ECONTECHMOD. AN INTERNATIONAL QUARTERLY JOURNAL – 2020, Vol. 09, No. 1, 19 – 24

Denoising and Analysis Methods of Computer Tomography Results of Lung Diagnostics for Use in Neural Network Technology

Oleksandra Slavova, Solomiya Lebid

Department of Electronics and Information Technology, Institute of Telecommunications, Radioelectronics and Electronic Engineering

Lviv Polytechnic National University, 12 Bandera street, Lviv, 79013

oleksandra.slavova.mbi.2020@lpnu.ua, solomiya.y.lebid@lpnu.ua

Received May 26, 2020, accepted June 22, 2020

Abstract. Any type of biomedical screening emerges large amounts of data. As a rule, these data are unprocessed and might cause problems during the analysis and interpretation. It can be explained with inaccuracies and artifacts, which distort all the data. That is why it is crucial to make sure that the biomedical information under analysis was of high quality to omit to receive possibly wrong results or incorrect diagnosis.

Receiving qualitative and trustworthy biomedical data is a necessary condition for high-quality data assessment and diagnostics. Neural networks as a computing system in data analysis provide recognizable and clear datasets. Without such data, it becomes extremely difficult to make a diagnosis, predict the course of the disease, and treatment result. The object of this research was to define, describe, and test a new approach to the analysis and preprocessing of the biomedical images, based on segmentation. Also, it was summarized different metrics for assessing image quality depending on the purpose of research. Based on the collected data, the advantages and disadvantages of each of the methods were identified. The proposed method of analysis and noise reduction was applied to the results of computed tomography lungs screening. Based on the appropriate evaluation metrics, the obtained results were evaluated quantitatively and qualitatively. As a result, the expediency of the proposed algorithm application was proven.

Keywords: computed tomography, CT scans analysis, convolutional neural network, image clustering, image denoising, k-means clustering.

INTRODUCTION

A. Quality of computed tomography images

During computed tomography scanning, high image quality is the result of a high dose of radiation. The lower dose leads to blurred images with a high level of noise. The following features are critical in examining low-contrast soft tissues, such as liver or abdominal tissue.

The relationship between image quality and radiation dose involves a combination of many factors, such as noise, axial and longitudinal resolution, and slice width [1]. Depending on the purpose of the diagnosis, these factors interact to determine the sensitivity of the image (the ability to distinguish low-contrast structures) and the visibility of details.

In the process of diagnostics and image formation, the attenuation coefficients for voxels are measured. Hounsfield units scale (HU) is in the range of values [- 1000; 1000] and shows how much of the generated X-ray is absorbed by body tissues per voxel. The color distribution scale corresponds to tissues with different densities. With help of computed tomography (CT) this scale can be changed to simplify the display and recognition of structures. Two identical data values may differ due to noise, and it is the major problem. As a result, this statistical difference is described as the image noise.

CT-scans are quite noisy by nature. This problem prevents physicians from distinguishing tissues with different densities and analyzing images taken under low-dose radiation. The main contribution to the total amount of noise in the image is quantum noise. This type of noise can be described as a random change in the attenuation coefficients for individual voxels of the tissue. However, noise is a form of image detailing, and the use of small voxel technology or some filters can only increase the visibility of noise. On the other hand, using the large voxels technique will increase blur and reduce the recognition of small details. Therefore, an important task is to provide a balance between detail and low noise [2].

Some methods of image processing can significantly reduce the radiation dose without compromising image quality. Such methods work as filters, reducing the amount of accidental noise and highlighting the structures of tissues and objects. As a result, it is possible to get high-quality images using low radiation dose [3].

B. Convolutional neural networks

Convolutional neural networks are multilayer neural networks. They can get the main features from the input image, such as edges, spots, and other patterns on the primary layer. Then they move to a higher level and discover the object. CNN training is unlike other machine learning algorithms -they are comparing individual parts of the image [4].

Medical image recognition is the process of identifying medically important features in an image, such as tumors, anatomical structures, and cells. Different studies demonstrate the effectiveness of using the DCNN in the study of breast cancer [5] and interstitial lung disease [6].

C. Image segmentation

Image segmentation allows dividing an image into coherent regions. In this way, clustering can be used to extract the global characteristics of the image, based on the task: segmentation of the body into organs or tissues to identify boundaries, detection, and segmentation of tumors and general recognition [7].

In nowadays, there are many types of research in the field of image segmentation using clustering and other methods of segmentation. One of the most popular clustering algorithms is the K-means clustering algorithm.

Studies [8] show that the use of clustering K-means algorithm in the initial stages of MRI image processing reduces the problem of over-segmentation. This allows identifying abnormalities and tumors on the background by common tissue types.

Clustering by the K-means method is simple and has a low computational complexity [8]. The number of clusters centers K equals to the amount of human anatomical area. This amount is usually known. This knowledge allows us to successfully apply this image clustering algorithm for biomedical images.

Therefore, an important task in computer vision technology is to filter out useless information and recognize objects in images. It is only on this condition searching algorithms will not be distracted by uninformative details and give false results. In addition to removing artifacts, it is also important to preserve useful image information.

There are problems with the analysis and interpretation of biomedical data because all the extracted data after any screening consist of millions of measurements. Inaccuracies and artifacts respectively distort each data stream. This problem creates a demand for the development of deep learning convolution neural network technology for the analysis of biomedical data.

The analysis of CT screening using neural networks is based on information about the contrast, size, and shape of individual elements. This knowledge allows you to identify the type of tissue, organ, or tumor in the patient's body. However, the presence of extra information on the scans often prevents a reliable result assessment. Commonly used noise reduction methods usually distort the image and useful information along with noise and artifacts.

I. MATERIALS AND METHODS

In this work, as an ideal (reference) image was used a CT scan of lungs made on a soft tissue window with W: 400 and L: 40. The research was done in open-source cross-platform IDE «Spyder» in the Python language.

The matrix size of the original image is 512 × 512 (Figure 1). The image was obtained during a lung examination on a «TOSHIBA Activion 16» in axial projection and in multiplanar reconstruction with the following parameters:

- Scan mode: spiral.
- Contrast enhancement: no contrast.
- Research area: lungs.
- 120.0 kV, 200.0 mA.
- Effective dose: 4.5 mSv.

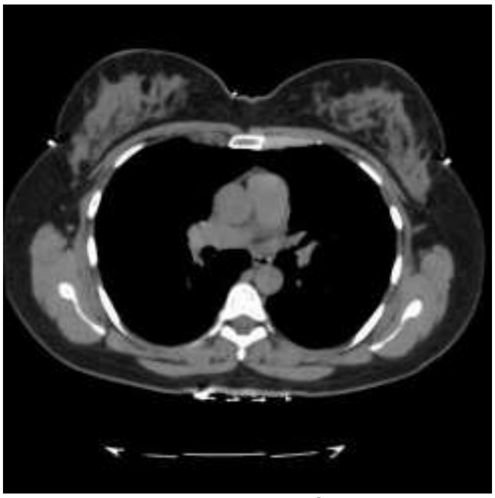

Fig. 1. Original image

A following approach was proposed to implement the processing and analysis algorithm. The reference (ideal) image was segmented using the K-means clustering algorithm and then smoothed using a Gaussian filter. The algorithm automatically recognizes and assigns six clustering centers which are also compared according to the color distribution in grayscale depending on the value of HU. The resulting image was post-processed by convolution with the edge detection filter core.

The algorithm stages are illustrated by the following diagram (Figure 2).

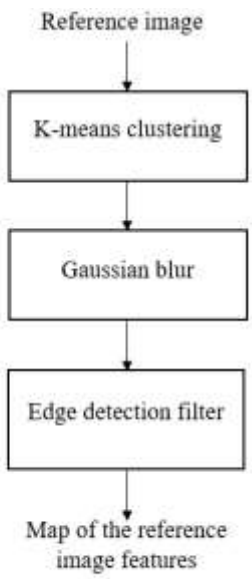

Fig. 2. The convolution algorithm with the edge detection filter core

To manage qualitative assessment of received results was used following metrics: Structure similarity index (or SSIM), Mean squared error (or MSE), Peak signal-to-noise ratio (or PSNR) and Structural dissimilarity index (or DSSIM).

To assess image quality in the Full-Reference approach, the commonly used methods are PSNR and MSE. These indicators are easy in calculation, understandable and are mathematically convenient to implement in the implementation of any optimization. Typically, this approach is suitable for correct and complete assessment of the differences between the reference and noisy images. However, sometimes they do not correspond to the perception of visual quality. The problem is also that PSNR can have different values for two almost indistinguishable images. Similarly, two images with the same PSNR can have the difference in quality. The PSNR and MSE can`t be as informative indicators to predict and assess a visual response to image quality. An important task is to keep the useful information instead of eliminating or distorting it along with the noise component. Therefore, structural changes are also investigated for this task and taken into account.

Because the PSNR and MSE are based an image intense, it is also necessary to evaluate and record the lost structures in the image. For this task is used an IQA metric based on the human visual system - SSIM (or structural similarity index). This metric is a measure of similarity between ideal (reference) image and test image. SSIM evaluates three components: brightness, structure and contrast, which are independent of each other (1). In addition, deterioration of image quality is considered as a change in the perception of structural information. As a result, the SSIM method allows normalizing the average value of structural similarity between two images.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (1)$$

Research results show that based on the human visual system, SSIM is better than MSE and PSNR. This is explained by the fact that SSIM is normalized (takes values from 0 to 1), unlike MSE and PSNR [9]. MSE and PSNR estimate the root mean square difference between the estimated value and the actual value. SSIM shows deviation based on the perception and severity of the error itself. As a result, if the noise level increases, then the quality of reconstruction of the output image decreases.

The results of medical research usually already have noise and artifacts. Accordingly, in this case, the image is assessed without a reference image (No-Reference approach). In different imaging modalities, these artifacts can be different by nature. Therefore, the main task is the development of an algorithm that will work equally effectively regardless of the artifact typology.

II. THE RESULTS OF THE STUDY AND DISCUSSION

After clustering, the SSIM between the original image and the clustered was 0.9216, and MSE was 42.7532. The obtained result indicates about high similarity level between the images and about minimum useful information loss after segmentation.

To achieve the noise reduction goal, it was added three types of noise to a reference image. It was: random Gaussian noise (Figure 3.a), random noise «salt & pepper» (Figure 3.b), and random speckle noise (Figure 3.c). This step also helps to check the effectiveness of clustering method.

As an all three images clustering result, it was found that SSIM for all of them is equal to one, and MSE equals zero. Based on it, it is fair to say all three-segmented images are identical.

The SSIM and MSE between clustered reference image and clustered image with noise are, respectively, 1.0 and 0.0. According to the results, clustered reference image and clustered noisy images are identical. The original image clustering outcome in the comparison with segmented noise images are shown in Figure 4.

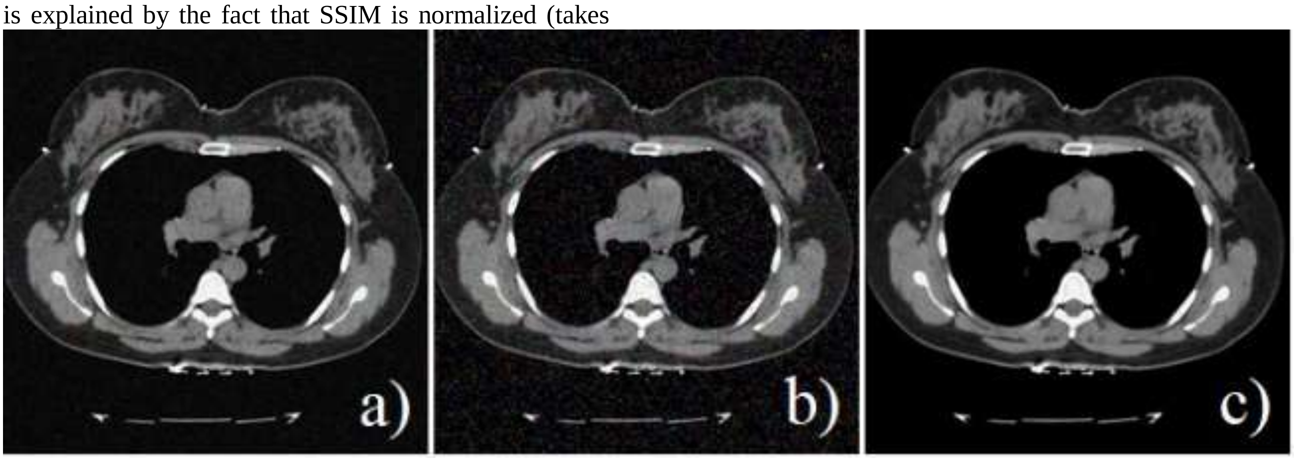

Fig. 3. Original image with a) random Gaussian noise, b) random noise «salt & pepper», c) random speckle noise

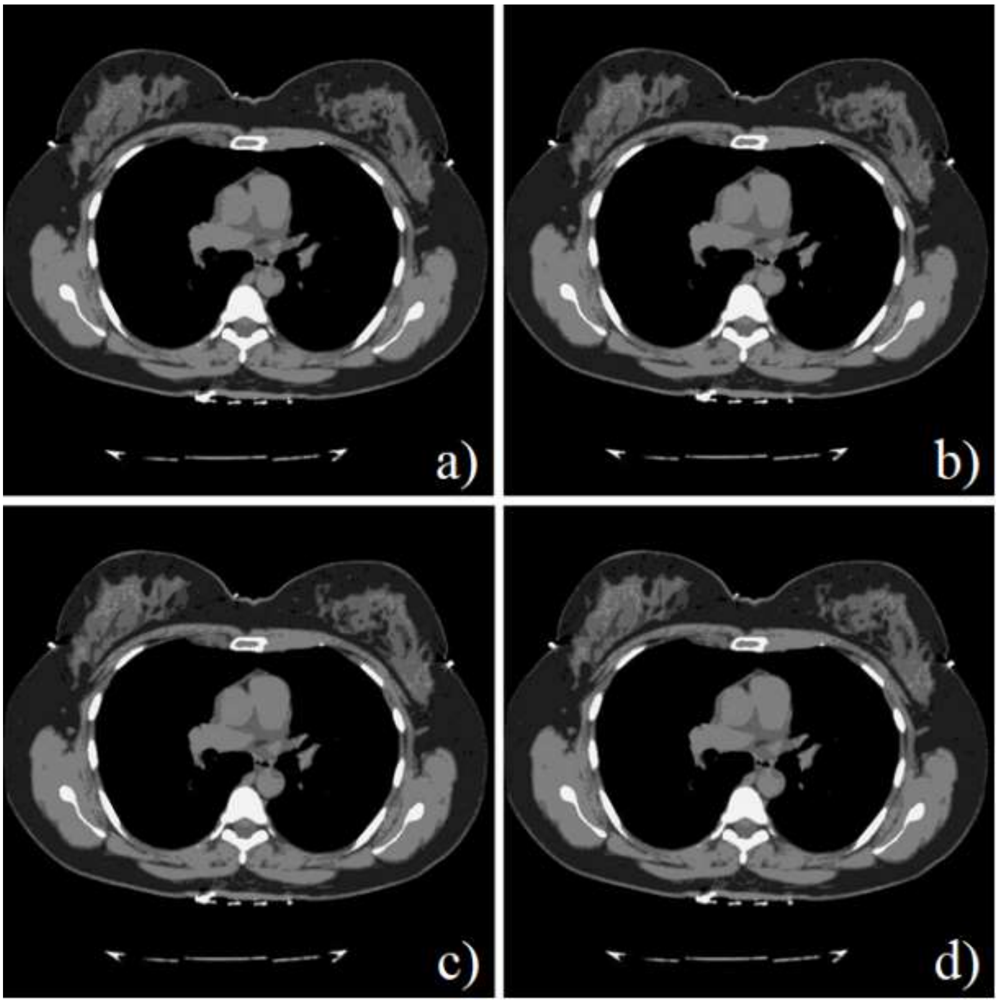

Fig. 4. Clustering results, where a) original image, b) image with Gaussian noise, c) image with noise «salt & pepper», d) image with speckle noise

Here, it is possible to see significant changes in SSIM and MSE between reference and noisy images. Therefore, can be confirmed the effectiveness of the clustering method in the image denoising task. For example, after segmentation, the SSIM of all three images was increased by an average of 1,702 times. Also, accordingly, the MSE rate decreased by an average of 92,341 times.

Moreover, to the above indicators, this work investigated the impact of the proposed approach to the analysis of the efficiency to eliminate the noise component of the image. To do this the PSNR metric was introduced.

It was used RSNR metric in noise eliminate efficiency analysis. As a result, PSNR increased by an average of 2.6183 times after image segmentation.

Here is the first conclusion: image clustering algorithm by the K-means method allows to eliminate the noise effectively. Besides, the proposed approach makes it possible to maintain useful original information available on scans.

After segmentation, the image was post-processed using a convolution with a Gaussian kernel. For this purpose, was used a convolution matrix kernel size 3 × 3 with the $\sigma = 0$. As a result, after all processing steps, the SSIM was increased by 0.412, MSE decreased by 3920.652 and PSNR increased by 19.9389.

In conclusion, quantitative indicators after convolution with the Gaussian kernel show advisability to include this stage into the processing algorithm.

The SSIM and MSE results of all processing stages are presented in Table 1 and Table 2. Table 3 presents the PSNR calculations results to the reference image.

TABLE 1. SSIM METRICS

	Image with noise	Segmented image	Segmented and blurred image
Gaussian noise	0.5415969	0.9216687	0.9428830
Noise «salt & pepper»	0.5414091	0.9216687	0.9428830
Speckle noise	0.5413494	0.9216687	0.9428830

TABLE 2. MSE METRICS

	Image with noise	Segmented image	Segmented and blurred image
Gaussian noise	3960.8201	42.7532	40.1681
Noise «salt & pepper»	3960.4981	42.7532	40.1681
Speckle noise	3960.8773	42.7532	40.1681

TABLE 3. PSNRMETRICS

	Image with noise	Segmented image	Segmented and blurred image
Gaussian noise	12.1529	31.8211	32.0919
Noise «salt & pepper»	12.1533	31.8211	32.0919
Speckle noise	12.1528	31.8211	32.0919

Structural difference (Structural Dissimilarity, or DSSIM), which comes from structural similarity (SSIM) is image similarity assessing metric and expressed as:

$$DSSIM(\mathrm{x}, \mathrm{y}) = \frac{1 - SSIM(\mathrm{x}, \mathrm{y})}{2}$$

The DSSIM results are present in Table 4.

As can be seen from the DSSIM table results and equation, this metric correlates with SSIM. The obtained values also improved after segmentation: the measure was increased by 1.37 times. A convolution with a Gaussian filter improves the similarity degree by 0.0106.

Sobel's algorithm was used to find the image edges. As a result, it was obtained a features edge map for the input image (see Fig. 8). The Sobel operator has an advantage over the others because his convolution kernels are located vertically and horizontally relative to the pixel grid. It allows exploring the edges in two directions at the same time.

Figure 5 prove the multilevel convolutional network algorithm efficiency. After analyzing both image convolution results with a Sobel filter, a second conclusion can be confirmed. The screening results analyzed using “computer vision» technology due to the improved algorithm will not contain uninformative artifacts obtained by finding noise boundaries. Therefore, search algorithms will not be distracted by uninformative details and give false results.

TABLE 4. DSSIM METRICS

	Image with noise	Segmented image	Segmented and blurred image
Gaussian noise	0.729201	0.539165	0.5285584
Noise «salt & pepper»	0.729295	0.539165	0.528558
Speckle noise	0.729325	0.539165	0.528558

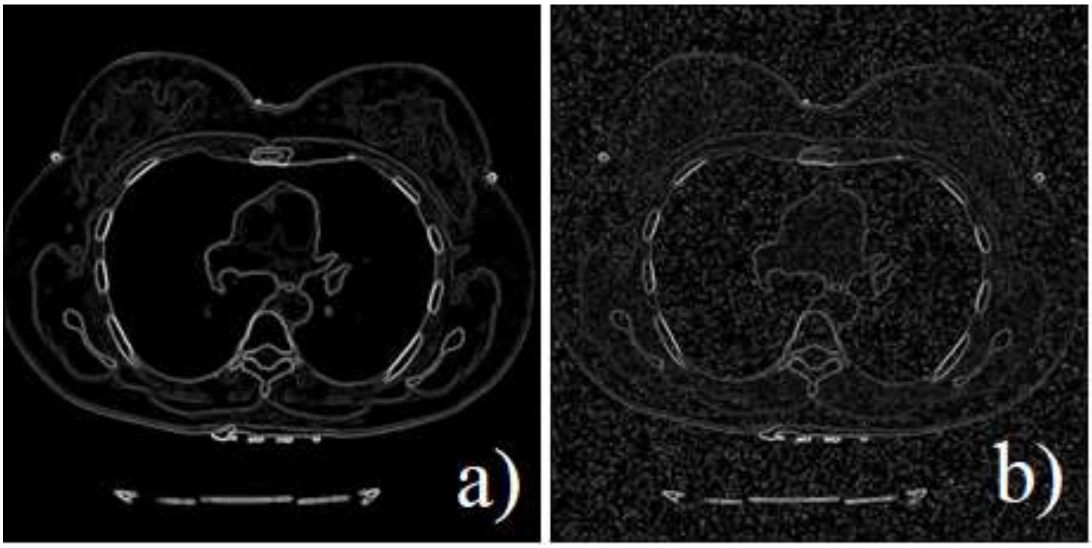

Fig. 5. Results after convolution with Sobel kernel, where a) segmented denoised image, b) image with noise «salt & pepper»

III. CONCLUSIONS

1) Based on CT lungs screening, it was defined, described, and tested a new analysis and preprocessing biomedical images segmentation-based approach.

2) The quantitative indicators results tell about a high noise reduction level together with maximum preservation of scan useful information.

3) Qualitative indicators prove that such an image boundary detecting approach in neural networks will not be distracted by non-informative artifacts and distort the evaluation of tomographic examination results.

4) Proposed algorithm saves a compromise between the high scan quality and maintaining screening results value.

IV. ACKNOWLEDGMENTS

We would like to acknowledge the modern diagnostics center “Inmedico» from Melitopol, Ukraine for providing computed tomography research.

REFERENCES

1. **Kachelrieß, M. Kalender, W. A. 2005**. Presampling, algorithm factors, and noise: Considerations for CT in particular and for medical imaging in general, Medical Physics, 32 (5), pp. 1321–1334.

2. **P. Sprawls. Sep. 1992**. AAPM Tutorial. CT Image detail and noise. Radiographics, Vol.12, no. 5, Pp. 1041-1046.

3. **Attivissimo, F. Cavone, G. Lanzolla, A. M. L. and Spadavecchia, M.. 2010.** A technique to improve the image quality in computer tomography. IEEE Trans. Intrum. Meas., vol. 59, no. 5, pp. 1251-1257.

4. **Chen, Y.C. Hong, D. Wu, C.W. Mupparapu, M. 2019.** The Use of Deep Convolutional Neural Networks in Biomedical Imaging: A Review, pp. 3-10.

5. Bejnordi, E.B., Mullooly, M., Pfeiffer, R.M., Fan, S., **Vacek, P.M., Weaver, D.L. et al. 2018.** Using deep convolutional neural networks to identify and classify tumor-associated stroma in diagnostic breast biopsies. Mod Pathol; 31, pp. 1502-1512.

6. **Gao M, Bagci U, Lu L, Wu A, Buty M, Shin HC et al. 2018.** Holistic classification of CT attenuation patterns for interstitial lung diseases via deep convolutional neural networks. Comput Methods Biomech Biomed Eng Imaging Vis: 6, pp. 1-6.

7. **Guo, Y. Ashour, A. S.. 2019.** Neutrosophic sets in dermoscopic medical image segmentation, pp. 229-243.

8. **Ng, H.P. Ong, S.H. Foong, K.W.C. Goh, P.S. Nowinski, W.L. 2006.** Medical image segmentation using k-means clustering and improved watershed algorithm. Image Analys. And Interpret, IEEE Southwest Sympos, pp. 61-65.

9**. Sara, U., Akter, M. and Uddin, M.S. 2019** “Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study», Journal of Computer and Communications, pp. 8-18.