КОМП'ЮТЕРНІ НАУКИ ТА ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ

COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

UDC 004.05
DOI https://doi.org/10.32782/tnv-tech.2024.6.1

ASPECTS OF USING NEURAL NETWORKS TO IMPROVE THE QUALITY OF IMAGES

***Antonenko A. V.** – PhD in Technical Sciences, Associate Professor,*
Associate Professor at the Department of Standardization and Certification of Agricultural Products of the National University of Life and Environmental Sciences of Ukraine
ORCID ID: 0000-0001-9397-1209

***Solobaiev S. H.** – Postgraduate Student at the Department of Computer Engineering of the State University of Information and Communication Technologies*
ORCID ID: 0009-0008-6298-4777

***Vostrikov S. O.** – Postgraduate Student at the Department of Computer Engineering of the State University of Information and Communication Technologies*
ORCID ID: 0009-0008-8425-8872

***Balvak A. A.** – Postgraduate Student at the Department of Computer Engineering of the State University of Information and Communication Technologies*
ORCID ID: 0000-0002-6441-8225

***Mishkur Yu. V.** – Postgraduate Student at the Department of Computer Engineering of the State University of Information and Communication Technologies*
ORCID ID: 00009-0004-6807-6914

***Prykhodko A. P.** – Master of the Interregional Academy of Personnel Management*
ORCID ID: 0009-0001-2365-9903

The article presents an overview of image enhancement and noise reduction methods based on convolutional and recurrent neural networks with the addition of non-local operations blocks. These methods are widely used in various industries. In medicine, they help improve *the quality of MRI images, which, in turn, contributes to the accuracy of doctors' diagnoses. In the field of security, these technologies enable image enhancement and detail enhancement. The article covers the main available approaches to image enhancement. The article analyzes the main characteristics of the considered neural networks, as well as the scenarios in which they demonstrate the greatest effectiveness. A table with the performance of different image enhancement methods is also presented, to which the investigated method is added to evaluate its effectiveness in image enhancement. The paper emphasizes the advantages of each of these approaches and their effectiveness in different conditions. Considering the specific features of the denoising task, such as the type of noise, image type, and processing constraints, will help select the most appropriate architecture to achieve the desired result. The article also discusses the use of the non-local operations block to improve image quality. This block serves to identify global interrelationships between pixels, which contributes to better modeling of relationships between different parts of the image. Thanks to the non-local operations block, it is possible to efficiently detect long-term dependencies and contextual information, which in turn leads to improved noise disaggregation and image restoration. The article offers a comprehensive overview of image enhancement and denoising methods that use convolutional and recurrent neural networks with the addition of a non-local operations block, and also provides information on existing approaches. The information and guidelines provided in this article can be helpful in choosing appropriate methods for solving image processing tasks. The article is useful for image processing and machine learning researchers who want to understand the main differences between convolutional neural networks (CNNs) and recurrent neural networks (RNN), as well as with already known approaches to improving and reducing noise in images.*

Key words: *image quality, convolutional neural networks, recurrent neural networks, Non-local operations, image denoising.*

Антоненко А. В., Солобаєв С. Г., Востріков С. О., Балвак А. А., Мішкур Ю. В., Приходько А. П. Аспекти використання нейронних мереж для покращення якості зображень

У статті представлений огляд методів покращення та зменшення шуму в зображеннях, які ґрунтуються на згорткових і рекурентних нейронних мережах із додаванням блоків non-local operations. Ці методи знаходять широке застосування в різних галузях. У медицині вони допомагають поліпшити якість МРТ-знімків, що, в свою чергу, сприяє точності діагнозу лікарів. У сфері безпеки ці технології дозволяють покращувати зображення та підкреслювати деталі. Стаття охоплює основні наявні підходи до поліпшення зображень. У статті проведено аналіз основних характеристик нейронних мереж, що розглядаються, а також сценаріїв, у яких вони демонструють найбільшу ефективність. Також представлено таблицю з результатами роботи різних методів покращення зображень, до якої додано досліджуваний метод для оцінки його ефективності у покращенні зображень. У роботі підкреслено переваги кожного з цих підходів і їхню результативність у різних умовах. Врахування специфічних особливостей завдання знешумлення, таких як тип шуму, вид зображень та обмеження обробки, допоможе вибрати найбільш відповідну архітектуру для досягнення бажаного результату. У статті також обговорюється застосування блоку non-local operations для підвищення якості зображень. Цей блок служить для виявлення глобальних взаємозв'язків між пікселями, що сприяє кращому моделюванню відносин між різними частинами зображення. Завдяки блоку non-local operations можна ефективно виявляти довготривалі залежності та контекстну інформацію, що, в свою чергу, призводить до покращення дезагрегування шуму та відновлення зображень. Стаття пропонує всебічний огляд методів покращення та знешумлення зображень, які використовують згорткові і рекурентні нейронні мережі з додаванням блоку non-local operations, а також надає інформацію про наявні підходи. Інформація та рекомендації, наведенні в цій статті, можуть бути корисними для вибору відповідних методів для розв'язання завдань обробки зображень. Стаття є корисною для дослідників у галузі обробки зображень та машинного навчання, які хочуть ознайомитися з основними відмінностями між згортковими нейронними мережами (CNN) та рекурентними нейронними мережами (RNN), а також з уже відомими підходами до покращення і зменшення шуму в зображеннях.

Ключові слова: *якість зображень, згорткові нейронні мережі, рекурентні нейронні мережі, Non-local operations, знешумлення зображень.*

Introduction. Existing approaches to improve image quality. Image enhancement is the process of improving image quality [1] by removing noise, restoring detail, increasing resolution, and improving the visual experience. The main methods of improving the image:

1. Image filtering: Application of filters to improve image quality. For example, a Gaussian filter or a median filter is good for reducing image noise.
2. Image restoration: Using algorithms to restore details and remove defects in the image. It can be recovery using a deconvolution algorithm, morphological recovery algorithms
3. Resolution enhancement: Methods that aim to improve the resolution of images. For example, interpolation, super-resolution and the use of algorithms based on artificial neural networks.
4. Deep learning: Using neural networks for image enhancement. Deep neural networks can be trained to analyze images and perform tasks such as noise reduction, detail recovery, blur removal, and more.

Formulation of the problem. The relevance of research on image restoration, denoising and quality improvement will always be high, because the field of use is very broad and often very important for human health. In many scientific disciplines, including medical imaging, astronomy, geology and biology, high-quality images are a key element for analysis, research and obtaining results. They provide valuable information and help uncover new knowledge in their respective fields. MRI images are used in medicine for diagnosis and treatment, camera images for facial recognition, video surveillance for object detection, photography and graphic design for visual enhancement, and many other fields. In case of quality deterioration due to external factors, it would be good to have a quality improvement tool. In this work, a comparative analysis of approaches to image enhancement using convolutional networks (CNN) and recurrent networks (RNN) is carried out. Both approaches show adequate results and have potential for improvement.

The aim of the study. The purpose of this work is a comparative analysis of two image enhancement methods based on the use of convolutional and recurrent neural networks.

The work examines practical and theoretical aspects. In accordance with the goal, the following tasks were formed: to analyze the architectural features of the investigated networks; to compare the results of the research method based on RNN with existing methods; determine the future direction of research.

Analysis of recent research and publications. Convolutional Neural Networks (CNNs) are widely used in image restoration and are the most popular neural network for image enhancement. The vast majority of researchers [2] take it as a basis. The first CNNs were used to remove noise in images. A significant role in this multilayer perceptron (MLP) to eliminate noise. The MLP was trained to directly correlate noisy areas of an image with clean areas using a large dataset.

The next step was to apply CNN to enhance the resolution of low-resolution images. SRCNN (convolutional neural network with high resolution) presented in [3] was a breakthrough work. The key idea behind SRCNN is to train the network using a large dataset of low– and high-resolution image pairs. During the training process, the network learns to optimize its parameters to minimize the difference between the generated high-resolution image and the corresponding input image.

Using the power of deep convolutional neural networks, SRCNN achieves impressive results. Another area of use for CNN is image denoising, turning blurry images into more. Several CNN-based methods have been proposed to handle different types of blur. One well-known approach is DeblurNet. The principle of this approach is to process input frames that are located next to each other through several convolutional layers until a blurred central frame is output.

DnCNN-SR [4] became a logical development in the direction of image improvement. The author combined approaches to reduce noise and increase image resolution. This combined approach improved the quality of reconstruction by simultaneously reducing noise and increasing image resolution. Overall, CNNs have played a crucial role in improving image restoration techniques. They have demonstrated exceptional capabilities in denoising, ultra-high resolution, deblurring and other restoration tasks.

Presentation of the main research material. An interesting approach is the use of recurrent neural [5] networks in the field of image processing. The author of this article used a recurrent neural network and added a non-local operation module to improve the performance of the neural network. Recurrent Neural Network (RNN) is a powerful tool for image processing with several advantages, and in combination with Non-Local Operation, the result of work improves many times [6].

The combination of recurrent neural network (RNM) with non-local operation opens up new possibilities for image processing. Here are some of them:

1. Taking into account long-term dependencies: RNM allows the model to collect and use long-term dependencies in images, taking into account context and relationships between objects. Adding a non-local operation allows you to collect information from all positions of the image, not limited to only the local area. This helps the model better understand the relationships between different parts of the image and provides better processing quality.

2. Ability to work with variable length input images: RNM can adapt to images of different sizes, which allows processing large or small images without loss of quality. The combination with non-local operation allows the model to collect information from all parts of the image, regardless of their size. This is especially useful when we are dealing with large images or when the sizes of the objects in the image are different.

3. Overall better quality of processing: The combination of recurrent neural networks with non-local operation can lead to an improvement of the overall quality of image processing. This is explained by the fact that non-local operation allows the model to take into account the wider context and dependencies in the image, while the RNM ensures the preservation and use of this information at each processing step.

The idea of combining neural networks with additional modules is not new. The mechanisms [7, 8] for improving images considered in this work are based on the use of neural networks to which it is advisable to add a Non-Local Operation module to solve these problems.

Non-Local Operation is an element for detecting dependence in neural networks [9]. Intuitively, the non-local operation calculates the value at a point as a weighted sum of the characteristics at all positions in the input data. Based on this, you can submit images and videos to the input.

The general formula looks like [9]:

$$\gamma i = \frac{1}{C_{(x)}} E_{\forall j} f\left(x_j, x_j\right) g\left(x_j\right) \tag{1}$$

Here, *i* is the index of the initial position (in space, time), the value of which needs to be calculated, and j is the index that lists all possible positions. x is the input signal (image, sequence, video) and y is the output signal of the same size as x. The pairwise function f computes a scalar (representing a relationship, such as relatedness) between i and all j. The unary function g computes the representation of the input signal at position j. The response is normalized by the coefficient C(x).

Non-local operation is a flexible building block and can easily be used together with convolutional/recursive layers. It can be added to the initial part of deep neural networks, unlike the fully connected layers that are often used at the end. Such flexibility allows building a more diverse hierarchy that combines both non-local and local information.

Based on this approach, [8] proposed the use of the Euclidean distance with a linearly embedded Gaussian kernel as a distance metric. Thus, the proposed non-local operation can be written as:

$$Z_i = \frac{1}{\delta_i(\mathrm{X})} \Sigma_{j \in S_i} exp\{X_i W_\theta W_\psi^T X_j^T\} X_i W_{g,} \forall i \qquad (2)$$

The proposed non-local operation can be implemented by ordinary differential operations, and thus can be trained by adding to the neural network.

Let's consider the methods of improving images based on neural networks for improving images based on the articles under study:

1. Removal of color image noise using convolutional neural networks based on Non-Local Operation

The basis is the objective function [7]:

$$E_{(x)} = D(x, y) + \lambda J(X) \qquad (3)$$

Based on the use of a neural network, the selection of parameters based on the training dataset of images is implemented.

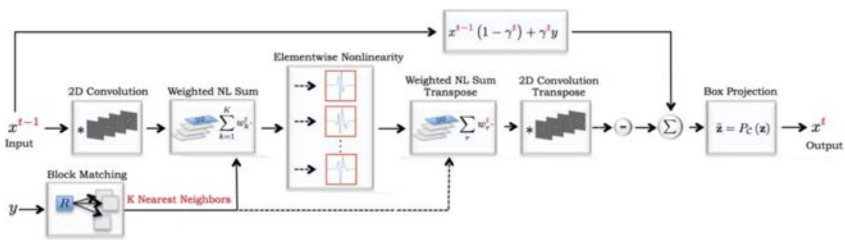

Fig. 1. Architecture of a separate stage of the proposed non-local convolutional network [7]

In [8], the block matching approach [10] using the Euclidean distance with a linearly embedded Gaussian kernel is used.

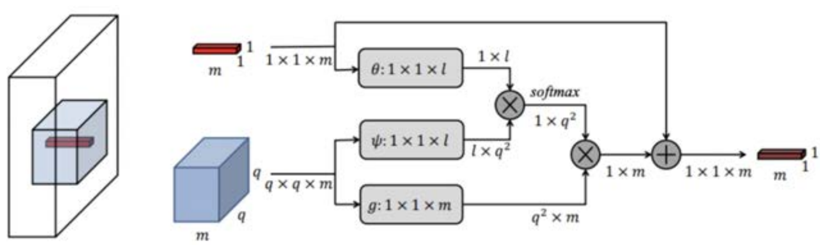

Fig. 2. Illustration of the non-local module [6]

Table 1 shows the comparative characteristics of recurrent, convolutional neural networks and multilayer perceptron according to the most important characteristics for the study.

Based on Table 2, it can be seen that convolutional and recurrent neural networks are able to cope well with the task of improving image quality. The advantage of recurrent

Table 1

Comparative table of neural networks

	Recurrent neural chain	**Convolutional neural network**	**Multilayer perceptron**
Memory	Memory usage for sequential data processing	There is no explicit memory of past inputs	There is no memory, each input is processed independently
Sharing settings	Joint weighting coefficients by time steps	Common weighting factors in spatial dimensions	There is no weight distribution, each neuron has its own set of weights
Contextual information	Captures long-term dependencies and context	Limited field of perception and local context	Lack of explicit modeling of context or dependencies
Effectiveness of noise elimination	Captures global dependencies, processes complex noise patterns	Effectively reduces noise in local areas	Limited ability to process complex noise patterns

Table 2

Performance of different image enhancement methods based on the BSD68 image dataset, with different noise levels (15, 25 and 50)

Метод	**15**	**25**	**50**
BM3D	31.07	28.57	25.62
WNNM	31.37	28.83	25.87
EPLL	31.21	28.68	25.67
MLP	-	28.96	26.03
CSF	31.24	28.74	-
TNRD	31.24	28.92	25.97
ECNDNet	31.71	29.22	26.23
RED	-	-	26.35
DnCNN	31.72	29.23	26.23
DDRN	31.68	29.18	26.21
PHGMS	31.86	-	26.36
MemNet	-	-	26.35
EEDN	31.58	28.97	26.03
NBCNN	31.57	29.11	26.16
NNC	31.49	28.88	25.25
ELDRN	**32.11**	**29.68**	**26.76**
PSN-K	31.70	29.27	26.32
DWDN	31.78	29.36	-
MWCNN	**31.86**	**29.41**	**26.53**
BM3D-Net	31.42	28.83	25.73
FFDNet	31.62	29.19	26.30
BRDNet	31.79	29.29	26.36
NN3D	-	-	26.42
NLRN	**31.88**	**29.41**	26.47

networks over convolutional networks is the presence of data of previous calculations in memory. Due to this, greater efficiency is achieved in finding long-term dependencies, which greatly increases the quality of improving complex images.

Table 2 shows the results of various image enhancement methods with different levels of noise on one BSD68 dataset [11].

Table 2 highlights three methods with the best results, which include the NLRN approach under study. It demonstrates good performance because the specificity of recurrent neural networks in combination with non-local operations is well suited for image enhancement and has significant potential for improvement.

Conclusions. Thus, both convolutional networks and recurrent networks have their strengths and weaknesses in image processing and noise reduction tasks. Convolutional networks are very effective at detecting local features, which makes them more suitable for denoising small images. On the other hand, the recurrent network has the advantage of finding global dependencies due to its architectural features, which makes it suitable for denoising tasks involving sequential data and complex noise patterns. Further research can be developed in the direction of improving the Non-Local Operation of the block in order to improve the results of image processing.

BIBLIOGRAPHY:

1. Михайлов, В. С., Дослідження та розробка методів покращення зображень. 2019. http://openarchive.nure.ua/handle/document/11968 (дата звернення: 22.08.2024).

2. Зінченко О. В., Звенігородський О. С., Кисіль Т. М., Згорткові нейронні мережі для вирішення задач комп’ютерного зору. 2022. http://tit.dut.edu.ua/index.php/telecommunication/article/view/2417 (дата звернення: 22.08.2024).

3. Chao Dong, Chen Change Loy, Member, IEEE, Kaiming He, Member, IEEE, and Xiaoou Tang, Fellow, IEEE Image Super-Resolution Using Deep Convolutional Networks. 2015. https://arxiv.org/pdf/1501.00092.pdf (дата звернення: 22.08.2024).

4. Kai Zhang, Wangmeng Zuo, Lei Zhang Learning a Single Convolutional Super-Resolution Network for Multiple Degradations. 2018. https://openaccess.thecvf.com/content_cvpr_2018/papers/Zhang_Learning_a_Single_CVPR_2018_paper.pdf (дата звернення: 22.08.2024).

5. Bohdan V. Chapaliuk, Yuriy P. Zaychenko Використання рекурентних нейронних мереж для автоматичної діагностики раку легенів. 2019 http://journal.iasa.kpi.ua/article/view/177906 (дата звернення: 22.08.2024).

6. Anakhov P., Zhebka V., Berkman L., Koretska V. Increasing Functional Stability of Telecommunications Network in the Depressed Zone of HPS Reservoir / Lecture Notes in Electrical Engineering, 2023, 965 LNEE, p. 214–230

7. Stamatios Lefkimmiatis Non-local Color Image Denoising with Convolutional Neural Networks. 2016. https://arxiv.org/pdf/1611.06757.pdf (дата звернення: 22.08.2024).

8. Ding Liu, Bihan Wen, Yuchen Fan, Chen Change Loy, Thomas S. Huang Non-Local Recurrent Network for Image Restoration. 2018. https://proceedings.neurips.cc/paper_files/paper/2018/file/fc49306d97602c8ed1be1dfbf0835ead-Paper.pdf (дата звернення: 22.08.2024).

9. Wang et al Non-Local Operation. 2018. https://paperswithcode.com/method/non-local-operation

10. Xiaolong Wang, Ross Girshick, Abhinav Gupta, Kaiming He Non-local Neural Networks. 2018 https://arxiv.org/pdf/1711.07971.pdf (дата звернення: 22.08.2024).

11. Chunwei Tian, Lunke Fei , Wenxian Zheng , Yong Xu , Wangmeng Zuo, Chia-Wen Lin Deep Learning on Image Denoising: An Overview. 2019. https://arxiv.org/pdf/1912.13171.pdf (дата звернення: 22.08.2024).

REFERENCES:

1. Mykhaylov, V. S., Research and development of image enhancement methods. 2019. http://openarchive.nure.ua/handle/document/11968 (accessed 22.08.2024).

2. Zinchenko O. V., Zvenigorodskyi O. S., Kysil T. M., Convolutional neural networks for solving computer vision problems. 2022. http://tit.dut.edu.ua/index.php/telecommunication/article/view/2417 (date of access: 22.08.2024).

3. Chao Dong, Chen Change Loy, Member, IEEE, Kaiming He, Member, IEEE, and Xiaoou Tang, Fellow, IEEE Image Super-Resolution Using Deep Convolutional Networks. 2015. https://arxiv.org/pdf/1501.00092.pdf (accessed 22.08.2024).

4. Kai Zhang, Wangmeng Zuo, Lei Zhang Learning a Single Convolutional Super-Resolution Network for Multiple Degradations. 2018. https://openaccess.thecvf.com/content_cvpr_2018/papers/Zhang_Learning_a_Single_CVPR_2018_paper.pdf (accessed 22.08.2024).

5. Bohdan V. Chapaliuk, Yuriy P. Zaychenko Using recurrent neural networks for automatic diagnosis of lung cancer. 2019 http://journal.iasa.kpi.ua/article/view/177906 (access date: 22.08.2024).

6. Anakhov P., Zhebka V., Berkman L., Koretska V. Increasing Functional Stability of Telecommunications Network in the Depressed Zone of HPS Reservoir / Lecture Notes in Electrical Engineering, 2023, 965 LNEE, p. 214–23

7. Stamatios Lefkimmiatis Non-local Color Image Denoising with Convolutional Neural Networks. 2016. https://arxiv.org/pdf/1611.06757.pdf (accessed 22.08.2024).

8. Ding Liu, Bihan Wen, Yuchen Fan, Chen Change Loy, Thomas S. Huang Non-Local Recurrent Network for Image Restoration. 2018. https://proceedings.neurips.cc/paper_files/paper/2018/file/fc49306d97602c8ed1be1dfbf0835ead-Paper.pdf (accessed 22.08.2024).

9. Wang et al Non-Local Operation. 2018. https://paperswithcode.com/method/non-local-operation

10. Xiaolong Wang, Ross Girshick, Abhinav Gupta, Kaiming He Non-local Neural Networks. 2018 https://arxiv.org/pdf/1711.07971.pdf (date of access: 22.08.2024).

11. Chunwei Tian, Lunke Fei, Wenxian Zheng, Yong Xu, Wangmeng Zuo, Chia-Wen Lin. Deep Learning on Image Denoising: An Overview. 2019. https://arxiv.org/pdf/1912.13171.pdf (accessed 22.08.2024).