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FRAME GENERATIVE NEURAL NETWORK FOR DENOISING SEVERELY NOISY IMAGES

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Abstract - Object recognition in extreme noisy environments has been an exceedingly difficult task for a long time. The existing denoising technologies still have been challenging either under low PSNR environment or under multiple types of noises. The purpose of this paper is to introduce a new deep learning neural network model named Frame Generative Neural network (FGNN) for denoising extremely noisy images. The FGNN utilizes multiple neural networks connected in parallel to generate many frames. Although each net produces the image with less noise but surely not sufficient, when these frames are synchronously combined, it can produce a much better quality of image with plenty of detail. The experimental results show how effective and promising the FGNN model can be as a tool reducing noise in low PSNR image.

Keywords - PSNR, Denoise, Noise, Neural Network, Deep Learning, Frame

I. INTRODUCTION

Denoising technologies in image processing are becoming more and more widely used to improve the visual quality of images. In recent years a new class of techniques, deep neural network model, has shown remarkable success in artificial intelligence. For instance, many studies employed deep learning models, which are largely used and are known to have good performance, such as U-Net [1], DnCNN [2] and PCANet [3] to reduce noise from images.

Rina Komatsu and Tad Gonsalves [4] reformed U-Net model to denoise images. It is enhanced from the traditional U-Net model by replacing pooling layers with fractional-stride convolutions and batch normalization. However, it still cannot give satisfying result when given a low PSNR image. This is due to the difficulty of training low PSNR images. As a result, the output of the model is unable remove all noise and loses many important details from the input.

Kai Zhang et al [2] used a DnCNN to denoise Gaussian noise at unknown noise level. It uses residual learning with batch normalization to increase the speed during training process and improve denoising performance. Yet, the DnCNN is unable to effectively remove other types of noise, including speckle and salt and pepper.

Houqiang Yu et al [3] proposed a method using PCANet with parametric rectified linear unit activation function as an alternative for the binary hashing and block histograms.

This model is trained on the ultrasound database to learn the convolution kernels. While this model had good results to remove speckle noise, it mainly only focuses on removing speckle and no other types of noise.

In this paper, to tackle the above problems we propose a novel model called Frame Generative Neural Network (FGNN) generating multiple frames, eventually being able to improve denoising performance of low PSNR images at a wide range of types of noises. The FGNN consists of two stages:

(1) Frame generation: It uses M pretrained U-Nets through transfer learning, where the M indicates the number of U-Nets interconnected in parallel to simultaneously generate M frames with less noise than the original input.

(2) Noise cancellation: It combines the M frames generated by the frame generation into a single frame to recover the lost details of the image by removing remaining noises.

The rest of the paper is organized as follows: Data preparation is discussed in Section 2.1. Section 2.2 describes the proposed Frame Generative Neural Network.

Using the experimental results, the quality of the proposed FGNN is illustrated in Section 3 where it provides the comparison of the performance of other conventional methods with the proposed algorithm. Finally, the work is concluded.

II. METHOD

2.1 Data preparation

10,000 hand-written digit images in MNIST database were used as label in frame generation, which made of M pretrained U-Nets connected in parallel, was transfer learned with noisy images. The same number of images corresponding to 10,000 images on MNIST database were created to form the noisy images. The database was randomly split into training, validation, and test sets with an 8:1:1 ratio, respectively.

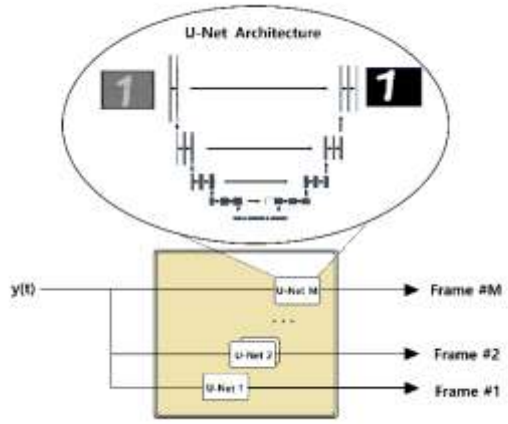

Figure 1: FGNN model consists of M U-Nets which of each is supervised learned by noisy images labeled with MNIST database.

As it is seen in figure 1, the FGNN model uses parallel connected M pretrained U-Nets. Each one is independently trained through transfer learning with randomly chosen 3,000 noisy images with their own label. As each U-Net uses randomly and independently chosen images during training process, it will have its own unique weights and biases. In our study, three kinds of noises [5,6,7], most commonly appear in images, were considered, including speckle, salt & pepper and additive white Gaussian noises, and thus these three kinds of noises were together added to the images on MNIST database to produce very highly contaminated images whose PSNR is around 4 to 6 db. Equation (1) explains how to get the noisy images from the images on MNIST database:

$$y(t) = x(t) + noise, \qquad (1)$$

where $x(t)$ indicates the image on MNIST database and $y(t)$ is the noisy image.

As the result from using (1), a total of 10,000 noisy images, i.e., $y(t)$, were generated. Each $y(t)$ is applied to each parallel connected U-Net input simultaneously with $x(t)$ as its label while being trained.

2.2 Frame Generative Neural Network (FGNN)

The simplified block diagram of the proposed model, Frame Generative Neural network, is shown in figure 2. It goes through two phases of process to reduce the noise from a given input image $x(t)$. The following sections detail the two stages, frame generation and noise cancellation.

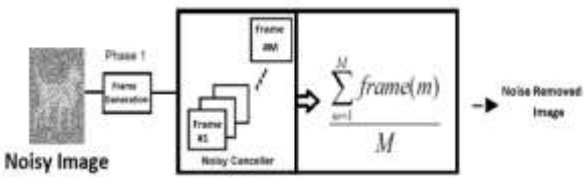

Figure 2: Simplified block diagram of FGNN that consists of frame generation and noise cancellation.

2.2.1 First phase: Frame Generation

Frame Generation is the first stage of FGNN. This stage uses M U-Nets to generate independent M different frames from a noisy image input. Each U-net produces a better-quality image than the input noisy image. This is because each U-net is already trained such a way to reduce the amount of noise. Here, let $z_m(t)$ denote the resulting image from U-Net, with the index of m representing a frame number $(m = 1, 2, \cdots, M)$. Therefore, we have M images from the U-Nets, $z_1(t), z_2(t), \cdots z_M(t)$. However, it still suffers from removing still remaining noise components as well as losing some important details from the original image.

2.2.2 Second phase: Noise Cancellation

Noise cancellation is for cancelling noise components out, as indicated by its name. For example, with multiple frames created from the first phase, we add all the frames into a single frame and then take the average to cancel the remaining noises out. Fig.3 describes the operation of noise cancellation operation to get the noise removed image $I(t)$. Here, we can represent each $z_m(t)$, denoted by below:

$$z_m(t) = I(t) + n_m(t) \text{ for a given } m, \qquad (2)$$

where $z_m(t)$ indicates each frame independently generated by different U-Nets and $n_m(t)$ is a random noise.

Therefore, with M frames, applying the operation of noise cancellation gives:

$$\frac{\sum_{m=1}^{M} z_m(t)}{M} = I(t) + \frac{\sum_{m=1}^{M} n_m(t)}{M} \qquad (3)$$

Because the second term in the right side of equation (3) approaches zero when M goes to infinity, the noise cancellation is done. This means that the noises are cancelled out while the generated many frames from parallel connected U-Nets are added and averaged pixelwise into a single frame for every pixel position in the depth direction, eventually causing the noise value on that pixel position to be close to zero.

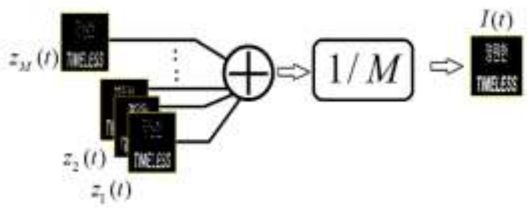

Figure 3: Noise cancellation in which it adds the generated frames and takes an average of the result via pixel wise operation to cancel the noises out, thus being able to recover the lost details.

III. EXPERIMENTAL RESULTS

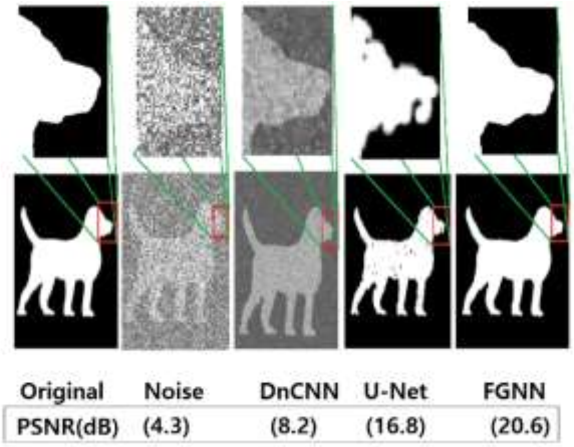

Figure 4: Quality comparison of different denoising methods: (a) input image (b) noisy image (c) DnCNN [2] (d)U-NET[1] (e) FGNN. (M=30)

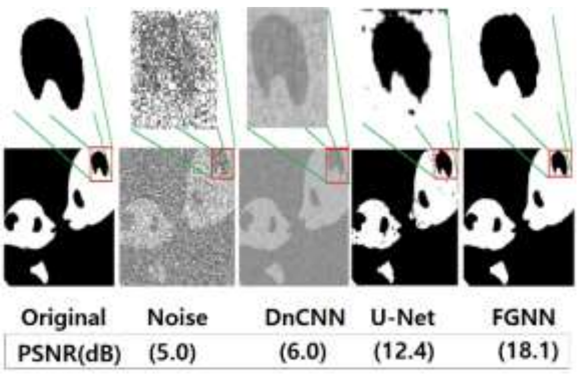

Figure 5: Quality comparison of different denoising methods: (a) input image (b) noisy image (c) DnCNN [2] (d)U-NET [1] (e) FGNN. (M=30)

Fig. 4 and 5 show the comparison between the performance of the new proposed Frame generative neural network and other conventional deep learning denoising algorithms when given an extremely low PSNR input image. In DnCNN, while all the details were kept, it removed almost no noise from the input image, where there was only a slight improved change in PSNR value. In contrast, using U-NET was able to remove noise at a significant amount. However, many details from the input image were lost as shown in figures 4 and 5. When using the proposed FGNN, it was able to keep most of the details from the input image while removing most of the noise. The resulting PSNR value almost quadrupled in each example.

IV. CONCLUSION

Frame Generative Neural network was presented to reduce noise severity even at extreme level. The experimental results showed an excellent performance in terms of recovering the details of images and improving their PSNR. It says that when adding many frames, generated by multiple neural networks, in a pixel wise manner, it has a significant effect on removing noises, thus leading to restore the details lost by noises. However, we used only binary image (black and white image), it should be further studied with natural gray images. We expect that the more the neural networks are connected in parallel, the better the quality of the resulting image is. Therefore,

we are confident that the quality of image can be improved more and more according to increasing the number of parallel connected neural networks.

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