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Fatma Albluwi
Trinity College Dublin, Ireland

Vladimir A. Krylov
Trinity College Dublin

Rozenn Dahyot
Trinity College Dublin

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Denoising RENOIR Image Dataset with DBSR

Fatma Albluwi, Vladimir A. Krylov & Rozenn Dahyot

School of Computer Science and Statistics, Trinity College Dublin, Ireland

Abstract

Noise reduction algorithms have often been evaluated using images degraded by artificially synthesised noise. The RENOIR image dataset [3] provides an alternative way for testing noise reduction algorithms on real noisy images and we propose in this paper to assess our CNN called De-Blurring Super-Resolution (DBSR) [2] to reduce the natural noise due to low light conditions in a RENOIR dataset.

Keywords: image denoising, super-reolution, RENOIR dataset, DBSR.

1 Introduction

Low-light conditions and short exposure time severely corrupt images captured by imaging devices. Different methods for noise reduction (or denoising) have been proposed to deal with this issue and in particular in recent years deep learning based techniques have shown leading excellent performances [1, 2, 8] . Dong et al.[8] and Mao et al.[10] have first shown that Deep Neural Networks (DNN) surpass traditional (Non-Neural Network-based) methods for image restoration such as image denoising and image super-resolution. However, it has been recently shown that when considering real noisy image dataset, traditional techniques such as BM3D[7] outperform the state of the art methods for denoising [3]. We have recently proposed a DNN pipeline [2], and this paper is comparing its performance on the real dataset (RENOIR)[3] and show how it competes against the leading techniques.

2 Deblurring and Super-Resolution

Many different methods have been applied to deal with the low-light image noise problem, such as: Block Matching and 3D Filtering (BM3D) [7], Active Random Fields (ARF) [4], Multi-Layer Perceptron (MLP) [5], Bilevel optimization (opt-MRF) [6], etc. Most of these algorithms however have been evaluated solely on noisy images where the noise is artificially added to ground truth (clean) images to construct noisy images. Gaussian noise, Poisson noise, and the salt-and-pepper noise are the typical choice for artificial noise. Such evaluation of denoising algorithms might not be as accurate as evaluating their performance on real noisy digital camera images in low-light conditions. This is because the noise caused by low-light conditions is not i.i.d and is more complex with its variance based on the intensity of the image. In addition, different digital cameras produce various types of noise due to many factors in the imaging systems, such as sensor type, size, etc. Although obtaining real noisy images is easy, it is difficult to know what their noise-free counterparts should be. Therefore, the evaluation of noise reduction algorithms mostly depends on adding synthetic noise such as i.i.d. Gaussian noise to the clean images. The RENOIR image dataset [3] is a dataset with different noisy-clean image pairs from different digital camera with diverse types of realistic noise.

The De-Blurring Super-Resolution (DBSR) model[2] is designed to recover the deblurred High-Resolution image from the blurred Low-Resolution image, by learning an end-to-end mapping. This network includes eight convolutional layers. In this paper, DBSR is trained to denoise images in the real RENOIR dataset to assess its performance on real noise, while it was previously tested with artificial noise [2]. DBSR is a deeper version of DBSRCNN [1]; it is shown in Figure1.

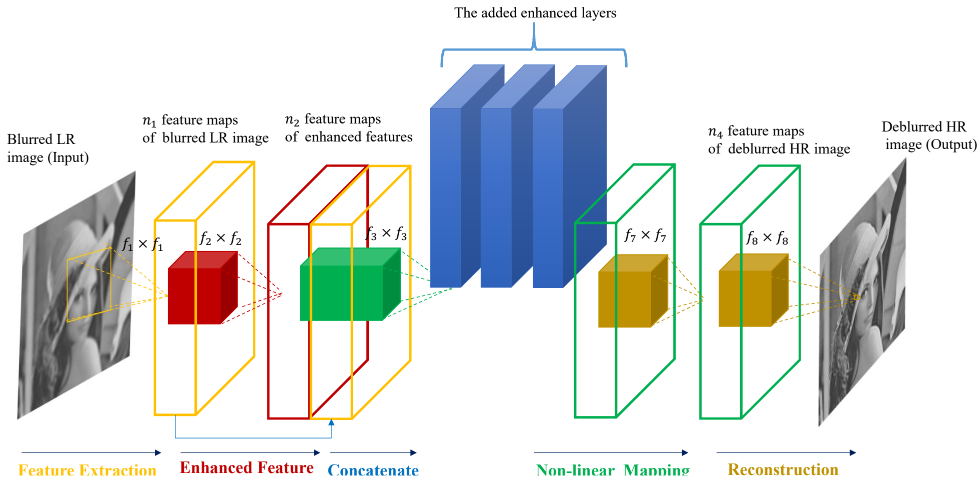

Figure 1: The DBSR architecture comprising eight layers[2].

3 Experiments

3.1 RENOIR Dataset

Anaya et al.[3] have proposed a method to capture noisy-clean image pairs; naturally degraded low-light images and their low-noise counterparts, called RENOIR dataset. This dataset has been used to test some of the popular algorithms proposed to perform noise reduction. The dataset consists of 120 static scenes taken from three different cameras with different sensor sizes, and these cameras produce different kinds of noise. An equal number of scenes were taken: 40 scenes for Xiaomi Mi3 (small sensor), 40 for Canon T3i (mid-size sensor) and 40 for Canon S90 (slightly larger sensor). Also, each camera captured many images with different noise levels. Four or three images were captured per each scene; one or two images involve noise and two noise-free (low-noise) images. The low-noise images (reference (I^r) and clean (I^c)) are noisy versions of unknown ground truth image (I^{GT}), these images were used to give the best estimate to unknown ground truth image, which is: $I^{GT} = (I^r + I^c)/2$. The Peak Signal to Noise Ratio (PSNR) measurement is calculated according to this equation, where the PSNR is estimated as the difference between the average of the two low-noise images (reference and clean images) and a noisy image, but not from applying the standard noise estimate (the difference between a noisy-clean image pair).

3.2 Training and Testing Data

The DBSR model is trained on 291 images; 91 images from Yang et al.[13] in addition to 200 images from Berkeley Segmentation Dataset[11], with the augmentation strategy. The training dataset is divided into sub-images of size $f_i = 50$ by employing a stride of 15. The model is trained on corrupted images with Gaussian noise at $\sigma = 25$, 30, 35 and 50. MatConvNet is used to train the network for image denoising. We train our network for 100 epochs with a batch size 64 and learning rate 0.0001. The activation function used is Rectified Linear Unit (ReLU = max(0,x)). The lost function is minimised using Adam optimisation. The number of feature maps (and filter size) of each layer is as follows 64(9), 32(5), 32(5), 32(5), 32(5), 32(5), 32(5) and 1(5).

3.3 Evaluation of Denoising Methods

Anaya et al. have selected six of popular algorithms for image denoising to evaluate their performance using this real dataset: the ARF[4], the BM3D[7], the opt-MRF[6], the MLP[5], Non-local means using a James-Stein estimator (NLM-JS)[12], and Non-local means with a soft threshold (NLM-ST)[9]. These algorithms were selected because they are efficient enough to deal with the large images, and their implementations are available online. These methods depend on the level of noise σ. For the two versions of Non-local Means:

the NLM-JS and NLM-ST methods, the noise parameter value was estimated for each image using the noise estimation method which is discussed in[3]. For denoising, a patch size used for the NLM-JS method is 3×3, with a search window 15×15, and block size 15×15. However, a patch size used for the NLM-ST method is of 5×5, with a search window of 13×13, and block size of 21×21. The algorithms [4], [6] and [5] train their models using the noisy and clean images, to generalise on unseen noisy images. The algorithms were trained on Gaussian noise using different values of σ. The ARF model was trained on Gaussian noise using different values of noise at σ = 10, 15, 20, 25 and 50, with four iterations. Also, to evaluate the performance of the opt-MRF model, it was trained on Gaussian noise using σ = 15 and 25 with 30 iterations. For the MLP algorithm, the model is trained on Gaussian noise at σ =10, 25, 35, 50, and 75. The performance of BM3D for colour image denoising was evaluated at σ = 5, 10, 15, 20, 25, and 50. The trained filters, for the different noise level values σ, were used to denoise the images in this dataset. Then the parameter σ which gave the best results is selected for each method.

Table1 shows the PSNR results for the three cameras and different methods. The PSNR values were computed between the restored images and the best ground truth estimate (which is the average of the reference-clean images). The best result for BM3D is obtained with σ = 50, however the best results for the ARF, opt-MRF, and MLP algorithms occurred with σ = 25. We used our DBSR model to denoise the RENOIR dataset, the best result is for σ = 35. Therefore, we recorded the results for this value in the Table 1. The PSNR results of all three cameras display that the BM3D outperformed the other algorithms. Our DBSR model gives the second best result on average after BM3D method, and it achieves better performance than the other techniques. But for the S90 camera, the second-best result was for opt-MRF technique, in which case our method gives the third-best result. Note that the SSIM metric was computed to the three cameras, but the published results in[3] were higher for noisy images than denoised images, then these results did not reflect the improvement for the different methods, and they could not interpret the SSIM results. Also, when we computed the SSIM gave us different values, where the SSIM values for noisy images were lower than the values for reconstructed images, hence the PSNR metric is only used.

Table 1: PSNR (in dB) performance of DBSR and other denoising algorithms reported from[3] on the RENOIR real dataset; the best result **in bold**, the second-best *in italic*.

Camera	Before Denoising	NLM-ST [9]	ARF [4]	MLP [5]	NLM-JS [12]	opt-MRF [6]	DBSR [2]	BM3D [7]
Mi3	23.49	30.87	30.92	31.23	31.35	31.64	*32.12*	**32.35**
S90	26.19	33.08	33.80	34.07	34.14	*34.98*	34.83	**36.75**
T3i	27.44	36.82	36.55	37.58	37.40	38.65	*38.76*	**39.97**
Average	25.71	33.59	33.76	34.29	34.30	35.09	*35.24*	**36.36**

4 Conclusion

We have compared our DBSR model for denoising the images in the RENOIR dataset. Based on PSNR, DBSR gives the second-best results on average after BM3D, confirming the results of Anaya and Barbu [3] that BM3D has the best performance on this dataset. DBSR however is shown to outperform the other algorithms for denoising and qualitative results shown in Figure 2 indicate that both algorithms provide excellent rendering compared to the clean images used as ground truth.

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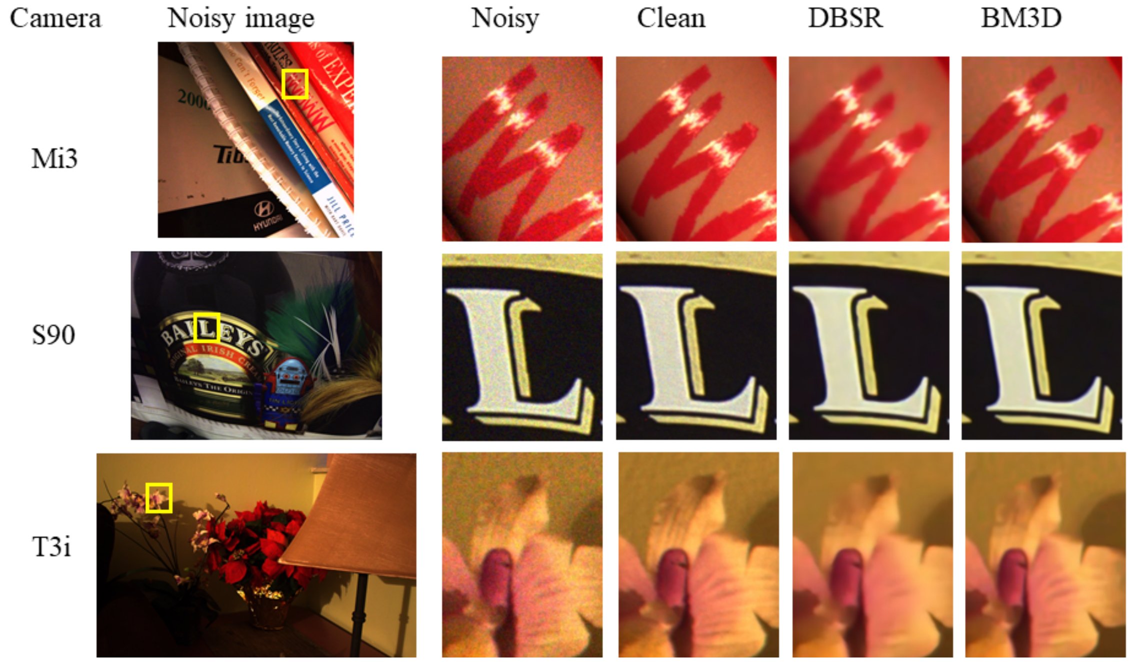

Figure 2: Results of DBSR and BM3D method on the RENOIR dataset with zoomed crops.

References

[1] F. Albluwi, V. A Krylov, and R. Dahyot. Image deblurring and super-resolution using deep convolutional neural networks. In *2018 IEEE 28th International Workshop on MLSP*, pages 1–6. IEEE, 2018.

[2] F. Albluwi, V. A. Krylov, and R. Dahyot. Super-resolution on degraded low-resolution images using convolutional neural networks. In *European Signal Processing Conf. (EUSIPCO)*, Spain, 2019.

[3] J. Anaya and A. Barbu. RENOIR–a dataset for real low-light image noise reduction. *Journal of Visual Communication and Image Representation*, 51:144–154, 2018.

[4] A. Barbu. Training an active random field for real-time image denoising. *IEEE Transactions on Image Processing*, 18(11):2451–2462, 2009.

[5] Harold C Burger, Christian J Schuler, and Stefan Harmeling. Image denoising: Can plain neural networks compete with bm3d? In *2012 IEEE conference on CVPR*, pages 2392–2399. IEEE, 2012.

[6] Y. Chen, T. Pock, R. Ranftl, and H. Bischof. Revisiting loss-specific training of filter-based mrfs for image restoration. In *GCPR*, pages 271–281. Springer, 2013.

[7] K Dabov, A Foi, V Katkovnik, and K Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. image processing, ieee transactions on 16 (8), pp. 2080-2095. 2007.

[8] C. Dong, C. C. Loy, K. He, and X. Tang. Image super-resolution using deep convolutional networks. *IEEE transactions on PAMI*, 38(2):295–307, 2016.

[9] L. Lu, W. Jin, and X. Wang. Non-local means image denoising with a soft threshold. *IEEE Signal Processing Letters*, 22(7):833–837, 2015.

[10] X. Mao, C. Shen, and Y.-B. Yang. Image restoration using very deep convolutional encoder-decoder networks with symmetric skip connections. In *Advances in NIPS*, pages 2802–2810, 2016.

[11] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *ICCV*, 2001.

[12] Yue Wu, Brian Tracey, Premkumar Natarajan, and Joseph P Noonan. James–stein type center pixel weights for non-local means image denoising. *IEEE Signal Processing Letters*, 20(4):411–414, 2013.

[13] C.-Y. Yang, C. Ma, and M.-H. Yang. Single-image super-resolution: A benchmark. In *ECCV*, 2014.