dataset is interesting to apply to RIDNet, because it is of a different domain from initial datasets used to train the model in the paper. While one of the initial datasets of the paper does provide low light pictures, the FMD dataset provides a more extreme case of low light and different noise type. The optical signal of these photographs is quantized due to the discrete nature of photons, making Poisson noise present, instead of Gaussian that is normally present in standard photography [3].

We believe in the importance of pairing RIDNet with FMD because of its potential in the biomedical field. Using an excitation laser to reduce the noise in image acquisition is not possible, due to the nature of the fluorescent saturation rate that will stop increasing once the laser is too high [3]. While the FMD paper acknowledges other denoising models like CBDNet and FFDNet and their potential, we recognize

that RIDNet proposes a far superior method of blind, single-staged denoising based on the results of their paper compared to the methods mentioned previously [1], and produces satisfying results with variant noise images, just like fluorescent microscopic images.

V. IMPLEMENTATION

RIDNet provides a link to their <https://github.com/saeed-anwar/RIDNet>. We cloned it into Google Drive. A fork and adaptation of the original repository for our project can be found here: <https://github.com/SVA-BL00/RIDNet-on-FMD>. It was easier to work with Google Colab for GPU access and training. Fortunately, a download link for the pretrained model was also provided, so it was easy to set up and begin testing.

During the testing, we identified one main challenge: code deprecation. A majority of the code that made up RIDNet is deprecated or not supported by Google Colab. The code required an older version of Python and Pytorch. A solution to be able to use the code as is was to use a virtual environment to downgrade, which was difficult to setup. Instead, we opted to modify the code. The first step was to identify the modules that were not compatible anymore and upgrading to the correct version.

Downloading, organizing the datasets, and setting up the corresponding dataset python file to follow RIDNet's convention to add more datasets was a long process.

After debugging, the process to test and to train was fairly simple with FMD. We trained and tested using a NVIDIA A100 Tensor Core GPU from Google Colab.

To ensure we had enough data and safety that the model proposed by the paper was the same as the pretrained one, we tested on the same testing data described by the original paper. It was not possible to obtain the files for DND dataset since they are not available for the general public, getting SIDD was possible and we used the exact test data to check the PSNR values with the ones reported in the original paper, and we also obtained NAM. As described, RNI15 was only for qualitative comparison and do not provide a PSNR value since there is no ground truth.

For FMD, we used 3000 images to train and 600 images to validate. Every subdataset contained 1000 pair images, where we used 250 to train and 50 to validate, maintaining a 80-20 ratio. We did 30 epochs with patch sizes of 32. Then, we used FMD's test mix, a combination of all 12 subdatasets in 48 images.

VI. RESULTS

We will be using PSNR and SSIM as our evaluation metrics. The loss of our fine-tuned model is represented in Figure 1. Our fine-tuned model was able to remove uncorrelated information (noise) efficiently, as the curve of the loss resembles an inverse logarithmic function. Then, the PSNR value as a dependent value of the Epochs is shown in Figure 2. In Table 1, we present the PSNR and SSIM values of the pre-trained RIDNet and our fine-tuned model on the FMD dataset. As shown, there is an improvement on the denoising process in comparison to the original RIDNet model. Then,

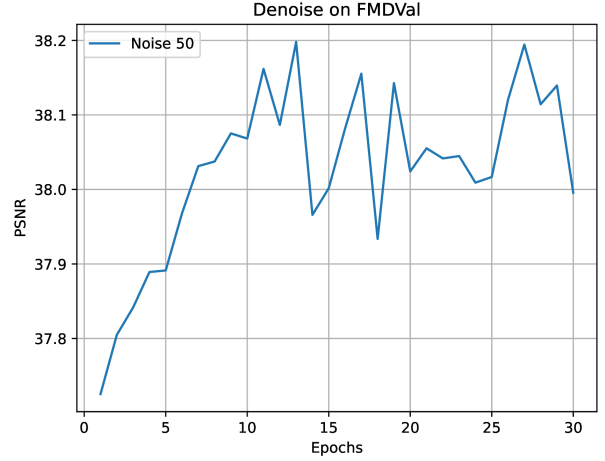


Fig. 1. Validation results while training

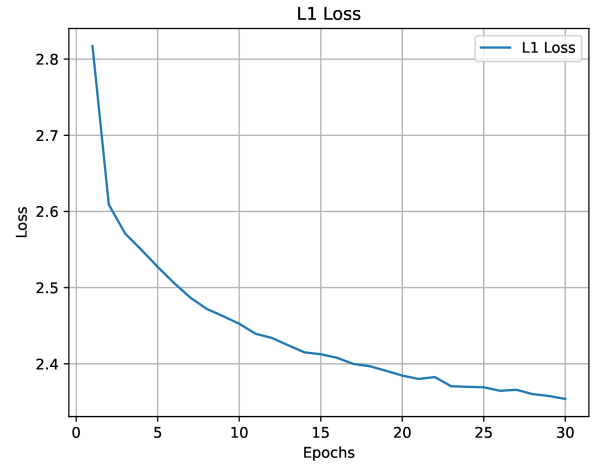


Fig. 2. L1 loss when fine tuning

we visually compared the results from our fine-tuned model with the results of the pre-trained RIDNet. From Figures 3-5, the results from the fine-tuned model appears to produce clearer results than the pre-trained model, especially in the

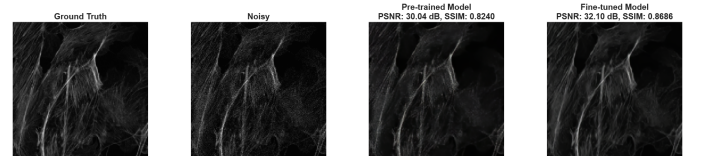


Fig. 3. Confocal BPAE G comparison

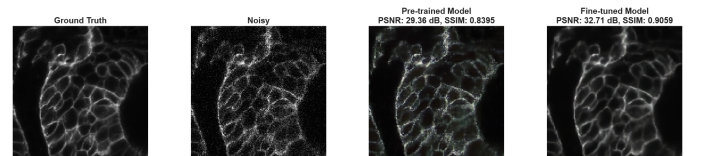


Fig. 4. Confocal FISH comparison

Subdataset	Finetune PSNR	Pretrained PSNR	Finetune SSIM	Pretrained SSIM
Confocal_BPAE_B	38.3594	36.0027	0.9751	0.9399
Confocal_BPAE_G	33.1083	32.0254	0.8856	0.8516
Confocal_BPAE_R	38.0769	36.9483	0.9589	0.9212
Confocal_FISH	32.7559	29.3641	0.9060	0.8400
Confocal_MICE	38.1072	35.0075	0.9647	0.9490
TwoPhoton_BPAE_B	32.2387	29.8732	0.9297	0.9132
TwoPhoton_BPAE_G	33.0230	31.7055	0.8268	0.7952
TwoPhoton_BPAE_R	38.4224	37.1920	0.9291	0.9123
TwoPhoton_MICE	35.2922	32.9556	0.9287	0.9107
WideField_BPAE_B	33.5005	27.7443	0.9386	0.5355
WideField_BPAE_G	32.9220	26.4645	0.8335	0.4771
WideField_BPAE_R	35.4598	28.5798	0.9232	0.5789

TABLE I

PSNR AND SSIM COMPARISON BETWEEN FMD FINE-TUNED AND PRETRAINED, STANDARD RIDNET MODEL

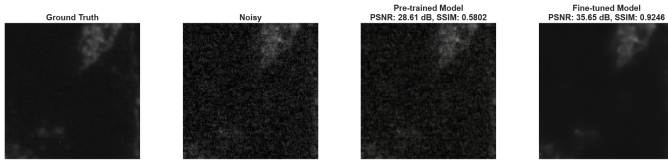


Fig. 5. WideField BPAE R comparison

Confocal FISH images. The most noticeable change in image quality can be seen in the WideField images, the pre-trained model smooths the noise but only the fine-tune was able to fully remove it, quantitatively we can see a difference in the PSNR of 6 points in average.

VII. CONCLUSION

In this paper, we tested the single-stage real image denoising network RIDNet against the FMD dataset. Then, we fine-tuned the RIDNet model to possibly improve the denoising algorithm for the FMD dataset. Our results show that the fine-tuned model was more effective than the RIDNet model to denoise images for the FMD dataset. It also demonstrates the potential RIDNet has as a starting point to develop an accurate fluorescent microscope image denoiser.

REFERENCES

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