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USING A NEURAL NETWORK TO REMOVE NOISE FROM IMAGES

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Annotation: *This article proposes modern approaches to the problem of noise reduction in images using neural networks and also analyses the possibilities of noise reduction using neural networks. The convolutional neural network model and the Mediana, Sobel filter were considered for image denoising. The quality improvement of the trained neural network and the comparison with classical noise reduction methods have been carried out.*
Keywords: *Deep Learning, noise reduction, digital noise, algorithms, digital image, convolutional neural network, ReLU activation function, Fure transform, Sobel filter.*

Annotatsiya: *Ushbu maqola neyron tarmoqlardan foydalangan holda tasvirlardagi shovqinni pasaytirish muammosiga zamonaviy yondashuvlari taklif qilingan bo'lib, neyron tarmoqlar yordamida shovqinni pasaytirish imkoniyatlari tahlil qilingan. Tasvirni shovqinlardan tozalash uchun konvolyusion neyron tarmoq modeli va Mediana, Sobel filtrlari ko'rib chiqilgan. O'qitilgan neyron tarmog'i orqali tasvirning sifatini oshirish jarayoni va shovqinini pasaytirishning klassik usullari bilan taqqoslash amalga oshirilgan.*
Tayanch so'zlar: *Deep Learning, shovqinni pasaytirish, raqamli shovqin, algoritmlar, raqamli tasvir, konvolyusion neyron tarmoq, ReLU faollashtirish funksiyasi, Furye almashtirishi, Sobel filtri.*

Аннотация: *В работе обсуждаются современные подходы к проблеме снижения шума на изображениях с помощью нейронных сетей, а также анализируются возможности снижения шума с помощью нейронных сетей. Для шумоподавления изображения были рассмотрены модель сверточной нейронной сети и фильтр Медианы, Собела. О существлен процесс повышения качества обученной нейронной сети и выполнено сравнение с классическими методами шумоподавления.*
Ключевые слова: *Deep Learning, шумоподавление, цифровой шум, алгоритмы, цифровое изображение, сверточная нейронная сеть, функция активации ReLU, преобразование Фурье, фильтр Собеля***.**

Introduction

Recently, the development of deep learning technologies, in particular convolutional neural networks (CNN), has increased the possibilities for developing various advanced methods of removing noise from images. Neural networks, unlike previous technologies, have a positive effect on the quality of the obtained images, including the fact that these methods reduce the "dimness" of the image. Convolutional neural networks are well suited for image processing tasks, including removing noise from images, due to their ability to manually incorporate spatial hierarchies and local representations.

A powerful approach to image denoising, often referred to as Fourier field filtering, is the use of the Fourier transform and related techniques. This method separates and manipulates the different frequency components of the image using the properties of the Fourier transform.

Fourier transforms the image into its sinusoidal components, transforming it from spatial to frequency domain. Each point in the frequency domain represents a specific frequency in the spatial domain image, and the amplitude indicates the intensity of that frequency [1,3].

Setting the issue

This work considers image noise reduction, two-dimensional Fourier transform without image quality degradation, and neural network trained image noise feature detection.

Research Methods and the Received Results

Neural networks for solving various tasks such as image generation, text writing, and even programming are widely available today. Among them, modern algorithms deserve special attention. These algorithms improve the quality of images.

The steps involved in the construction of a neural network architecture are as follows:

1. Instead of building a network that removes noise from images, it is necessary to build a network whose output is equal to the noise removed from the image.

2. The input of the neural network is located in a block of the size 64x64 (a part of the image, a patch).

3. The first layer contains 64 filters creating 64 character maps. Each filter has a size of 3 x 3 x 3 (a separate 3 x 3 subpixel filter is created for each color channel).

4. The ReLU Activating Function is applied to functions obtained by filtering.

5. The internal layers are similar to the first layer, with the exception that the packet normalization algorithm is applied in addition. Number of layers: 19.

6. The last layer is a Convolution which will output a noisy image.

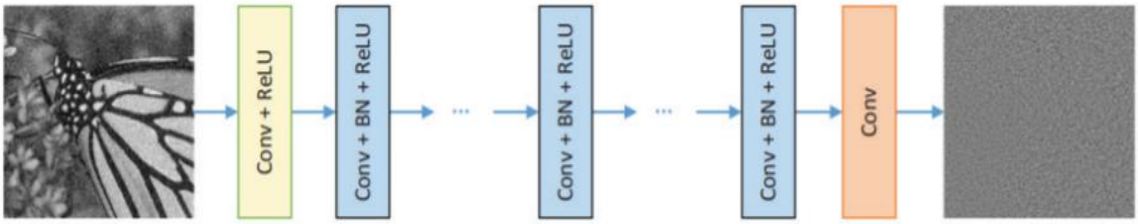


Fig. 1. ***Neural network architecture.***

The problem of reducing noise in images has existed for a long time, and algorithms for reducing noise can be divided into two groups. The first group consists of algorithms that provide the best results in reducing noise and require manual setting for each image. The second group consists of algorithms which provide low quality denoising but are easy to implement (Fig. 1).

The purpose of this work is to make a hybrid of the positive qualities of the two groups of algorithms. This includes the testing of new approaches to image noise reduction. In order to perform this task, it is proposed to use a convolutional neural network model and the MATLAB software.

The quality of algorithms can be a measure of the quality of algorithms and can be a measure of the quality of algorithms. These are, first of all, the evaluation of the quality of noise reduction, the time required to execute these algorithms, as well as the hardware resources on which the image processing is performed. In general, two types of evaluation can be used for quality assessment: expert and mathematical. When assessing the image quality, such indicators allow to evaluate the result both from the point of view of the adequacy of the image for human perception and from the point of view of the maximum accuracy of the algorithms.

Algorithm quality evaluation in expert metrics is based on the personal opinion of a group of experts who review the results of the algorithm on the same data.

A mathematical metric evaluates the quality of an algorithm as a function of the difference between the reconstructed image and the original image. In particular, such a metric can be the mean square deviation from the reference image.

Hardware metrics and time-cost indicators allow you to estimate the resources used by various hardware devices, as well as the time required to perform operations. This group of algorithms is based on the idea that most of the useful information in the image is low or mid-frequency, and the high-frequency component of the image is dominated by noise.

There are many ways to implement this group of algorithms, one of which is to convert the image to amplitude-frequency, remove the high frequency components, and use the fast Fourier transform to perform the inverse Fourier transform. [4, 5].

However, there are some disadvantages of FFT series, in particular, all calculations must be performed with complex numbers, the series converges very slowly, and some information may be lost when processing contrast images [6].

The quality of noise reduction is evaluated using two criteria. The first criterion is the mean squared deviation of the brightness of the color channels of the image, calculated per pixel. The second criterion is the variance of this value. To calculate the criteria, error vectors are constructed for each evaluated algorithm. In addition, it is necessary to ensure that the received image is adequate. Table 1 shows a mathematical comparison of all the methods considered in the research. In cases where one sequence is much longer than another, the long sequence is divided into shorter parts. Then, short convolutions are calculated and the final result is generated from them. This situation occurs in digital filtering, after the filtered sequences, a noise-free image is created. Deep neural networks, especially convolutional neural networks (CNNs), show high performance in denoising images using neural networks. They preserve many details of the images and clearly separate the noise.

In the learning process of the model, a large number of noisy and noise-free images are required as training data. The method of filling the data with artificial noise is used.

Table 1

Mathematical comparison of methods

The method used	Mean squared error	Mean squared deviation	Hypothesis about the normality of the error distribution	Null mathematical expectation hypothesis of error (confidence interval)
Convolutional neural network	0,3525	10,2918	Confirmation for all 3 color channels	Exclusion (0,57; 0,61)
Median of the filter	8,2212	17,0247	Confirmed	Exclusion (-2,90; -2,82)
Sobel filter to minimize noise	0,6999	19,0536	Confirmation for all 3 color channels	Exclusion (-0,87; -0,79)
Photoshop default noise reduction settings	1,7418	20,6765	Confirmation for all 3 color channels	Exclusion (-1,36; -1,27)

Analyzing the results shown in Table 1, it can be seen that the mean squared error and variance values are much lower than other methods. This shows that the denoising efficiency can be further improved by using a convolutional neural network-based algorithm.

In general, any system containing the required number of orthogonal functions can be used to solve spectral analysis problems. The choice of a system of functions is determined by all the requirements for ease of computation and the complexity of the algorithms for implementing the necessary transformations. A methodical understanding of the possibility of using alternative systems of basic functions and solving their tasks is also required [7-14].

The Fourier series is used in many fields and directions, and is a very effective tool for solving various problems related to partial differential equations. A Fourier series allows you to model any periodic signal using a combination of sines and cosines (1).

Fourier transforms are a mathematical operation in which a signal is transformed from the time domain to the frequency domain, which has the form:

$$f_{xt} = \sum_{i=0}^{N-1} \sum_{k=0}^{N-1} s_{ik} exp\left\{-\frac{2\pi j}{N}(xi + tk)\right\} \quad (1)$$

where $j = \sqrt{-1}$; f_{xt}– spectral conversion coefficients $x, t = 0,1, \dots, N-1$

A two-dimensional discrete inverse Fourier transform looks like this:

$$s_{ik} = \frac{1}{N^2} \sum_{i=0}^{N-1} \sum_{k=0}^{N-1} f_{xt} exp\left\{\frac{2\pi j}{N}(xi + tk)\right\} \quad (2)$$

The Fourier spectrum, phase and energy spectrum are defined as in the one-dimensional case

$$|f_{xt}| = \left[R_{xt}^2 + I_{xt}^2\right]^{1/2}, \varphi_{xt} = arctg\left[\frac{I_{xt}}{R_{xt}}\right], P = p_{xt} = |f_{xt}|^2 = R_{xt}^2 + I_{xt}^2,$$

where $R(x,t)$ and $I(x,t)$ are quantities representing the real and unreal parts of f_{xt}, respectively. A two-dimensional transformation can be performed in the form of successive one-dimensional transformations along the rows and columns of the image matrix. It is known that basic transformation functions are indicators with complex indicators, which can be divided into parts.

Sine and cosine components based on Euler's formula:

$$exp\left\{-\frac{2\pi j}{N}(xi+tk)\right\} = cos\left\{\frac{2\pi}{N}(xi+tk)\right\} - j \cdot sin\left\{\frac{2\pi}{N}(xi+tk)\right\};$$

$$exp\left\{\frac{2\pi j}{N}(xi+tk)\right\} = cos\left\{\frac{2\pi}{N}(xi+tk)\right\} + j \cdot sin\left\{\frac{2\pi}{N}(xi+tk)\right\}.$$

The image spectrum has a number of structural properties. For example, the spectral component (constant component) at the origin of the frequency plane is equal to the average value of the image brightness raised N times (from the original plane)

$$f_{00} = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{k=0}^{N-1} s_{ik} \qquad (3)$$

The simplest example of image filtering is the input of the mean value in the image is zero. It is known that the average value is given by the value f_{00} (3). If we set this term to zero in the frequency domain and perform the inverse transformation, the average value of the resulting image will be zero. Substituting $x = x + mN$ directly into the Fourier transform equation and $t = t + nN$, where m and n are constants, we have

$$f_{x+mN,\ t+nN} = \frac{1}{N}\sum_{i=0}^{N-1}\sum_{k=0}^{N-1} s_{ik} exp\left\{-\frac{2\pi j}{N}(xi+tk)\right\} exp\{-2\pi j(mi+nk)\} \qquad (4)$$

For any integer values, the second exponential factor of the equation becomes one. Thus, $m, n = 0, \pm 1, \pm 2, \ldots$:

$$f_{x+mN,\ t+nN} = f_{x,t},$$

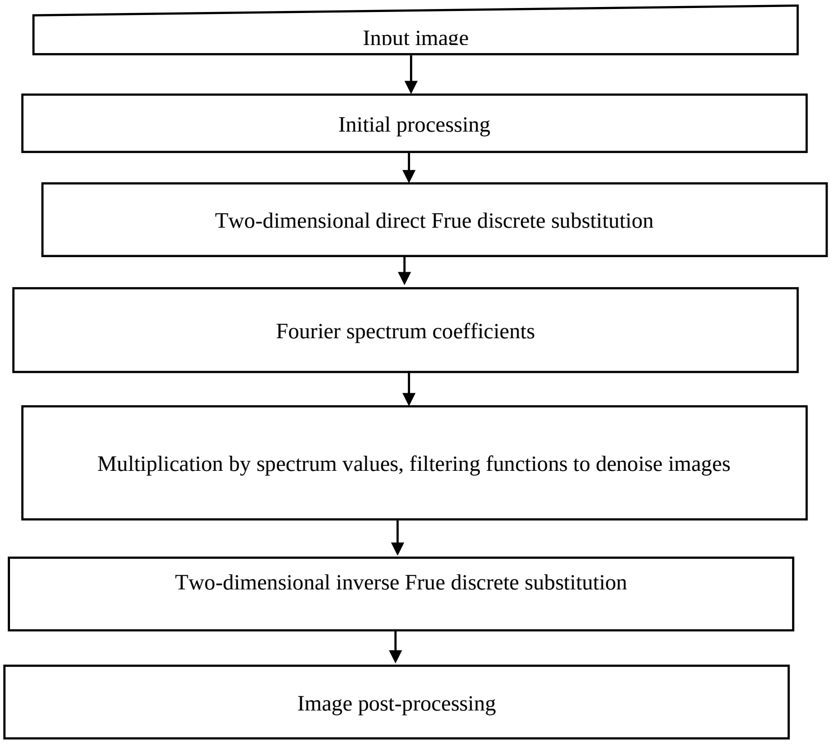
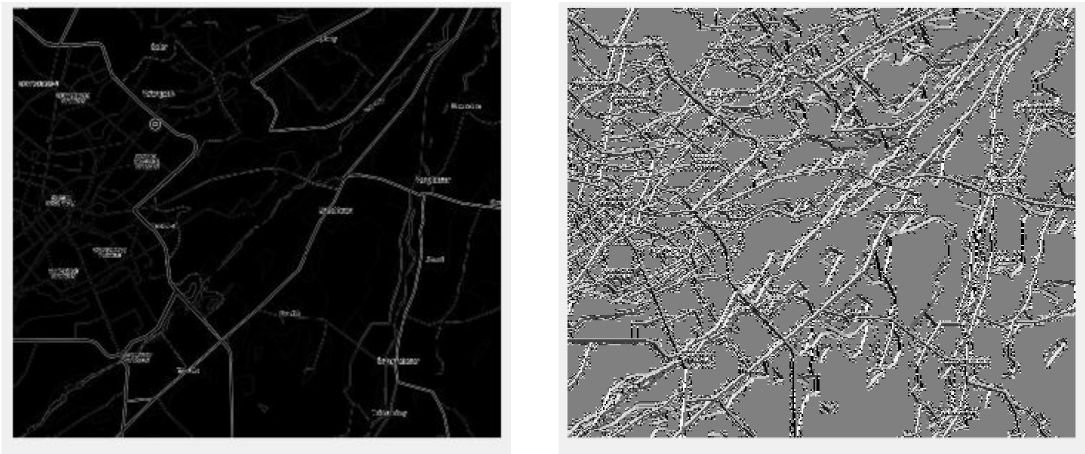


Fig. 2. ***Basic steps of image filtering in the frequency domain.***

This shows the periodicity of the frequency plane [1]. The two-dimensional Fourier transforms spectrum of an image is essentially a representation of the Fourier transforms of a two-dimensional field (Figure 2). In the mathematical analysis of image signals, the origin of the frequency plane is usually placed at its geometric center. A computer-generated two-dimensional discrete Fourier spectrum can be modified by simply changing the coefficients so that the origin of the coordinates is also at the center of the field. The same result can be obtained in another way, if the image samples are first multiplied by coefficients of the form $(-1)^{i} + k$. Then the quadrants of the spectrum calculated directly by the Fourier transform formula are automatically replaced during the calculation[1,2].

As a denoising function, MSE (Mean Squared Error) is effective in reconstructing noise-free images. For testing and evaluation, metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are useful in assessing the effectiveness of noise reduction.



a *b*

Fig. 3. ***a) Median filter results, b) Sobel filter results.***

The input data table for image denoising using neural network is given in Table 2.

Table 2

An image that has not been denoised

Image ID	Noisy image PSNR	Clean up the noise in the image PSNR	Noisy image SSIM	Image noise removal SSIM
1.	20.5	30.2	0.75	0.92
2.	18.9	28.6	0.72	0.90
3.	22.1	32.8	0.79	0.94
...	...	...	...	...

Based on this table, the result table obtained using the convolutional neural network method will look like this:

Table 3

Denoised image

Image ID	Noisy image PSNR	Image noise loss PSNR	Noisy image SSIM	Image noise reduction SSIM	Noisy image PSNR	Image noise removal SSIM
1.	20.5	30.2	0.75	0.92	28.3	0.88
2.	18.9	28.6	0.72	0.90	27.1	0.86
3.	22.1	32.8	0.79	0.94	29.6	0.91
...	...	...	...	...	...	...

Visually inspecting images is important because mathematical metrics may fail to capture all the nuances of image quality.

Conclusion

In this paper, the neural network architecture of the image noise reduction algorithm based on convolutional neural networks has been reviewed, and a new approach to dataset generation has been proposed. In the mathematical analysis of continuous signals, the origin of the frequency plane is usually placed at the geometric center. A computer-generated two-dimensional discrete Fourier spectrum can be modified by simply changing the coefficients so that the origin of the coordinates is also at the center of the array. Image Denoising Neural network architectures such as U-net and Resnet are widely used in image denoising and provide high quality results.

The network built on the basis of this approach does not reduce the clarity of the image and does not blur it, including effective noise removal. However, to further improve the effectiveness of the proposed approach, this approach needs to be improved.

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