Hindawi
Journal of Electrical and Computer Engineering
Volume 2024, Article ID 2606485, 9 pages
https://doi.org/10.1155/2024/2606485

Research Article

Denoising Method for MRI Images Using Modified BM3D Filter with Complex Network and Artificial Neural Networks

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Received 24 January 2024; Revised 27 March 2024; Accepted 22 April 2024; Published 6 May 2024

Academic Editor: Shibendu Mahata

Noise is an undesirable and disturbing effect that degrades the quality of an image. The importance of noise reduction in images and its wide-ranging applications are essential. Most popular image noise filters rely on static parameters that are often challenging to fine-tune. Dynamically adapting these static parameters for image noise filters is a critical area of research. In this study, a combination model between the features of complex networks and artificial neural networks is proposed to automatically find the noise reduction parameter of the block-matching and 3D filtering method. Experimental results on the black and white MRI image set have shown that the model correctly predicted the parameters of the BM3D filter and removed the noise in the images of those MRI images. The model gave high denoising results with PSNR of 51.94 and SSIM of 0.998.

1. Introduction

Due to the inherent physical limitations of different recording devices, images tend to have random noise during image acquisition. Noise can be understood as the basic signal distortion that hinders the process of observing images and extracting information. With the dramatic increase of digital image generation often taken in low light conditions, image restoration methods have become indispensable tools in the era of image analysis with computer support. Additionally, noise can manifest in the image for various reasons, including fluctuations in probe sensitivity, alterations in the environment, inherent material properties, quantization errors, etc.

In MRI images [1], noise may come from the movement of the patient during the MRI or from the error of the MRI machine. Noise is a huge challenge in the field of medical imaging research because it reduces important image attributes, making it difficult to diagnose and treat medical examinations.

In the field of machine learning, specifically in the process of classifying MRI images or segmenting MRI images using machine learning algorithms, image noise will distort and reduce the quality of machine learning algorithms. Therefore, noise removal is very important in the image preprocessing step for further works. In recent years, noise filters have been widely used in processing MRI images of the human brain [2]. The BM3D filter [3] is a very good performing image noise filter. One drawback is that the filter needs to consider the input parameter. However, the input parameter is very difficult to adjust. It is usually randomly generated, and it is not known what the best value for the input image is.

Complex network [4] was defined as a network that comprises nodes with intricate properties. In order to form a complex network, a large amount of information is needed to fully describe the topology of all network elements. Therefore, complex networks are expected to have outstanding advantages over conventional networks. In real life, complex networks can be used to describe many different real-world networks such as social networks, networks of neurons in the brain, biological networks, etc.

By far, the BM3D Filter is one of the most powerful traditional filters. Filter inputs are random parameters, which makes it difficult to find input parameters so that the filtered image has the best denoising results. Currently, manually finding these parameters for the filter takes a lot of time and the efficiency is not high. This study focuses on developing a method to automate the process of finding the noise reduction parameter of the BM3D filter [3]. In which, the core of the research is the proposal of a new model which is a combination between the features of complex networks and Artificial Neural Networks (ANN) [5]. The complex network plays the role of extracting features of each brain MRI image. Based on this feature, we can find the input parameter of the BM3D filter for the corresponding brain MRI image, so that the PSNR index between the filtered brain MRI image and the original image has the highest result. To evaluate the effectiveness of the proposed method, the two most important parameters in image noise processing, peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), are used. The experimental results will also be carefully evaluated and compared with the results of previous studies.

For chronological techniques, the study [6] utilized a self-adjusting parameter GANs network to facilitate the process of extracting smooth edges of noisy digital images, thereby enhancing the actual signal in high-frequency components where the main parts of pixels without noise can be considered as noisy pixels. However, the attempt to remove unwanted noise from the tested images may result in excessive smoothing of the obtained images. Additionally, article [7] proposed a method for rapidly and accurately removing mixed noise by combining pulse-coupled neural network (PCNN) and Perona–Malik equation normalization (P-M equation) to eliminate unwanted noise.

The article is organized as follows. Section 2 presents previous work on denoising brain MRI images. An overview of brain MRI images and proposed model are introduced in Section 3. Experiment results are described in Section 4. Conclusion and development direction are in Section 5.

2. Related Work

Some methods of denoising MRI images from 2019 up to now are summarized in Table 1. Image noise filtering technologies today are quite diverse, ranging from the use of basic image noise filters such as bilateral filters, median filters, or the combination of basic noise filters with machine learning algorithms to optimize filter parameters. There is also a novel approach that involves using pure algorithms for noise filtering. The common goal of these algorithms is to eliminate various types of noise such as Gaussian, Rician, Shrinking, Free, etc., from MRI images.

The study of Chang et al. [8] was different from the rest of the studies. This study focused on the problem of finding the best input parameter for bilateral filter with MRI image dataset without random selection of parameters like other traditional filters. Results with Gaussian noise at 1% for the highest PSNR index of 39.29, for the highest SSIM index of 0.983. Although the results were not high, this was a new idea, and the system implementation time has been significantly reduced.

The authors in Tripathi et al. [9] proposed a CNN-DMRI model to be trained on a noisy MRI dataset using an automated method to generate training data pairs. This model used convolutional layers and ReLU activation layers to learn hidden characteristics of MRI images and produced denoised MRI images, resulting in the highest PSNR index of 43.18, the highest SSIM index of 0.987.

Moreno López et al. [10] used the model using Unsupervised Learning to train noisy and noiseless MRI image datasets. Since then, the features of noisy MRI images have been found to eliminate noise. The study obtained the highest PSNR index of 38,015, the highest SSIM index of 0.8977.

The authors in the study by Sreelakshmi et al. [11] proposed a method that combines model of adaptive median filter (ADMF) and convolutional neural networks (CNN) to solve the noise problem in MRI images. This method also uses a machine learning system based on Gradient Boosting Machine Learning (GBML) algorithm to classify and extract features from MRI images, thereby helping to improve the quality of MRI images. The results obtained in that study were very good with the PSNR obtained for Gaussian noise at 50% level was 48.68, with Shrinking noise at 10% was 68.85.

The study by Wang et al. [12] focused on noise processing methods for magnetic resonance imaging (MRI) images based on two main techniques, namely Nonlocal Structural Similarity and Low-Rank Sparse Representation. The image data in this study was obtained from the Brainweb 3D T1-weighted dataset. Rician noise was used in the experiment, with a Rician noise ratio set at 4%. The evaluation results of image quality after noise processing showed a PSNR score of 38.503 and an SSIM of 0.976. The high PSNR score and SSIM close to 1 indicate that the noise processing method has achieved high performance in noise reduction and preservation of essential information in MRI.

The study by Mehta et al. [13] focused on noise processing for MRI images using the U-net architecture and image processing techniques. The image data in this study consists of 253 MRI images. Gaussian noise with a noise level of 25% (Gauss 25%) was used. The Peak Signal-to-Noise Ratio (PSNR) score was used to evaluate the image quality after noise processing, and the result showed a PSNR of 30.96.

The most recent study by Kollem et al. [14] introduced a novel method using the diffusivity function to process noise for medical MRI images. The image data in this study are medical MRI images and are assumed to be originally noise-free images but with added Poisson noise. The evaluation results of image quality after noise processing showed a Peak Signal-to-Noise Ratio (PSNR) score of 42.78 and a Structural Similarity Index (SSIM) of 0.99645. The high PSNR score and SSIM close to 1 indicate that the noise

Table 1: Summary of studies on denoise MRI image.

Author	Denoise method	Noise	Dataset	Metrics highest	
Chang et al. 2019 [8]	Bilateral filter & neural network	Gauss	Local datasets	Gauss 1%	PSNR: 39.29 SSIM: 0.983
Tripathi et al. 2020 [9]	CNN	Rician	Local datasets and brainweb dataset	Rician 1%	PSNR: 43.18 SSIM: 0.987
Moreno López et al. 2021 [10]	Unsupervised learning	Standard deviation of the noise	Local datasets: 1172 MRI images and brainweb dataset	Standard deviation of the noise $\sigma = 50$	PSNR: 38.015 SSIM: 0.8977
Sreelakshmi et al. 2021 [11]	Adaptive median filter and CNN	Gauss, sat and pepper, shrinking	Local datasets	Gauss 10% Gauss 50% Shrinking 10% SSIM: 0.989	PSNR: 55.59 PSNR: 48.68 PSNR: 68.85
Wang et al. 2022 [12]	Nonlocal structural similarity and low-rank sparse representation	Rician	Brainweb 3D T1-weighted	Rician 4%	PSNR: 38.503 SSIM: 0.976
Mehta et al. 2022 [13]	U-NET architecture	Gauss	253 MRI images	Gauss 25%	PSNR: 30.96
Kollem et al. 2023 [14]	Diffusivity function	Noise free image + poisson noise	BraTS2020	PSNR: 42.78 SSIM: 0.99645	

processing method has achieved very high performance in noise reduction and preservation of important information in MRI images.

3. Materials and Methods

3.1. MRI Image. Magnetic Resonance Imaging–MRI is a technique that uses magnetic fields, radio waves, and computer systems to produce images of parenchymal structures that are clearer and more detailed than conventional diagnostic methods. Based on MRI images, doctors can detect abnormalities in the brain parenchyma in general, as well as vascular tumors, arterial occlusions, invasion of the venous sinuses, as well as the relationship between the tumor and the around structures. MRI has two basic pulse sequences, T1 Weight and T2 Weight. As in Figure 1, a T2-weighted image is presented. In addition, there are other pulse sequences such as PD or FLAIR. In general, the efficiency of MRI is very high, especially in diagnosing brain tumors.

3.2. Gauss Noise. There are many sources of noise in an image and these noises come from many different aspects such as image acquisition, transmission and compression. Mathematically, a noisy image $v(x)$ is expressed as the sum of the original, unnoised image, $u(x)$ and the noise function $\eta(x)$, as described by the following formula:

$$v(x) = u(x) + \eta(x). \tag{1}$$

The goal of noise reduction methods is to reduce noise in natural images while minimizing the loss of original features and enhancing the signal-to-noise ratio (SNR).

Gaussian noise [15] is a popular model for approximating noise in many different applications. The probability distribution density of the noise is a Gaussian function, which is characterized by the mean μ and the variance σ^2.

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\mu)^2/2\sigma^2}, \tag{2}$$

where $p(z)$ is the equation for the distribution of Gaussian noise in the MRI image; μ and σ are the mean and standard deviation, respectively.

3.3. Denoise Algorithm–BM3D. Block matching and 3D filtering–BM3D [3], was proposed by K. Dabov, is the most advanced algorithm available for noise reduction. BM3D algorithm uses block-matching technique to detect and search for similar blocks in the image. Then, these blocks are grouped into groups with similar properties, and 3D filtering is applied to reduce noise for each group. 3D filtering technique uses spatial information and frequency information of blocks to effectively reduce noise. This helps the BM3D algorithm to achieve good noise reduction performance and low computational complexity, suitable for processing high noise images. BM3D has been widely used in photo and video processing applications, from image noise reduction to video restoration or image compression. This algorithm has been improved and developed with new versions to improve accuracy and processing speed.

In the most recent study by Mäkinen et al. [16], it has been shown that one of the most important input parameters of the BM3D filter is the power spectral density standard deviation of the image noise which is denoted by σ_{psd}. This parameter σ_{psd} is in the range $[0, 1]$.

3.4. Complex Networks. Complex network has been successfully applied in many fields [17]. There have been many studies successfully using complex networks by building graphs on image processing problems. In previous research by Lima et al. [18] on image processing using complex networks, the study analyzed basic graph features such as Degree, Centrality, Communities. From these basic features of the graph, the author modeled the image again, thereby giving the basic features of the image.

An image can be described and graphed based on color patterns, textures, and image shapes. An undirected graph $G = (V, E)$ consists of V being the set of non-empty vertices, and E being the set of unordered pairs of different elements of V called edges or connections between two pixels i and j. The features of the graph can be mentioned as follows:

(1) Vertex degree: Degree of a given vertex i is the number of vertices connected to it (it's neighboring vertices).

(2) Average degree: The average degree $(\varnothing_\mu)$ is the sum of the number of edges of the graph divided by the number of vertices of the graph.

(3) Average minimum path: The average minimum path is the average of all the minimum paths of the network.

(4) Mean centrality: The central mean is a measurement that represents the mean of the central peaks (the peaks that matter to the minimum paths of the network).

(5) Number of communities: For a graph $G(V, E)$, a community in this graph is a subgraph $G'(V', E')$ in which the vertices are strongly connected. There are many ways to measure a subgraph because there are different definitions of community structure. The most accepted definition is the one that requires all nodes of the community to be interconnected. This leads to the definition of a cluster. A cluster is the densest subgraph between three or more vertices, meaning that each vertex of the graph needs to be connected to another vertex, in such a way that there are no other adjacent vertices between them.

(6) Entropy of subgraphs: Quantify the randomness of the subgraphs G' generated in the graph G.

From the above features of the graph, we obtain the features of the image graph, shown in Table 2.

3.5. ANN. An artificial neural network (ANN) is a type of machine learning model that is inspired by how the human nervous system works. An ANN is a network of nodes (neurons) connected by weights. The nodes represent inputs

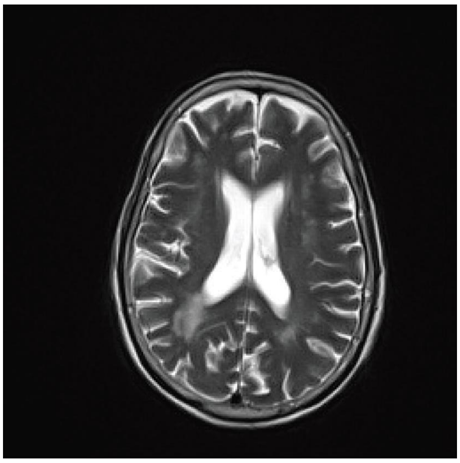


Figure 1: Brain MRI with T2 pulse sequence.

Table 2: Some features of images using complex networks.

Features
Average degree
Mean centrality
Number of communities
Average minimum path
Entropy of subgraphs

and outputs, and the weights represent the importance of each input in computing the output. ANN consists of 3 main components: Input layer, output layer (They only include 1 layer) and hidden layer (this layer can have 1 or more layers depending on the specific problem). ANN works in a way that describes how the nervous system works with its interconnected neurons.

In ANN, except for the input layer, all the nodes of the other layers are fully connected to the nodes of the previous layer. Each node of the hidden layer receives the input matrix from the previous layer and combines it with the weights to get the result. The purpose of ANN is to learn and automatically find complex relationships in the input data by adjusting the weights. ANN networks are capable of learning and self–adjusting weights based on known input–output data pairs, through training. After being trained, ANNs can be used to predict and classify new data.

3.6. Metrics

3.6.1. PSNR. Peak signal-to-noise ratio (PSNR) [19] is a technical term that compares the maximum potential signal power to the power of undesirable noise, affecting its quality. PSNR is determined through mean square error (MSE), for 2 monochromatic MRI images I and K, in which I is the noisy MRI image and K is the original MRI image, MSE is calculated by the following formula:

$$\mathrm{MSE} = \frac{1}{\mathrm{mn}} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2, \tag{3}$$

where, m is the number of rows of the pixel matrix; n is the number of columns of the pixel matrix; i is the row index, representing the i^{th} row of the pixel matrix; j is the column index, representing the j^{th} column of the pixel matrix.

Therefore, PSNR is defined as follows:

$$\begin{aligned} \mathrm{PSNR} &= 20 \cdot \log_{10}\left(\frac{\mathrm{MAX}}{\sqrt{\mathrm{MSE}}}\right) \\ &= 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right), \end{aligned} \tag{4}$$

where MAX is the maximum pixel value of the MRI image, usually 255 in the baseline MRI.

3.6.2. SSIM. The SSIM index [19] was used to measure the similarity between two different images, specifically in this study, the initial MRI image and the MRI image after noise filtering. The SSIM formula is based on three parameters for comparison: luminance, contrast, and structure. The formula is shown as as follows:

$$\mathrm{SSIM}\ (x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}, \tag{5}$$

where $\mu_x, \mu_y, \sigma_x, \sigma_y$ and σ_{xy} are the mean, standard deviation and covariance of x and y images, respectively, and C_1, C_2 are constants.

3.7. Proposed Model. The recommendation system consists of two phases: training phase and testing phase, the purpose of the model is to automatically find the best σ_{psd} parameter of the BM3D filter for the input image. The procedure is described as figures below.

Figure 2 shows the training process to find the parameter value σ_{psd}. From the input MRI image, after adding Gaussian noise at 50% level, we get a noisy MRI image. Next, by using a complex network to model the noisy MRI image, 5 features of the image are extracted. Along with this step the best parameter σ_{psd} for the BM3D filter will be estimated. The PSNR mentioned in Figure 2 shows the correlation between the pixels of the noisy MRI image and the noise-free MRI image. This index will be estimated through the parameter σ_{psd} in the range [0, 1]. The σ_{psd} value which gives the highest PSNR, is the best value for that noisy MRI image. In the above diagram, the ANN network is used. The network is a sequential neural network designed for regression tasks. It begins with a dense layer of 1024 neurons, this is followed by multiple dense layers with decreasing numbers of neurons: 512, 256, 128, 64, and 32, each with "relu" activation, improving the model's ability to learn complex patterns. The final layer has a single neuron, with "he_uniform" initialization, designed to output a continuous value.

The essence of the problem here is the use of back propagation algorithm [20] and neural networks to increase the accuracy of the training process, thereby obtaining the ANN model. Five features $[X_1, X_2, X_3, X_4, X_5]$ of each noisy MRI image will be extracted by the complex network. They are the input to the Back Propagation algorithm and the output is the best parameter σ_{psd} found above, called [Y]. In the back propagation algorithm, input values are passed through the neural network to compute the output. Then the error between

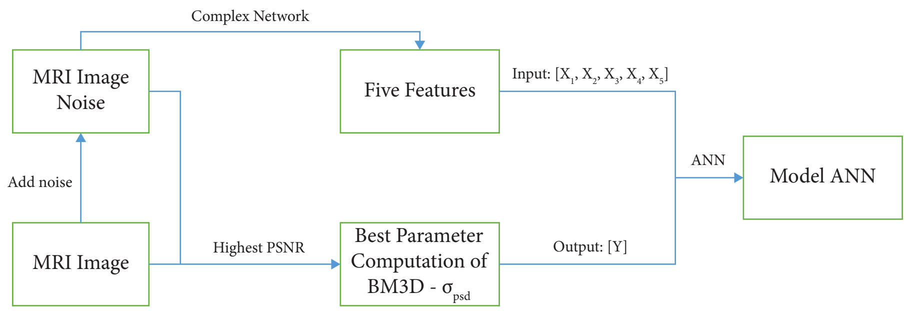


Figure 2: Training process of the proposed model.

the actual output and the predicted output is calculated, the inputs $[X_1, X_2, X_3, X_4, X_5]$ will be respectively with an output of a certain $[Y]$. The algorithm then propagates the error back from the output layer to the input layer, calculating the partial derivative for each weight in the network. The weights are then updated using an optimization algorithm such as gradient descent to minimize the error. Therefore, each noisy MRI image has its own characteristics, from which these particular features will correspond to a best noise filter parameter. The ANN model is used in Figure 3 to test and evaluate the above training process.

The proposed model in this study is a general model, not only applicable to MRI brain image data but also can be applied to various other image datasets. However, each image dataset has a different data distribution, so applying the proposed model needs to be customized to each type of image data to achieve the best results.

4. Experiments and Results

4.1. Data Collection. In this study, the dataset was collected from 230 brain tumor patients at Bach Mai Hospital, Hanoi, Vietnam, covering all age groups. The dataset consists of various magnetic resonance imaging sequences such as T1, T2, T1ce, and T2 Flair. To perform the model described above, this research utilized T2 MRI sequences, which effectively depict the characteristics of white matter and gray matter. The dataset used includes 500 T2 pulse sequence MRI images of the human brain. They are in jpeg format with dimensions of 256×256 pixels. The set of images is divided into 3 sets, the training set includes 300 images, the validation set includes 100 images and the test set includes 100 images.

4.2. Results of the Training Process. To evaluate the efficiency of the model training process, in this paper, the Mean Absolute Error (MAE) [21] parameter is used to calculate the loss function for the above proposed ANN model. Mean Absolute Error measures the average magnitude of errors in a set of predictions without considering their direction. It is the mean over the sample of the absolute difference between the prediction and the actual observation. This factor is calculated as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left| y_i - x_i \right|}{n}, \quad (6)$$

where n is the number of data points, x_i is the actual value (real value of σ_{psd}), and y_i is the predicted value (predicted value of σ_{psd}) of the model.

The loss function of the proposed model is illustrated in Figure 4. The model was trained over 300 epochs with an initial learning rate of 0.01. Figure 4 shows that the model converged to its lowest loss value after 200 epochs.

4.3. The Results of Image Denoising by the Proposed Model. With the proposed model combined with a training dataset of 300 MRI images, this proposal can denoise any other brain MRI images with a very good PSNR result. Test results with 10 MRI images with Gaussian noise at 50% are shown in Table 3. Experimental results show that the PSNR results of 10 images are quite high, the average is 51.83. From the results shown in Table 3, it can be seen that the best parameter values of σ_{psd} are in the range $[0.3 - 0.5]$.

Figure 5 displays the outcomes of denoising an MRI image corrupted by 50% Gaussian noise. Figure 5(a) represents the original MRI image, Figure 5(b) depicts the noisy MRI image, and Figure 5(c) showcases the image after denoising with our proposed method. Clearly, from these images, it is evident that our method excels in restoring noisy images. Distinguishing between Figures 5(a) and 5(c) with the naked eye is quite challenging.

4.4. Calculation Time. Using our proposed model in Gaussian denoising for MRI images has also reduced the processing time relative to some other methods. Finding the best σ_{psd} value is the process of denoising the MRI image for the highest PSNR value To find the best σ_{psd} parameter for the BM3D filter manually, the required time is 156s, which when using the proposed model, the time to find the parameter σ_{psd} only takes 10s. This time is 15 times faster than manually searching for parameters. Obviously, with the same PSNR value obtained, the proposed method took significantly less time than the manual method.

4.5. Compare the Results with Some Recent Studies. Table 4 provides a comparison based on the PSNR index between recent research works and our current study. Our present research in brain MRI denoising has achieved several notable advantages compared to previous studies. First, we employ a combination of the BM3D method and

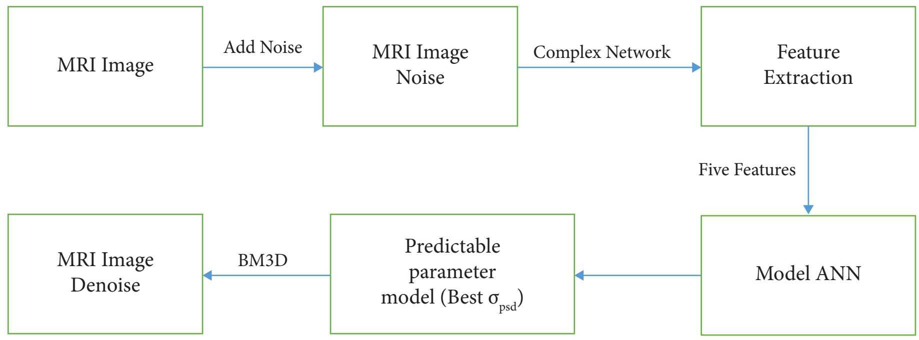


Figure 3: The process of re-testing the proposed model after training.

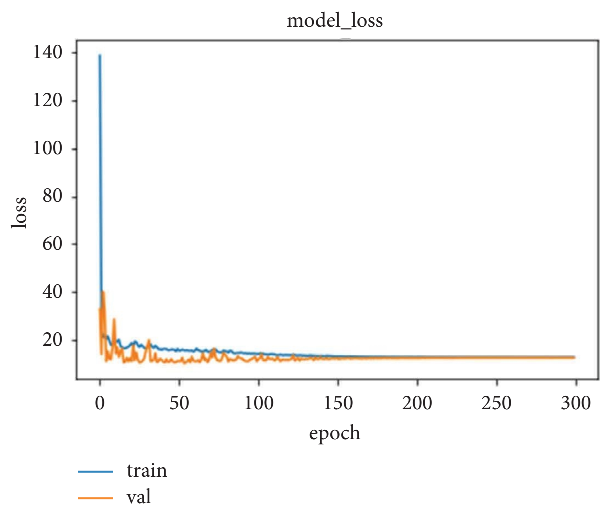


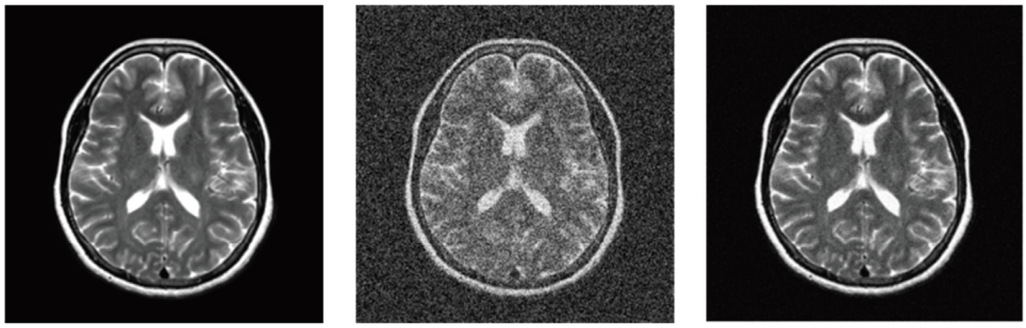
Figure 4: The loss function of the training process.

Table 3: Experimental results with 10 MRI images with 50% gaussian noise.

No	σ_{psd}	Highest PSNR
1	0.44	52.03
2	0.43	51.78
3	0.40	51.87
4	0.38	51.85
5	0.39	52.06
6	0.34	51.79
7	0.35	51.74
8	0.37	51.67
9	0.36	51.75
10	0.41	51.72
Average	—	51.83

the proposed model, resulting in a relatively high PSNR value of 51.83, demonstrating significantly effective denoising capabilities. Compared to previous works, this indicates that our proposed method is more efficient in restoring original images from 50% Gaussian noise. Furthermore, our study has achieved an impressive PSNR value not only higher than previous works but also when compared to the same type of noise (Gaussian 50%), such as Sreelakshmi et al. [11] (PSNR 48.68). Another significant difference is that we have performed denoising of brain MRI images with a relatively high noise level (Gaussian 50%), while some previous studies focused on weaker noise. This demonstrates the broad applicability of our method in real-world scenarios when brain MRI images exhibit strong noise.

In this section, the SSIM index will be the comparison index. This is an index that measures the similarity of an image. The results of previous studies and this study are listed in Table 5. Based on the information from the research works mentioned above, our study has several important strengths. First, compared to previous studies such as Chang et al. [8], Tripathi et al. [9], Wang et al. [12], and Kollem et al. [14], our method employs BM3D in combination with a proposed model designed to handle high-level Gaussian noise up to 50%. This increases the accuracy of the denoising process and achieves a relatively high SSIM value of 0.998. Compared to Moreno López et al. [10], who used unsupervised machine learning to denoise with a standard deviation $\sigma = 50$, our method also achieves a higher SSIM value. Comparing with the study by Kollem et al. [14], it is evident that our method offers better accuracy and is a promising choice for denoising in images, even though the specific noise type is not explicitly defined in their study [15].



(a) (b) (c)

Figure 5: (a) Initial MRI image; (b) MRI image with 50% gaussian noise; (c) MRI image denoised from image (b).

Table 4: PSNR comparison with other previous studies.

Paper	Denoise method	Noise	PSNR
Chang et al. 2019 [8]	Bilateral filter + proposed model	Gauss 1%	39.29
Sreelakshmi et al. 2021 [11]	Adaptive median filter and CNN	Gauss 50%	48.68
Wang et al. 2022 [12]	Nonlocal structural similarity and low-rank sparse representation	Rician 4%	38.503
Mehta et al. 2022 [13]	U-NET architecture	Gauss 25%	30.96
Kollem et al. 2023 [14]	Diffusivity function	—	42.78
This paper	BM3D + proposed model	Gauss 50%	51.83

Table 5: SSIM comparison with other previous studies.

Paper	Denoise method	Noise	SSIM
Chang et al. 2019 [8]	Bilateral filter + proposed model	Gauss 1%	0.983
Tripathi et al. 2020 [9]	CNN	Rician 1%	0.987
Moreno López et al. 2021 [10]	Unsupervised learning	Standard deviation of the noise with $\sigma = 50$	0.8977
Wang et al. 2022 [11]	Nonlocal structural similarity and low-rank sparse representation	Rician 4%	0.976
Kollem et al. 2023 [14]	Diffusivity function	—	0.99645
This paper	BM3D + proposed model	Gauss 50%	0.998

5. Conclusion

Noise filtering for images is a long-standing research interest with many highly effective techniques. In this study, an automatic method for finding the power spectral density standard deviation of the image noise for the BM3D filter based on complex networks and ANNs is proposed. This method is not only applicable to find filter parameters for BM3D image noise filter, but also to other traditional noise filters whose input is random parameters. Experimental results have shown that MRI images with Gaussian noise have been restored quite effectively with significantly shortened execution time compared to traditional methods where the selection of parameters is a random process. The results of the study are very promising and are expected to be implemented practically in healthcare facilities based on embedded devices. In the future, the combination of complex network models and ANNs could be used to develop other biomedical data processing methods such as lung CT images, MRI joint scans, ECG.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This research is funded by the Hanoi University of Science and Technology (HUST), Vietnam under grant number T2023-PC-030. The authors would like to thank HUST for the financial support.

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