Deep Neural Network-based Methods for Brain Image De-noising: A Short Comparison

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***Abstract*—Various types of noise may affect the visual quality of images during capturing and transmitting procedures. Finding a proper technique to remove the possible noise and improve both quantitative and qualitative results is always considered as one of the most important and challenging pre-processing tasks in image and signal processing. In this paper, we made a short comparison between two well-known approaches called thresholding neural network (TNN) and deep neural network (DNN) based methods for image de-noising. De-noising results of TNNs, Dn-CNNs, Flashlight CNN (FLCNN) and Diamond de-noising networks (DmDN) have been compared with each other. In this regard, several experiments have been performed in terms of Peak Signal to Noise Ratio (PSNR) to validate the performance analysis of various de-noising methods. The analysis indicates that DmDNs perform better than other learning-based algorithms for de-noising brain MR images. DmDN achieved a PSNR value of 29.85 dB, 30.74 dB, 29.15 dB, and 29.45 dB for de-noising MR image 1, MR image 2, MR image 3 and MR Image 4, respectively for a standard deviation of 15.**

Keywords—*CNN; Deep neural network; de-noising; MR image; PSNR*

I. Introduction

Noise is considered as unwanted signals causing imperfections and low resolution in image and signal processing, and may happen during the receiving and transmitting processes. Thus, further image analysis and processing may not be possible until we discard or reduce the noise in the images. In image de-noising, the main goal is enhancing the visual quality. Various methods are available in literature for removing the possible noise from images.

Donoho and Johnstone proposed adapting to unknown smoothness [1] and ideal spatial adaptation [2] using wavelet shrinkage for de-noising in 1994 and 1995, respectively. These techniques became the foundation for further gradient descent learning based methods. Zhang took one step forward in de-noising by proposing a learning-based method for improving the conventional approaches [3]. He developed a thresholding neural network using an improved and non-linear hard-soft threshold function. Sahraeian et al., proposed an improved TNN and cycle spinning for image de-noising [4]. Nasri and Nezamabadipour tried to improve Zhang's results by proposing another data driven function with three shape tuning parameters [5]. To enhance the results of TNN based methods, instead of using gradient descent algorithm, the authors in [6] proposed an optimized based technique.

Although the results were satisfactory, the researchers did not want to stop at this stage, and they wanted to go beyond the conventional gaussian denoisers. In this regard, convolutional neural networks are widely used in image processing due to their excellent performance for obtaining high quality output images. Jian and Seung developed a combined CNN with unsupervised learning for natural image de-noising [7]. Vincent et al. developed a new training principle for unsupervised learning and it became one of the basic deep learning techniques for noise removal aspects [8]. While using deep convolutional neural networks there is an issue in which we cannot train deeper networks easily. To address this problem, Mao et al. proposed symmetric skip connection combined with auto-encoders [9]. Zhang in [10] proposed a Dn-CNN method consisting of two main stages, residual learning and batch normalization. Deeper networks also cause gradient dispersion in which residual learning has been utilized in Dn-CNNs to tackle this issue [11]. There are also some other issues which deep neural network-based methods are suffering from. One is diminishing feature reuse, and the other is that increasing the number of parameters and layers does not have any advantage for them [12]. To address these issues Bin et al. developed a flashlight CNN method based on deep residual and inception networks that is able to hold many parameters [12]. Additionally, J. Zhang in [11] developed a diamond denoiser to deal with the issue of losing network's gradient caused by deeper networks.

A self-supervised based method for fluorescence image denoising has been proposed by Huang et al., [16]. In this approach, the authors utilized Wiener filtering and wavelet transformation, as two classic denoising techniques as well as DeepCAD to perform comparative experiments [16]. In another study conducted by Yang et al. [17], an efficient auto-encoder technique using convolutional neural networks to perform both classification and de-noising has been developed.

Content-noise complementary learning has been presented in [18] to denoise medical images. In this study to validate the performance of various de-noising methods, MR, CT, and PET images have been utilized. Structural priors based deep MRI super resolution has been developed in a study conducted by Cherukuri et al., [19]. Low rank structure and sharpness priors have been utilized in this study to enhance the visual quality of images. Convolutional de-noising autoencoders to discard noise from MR images has also been proposed in [20]. This technique provided better accuracy with less computation and data for de-noising the medical images.

In this paper we have a brief survey on several state-of-the-art de-noising approaches. We analyzed the results for MRI brain image de-noising. Thresholding neural networks, Dn-CNNs, Flashlight CNNs, and Diamond de-noising networks have been taken into account. The results indicate that deep neural network based methods have superior results compared to TNN based techniques. Among these deep neural network based approaches, Diamond de-noising networks (DmDN) perform well, followed closely by FLCNN, and DnCNN.

The rest of the paper is organized as follows: Section II is about CNN based image de-noising. A brief discussion about CNNs and how to perform CNN based de-noising has been provided. In Section III, we discuss image de-noising using thresholding neural network. In Section IV, we discuss several deep neural network methods. Section V is results and discussion. Finally, Section VI concludes the paper.

II. De-noising Using CNN

Sitting as a contrast from more traditional methods, convolutional neural networks can be used to great effect on de-noising images. CNNs have been the neural network of choice in the field of image processing due to their high effectiveness and can also be used when de-noising. These networks use their convolutional layers. There are multiple different methods regarding deep learning, but the ones that we discuss in this paper are feed-forward convolutional neural networks (DnCNN) and flashlight CNNs (FLCNN).

In order to de-noise an image, CNNs traditionally require a large training sample size, and learns by training with input-output pairs, images of noisy scans, followed by its clean variation. The network learns kernels through its convolutional layers, small weights that can detect patterns over the input image. The convolutional layers create a hierarchical representation of the input and can use this separation to learn to differentiate between the noise and the features of an image. Non-linear activation functions are then applied for complexity, and the network's outputs are compared to the actual clean image through a loss function, where it can adjust and try again. After much iteration, it then is tested on new images that have had Gaussian white noise added to them, tasking the CNN to de-noise the image [22].

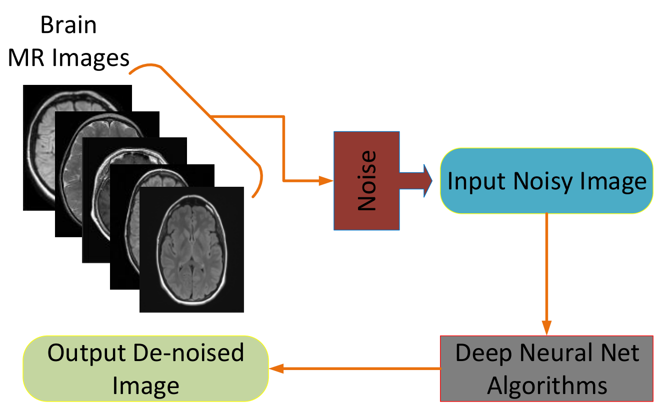

Fig. 1. The procedure of deep learning-based de-noising.

One of the methods we discuss however uses a deep feed-forward network, which can not only learn with overall smaller sample sizes but uses residual learning. It trains on images that already have noise and learns from it, working along with batch normalization in order to increase its accuracy [23]. In the case of the flashlight CNN, it uses a very similar strategy, while also using inception layers that help the network better handle Gaussian white noise. Fig. 1 shows the main procedure of de-noising using learning based approaches. Images have been obtained from [21].

III. TNN Based Methods

Standard hard and soft thresholding functions were first proposed in [3]. In this case, these functions became the basis and foundation of further thresholding based de-noising. Since the obtained results using these functions were not satisfactory, the researchers in the fields of image and signal processing attempted to enhance these methods and add more parameters to make them non-linear and differentiable to be used in a network called, "thresholding neural network''. These functions which are the enhanced version of standard thresholds are called "improved thresholding functions'' which were first introduced by Zhang [3]. The equations below indicate these improved soft and improved threshold functions:

$$L_{soft}(u,\tau) = u + \frac{1}{2}\left(\sqrt{(u-\tau)^2 + l} - \sqrt{(u+\tau)^2 - l}\right) \tag{1}$$

where, $L_{soft}(u,\tau)$ denotes the non-linear soft threshold, u is the WT components, τ is the threshold value and $l > 0$ is a function parameter (user defined) [3].

$$L_{hard}(u,\tau) = \left(\frac{1}{1+\exp\left\{\frac{-u+\tau}{\psi}\right\}} - \frac{1}{1+\exp\left\{\frac{-u-\tau}{\psi}\right\}} + 1\right)u \tag{2}$$

where, $L_{hard}(u,\tau)$ denotes the non-linear hard threshold, u is the WT coefficients, τ is the threshold value and $\psi > 0$ is a fixed function parameter (user defined) [3].

Although these functions have been used in various studies for image denoising, the results have not been quite satisfactory and there is some space for improvement. Thus, another nonlinear and differential threshold function has been presented by Sahraeian [4] as shown by Eq. (3). This function has been inspired by Zhang's improved hard threshold function.

$$L_S(u,\tau) = \begin{cases} m(e^{n|u|} - 1).\mathrm{sgn}(u) \quad , & |u| \le \tau \\ (|u| + he^{-n|u|}).\mathrm{sgn}(u), & |u| > \tau \end{cases} \tag{3}$$

where, $L_S(u,\tau)$ is the Sahraeian's nonlinear threshold, n controls the function's shape and refers to the thresholding effect's degree. Additionally, parameters m and h are used to preserve the continuity and derivative at τ [4].

The researchers did not want to stop here, and they moved forward to present a function with more flexibility and capability. Thereafter, Nasri and Nezamabadi-pour [5] presented other nonlinear functions with three shape tuning parameters which are formulated.

$$\Gamma(u,\tau,i,j,g)=\begin{cases} u-0.5\dfrac{\tau^{i}\times g}{u^{i-1}}+(g-1)\tau \quad , & |u|>\tau \\ 0.5\dfrac{g\times|u|^{j}}{\tau^{j-1}}\operatorname{sgn}(u) \quad , & |u|\le\tau \\ u+0.5\dfrac{(-\tau)^{i}\times g}{u^{i-1}}-(g-1)\tau \ , & |u|<-\tau \end{cases} \tag{4}$$

where, τ is the threshold value, u denotes the WT coefficient, i and j controls the function's shape, and g calculate the asymptote of the function [5]. For further details and information about the structure of TNN and WT based de-noising, please refer to [3].

IV. Deep Learning Based Methods

A. DnCNN

Nowadays, due to the availability of large-scale datasets and progress in deep learning algorithms, CNN approaches attract lots of attention in imaging technologies [10]. The construction of feed-forward convolutional neural networks (DnCNNs) for de-noising has become the basis for de-noising using deep learning [10]. In this structure, to improve the computational time and also to enhance the quality of the de-noised image, batch normalization and residual learning have been utilized, leading to this approach becoming one of the more efficient and effective gaussian denoisers. Conventional deep NNs can estimate a clean image directly, but DnCNNs can remove and discard the clean image by adapting it to the residual learning strategy [10]. Training a single DnCNN as a blind gaussian denoiser gives better results compared to alternative methods. As mentioned earlier, residual learning and batch normalization are used in this structure. Residual learning has been utilized for solving performance degradation issues [14].

The developed DnCNN utilizes only one residual unit for predicting the residual image [10]. If we compare residual mapping with the original unreferenced mapping in terms of learning, residual mapping is easier, so deep CNN models can be trained easily [14] [10]. On the other hand, although training based on stochastic gradient descent (SGD) is effective and simple, internal covariance shifts can largely reduce the training efficiency [15] [10]. So, alleviating the covariance shift is also a challenging task in deep CNN models and is the reason that batch normalization is used in these networks [15] [10]. The combination of residual learning and batch normalization provides us with stable training, fast training procedure (because of using batch normalization), better qualitative and quantitative results [10]. The main structure of the DnCNN model is depicted in Fig. 2.

As can be seen, the network's input is a noisy image corrupted by gaussian noise. Here, instead of learning a mapping function, we can proceed by adapting residual learning for training the residual mapping [10]. Additionally, in the proposed network with depth D, there are three types of layers [10]:

- Conv+ReLU is used for the first layer with 64 filters with the size 3×3×c. Note that c is the channels' number. Also, ReLU has been utilized to give nonlinearity.
- Conv+BN+ReLU is used from layer 2-D-1 with 64 filters of size 3×3×64. Batch normalization (BN) has also been used in these layers.
- Conv is utilized in the very last layer with c filter of size 3×3×64 for reconstructing the output image.

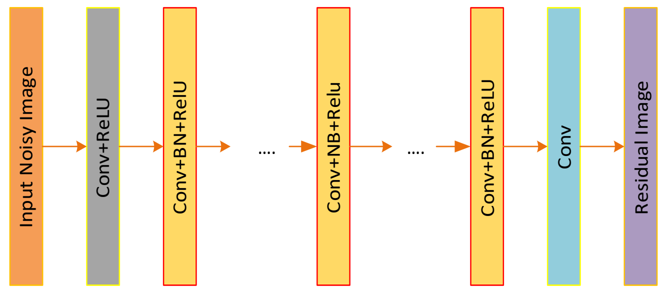

Fig. 2. The structure of DnCNN [10].

B. Flashlight CNN (FLCNN)

Flashlight CNNs are another type of convolutional neural network implementing deep NN for noise removal processes. The main structure of this method is based on the combination of deep residual and inception networks [12]. Utilizing inception layers provides us with overcoming and addressing the reuse of diminishing features while tackling additive white gaussian noise. As shown in Fig. 3, this network consists of two main phases [12]:

- Warmup phase which utilizes convolutional layers (typical or conventional CNN). There are two main stages in this phase. The first one employs 3×3 kernels with 64 features and the second one employs 5×5 kernels with 64 features.
- Boost phase utilizes wider inception layers (residual) leading to growth and increment in the number of networks' parameters while overcoming the reducing feature reuse.

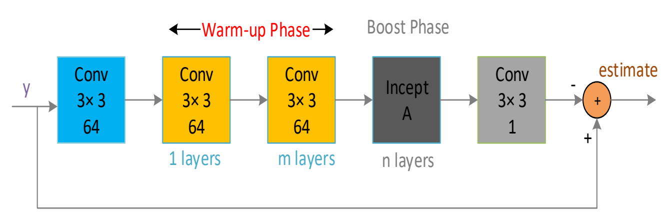

Fig. 3. The architecture of FLCNN with noisy input of y and estimate x [12].

C. Diamond De-noising Network (DmDN)

Images' detail and important characteristics and information may be diminished by doing excessive scaling [11]. Although the convolutional network is deeper, it may be easy to lose the gradient of the network. To address these issues, Diamond Shaped (DS) multi-scale feature extraction has been utilized in this network to extract the information of the images' features [11]. This fixed scale-based network is called a Diamond De-noising network (DmDN) [11]. This network contains three main parts as below [11]:

- Feature extraction of input noisy images.
- Feature extraction of multi scales.
- Clean image reconstruction or output image.

V. RESULTS AND DISCUSSIONS

In this part, we have performed two experiments to validate the efficiency of various de-noising methods. Note that the images have been contaminated by additive white gaussian noise (AWGN) with zero mean and different standard deviations. For TNNs we used "sym4" with one decomposition layer. The training parameters are available in [11] and are the same as the original works used in this study. Axial DWI brain imaging obtained from [13] is used in the experimental part. We have used four single images at various moments of the original data (see Fig. 4). The de-noising results in terms of PSNR values for various standard deviations are shown in Table I. As neatly shown, DmDNs perform better than other de-noising approaches as it achieved the highest PSNR values. The results indicate that deep learning-based techniques outperform TNN models for de-noising MR Images.

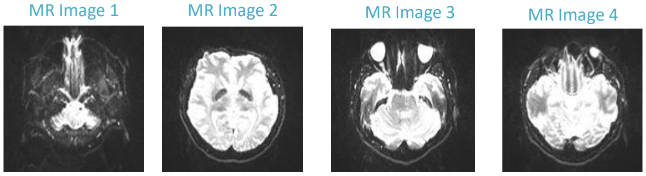

Fig. 4. Four test single images [13].

TABLE I. DENOISING COMPARISON OF VARIOUS LEARNING APPROACHES IN TERMS OF PSNR VALUES (DB)

MR Images	sigma	TNN-Zhang	TNN-Nasri	Dn-CNN	FLCNN	DmDN
MR Image 1	15	24.02	24.23	29.72	29.83	**29.85**
	25	21.98	22.14	27.23	27.36	**27.47**
	50	19.45	19.54	24.25	**24.47**	24.46
MR Image 2	15	24.65	25.16	30.61	30.72	**30.74**
	25	22.75	23.11	28.42	28.59	**28.62**
	50	19.86	20.10	25.44	25.61	**25.64**
MR Image 3	15	23.78	24.10	29.01	29.11	**29.15**
	25	21.83	22.05	26.84	27.01	**27.06**
	50	19.53	19.78	24.03	24.24	**24.29**
MR Image 4	15	24.01	24.31	29.33	29.41	**29.45**
	25	21.45	22.14	27.01	27.14	**27.17**
	50	19.20	19.84	23.84	24.02	**24.09**

In the next experiment we utilized another data set obtained from Kaggle [21] to compare the performance of various deep neural net based approaches quantitatively. Some of these images are depicted in Fig. 5. In this experiment, as can be seen from Fig. 6, we compared DmDn, FLCNN, DnCNN, TNN-Nasri and TNN-Zhang over several standard deviations. The results indicate that the first three deep learning methods perform well in de-noising brain MR images. Among the first three neural net approaches, DmDn outperforms the others. Although these methods perform well in de-noising MR Images, they may not work perfectly for other types of datasets such as hyper-spectral remote sensing and standard test images or even if we apply other types of noise and perturbations.

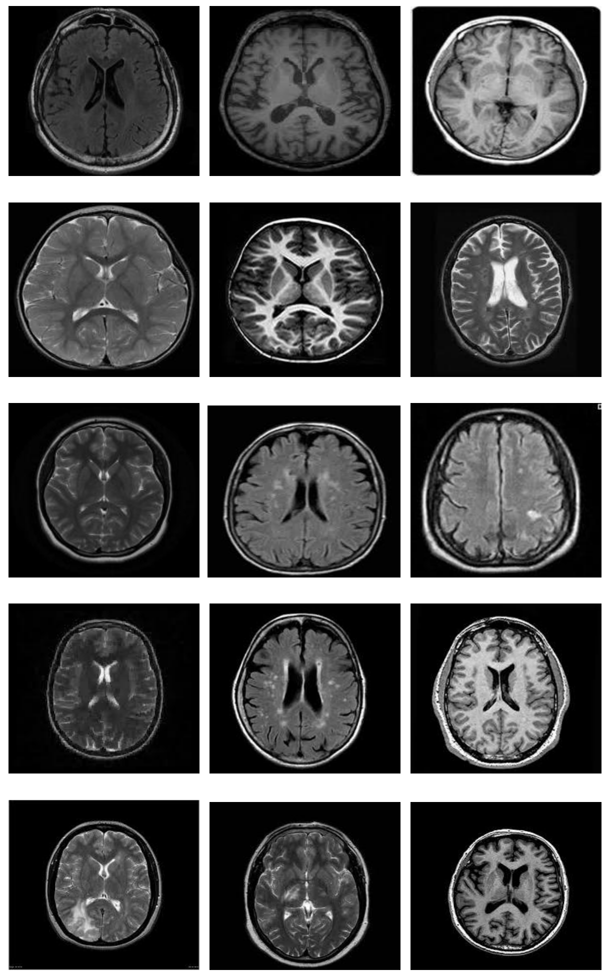

Fig. 5. Some of the brain MR images used in the experimental part [21].

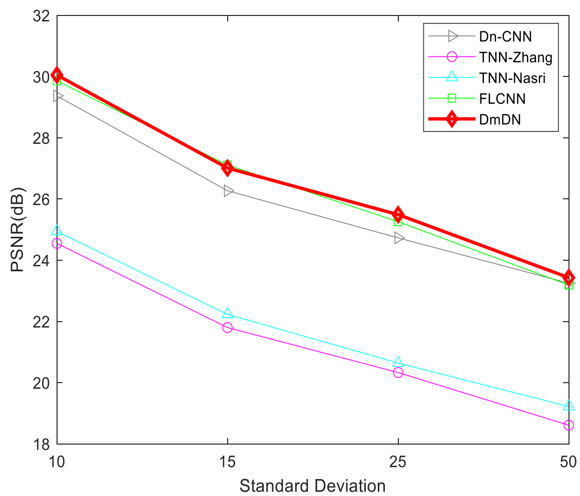

Fig. 6. Comparison of performance analysis of various learning algorithms for different standard deviations.

VI. CONCLUSION

Images may be influenced by many types of noise, leading to a decrease in their visual quality. Trying to find a suitable de-noising method for discarding this noise has always been categorized as a challenging task for researchers in the fields of signal and image analysis. This work provides a survey and comparison between several learning based de-noising methods such as TNNs, Dn-CNNs, Flashlight CNNs (FLCNN) and Diamond de-noising networks (DmDN) in terms of PSNR values. The quantitative results indicate that DmDN can be a promising method for brain MRI de-noising as it achieved the highest PSNR values for de-noising MR images 1-4 for a standard deviation of 15. In this study we have used AWGN, and we realized that increasing noise level decreases PSNR values. For future work, we will analyze the performance of some state-of-the-art methods in the presence of various types of noise.

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