BLIND ESTIMATION AND SUPPRESSION OF ADDITIVE SPATIALLY CORRELATED GAUSSIAN NOISE ON IMAGES

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ABSTRACT

The paper is devoted to the task of estimation of the parameters of spatially correlated noise and noise suppression in images. Several schemes of noise removal, including multiscale ones, are considered. A convolutional neural network (CNN) for blind estimation of the spectrum of spatially correlated noise images is proposed. It is shown that the proposed network in combination with the BM3D filter provides more efficient noise suppression than existing solutions. A CNN for prediction of the denoising parameters for DRUNet denoiser is also proposed and analyzed. It is shown that the usage of this network and DRUNet for multiscale denoising in comparison with other methods provides better quality of image denoising and processing speed for a wide range of sizes of “noise grain”.

Index Terms— image denoising, blind noise parameters estimation, spatially correlated noise, convolutional neural networks, deep learning

1. INTRODUCTION

The noise suppression is one of the oldest problems in digital image processing [1]. However, due to constantly increasing requirements to digital cameras (in particular, to produce high quality photos in low light conditions), increasing sensors resolutions by decreasing of pixel sizes, and other factors the problem of noise suppression becomes even more important [2-7].

In this paper, we consider a problem of recovery of original noise-free image $\mathbf{x}$ from its noisy observation $\mathbf{y} = \mathbf{x} + \mathbf{n} \otimes \mathbf{k}$, where $\mathbf{n}$ is an additive white Gaussian noise (AWGN) with standard deviation σ, $\otimes$ $\mathbf{k}$ denotes the two-dimensional convolution with a blur kernel $\mathbf{k}$. Thus, image $\mathbf{x}$ is degraded by an additive spatially correlated Gaussian noise (ASCGN), given by $\mathbf{n} \otimes \mathbf{k}$.

ASCGN may occur in images at the stage of image acquisition, or image processing, e.g., digital zoom, image super-resolution, presence of a residual noise after partial noise suppression, demosaicing, lossy compression of noisy images, etc. For a simplicity of noise modelling in this paper we assume that $\mathbf{k}$ is a rotationally symmetric Gaussian lowpass filter with a standard deviation σ_k. For this model, a noise level is characterized by σ value, while the size of “noise grain” (level of correlation between values of the noise in neighboring image pixels) is characterized by σ_k value.

While the problems of AWGN removal [2, 8] and estimation of AWGN variance [9, 10] are well studied, noise suppression and parameter estimation in the case of ASCGN noise model are studied much less and are more complicated. It is very difficult in case of ASCGN presence to separate a noise from informative image component since noise values in neighboring pixels are correlated. Potentially, the best effectiveness of ASCGN noise removal can be reached for known or estimated noise spectrum [9]. Some effective denoising methods such as BM3D [2, 11] can use this spectrum as a priori information.

At the same time, many recent denoising methods, such as DRUNet [5], are designed for AWGN removal and require estimation of AWGN’s σ value or a map of σ values for image pixels. Therefore, adaptation of such denoising methods for the case of ASCGN suppression is important.

Another class of CNN-based image denoising methods which can be applied for ASCGN removal are blind denoisers such as DnCNN [6] and CBDNet [7]. However, to be effective, these methods should be trained for a given noise spectrum which is unknown at the training stage. Due to this, effectiveness of these algorithms to suppress ASCGN is very limited.

In the paper, we propose two convolutional neural networks: the first one is intended for blind noise estimation for a given image, and the second one designed to predict the optimal σ for DRUNet’s input for a given image distorted by ASCGN. We analyze the applicability of the obtained estimates in different noise suppression schemes with both BM3D (which uses the estimated noise spectrum) and DRUNet (which is designed for AWGN removal and uses the estimated σ as an input).

Section 2 presents the ASCGN suppression schemes with different denoising methods, and corresponding multiscale extensions. Section 3 describes the proposed deep CNN for noise spectrum estimation in images, presents details of the training procedure, and the results of comparative analysis of ASCGN suppression using spectrums obtained by the network and BECNS method [9, 12]. Another modification of this architecture for prediction of an optimal σ for DRUNet denoiser is proposed and analyzed in Section 4. Section 5 is dedicated to quantitative and qualitative comparison of the methods. In this section, we also analyze computational complexity of the considered methods and their combinations.

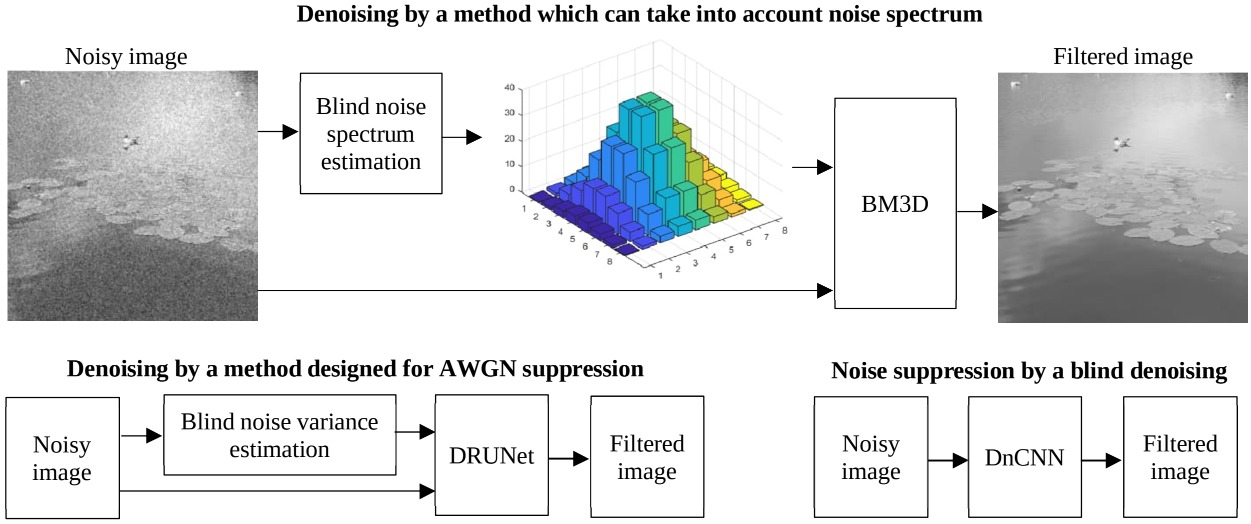

Fig. 1. Considered denoising methods for ASCGN removal

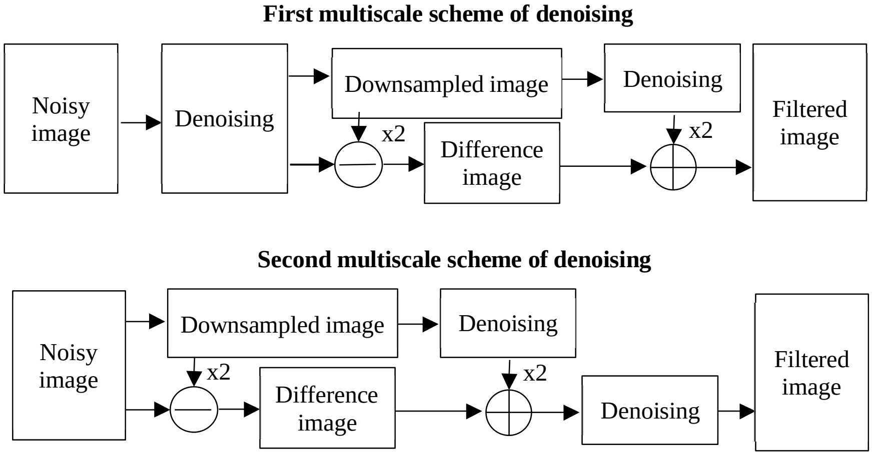

Fig. 2. Considered multiscale schemes of image denoising

2. DENOISING SCHEMES

In this section, we consider possible strategies of ASCGN denoising and perform a preliminary analysis of their efficiency. Two single step strategies are shown in Fig. 1, and two multiscale extensions, which can be applied to any methods from Fig. 1, are shown in Fig. 2.

2.1 Test set and noise models

For the efficiency analysis, we use 30 grayscale 512x512 images from "Tampere17" database [13]: {#1, #15, #34, #35, #42, #48, #52, #62, #63, #65, #66, #69, #71, #75, #83, #85, #89, #91, #94, #95, #99, #105, #115, #177, #182, #203, #209, #241, #256, #277}. Images are specially selected to complicate the task of noise parameters' estimation. The set contains many highly textured images. At the same time, images with large homogeneous regions are present as well to provide a good representativity.

"Tampere17" is a database of noise free images. Here we have used the sharpened versions of all images as well. Each image was used in the numerical analysis twice: as a given image and as an image slightly sharpened (for sharpening, we applied the Matlab function *imsharpen(im, 'Radius',1,'Amount',0.5)*, where "im" is a processed image).

For methods verification, we will use the model of ASCGN with the fixed σ=10, but with different σ_k from the set {0.5, 0.65, 0.75, 0.9}. It allows estimating the methods performance for different levels of noise correlation for a wide range of practical situations.

2.2 Denoising by a method which can use estimated noise spectrum

The block diagram of this approach is presented in Fig. 1. Noise spectrum is estimated for noisy image blindly and after that it is used for image denoising.

A typical denoising method which can utilize noise spectrum in the denoising scheme is BM3D filter [11], where different thresholds for different spatial frequencies are set at the hard thresholding step [11] according to a given noise spectrum.

Recently, more effective modification of BM3D with a convenient use of noise spectrum is proposed [2]. In our paper, we will use this modification.

To estimate the noise spectrum, we will use BECNS method [4] based on the analysis of similar image regions in the discrete cosine transform (DCT) domain. The method provides good precision of noise spectrum estimation; however, it is very slow. We will use this method in the paper for preliminary analysis in this section as well as to compare it with the proposed fast CNN for noise spectrum estimation.

BECNS provides spectrum estimation as a matrix of size16x16. The proposed network, described in Section 3, provides spectrum estimation as a matrix of size 8x8. BM3D is able to use both spectrum size as its input.

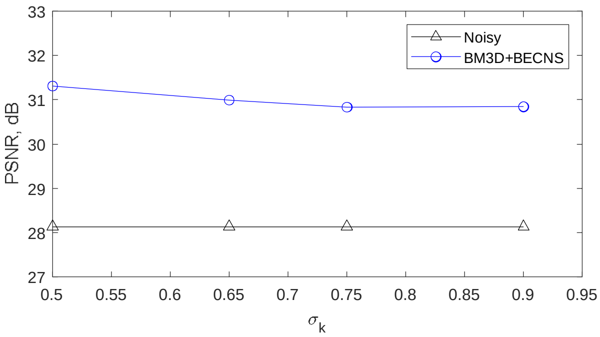

Fig. 3. Effectiveness of BM3D+BECNS scheme

It is clearly seen that BM3D+BECNS has stable efficiency for the wide range of σ_k, slightly decreased for larger σ_k values.

2.3 Denoising by a method designed for AWGN suppression

It is interesting to check the possibility to use for ASCGN suppression an effective method designed for AWGN removal such as the state-of-the-art denoising network DRUNet [5].

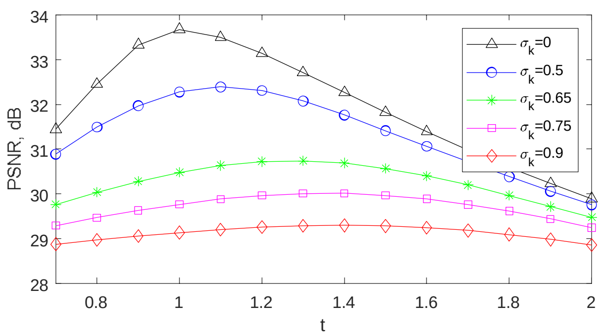

Fig. 4. Results of ASCGN noise suppression by DRUNet for known true σ

For simplicity of this experiment, let us suppose that we can precisely estimate the true value of σ. Note that for effective suppression of ASCGN one could set input for DRUNET as $t\sigma$, where t is a correcting factor.

Fig. 4 contains the results of ASCGN denoising by DRUNet with different t for different σ_k. Value σ_k =0 corresponds to the case of AWGN.

These results are very interesting. First, even for σ_k =0.5, DRUNet with an optimal t provides significantly better PSNR (approximately by 1 dB) than the combination of BM3D+BECNS. Second, there are no fixed optimal t for a wide range of σ_k values. Depending on σ_k, a quasi-optimal t changes from 1 to 1.4. Selection of non-optimal t can lead to losses in PSNR by up to 1 dB. Third, efficiency of DRUNet drastically decreases for large σ_k.

Thus, the use of DRUNet for ASCGN suppressions looks promising but needs some modifications to provide a good noise suppression for large σ_k. Also, a good algorithm for selection of optimal t is needed.

2.4 Noise suppression by blind denoising

It is possible to use totally blind methods of noise removal for ASCGN suppression. Fig. 5 shows the results for blind version of DnCNN denoising network (included in Matlab's deep learning toolbox).

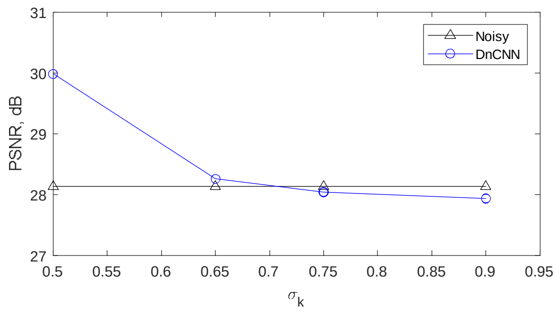

Fig. 5. Results of ASCGN noise suppression by DnCNN

It is clearly seen that DnCNN has poor efficiency of noise suppression for σ_k=0.5 and it is not effective for larger σ_k.

2.5 The first multiscale scheme of denoising

In this paper, we propose two multiscale extensions of the methods considered in Sections 2.2 – 2.4.

The main idea is that for a smaller version of a given image the noise becomes less correlated and, thus, simpler for suppression.

For the first multiscale scheme (M1), a given image is denoised by a selected denoising method. Then, the filtered image is decomposed into a smaller downsampled image and the difference between the filtered and upsampled image, like in image pyramid decomposition. In this paper, we use for this purpose the 2D discrete wavelet transform db13 from Daubechies family.

The same denoising method is applied to the downsampled image (containing a residual noise with smaller σ_k). After this, the output image is composed by adding difference image to the upsampled result of the second denoising (like in pyramid reconstruction). For image upsampling, we use inverse db13.

Let us denote a method using this scheme as XXX+M1, where XXX is the base denoising method. For example, BM3D+BECNS+M1 means the usage of the proposed multiscale method with BM3D+BECNS as the base method.

Fig. 6. contains the results for the proposed M1 scheme for the considered methods. We denoted DRUNet with a priori known quasi-optimal *t* as DRUNet+opt+M1, and DRUNet with the fixed *t*=0.9 as DRUNet+t09+M1.

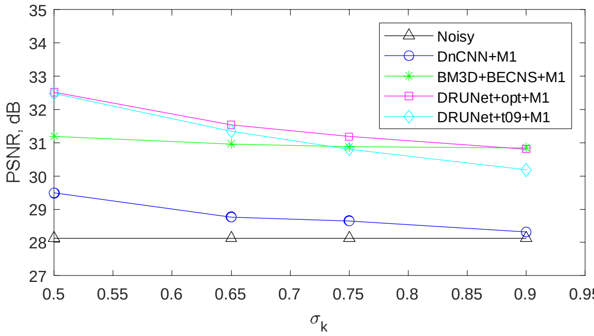

Fig. 6. Results of ASCGN noise suppression using the first multiscale scheme M1

It is clearly seen that M1 helps DnCNN to slightly improve its denoising efficiency, it does not help BECNS, but helps significantly DRUNet.

DRUNet+opt+M1 provides better noise suppression than BM3D+BECNS for almost all the range of σ_k. However, for the empirically selected t=0.9 the DRUNet+t09+M1 loses up to 1 dB for large σ_k. This proves that a good method of prediction of t value is needed.

2.6 The second multiscale scheme of denoising

For the second multiscale scheme (M2), a given image is denoised first on a smaller resolution (noise removal for low spatial frequencies), and after composing the result into a full-size image it is denoised again to remove a noise from its high spatial frequencies.

Fig. 7 shows the results for the proposed M2 scheme for the considered methods. Methods are denoted here similarly to the M1 scheme. BM3D+BECNS and DnCNN for M2 provide weak results, so, we show only the results for DRUNet equipped by M2 and M1.

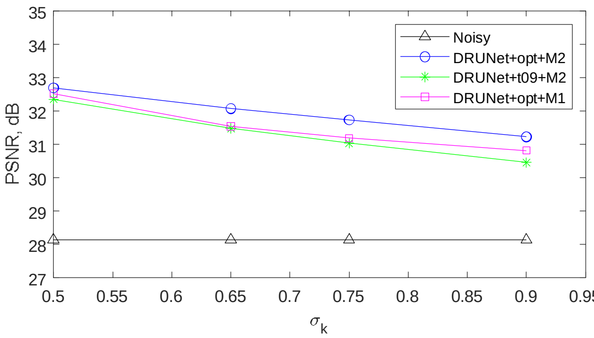

Fig. 7. Results of ASCGN noise suppression using second multiscale scheme M2 in comparison to M1

One can see that for M2 the DRUNet provides even better quality of filtered images than for M1, outperforming BM3D+BECNS for the whole range of σ_k.

3. CNN FOR NOISE SPECTRUM ESTIMATION

For blind estimation of noise spectrum, we have selected an architecture of deep convolutional network similar to DRUNet. It estimates spectrum on several image scales (well corresponds to the nature of spatially correlated noise).

A structure of the proposed network SPNet is drawn in Fig. 8. The symbols used in Fig. 8 are explained in Fig. 9.

In comparison to DRUNet, we have changed the input size, added convolutional layer with 64 filters and global average pooling layer. As a result, the network has 2D input of size 64x64 pixels and 1x64 output corresponding to spectrum 8x8. In fact, after training it can be applied to any 2D input size and always produces 1x64 output.

For the network training, we used 270 noise-free images from the database Tampere17 [13] and 1000 images from the database Tampere21 [14]. Fragments of size 64x64 were cropped from the ground truth images randomly, small sharpening has been applied, and then images were corrupted by ASCGN with a random σ in the range 0..20, and with random σ_k in the range 0.45..1.7. With a probability 3%, AWGN noise was generated to provide an ability of the network to estimate a spectrum of AWGN noise.

Network training was carried out in Matlab R2020a environment. We have used custom training loop with the minibatch size 8, initial learning rate 0.0001 and learning rate decay 0.00001. Adam optimizer was used and 160000 iterations were performed.

Fig. 10 shows the result of testing the trained SPNet for spectrum estimation for BM3D filter.

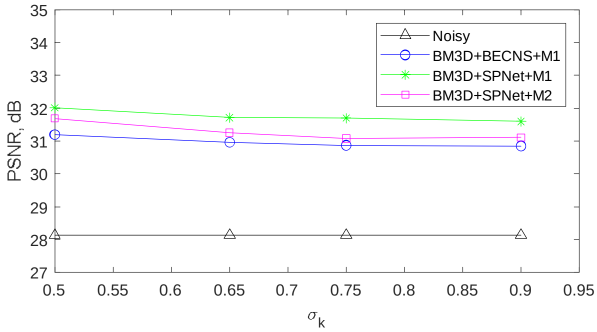

Fig. 10. Results of ASCGN noise suppression using the combination of BM3D and spectrum estimation by the trained SPNet

It is clearly seen that BM3D+SPnet works better in M1 multiscale scheme and significantly (up to 1 dB) outperforms the BM3D+BECNS combination.

4. PROPOSED NETWORK FOR PREDICTION OF OPTIMAL INPUT PARAMETER FOR DRUNET

For estimation of optimal *t* parameter for DRUNet, we designed and trained another convolutional network NLNet. The NLNet structure is similar to PSNet except of last two layers which are replaced by convolutional layer with 1 filter. As a results, the network has 2D input of size 64x64 pixels and the 64x64 output.

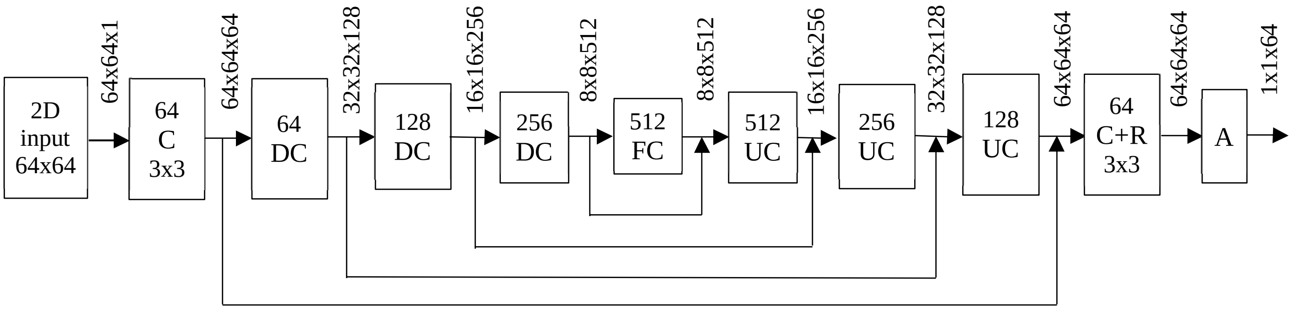

Fig. 8. Structure of the proposed convolutional network for blind noise spectrum estimation

C – Convolution layer with stride 1, SC – Strided convolution, TC – Transposed convolution, A – Global average pooling
UC – Upscaling cascade, DC – Downscaling cascade, FC – Filter cascade

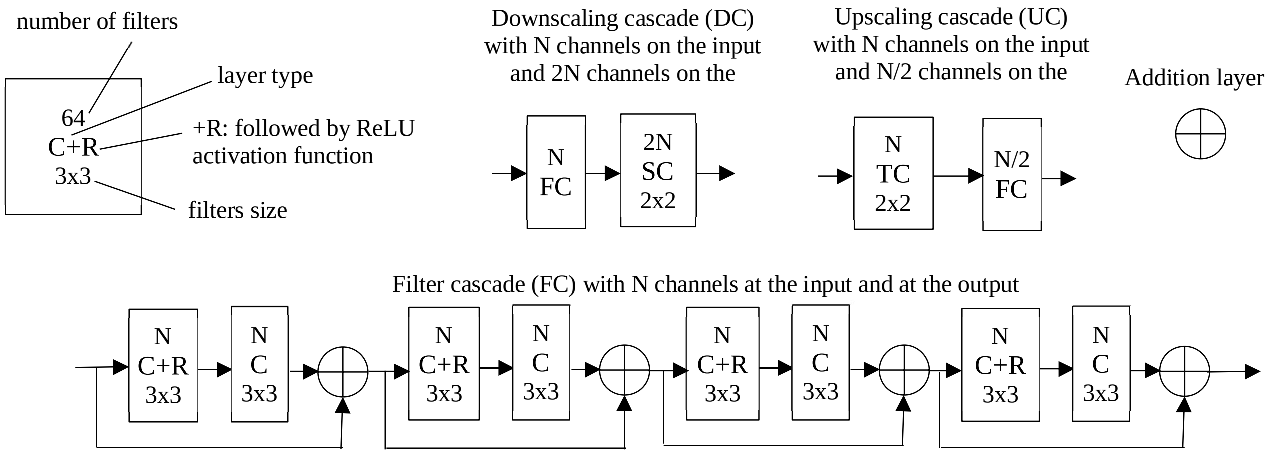

Fig. 9. Symbols description for figure 8

In fact, after training it can be applied to any 2D input size and produces output $t\sigma$ map of the same size.

The same training set was used, however, contrary to SPNet, the NLNet was trained to predict quasi-optimal value of $t\sigma$ for a given image which provides the smallest MSE between the true image and DRUNet output.

We have used custom training loop with the minibatch size 32, initial learning rate 0.0001 and learning rate decay 0.0001. Adam optimizer was used and 41500 iterations were performed.

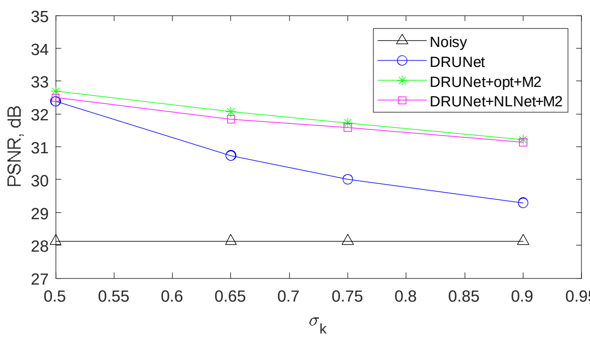

Fig. 11. Results of ASCGN noise suppression using combination of DRUNet and noise level estimation by NLNet

Fig. 11 shows the result of testing the trained NLNet in the combination with DRUNet. Input parameter for DRUNet is calculated as a median from the output map of NLNet.

It is clearly seen that DRUNet+NLNet+M2 provides almost the same denoising efficiency as DRUNET+M2 with a priori known quasi-optimal t parameter and the known σ of the noise.

5. COMPARATIVE ANALYSIS

Fig. 10 shows PSNR curves for the most efficient blind methods.

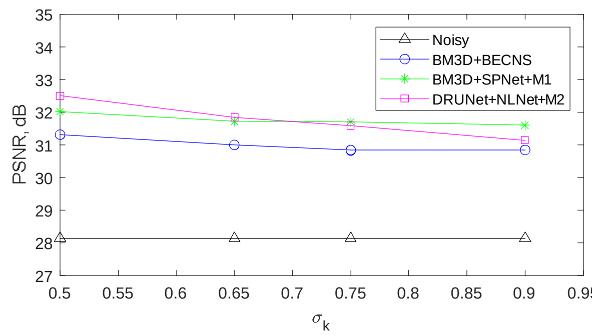

Fig. 11. Results of ASCGN noise suppression by the compared fully automatic denoising methods

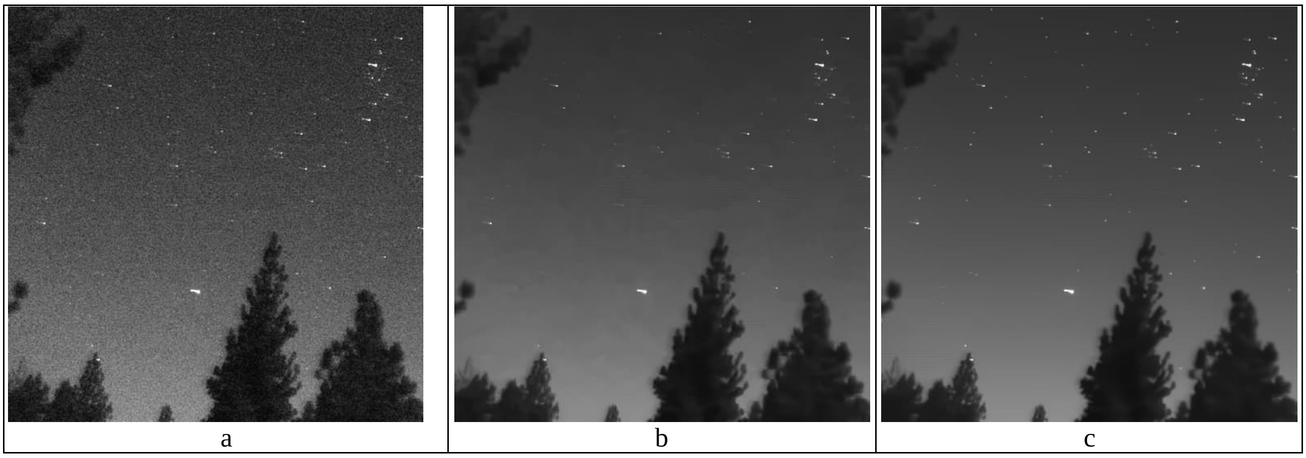

Fig. 11. Denoising of real life image: a) noisy image, b) BM3D+SPNet+M1, c) DRUNet+NLNet+M2

One can see that both proposed predictors provide better noise suppression than BM3D+BECNS.

DRUNet+NLNet+M2 scheme provides better noise suppression for smaller σ_k, while BM3D+SPNet+M1 provides better noise suppression for larger σ_k.

Table 1 contains computational time for the considered and proposed methods (CPU i5-9300H 2.40GHz, GPU: Nvidia GeForce GTX 1660 Ti).

Table 1. Computational time for compared methods for input image 512x512 grayscale image, sec

BM3D (CPU)	BECNS (CPU)	SPNet (GPU)	NLNet (GPU)	DRUNet (GPU)
30 sec	20 sec	0.2 sec	0.2 sec	0.2 sec

It is clearly seen that DRUNet+NLNet+M2 processing scheme provides both good noise suppression and fast image processing.

Fig. 11 shows a real-life image and the results of processing by the proposed methods. In contrary, DnCNN preserves the noise on this image almost unchanged, same happens if one applies DRUnet with the noise σ estimation by blind methods [13, 15] for AWGN noise.

CONCLUSIONS

The paper proposes novel methods of estimation and removal of ASCGN from images. It is shown that the proposed methods provide effective and fast noise suppression outperforming existing methods.

A link to pretrained network models and demo codes will be published in the camera-ready paper.

REFERENCES

[1] J. Astola, P. Kuosmanen, *Fundamentals of Nonlinear Digital Filtering*, CRC press, 288 p., 1997.

[2] Y. Mäkinen, L. Azzari, and A. Foi, “Collaborative Filtering of Correlated Noise: Exact Transform-Domain Variance for Improved Shrinkage and Patch Matching”, IEEE Trans. Image Process., vol. 29, pp. 8339-8354, 2020.

[3] K. Zhang, W. Zuo, and L. Zhang, “FFDNet: Toward a fast and flexible solution for cnn-based image denoising,” IEEE Transactions on Image Processing, vol. 27, no. 9, pp. 4608–4622, 2018.

[4] D. Li, S. Gong, S. Niu, Z. Wang, D. Zhou, H. Lu, “Image Blind Denoising Using a Generative Adversarial Network for LED Chip Visual Localization”, IEEE Sensors Journal, 20(12):6582-6595, IEEE, 2020.

[5] K. Zhang, Y. Li, W. Zuo, L. Zhang, L. Van Gool, R. Timofte, “Plug-and-play image restoration with deep denoiser prior”, arXiv preprint arXiv:2008.13751, 2020.

[6] K. Zhang, W. Zuo, Y. Chen, D. Meng, L. Zhang, “Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising”. IEEE transactions on image processing, 26(7), pp. 3142-3155, 2017.

[7] S. Guo, Z. Yan, K. Zhang, W. Zuo, L. Zhang, “Toward convolutional blind denoising of real photographs”, In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 1712-1722, 2019.

[8] M. Ponomarenko, S. G. Bahnemiri, K. Egiazarian, “Deep Convolutional Network for Spatially Correlated Rayleigh Noise Suppression on TerraSAR-X Images”, IEEE 6th International Symposium on Microwaves, Radar and Remote Sensing, pp.458-463, 2020.

[9] N.N. Ponomarenko, V.V. Lukin, K.O. Egiazarian, J.T. Astola, A method for blind estimation of spatially correlated noise characteristics, Proceedings of SPIE Conference Image Processing: Algorithms and Systems VII, San Jose, USA, 2010.

[10] V. Abramova, S. Abramov, V. Lukin, A. Roenko, B. Vozel , “Automatic estimation of spatially correlated noise variance in spectral domain for images”, Telecommunications and Radioengineering, No. 73(6), pp. 511-527, 2014.

[11] K. Dabov, A. Foi, V. Katkovnik, K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering", IEEE Transactions on Image Processing, 16(8), 2007, pp. 2080-2095.

[12] N. Ponomarenko, V.V. Lukin, K. Egiazarian, L. Lepisto, “Color image lossy compression based on blind evaluation and prediction of noise characteristics”, Proceedings of SPIE Conference Image Processing: Algorithms and Systems VII, San Francisco, USA, Vol. 7870, 2011, 12 p.

[13] M. Ponomarenko, N. Gapon, V. Voronin, K. Egiazarian, “Blind estimation of white Gaussian noise variance in highly textured images”, Proceedings of International Conference Image Processing: Algorithms and Systems, 5p., 2018.

[14] Link to download page for Tampere21 database (will be published in camera ready version).

[15] S. Pyatykh, J. Hesser, and L. Zheng, "Image Noise Level Estimation by Principal Component Analysis", IEEE Transactions on Image Processing, pp. 687-699, 2013.