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NOISE REDUCTION IN DIGITAL IMAGES BASED ON ORIGINAL RAW FILES USING NEURAL NETWORKS

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This paper presents a noise reduction method for RAW photo images, focusing on preserving the original information and improving the processing quality. Digital image processing is important for surveillance and vision systems where quality and detail play a key role. The proposed method is based on a combination of UNet and HQSNet neural networks. HQSNet performs semi-square partitioning of the input data, emphasizing key regions and reducing the dimensionality of less significant ones. UNet, in turn, efficiently processes the prepared data, preserving high granularity and tone transitions. The method is tested on real images, including complex night portrait and starry sky scenes, demonstrating high performance on MSE metrics and expert evaluations. Comparison with traditional methods, such as median and Bilateral filters, showed the superiority of the new approach in both noise removal quality and image detail preservation. The advantages of the method include preservation of dynamic range and the possibility of deep post-processing. The results obtained confirm its effectiveness in digital processing problems, which makes the development promising for application in automatic image analysis and enhancement systems.

Keywords: noise reduction; neural networks; UNet; HQSNet; RAW photo images.

Introduction

Digital image processing is one of the priority areas of science and technology, as images are widely used for information acquisition, display, and transmission in various fields, including surveillance systems, computer vision, medicine, and others. Over time, numerous approaches to photo image processing have been developed, differing depending on the ultimate goal: preserving details, processing speed, or focusing on specific objects.

One of the key problems in this area is noise reduction. Digital noise can significantly reduce image quality, complicating the analysis of details, shapes, and colors contained within the image. This is particularly relevant for RAW photographic images, which retain more raw information compared to compressed formats. Noise reduction on RAW data not only improves image perception but also offers extensive possibilities for subsequent editing and analysis.

Traditional image processing methods propose various approaches to noise reduction. Classical algorithms, such as median or bilateral filters, perform well for simple types of noise but struggle with complex scenes or high noise levels. With the advent of neural networks, architectures like UNet and RawCNN have demonstrated superior performance in noise reduction problem, delivering high detail and accuracy. However, most existing solutions either require large datasets for training or lack flexibility when processing images with diverse characteristics.

This study proposes a noise reduction method for RAW photographic images using a combined approach with UNet and HQSNet neural networks. HQSNet performs semi-quadratic splitting of the input image, isolating key regions and compressing less significant data, while UNet processes the prepared data, preserving high detail. This approach ensures high-quality results with minimal time requirements.

The architecture of the proposed method and an analysis of existing approaches are presented. The effectiveness of the solution is validated through testing on real-world images, including challenging scenes such as night portraits and starry skies, demonstrating its suitability for a wide range of digital image processing problems.

1. Overview of Existing Solutions

In the field of digital image processing, methods have long been applied that allow processing by using various mathematical filters. Such methods are mainly aimed at removing specific types of distortions and degradations. Due to the use of mathematical principles, this type of processing is characterized by high processing speed. Classical variants of image processing using filters consider the situation where the input image has passed through a degradation function, and then the filter is applied to minimize the effect of the degradation function.

Among the filters used for image processing, several of the most commonly used ones are distinguished, but in the context of modern methods, they are combined into a single filter called an adaptive median filter. The operation of this filter is based on the preliminary analysis of the image and the search for areas containing the largest amount of noise or blurring. After this step, the filter adjusts the filter window size and degradation correction method depending on the detected type. This type of filter includes several filters and their variations, allowing for the best results on various types of distortions. However, due to its operational characteristics, it is the slowest and may show poor results on low-resolution images. The use of such filters is possible for the initial processing of input images, but they cannot achieve significant results, especially for the RAW format. Therefore, the next step was the consideration of neural network methods for image processing. Over the past years, several generative adversarial neural networks have been developed to solve the problem of noise removal in RAW format images. Accordingly, approaches to solving this problem have been proposed and developed.

One of such solutions is the MultiNeRF neural network. It is based on synthesizing a full scene from several input RAW format images, which allows more information about scene illumination and details of individual objects to be transmitted to the neural network. This approach helps to achieve excellent noise reduction results since information about one object can be collected from multiple individual frames. However, this makes the neural network highly demanding in terms of the data volume for its training and imposes requirements for creating multiple frames of a single scene to remove noise from only a specific shooting angle. Another solution is the RawCNN neural network. This neural network is relatively simple in its architecture but achieves good results in solving the noise reduction problem due to well-chosen convolutional layer sizes and operations on feature maps deep within the network. A significant disadvantage of this approach is its difficulty in removing complex types of noise and image degradations, which is compensated by its high processing speeds for simple images. The solution used in this work is a combination of two neural networks, UNet and HQSNet. Both neural networks were developed relatively recently and are aimed at improving the quality of MRI images. By combining the features of these neural networks designed for image quality improvement and noise removal, and applying them to image parts sequentially, high-quality image results after noise removal can be achieved while maintaining high system operation speeds. Thus, the developed noise reduction method should correlate with the operating speed of lightweight neural network architectures for solving this problem and show good results in removing various types of noise from images.

2. Proposed Solution

At the first stage of developing this system, two key features of the neural networks used were identified, the combination of which allows for the advantages of both to be obtained for solving the noise reduction problem. These are the semi-quadratic splitting of HQSNet and the UNet architecture. At the first level of the system's operation, the incoming image undergoes semi-quadratic splitting by HQSNet, which works in two stages. In the first stage, the data is split into two parts: low-frequency and high-frequency. The low-frequency part of the data contains the main structure of the data or signal, while the high-frequency part contains the main and most important features of the data or signal. HQS compresses the low-frequency part of the data using the discrete cosine transform (DCT), and the high-frequency part of the data using classical quantization. In the second stage, HQSNet uses a convolutional neural network, consisting of several convolutional and fully connected layers. Convolutional layers allow the neural network to detect local patterns in the data. Fully connected layers perform the operation of full connection, allowing the neural network to combine information from different parts of the image.

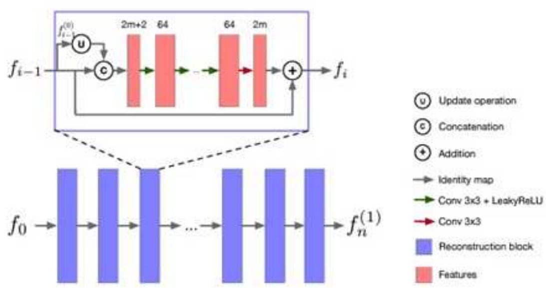

Fig. 1. Convolutional neural network block in HQSNet

The prepared data is then passed to the UNet network for training, with the input image dimension set to 256x256 pixels. This size allows for covering sufficiently large image areas while maintaining relatively low processing times. The configuration of the UNet network is presented in Table 1.

This approach (Fig. 2) ensures that continuous data enhancement using HQSNet, reduces the potential for fading of the training gradient of the UNet neural network, stabilizes its training process and improves the quality of the results compared to using the UNet architecture alone. The generative-adversarial neural network developed in the course of this work is not used for full-fledged generation of large photo images and has an addition to its architecture to stabilize the training and preprocessing of the data used during its training, the training cycle of this neural network is different from the classical training cycle of a generative-adversarial neural network.

Table 1

UNet Configuration

No.	Layer Type	Input Size	Output Size
1	Input Image	-	(1, 256, 256)
2	Independent Convolution	(1, 256, 256)	(10, 256, 256)
3	Downsampling UNet Block 1	(10, 256, 256)	(14, 128, 128)
4	Downsampling UNet Block 2	(14, 128, 128)	(14, 64, 64)
5	Downsampling UNet Block 3	(14, 64, 64)	(16, 32, 32)
6	Intermediate UNet Block	(16, 32, 32)	(16, 32, 32)
7	Upsampling UNet Block 3	(16, 32, 32)	(14, 64, 64)
8	Upsampling UNet Block 2	(14, 64, 64)	(14, 128, 128)
9	Upsampling UNet Block 1	(14, 128, 128)	(10, 256, 256)
10	Independent Deconvolution	(10, 256, 256)	(1, 256, 256)
11	Output Image	(1, 256, 256)	-

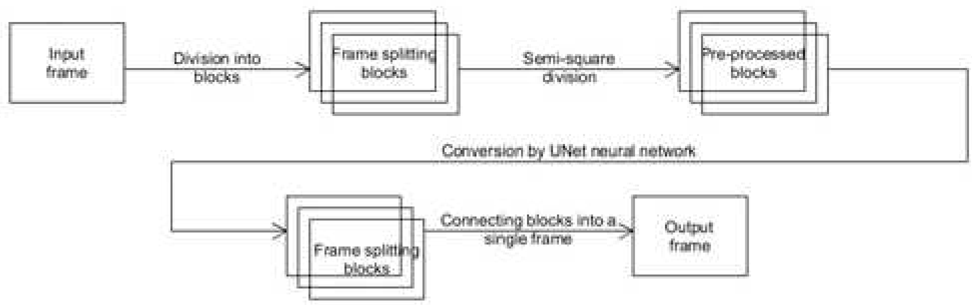

Fig. 2. Step-by-step decomposition of the noise reduction system algorithm

At the beginning of training (Fig. 3), the raw data is loaded and immediately divided into validation and training samples. Then the training cycle starts by the selected number of epochs. Inside the training cycle, the subset of photo images undergoes a preprocessing procedure, followed by the HQSNet half-square split cycle, where we split the data, apply the discrete cosine transform [14] to it, and quantization [15] to the second half of the data, merge the obtained data back together, and finally the obtained data is fed to the input of the UNet neural network. In the last steps of the training cycle, the current state of the network is validated on a validation sample of data and if the results are better than the previous one, the current model weights are stored. When a certain number of epochs is reached, the training cycle is terminated.

The raw RAW signal also undergoes several preprocessing processes to improve the quality of the RAW signal and increase the chances that the denoising process will capture as much noise as possible for removal.

3. Implementation of Noise Reduction System on RAW Photo Images

To further use and test the quality of the developed approach to noise removal on RAW format photo images, a test system for controlling this process was developed (Fig. 4). The

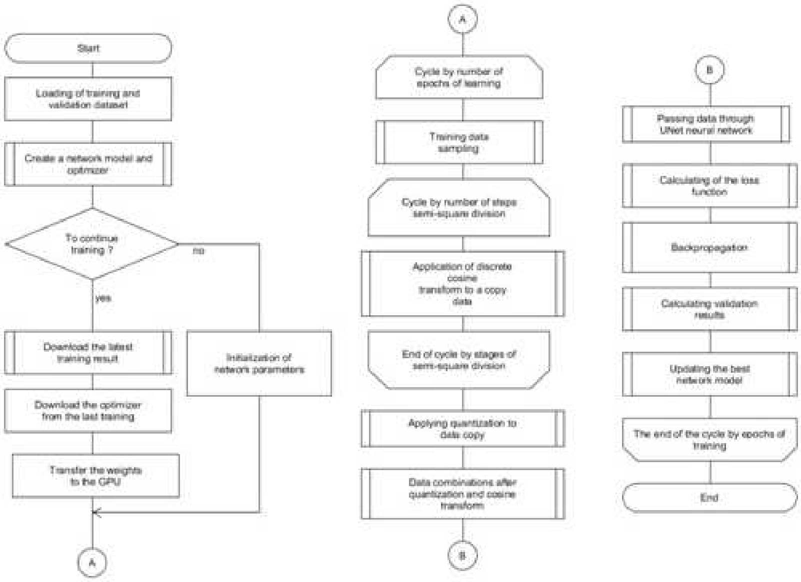

Fig. 3. Training algorithm of the developed neural network

input components of this system are: prepared data for training, namely, pairs of images with noisy and non-noisy photo images, images containing no noise, as well as the input image for processing. The finished image pairs for training are divided into 256 by 256 pixel components and written in binary format for easier storage. The unnoised photo images, depending on the choice of the type of superimposed noise, are exposed to the extracted real noise patterns from the camera's photo matrices and are also recorded in binary format. Thereby a preparatory step of data aggregation and compilation of the dataset for training and validation of the neural network takes place. The next step is to feed the obtained data into the neural network and according to the algorithm, the developed composition of neural networks is trained. This ends the preparatory stage and we get the trained neural network model. The input image for processing goes through the stage of signal extraction from the photo matrix and dividing it into blocks of 256 by 256 pixels with recording into a bit file for its further feeding into the neural network.

After all the blocks of the photo image have been processed by the neural network and recorded in bit format, they are collected into an initial single photo image, which is returned to the original size and the demosaicing procedure is performed [16], after which we get a color image in tiff or dng format, which stores a large amount of information about each pixel and allows for further editing and processing in specialized software, such as DxO Mark or Adobe Lightroom, in order to further improve the quality of the image.

4. Results

The effectiveness of the developed system was tested using a combined method, which started with an expert evaluation of the photo images. Expert evaluations were made in the following categories: overall quality of the photo image, amount of residual noise, quality of fine details, as well as quality of tones and halftones of the obtained photo image. An online form building service was used for scoring and collecting the results. Since it allows

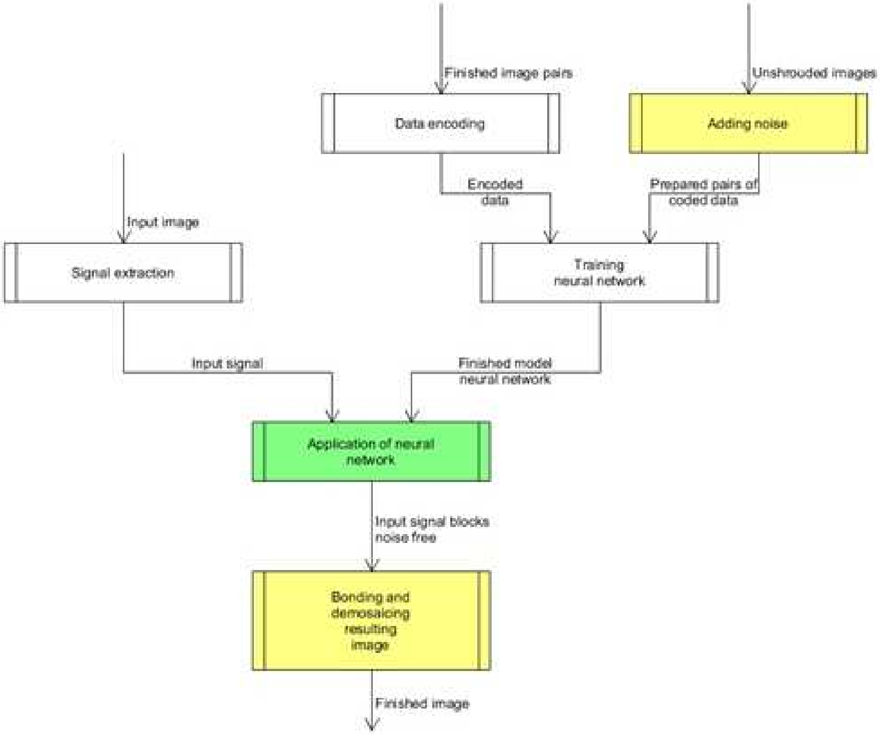

Fig. 4. Architecture of the developed noise removal system

in a convenient and anonymous format for each of the experts to leave their evaluations, and then analyze the obtained values and summarize the overall results, which can then be transferred to any available format. Both people with experience in photography and RAW shooting, amateur photographers with little experience, and ordinary people were invited as experts

The mean square error method with backward approach was used as a quantitative metric for quality comparison. Such use of the MSE method is necessary to analyze how much noise has been removed from the original photo image and it is important to have as large a value of this metric as possible. For the first experiment, we selected a night portrait photo image taken at low light level at high ISO against a background of a reasonably well illuminated building (Fig. 5a).

Digital noise caused by high ISO values is present in the presented photo image. It is expressed in black-and-white and color pixels over the whole frame area. Its presence worsens the perception of the photo image, as well as the perception of details of the person's face in the image, details of objects in the background and the quality of light transitions.

Fig. 5b shows a photo image after noise removal using the developed noise reduction system. The quality of fine details, smoother color and light tone transitions between and on the objects are much better in this photo image. This allowed us to conclude that the system has improved the quality of the obtained photo image for actual human perception.

The second test used a photo image of the starry sky taken in the mountains (Fig. 6a). In this photo there are partly mountains and forest, as well as a part of the starry sky

a) b)

Fig. 5. Photographic image of a night portrait: a – before noise removal; b – after noise removal

above them. Due to the fact that the frame was also taken at a high ISO value, there is a lot of noise throughout the frame. This impairs the perception of the starry sky, individual stars, as well as does not allow you to appreciate the details of the trees of the forest and mountains. Also the presence of all these defects does not allow to use this photo image for effective process of stitching of many astrophotographs obtained in one time interval to obtain a more detailed photo image of the starry sky.

Fig. 6b shows the photo image after noise removal. The details of the forest and mountains in the foreground became more distinguishable, the color rendering improved, and the overall amount of detail in the foreground improved. The absence of noise improved the perception of the starry sky, the details of individual stars became much more distinguishable. This suggests that the noise reduction system improved the overall perception of the photographic image as well as the quality of individual fine details.

a) b)

Fig. 6. Photographic image of the starry sky: a – before noise removal; b – after noise removal

The percentage of positive evaluations by experts for each category is presented in Table 2. Based on them we can conclude that in both cases the system showed good results in all four selected categories of photo image evaluation for both types of presented images. Also for testing the system we used photo images taken in low light conditions with more complex and lighter scenarios of scene filling, namely still lifes, photo images of objects and interiors, as well as shooting of human figures and groups of people at high

ISO values. After the main study of the performance of the developed algorithm, it was compared with existing noise reduction methods (Table 3).

Table 2

Survey results for photo images

Image type	Total quality, % positive ratings	Amount of residual noise, % positive ratings	Quality of fine details, % positive ratings	Quality of tones and halftones, % positive ratings
Night portrait	60.8	78.4	64.7	51
Starry sky	58.8	84.3	76.5	68.6

Table 3

Comparison of noise reduction methods

Type of photo image	Method	MSE	Time, msec
Night portrait	Original image	55.94	-
	Proposed method	47.64	10213
	Adobe Lightroom Denoiser	46.89	12539
	Median filter	30.65	21
	Bilateral filter	41.76	340
Starry sky	Original image	51.47	-
	Proposed method	48.78	11346
	Adobe Lightroom Denoiser	48.23	15702
	Median filter	32.11	29
	Bilateral filter	40.37	356

Based on the analysis and comparative study, we can conclude that the developed approach to the problem of noise removal on original RAW photo images demonstrates time characteristics comparable to the most productive existing methods presented in off-the-shelf solutions. This result indicates a high degree of optimization of the proposed method taking into account time and computational resources, which makes it practically significant for a wide range of image processing proplems.

Conclusion

In the course of the work the noise reduction problem was formulated, mathematical and neural network approaches to its solution were considered. A neural network approach was chosen, which consists in the combination of elements of the UNet neural network and HQSNet signal preprocessing methods.

An approach to photo image processing was developed and a neural network architecture was designed to solve the noise reduction problem. The training algorithm of the generative-adversarial neural network was also refined to incorporate the used elements of the selected neural networks.

The obtained results confirm the effectiveness of the proposed method, demonstrating its ability to provide high quality noise suppression while optimizing the time and computational cost. Thus, the developed approach is a promising tool for image processing problems, combining high performance and quality characteristics, which makes it relevant for further applications and research in this area.

The resulting images obtained using the developed approach are characterized by an increased dynamic range compared to traditional image formats such as JPG. This improvement provides additional opportunities for post-processing, including more detailed light and color correction at the level of the original RAW files, which is especially important for professional applications.

Further improvements in the performance of the noise reduction algorithm are possible by optimizing and refining the proposed architectural approach, adding the ability to analyze the input image in more detail and perform more detailed processing of individual frame sections, and passing more additional information to the network training.

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ШУМОПОДАВЛЕНИЕ В ЦИФРОВЫХ ИЗОБРАЖЕНИЯХ НА ОСНОВЕ ИСХОДНЫХ RAW КАДРОВ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННЫХ СЕТЕЙ

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В статье представлен метод шумоподавления для RAW фотоизображений, ориентированный на сохранение исходной информации и улучшение качества обработки. Цифровая обработка изображений важна для систем наблюдения и технического зрения, где качество и детализация играют ключевую роль. Предложенный метод основан на сочетании нейронных сетей UNet и HQSNet. HQSNet выполняет полуквадратичное разделение входных данных, выделяя ключевые области и снижая размерность менее значимых. UNet, в свою очередь, эффективно обрабатывает подготовленные данные, сохраняя высокую детализацию и тоновые переходы. Метод тестировался на реальных изображениях, включая сложные сцены с ночным портретом и звездным небом, демонстрируя высокие результаты по метрике MSE и экспертным оценкам. Сравнение с традиционными методами, такими как медианный и Bilateral фильтры, показало превосходство нового подхода как по качеству удаления шума, так и по сохранению деталей изображения. Преимущества метода включают сохранение динамического диапазона и возможность глубокой постобработки. Полученные результаты подтверждают его эффективность в задачах цифровой обработки, что делает разработку перспективной для применения в системах автоматического анализа и улучшения изображений.

Ключевые слова: шумоподавление; нейронные сети; UNet; HQSNet; RAW фотоизображения.

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