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NERUAL NETWORK IMAGE PROCESSING ALGORITMS

© Getman D.G., Nikonorov A.V., Agureeva A.V.

Samara National Research University, Samara, Russian Federation

e-mail: getman.darya@mail.ru

MemNet is a permanent memory network for image recovery [1]. Image restoration [2] is a typical problem that evaluates an undamaged image by noisy or blurry. This mathematical model helps to carry out a comprehensive study on many image recovery tasks, such as image noise reduction [3–6], single image super resolution (SISR) [7; 8] and JPEG deblocking [9; 10].

This work aims to investigate and launch the MemNet neural network for image reconstruction. In this research, the recovery of images in png format is considered. The authors suppose the images in png format with a size of 1024 x 1024 pixels as input to the network. To generate training data, they use the TFRecords format. In the process of generating the TFRecords file, two types of images are implemented – the original and the noisy ones. When training MemNet, all the training data is converted to two-channel images and resized to 256 by 256. To generate noisy images, the OpenCV image processing libraries for Python are studied and used. The authors choose the images that have been processed on the Unet architecture network [11; 12] as the data to train MemNet, and the PSNR calculation (PSNR = 29.462 dB) – to evaluate the network training results. The figures show the images that the network received during the training process. The first column represents the input noisy image converted to b/w and compressed to a size of 256 by 256, the second column – the output, restored image (Fig. 1–3).

Fig. 1. The result after 500 iterations. PSNR = 14.837 dB. Loss function = 0.244

Fig. 2. The result is after 75000 iterations. PSNR = 21.381 dB. Loss function = 0.000004

Fig. 3. The result is after 100000 iterations. PSNR = –. The images are identical. Loss function = 0

In the course of this work, the architecture of the CNNs – MemNet was studied. In order to solve the problem of restoring a noisy image, the network was launched and trained. It successfully achieved the identity of the restored images. The peak signal-to-noise ratio was calculated. A significant improvement in the PSNR score was shown by increasing training iterations. The authors trained the neural network to process images in png format (not jpg as the previous scholars did). A software implementation of the PSNR calculator in python was also written. As a result of working with two neural network architectures, Unet and MemNet, it was possible to obtain identical images after 1 training epoch (100 000 iterations).

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