DEEP LEARNING-BASED NOISE REDUCTION FOR SEISMIC DATA

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1. ABSTRACT:

For the noise removal problem of noisy seismic data, an improved noise reduction technique based on feedforward denoising neural network (DnCNN) is proposed. The previous DnCNN, which was designed to minimise noise in seismic data, had an issue with a large network depth, which hampered training efficiency. The revised DnCNN technique was previously introduced for noise reduction in natural data sets, and after modifying the essential parameters, this study extends the algorithm to noise reduction in seismic data. The DUDnCNN algorithm can reduce noise with high efficiency, according to the analysis and comparison of the experimental findings, and the method has certain feasibility and significance for further seismic data noise reduction research.

2. INTRODUCTION

With the growing difficulty of exploration, seismic data fidelity and noise reduction remain a major technical challenge. The accuracy of seismic data is especially crucial in following exploration since it serves as the foundation for resource exploitation, and complex geological conditions frequently obstruct data collecting. As a result, seismic data noise reduction is an important step in improving the signal-to-noise ratio.

Many noise reduction strategies were suggested in the early years as a classic topic in the field of image processing. Initially, noise reduction techniques like median filtering[1] and mean filtering[2] were gradually abandoned due to their weak adaptive ability in executing picture noise reduction and lack of edge information extraction. f-x domain[3], least square filtering[4], and block matching based three-dimensional filter transform (BM3D) algorithm[5] are also traditional noise reduction algorithms. David Bonar and Mauricio Sacchi[6] introduced a nonlocal mean algorithm to attenuate random noise in seismic data, which has the advantage of noise reduction for all pixels in the image while avoiding certain noise reduction constraints. For noise reduction of seismic data, CAO et al[7] introduced a second generation wavelet transform method, which is a flexible construction approach based on the wavelet transform algorithm that has been enhanced. A non-diagonal seismic noise reduction technique based on continuous wavelet transform and hybrid block thresholding was proposed by Mousavi et al[8]. The full-variance regularised nonlocal mean approach was used by Li et al[9] to reduce noise in seismic data, which efficiently removed the noise while maintaining the edges. A noise reduction technique based on dynamic clustering with singular value decomposition was suggested by Wang Wei et al[10]. The adaptive thresholding approach based on the shearlet transform was used to reduce seismic data noise by Cheng Hao et al [11]. Although many of the aforementioned algorithms have shown promise in the processing of seismic data noise, further research is needed to increase the efficiency and accuracy of noise reduction

processing, and it is critical to investigate more accurate and efficient noise reduction algorithms for seismic data.

With the rapid growth of computer networks in recent years, a growing number of deep learning algorithms have been applied to the study of seismic data noise reduction, with promising results. Tang J. et al.12, for example, integrated the K-SVD denoising technique with a deep learning network to investigate a seismic random noise suppression method based on deep learning's sparse representation of overcomplete dictionary signals. Wang Qiqi et al.13 introduced a multilayer perceptron (MLP) noise reduction approach for seismic data and obtained a noise reduction model with improved efficacy after successful model training and parameter tweaking. Many researchers have looked at the development of convolutional neural networks (CNN) based on artificial neural networks for seismic data noise reduction. Han Weixue et al. [14] introduced a CNN-based random noise removal algorithm for seismic data and compared it to classic denoising algorithms such as wavelet transform and curvilinear wavelet transform, finding that CNN provided superior denoising results. Mandelli et al.[15] investigated the use of a convolutional neural network structure dubbed U-Net for seismic data noise reduction and interpolation. As can be observed, academics in seismic data noise reduction research adore CNNs with excellent feature learning capabilities. DnCNN is a classical feedforward denoising convolutional neural network, which is a more advanced denoising algorithm in the field of deep learning at the moment. CNN has a variety of structures, and DnCNN is a classical feedforward denoising convolutional neural network, which is a more advanced denoising algorithm in the field of deep learning at the moment. Some researchers have previously led the way in applying DnCNN to seismic data noise reduction studies, with promising results, but the deeper network structure makes it more challenging to train.

The DuDnCNN network framework utilised in this paper is a hybrid of the DnCNN and U-Net networks. When utilised in the noise reduction processing of the natural dataset BSDS300, the network initially showed good noise reduction, and the network topology is relatively basic with little depth, which can enhance training efficiency to some extent. As a result, after modifying the required parameters, the network is applied to the seismic data under investigation. The experimental dataset is a set of underground random seismic data obtained from the kaggle competition's official website, to which we add noise to create a noisy dataset and a clean dataset. The test set and analysis of the results can confirm the DUDnCNN algorithm's practicality in the field of seismic data noise reduction processing.

1.2. Noise reduction principle of seismic data based on DnCNN

(1) Principle of noise reduction

The following equation can be used to define seismic data that is sensitive to noise interference:

$$y = x + n$$

(1) Where x represents the original noise-free seismic data, y represents the noisy seismic data, and n represents the noise, which is commonly additive Gaussian noise with a normal distribution. According to the above equation, the main goal of noise reduction is to recover x from y as much as possible, i.e., the ultimate goal is to remove noise from noisy data using noise reduction processing, so that the obtained seismic data is as close as possible to the original seismic data without noise, and the seismic data used in the subsequent experiments in the paper are all seismic images. The following equation can be derived by using neural networks to improve the denoising model into a learnable process:

$$\min_{\phi} \sum \left(x_i^n - F_\phi \left(n(x_i) \right) \right)^2 \quad_{i=1}$$

(2) in which xi

is the noise-free original seismic profile image, while n xi is the noisy image after noise
In addition, F stands for the neural network's forward propagation process, and refers to the weights.

To reduce the distance between the outputs, the AdamW algorithm is utilised.

$F \square \square n \square x_i \square \square$ and x_i

Through the goal of network training is to find the best network model with the best parameters.

Original DnCNN network

DnCNN's network structure is depicted in Figure 1 below. The network is divided into three parts, the first of which is the C1 layer, which contains the Conv and ReLu activation layers. Conv is primarily used for data feature extraction in the learning process, while ReLu is a common activation function that effectively prevents gradient explosion and zeros out all negative values. The C2 layer's second section consists of six levels, each of which contains Conv, BN, and ReLu activation layers, with one more BN layer than the C1 layer. The BN layer's primary function is to modify and normalise the data following convolution. After multi-layer convolution, the third half of the convolutional layer is employed for picture reconstruction, where noisy images are learned. A global jump is built between the network's input and output, and the noise-bearing image is reoperated with the learned output noise image to create a clean denoised image, which is a DnCNN residual learning characteristic.
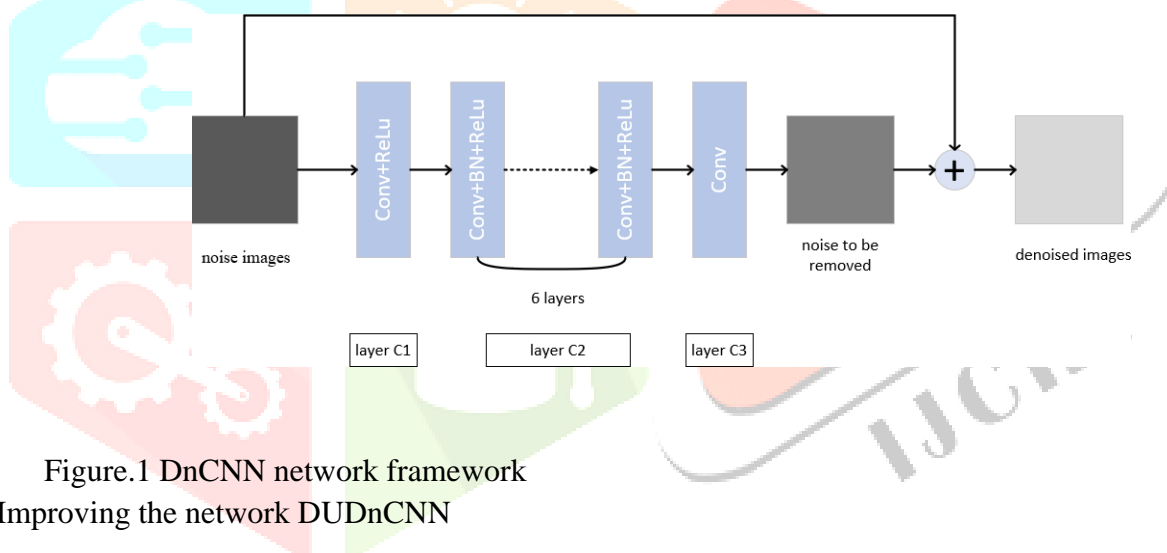

Figure.1 DnCNN network framework

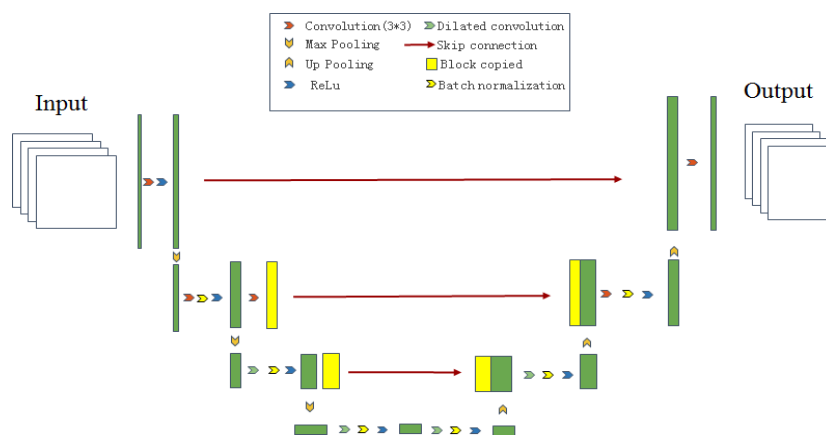**2.** Improving the network DUDnCNN

Figure.2 Improved noise reduction network DUDnCNN

Figure 2 depicts the improved network topology based on DnCNN, with the following benefits summarised:

(1) DnCNN combined with U-Net: The composition of DUDnCNN is a good combination of the advantages of the two networks. DnCNN's batch normalisation and residual learning can prevent internal variable movement, whereas the U-Net network's outstanding advantages are downsampling, upsampling, and jump linking. Upsampling is a process of decoding and recovery, and the connection is cleverly added in the middle to fully combine the different levels of information obtained, so that the network can learn more comprehensive information about the data. Downsampling is a process of encoding and compression, and the low-frequency information of the data is gradually perceived as downsampling progresses.

(2) Expanded convolution: The convolution kernel of the DUDnCNN network is designed using the expanded convolution operator. The size of the convolution kernel in the left half of Figure 2 after adding the interval is known as downsampling. The sizes are 3 3, 7 7, and 15 15, and the gradually increasing receptive field can better extract the image data's low-frequency information, and the convolution kernel size design of the up-sampling process in the second half is exactly the opposite of the left half, which is also the process of image restoration.

3. LITERATURE SURVEY

In order to improve training efficiency, the framework converts the goal function from effective signal learning to noise learning via residual learning. Unsupervised noise reduction necessitates a high level of training data representativeness and a large number of training data sets. We use residual learning and batch normalisation (BN) in the network architecture to lower the network's training parameters and hence reduce feature learning time. The activation function with leakage correction can effectively retain negative information, and when combined with the double convolutional residual block, the network's generalisation ability and feature extraction performance can be significantly improved. Synthetic data and sophisticated field data with uncertain noise levels were put to the test.

We look at the architecture of deep Convolutional Networks (ConvNets) for seismic data denoising in this letter. The untrained ConvNets are applied to a single seismic data profile with Gaussian noise as a generative network. Starting with random initialization parameters, generative networks with various handmade architectures can map seismic data at different iterations and can isolate Gaussian noise as residuals. The key components of a generative network, depth, width, and skip connection, are formed as various architectures to match Gaussian noise, clean, and noisy seismic data, respectively, with the objective of studying the capacity of Gaussian noise separation. Extensive experiments on synthetic and real-world data demonstrate the effectiveness of the chosen ConvNet, and the benefits are assessed by comparing the denoising results to those of f-x multi-channel singular spectrum analysis (MSSA) and a state-of-the-art unsupervised neural network (NN)-based method.

We introduced a fast and flexible convolutional neural network (FFCNN) based on DnCNN in this paper. In contrast to existing DnCNN and other AI-based denoisers, FFCNN has several appealing features: 1) downsampling and upscaling operations, which can significantly reduce runtimes and memory requirements while maintaining denoising performance, and 2) we introduced noised level maps, which can allow a single convolutional neural network (CNN) model to handle noise models with varying parameters. The main work and benefits of this article are focused on the following two components for

real seismic data denoised work: 1) To overcome the paucity of well-labeled samples, we used a data augmentation technique, and 2) transfer learning was introduced to the training processing, which used the well-trained synthetic seismic data denoising network as a pretrained model. Finally, numerical studies show that our strategy works in both synthetic and actual seismic data.

As a result, we offer a unique unsupervised learning approach that uses noisy data to learn. The method is based on two key characteristics of seismic data: 1) geographically connected legitimate signals from nearby seismic traces, and 2) random noise that is spatially independent and unexpected. The denoising issue was solved using an end-to-end deep convolutional neural network (CNN). The training set's inputs and labels were taken from adjacent traces of seismic data with similar seismic phases and interface properties. The suggested CNN denoising model was tested with synthetic and field data. When compared to two commonly used state-of-the-art denoising approaches, the experimental results show that random noise attenuation while keeping amplitude is more successful.

Deep learning (DL) methods have recently shown promising results in seismic data denoising, one of which is supervised DL denoising methods that use clean data as the training label, despite the significant expense of getting clean data. Without using clean data, we study a viable self-supervised DL denoising approach. The NN is trained using Bernoulli-sampled training pairs of the raw noisy data produced by the dropout layer, and a Monte Carlo self-integrated approach improves the denoising quality of the trained NN during testing. Using simulated and real data examples, the suggested method outperforms the f-x deconvolution (FXDECON), deep image prior (DIP), and sparse autoencoder (SAE) methods in terms of improving signal-to-noise ratio (SNR) and decreasing signal loss.

The field seismic data, on the other hand, falls short of this criteria. To get around it, several researchers used labels made from realistic-looking synthetic data or denoised results obtained using traditional approaches. Because it requires the same distribution of test and training data, the former ones have a problem with poor generalisation ability. We present a novel deep learning framework for attenuating random noise in prestack seismic data in an unsupervised manner to avoid constructing noise-free labels. The self-similarity of prestack seismic data like common-reflection-point (CRP) collects and common-midpoint (CMP) gathers after normal moveout (NMO) correction is very high. Because their events are time–space coherent and roughly horizontal from shallow to deep layers, this is the case. Before learning anything else, the generator convolutional neural network (GCN) learns self-similar features.

Despite the fact that deep neural networks (DNNs) typically outperform traditional denoising methods, their performance is not assured since neural networks still lack good mathematical interpretability. We suggested an unsupervised denoising technique based on model-based deep learning, which merged domain knowledge with a data-driven method to reduce the reliance on labelled data and explore insights into the denoising system. We created a network using the modified iterative soft threshold algorithm (ISTA), which omitted the soft threshold to reduce the uncertainty caused by empirically chosen thresholds. The lexicon and code are trainable parameters in this network. To ensure that network training can be done without supervision, a loss function with a smooth penalty was created.

4. EXPERIMENT

This section goes over the specifics of this noise reduction experiment, such as how to prepare the dataset and how to train and evaluate the noise reduction network. The noise reduction effect plots of DUDnCNN with different parameters are compared and analysed in the test and result analysis section at the end of this section, and the result outputs of both DnCNN and DUDnCNN are also compared to demonstrate the advantages of DUDnCNN in seismic data noise reduction.

(1)   *Data preparation*

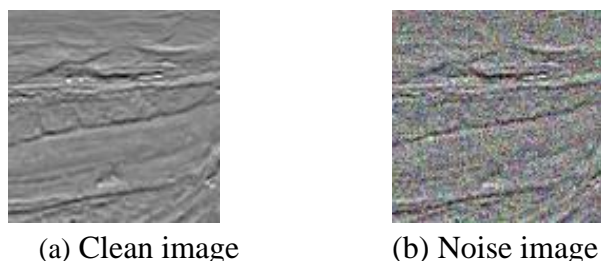(a) Clean image   (b) Noise image

Figure.3 Comparison of images before and after adding noise

The dataset utilised in the experiment is the salt body segmentation competition dataset published by Kaggle's official website. The data consists of a collection of 101101 pixel photographs taken at various positions around the underground. A total of 3100 photos were chosen from the dataset, with 3000 serving as the training set and 100 serving as the test set. All of the images were clean and noise-free. In the data processing, Gaussian noise is first applied to the 3000 photos of the training set to create noisy images, resulting in a processed training set that has 3000 clean and 3000 noisy images, and the test set is handled similarly. On the left are the clean images from the original data set, and on the right are the noisy images after adding Gaussian noise.

(1) *Training*

The training and testing processes of the experiment are depicted in Figure 4, with the training procedure in the upper half. In the training phase, the image size is 101101, and the output image is the same size. In the training phase, the image size is 101101, and the output image is the same size. The training process entails batching the noisy data from the training set into the improved DnCNN noise reduction network, extracting and removing the noise features to obtain a clean image, calculating the error between the clean image and the clean image in the training set before adding noise, and then back propagating to update various parameters in the network, and looping this process until the error is minimised and the model is finished, at which point the model should be finished. The model should achieve the best convergence effect possible, and the network training process parameters are selected as indicated in Table 1.
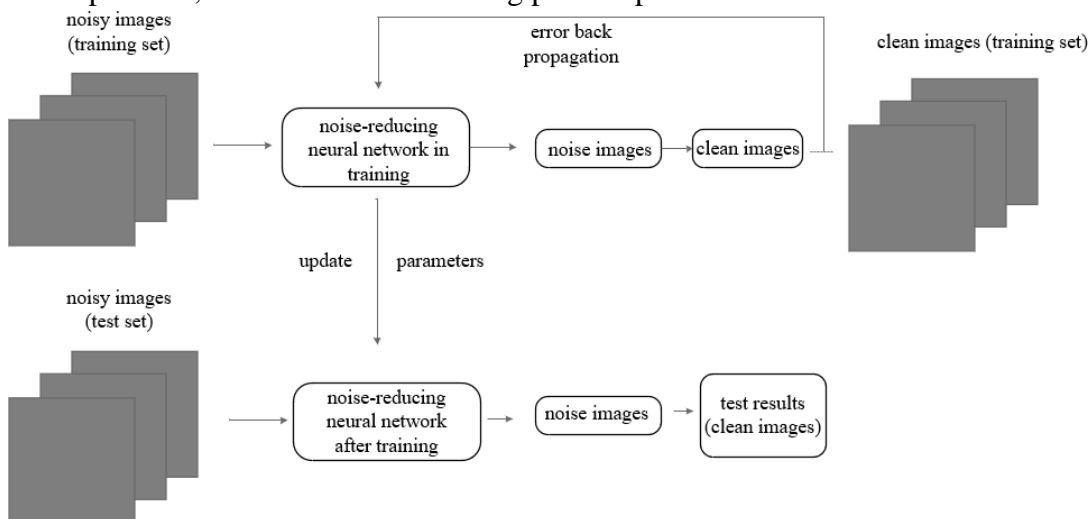

Table.1 Training parameter setting

Training parameters	Numerical settings
Epoch	30
Learning rate range	0.0001
Batch size	8
Image size	(101,101)

(2) Test and Result Analysis

In this section, we primarily evaluate the DUDnCNN algorithm by feeding seismic data from the test set into the network and comparing the noise reduction effect of different parameters and optimizer settings.

(a) Denoising results of Adam optimizer

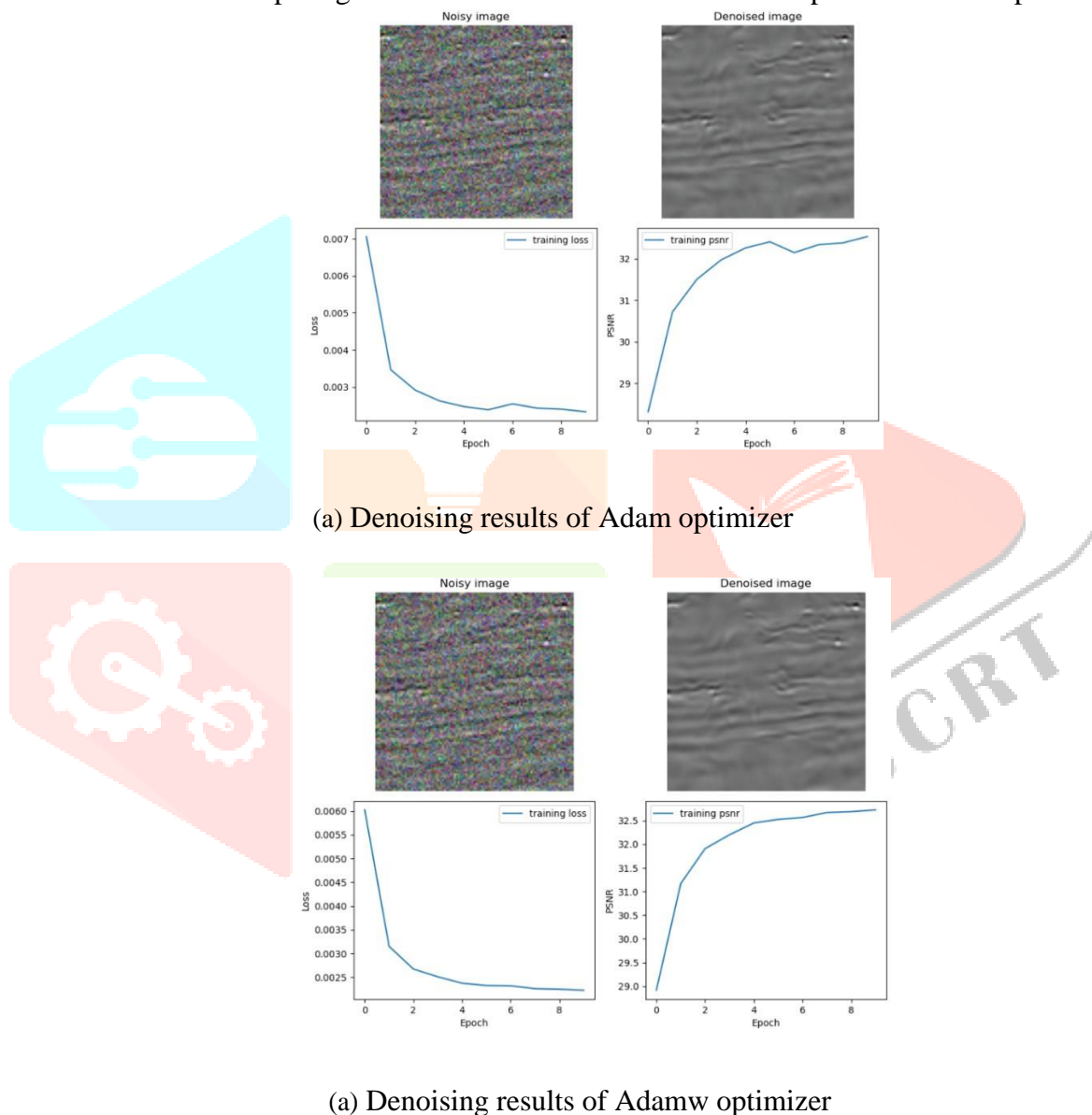(a) Denoising results of Adamw optimizer

Figure.5 Denoising results under different optimizers

Figure 5 shows the noise reduction outcomes of the two optimizers. (a) depicts the Adam optimizer's noise reduction effect, which combines the benefits of both AdaGrad and RMSprop and is known for its fast convergence speed. (b) shows the noise reduction effect of the AdamW optimizer, which is a version of Adam, and how its weight decay and L2 regularisation may successfully ease the overfitting problem in training, as well as Adamw's superior generalisation ability. AdamW can also minimise the loss to a lower magnitude and converge faster at the same epoch, as shown by the training loss curve at the bottom of Figure 5. However, both optimizers' noise reduction effects have the same issue: the effective

information is damaged throughout the noise reduction process, and we must alter the learning rate and epoch to improve the problem.

The effect of the two algorithms DnCNN and DUDnCNN on noise reduction is shown in Figure 6. DnCNN exhibits smoothing over and overfitting for the same data set during training and testing. And the DUDnCNN loss change curve shows that the training loss has basically converged at 20 iterations, and the peak signal-to-noise ratio has also improved significantly before and after iteration, but even though we try to alleviate the problem of effective information being removed by adjusting the learning rate and Batch size several times, the problem of effective information being removed persists. Graphic 7 shows that the DUDnCNN algorithm's noise reduction result still loses more effective information than the original seismic data figure (a). As a result, the next problem to overcome is assuring DUDnCNN integrity while ensuring noise reduction efficiency.

(a) DUDnCNN noise reduction effect

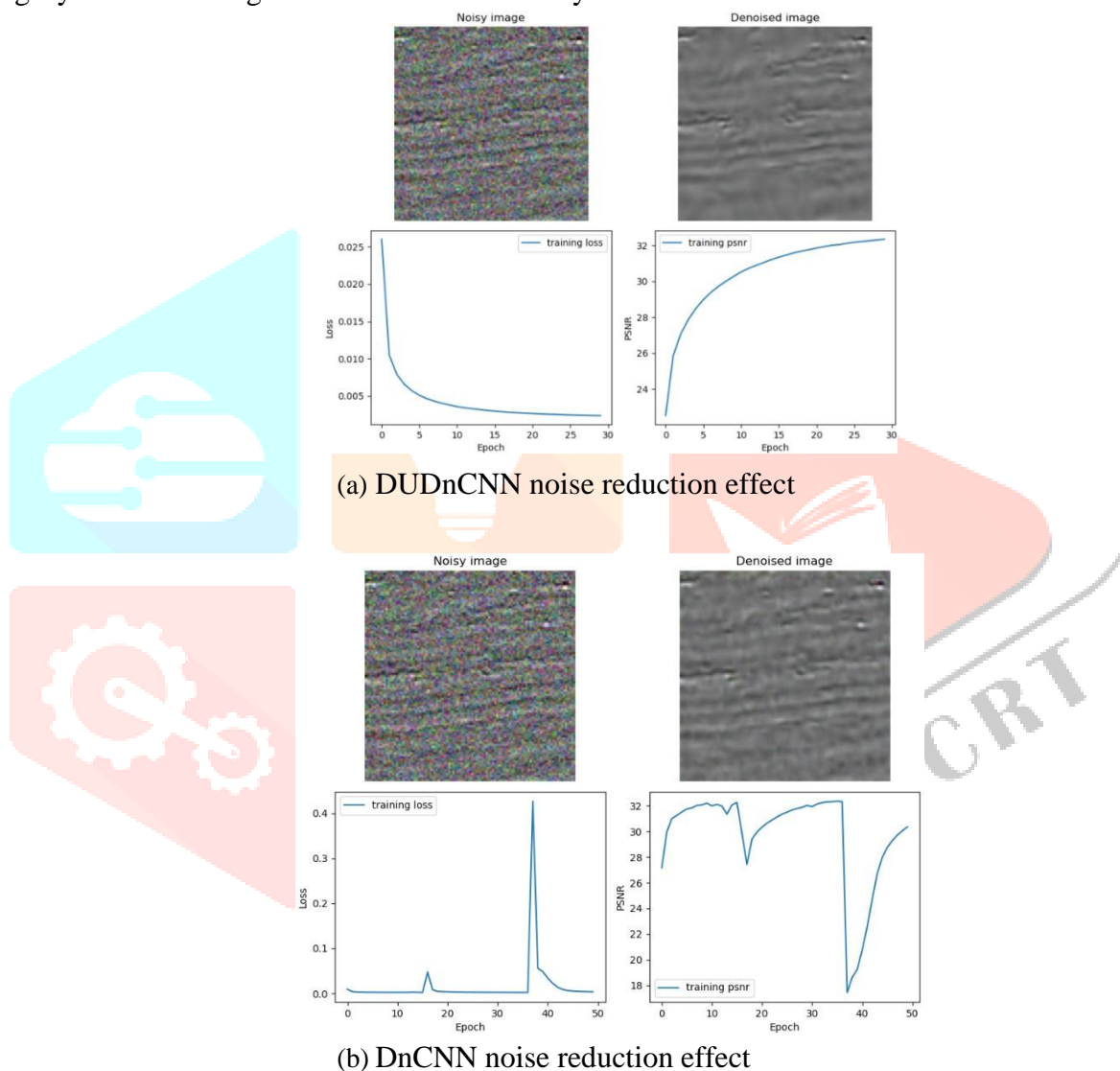(b) DnCNN noise reduction effect

Figure. 6 Comparison of noise reduction effect of DUDnCNN and DnCNN

(a) Original seismic data (b) Seismic data after noise addition   (c) Seismic data after noise reduction by DUDnCNN

Figure. 7 Test set data noise reduction results

5. CONCLUSION

To solve the issue of excessive noise reduction network depth affecting training efficiency, this research recommends using a DUDnCNN with a reduced depth to reduce seismic data noise. DUDnCNN combines the benefits of DnCNN batch normalisation with an end-to-end U-Net neural network, and the network's skip-connection operation prevents shallow information from being lost during the feature learning process, allowing it to successfully extract feature information. The dilation convolution operator is introduced to the kernel, allowing the perceptual field to be increased throughout the convolution process. The training data set for the network consists of 6,000 101101 seismic data points, with 3000 noise-free and 3000 noise-containing data points. The difference between the network output and the initial noise-free data is back-propagated and tweaked to reduce the difference, and the optimised network model demonstrates a good noise reduction effect after being tested using test samples. The DUDnCNN algorithm has a higher noise reduction efficiency, but it still has fidelity issues, according to the results. Although the algorithm achieved near-optimal noise reduction in the BSD300 dataset, more network tuning and better parameter selection are urgently needed to obtain ideal noise reduction in the application of noise reduction in seismic datasets.

6. REFERENCES:

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