DENOISING SEISMIC SIGNAL USING A S TRANSFORM BASED CNN

BY

LINLANG ZHOU[1], ZIKE MA[1], LIMEI REN[1], JIANDONG YANG[1], LONGYAN YI[1], QING ZHAO[1], JIACHUN YOU[2]*

[1]Chuanzhong oil and gas mines of PetroChina Southwest Oil & gas field company, Suining, Sichuan, China

[2]School of Geophysics, Chengdu University of technology, Chengdu, Sichuan, China

*E-mail: youjiachun@cdut.edu.cn

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Abstract: *In the field of seismic data processing, signal denoising is an unavoidable and emerging topic. Effectively denoising of seismic signals is a necessary prerequisite for seismic data interpretation and processing. With the development of deep neural networks, a convolution neural network (CNN) denoising method based on continuous S transform (S-transform) is adopted, which is different with the denoising approaching in time domain. In numerical experiments, we denoise the seismic signals with different degrees of noises, by transforming signal within the time domain into the time-frequency map through S-transform method. Then we use CNN for the denoising processing and compare the time-frequency image based on the energy spectrum with the complex spectrum. We have compared the performance of our proposed denoising method with traditional filtering methods including a low-pass denoising filtering, wavelet denoising filtering and median denoising filtering. The three indexes, PSNR, SSIM and RMSE, are used to evaluate the denoising performances, denoising results shows the superiority and effectiveness of our proposed CNN method. In order to improve the performances of signal denoising (with other features) by using our proposed method, we introduce transfer learning to fine-tune our pretrained model. The application of transfer learning shows that our method can be applicable for practical signal processing.*

INTRODUCTION

In seismic exploration, the collected seismic signals often contain random and coherent type noise. These noises often pollute seismic data, so suppressing seismic noise is very important in seismic data processing, and it is usually the first step of seismic data processing. In our manuscript, we focus on dealing with the rand noise.

As for rand noises, researchers proposed many strategies to suppress them. Li et al. (2008) used singular value decomposition and wavelet transform to denoise synthetic seismic signals. Liu et al. (2014) used Shearlet transform (S-tranform) to process seismic signals for random noises. This method has higher computational efficiency than wavelet transform and other methods. Sid and Aliouane (2014) used the combination of discrete wavelet transform and continuous wavelet transform to suppress random noises. However, most of these methods rely on artificial prior experience to adjust multiple parameters, which are limitations of conventional methods.

Convolutional neural network is a typical algorithm for deep learning. Because of its good image processing performance, it is widely used in the fields of image classification and image denoising. Compared with other methods that we mentioned above, neural network does not need much prior experience in image processing, and only needs enough training samples to make the network have enough image processing capability. Lecun et al.(1998) put forward an image classification method based on neural network, and developed a CNN network structure called LeNet, which embodies the ability of neural network in image processing. Ronneberger et al. (2015) applied a network structure U-net to biological image segmentation task and achieved good results. Krizhevsky et al. (2017) mentioned a more complex

AlexNet structure, which has a deeper structure than that of LeNet, and adopted the normalization layer and dropout layer. Zuo et al. (2018) also proposed the application of residual CNN to natural image denoising and restoration, which further proved the powerful ability of convolutional neural network in image processing. In the aspect of image denoising, Jifara et al. (2019) proposed a convolution neural network method based on residual learning to denoise medical images, and this method achieved good results.

In addition, neural networks have many applications in seismic signal processing. Some researchers applied neural networks to implement the classification of seismic signals (Romeo et al. 1995; Dai et al. 1995; Scarpetta et al. 2005), Titos et al. (2018) applied it to automatically identify seismic events, and neural network is also applied to the noise suppression of seismic signals (Yang et al. 2020; Wu et al. 2019; Zhang et al. 2019). Wang and Chen (2019) use residual network for seismic image denoising, and Othman et al. (2021) employed residual convolution neural network for seismic event detection and seismic signal denoising. Zhang et al. (2019) used an unsupervised strategy based on a deep convolution neural network to deal with rand noises. Most of these seismic signal denoising methods are carried out in time domain, and do not make full use of the characteristics of seismic signals in frequency domain. You et al. (2020) use STFT to transform the signal in time domain into the signal in frequency domain, and then denoise the processed signal. This method has some advantages over the method in the time domain. However, the window width of STFT in time domain is fixed, so the resolution in time domain and frequency domain cannot be obtained at the same time. Compared with STFT, S-transform has higher resolution both in time and frequency domain.

Therefore, in order to make full use of the information in time domain and frequency domain, we tend to transform the seismic signal in time domain into frequency domain by using the S transform. This makes both time domain and frequency domain have good resolution. Then, the seismic signal and the seismic signal with random noise are performed with the S transform and then they are sent to the network for training. Therefore, the trained network can be used to remove random noises. In order to show the performance of CNN denoising, we use some indexes to measure the level of denoising.

THE STRATEGY OF APPLYING CNN TO DENOISING SEISMIC SIGNAL

The main idea of our manuscript paper is to convert one-dimensional seismic signals in the time domain into two-dimensional images through the S transform. Convolutional neural network (CNN) has strong image processing ability and can be used for image regression or classification. The process of our method is as follows: firstly, one-dimensional noise signal is converted to time spectrum by S-transform; Secondly, the transformed result is used as the input of CNN, and the clear spectrum without noise is used as the output of CNN. Therefore, the trained CNN model output provides a denoised image. Finally, we transform the denoised image back to the time domain signal by inverse S-transform.

In order to train our network, we use the signal mixed with different degrees of noise and its corresponding clean signal as the training samples. After many times of training, the network parameters can reach the desired state. In numerical experiments, we compare the denoising effect of this method with that of traditional methods.

S-TRANSFORM AND CNN THEORY

Fourier transformation actually converts signals into superpositions of a triangular function of many different frequencies, but this will loss the time domain resolution of the signal which is the shortcoming of Fourier transformation, because its principle is to divide the signal into a lot of copies in the time domain. In order to overcome this issue, the short time Fourier transform was proposed (Mitra et al. 2001). The basis function of short time Fourier transform is the basis function of Fourier transform multiplied by a window function. After application of short-time Fourier transform, the time-frequency spectrum of the signal is produced and it shows the resolution capability in time domain. However, the time-domain and frequency-domain resolution of the short-time Fourier transform is not adjusted dynamically according to the time-domain and frequency-domain resolution as required.

The S-transform proposed by Stockwell et al.(1996) has a higher time-frequency resolution than that of

STFT. Because this feature, we prefer to introduce the S-transform in our research. The 1-D signal in time domain is transformed into 2-D matrix or two channel 2-D matrix. After using S-transform, the 2-D time-frequency signal disperses the information carried by 1-D into a whole matrix, which shows more characteristics of the signal and is more convenient for our denoising processing.

CNN (convolutional neural networks) is a kind of neural network, which is widely used in the field of image processing as a deep learning algorithm. It is widely used in image recognition and classification, target detection, face recognition, image processing and other fields. The network includes a convolution layer, a normalization layer, a activation layer and a pooling layer. The function of convolution layer is to extract features from input data,

which contains multiple convolution kernels. The activation layer is used to express complex features. After feature extraction in the convolution layer, the output feature map will be transferred to pooling layer for feature selection and information filtering. In our manuscript, we have taken the noise signal as the input data and the clean signal as the standard output result. The gradient descent algorithm is used to adjust the network parameters for the optimization. After many times of training, the parameters of CNN tend to be stable and the training stage is completed. When the new data is feed through the trained CNN, CNN can generate a signal with less noisy.

In real cases, the original time domain seismic signal Y (t) is often composed of two parts.

$$Y(t)=X(t)+S(t) \tag{1}$$

Where X (t) is the clean signal, and S (t) is the noises which are caused by complex environments. The work of this paper is to restore X (t) from signal Y (t) with noises. Y (t) is a time domain signal. In order to display more characteristics of Y (t), the S-transform method is used for processing. In this research, Y (t) is treated by S-transform, which can be written as

$$Y(t)\xrightarrow{\text{S-transform}}Y(t,\omega) \tag{2}$$

Where $Y(t,\omega)$ is a spectrum of signal Y (t), which contains more frequency information.

The data becomes a matrix of two-dimensional time-frequency information after S-transform. CNN is just good at handling such multidimensional information. The method of this paper is to separate the effective part of the converted signal from the noise part by convolutional neural network.

NUMERICAL EXPERIMENTS

The experimental process is as follows. We use four groups of different Gaussian white noise and added them to the seismic signal (intensity is -5dB, -3dB, 3dB, 5dB, respectively). Four groups of data are obtained for CNN training. Each group of data and the corresponding original signal are picked out to form the training sample group, and then a small amount of data different from them are taken out to form the verification data set. The process is shown in Figure 1. We use the MSE (mean square error) as the loss function. PSNR is used as the evaluation index in training.

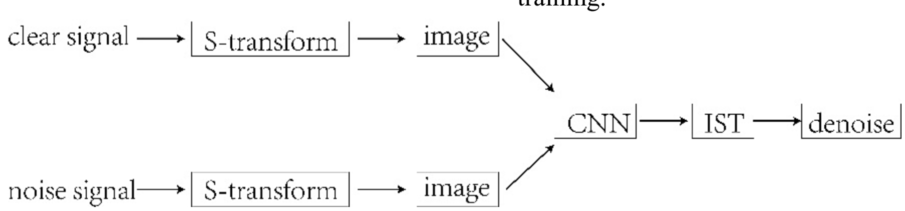

Fig 1. Flow chart of S-transform-CNN. IST means the inverse S transform

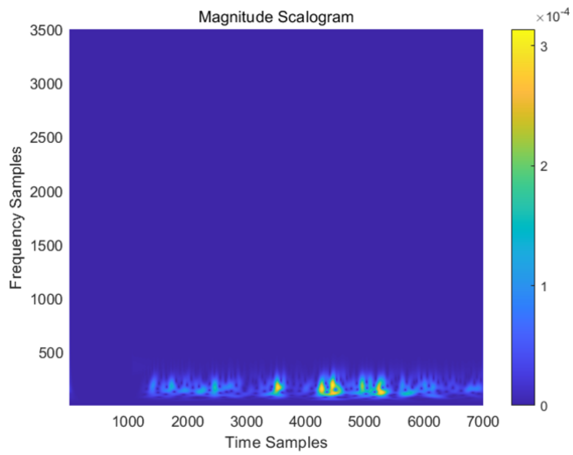

Fig. 2 S-transform result of clean signal

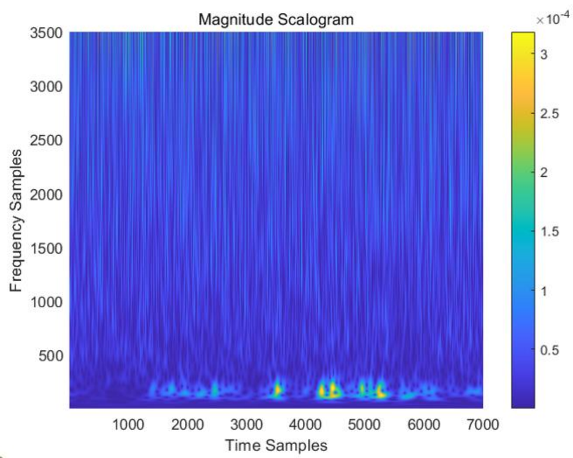

Fig. 3 S-transform result of noisy signal

As shown in Figures 2 and 3, we can find that the added Gaussian noise are full with the original signal in both the frequency domain and the time domain.

We selected 1000 relatively clean seismic signals as training samples. First, add - 5dB Gaussian white noise to these signals to generate noisy signals. Then, the original signal and the noisy signal are subjected to perform S-transform to generate a corresponding spectrum diagram, which is numerically expressed as the amplitude of the complex matrix generated after S-transform.

After that, the clean signal spectrum diagram and the corresponding noisy signal spectrum diagram are matched one by one to form training samples. The noisy signal spectrum diagram is the input of the neural network, and the original signal spectrum diagram is the standard output of the neural network. Then the training samples are fed into the neural network to train the network. At the same time, another 50 seismic signals are used as the verification set of the network. For the training speed of the network, we use bilinear interpolation to reduce the image size. In terms of network structure, this paper uses a classical U-net as the denoising network. The first half of the network structure is used for feature extraction and the second half is up sampling. Because its shape similar to the letter U. The network structure is shown in Figure 4:

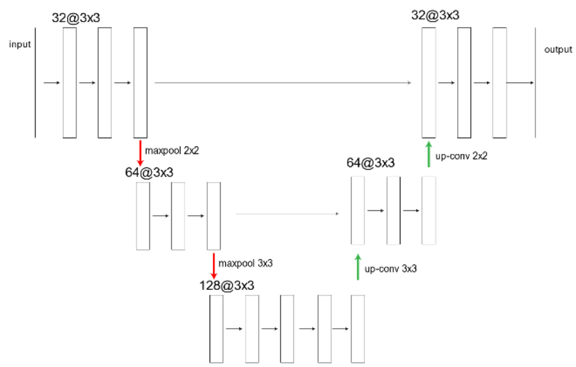

Fig.5 Network structure used in this paper

TEST OF NETWORK DENOISING PERFORMANCE

After training the network, we select a seismic signal different from the training set and the test set as the test. First, add 3dB noise to the signal, and then we perform S-transform to obtain the spectrum diagram. As shown in Figure. 5a

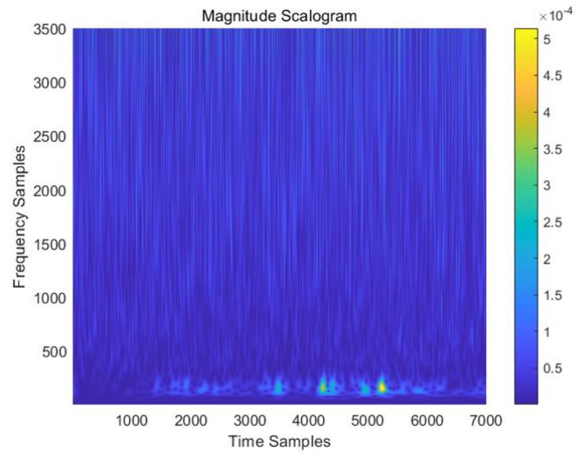

Fig. 5a S-transform result of noisy signal

We feed the spectrum diagram of Figure. 5 into our pre-trained neural network for denoising. We get the spectrum after denoising, and the results are shown in Figure. 6. It can be seen that the convolutional neural network trained by us has a good suppression on noises.

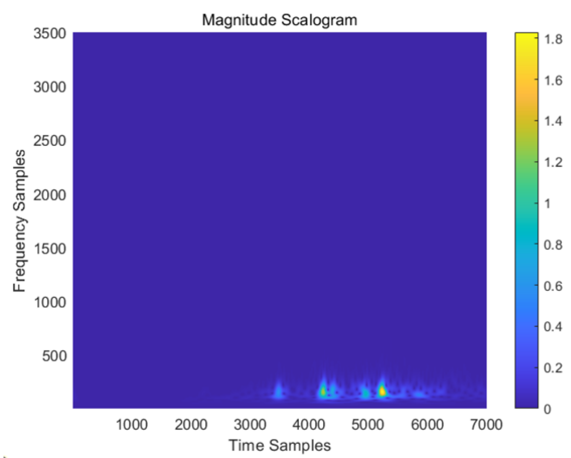

Fig. 6 S-transform result of signal after denoising

Because the result of s transformation is a complex matrix, a complex values X is composed of amplitude spectrum A and phase spectrum θ, which can be expressed as

$$X = Ae^{-i\theta t} \quad (1)$$

Our denoising process is aimed to deal with amplitude spectrum A, rather than phase information. The recovered one-dimensional seismic signal is depended on the inversed S transform (IST), in which we use the original phase spectrum and the denoised amplitude spectrum to recover a denoised signal, its processing flow is shown in Figure. 7. We use IST to recover the one-dimensional seismic signal after denoising through the following process. The comparison between the recovered one-dimensional seismic signal and the original signal is shown in Figure. 8. We can clearly see that our proposed method suppresses the noises successfully. This example shows a good performance of proposed method.

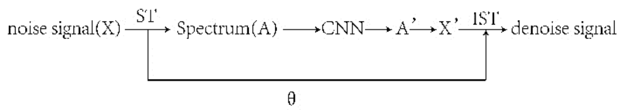

Fig. 7 flow of recovering one-dimensional signal

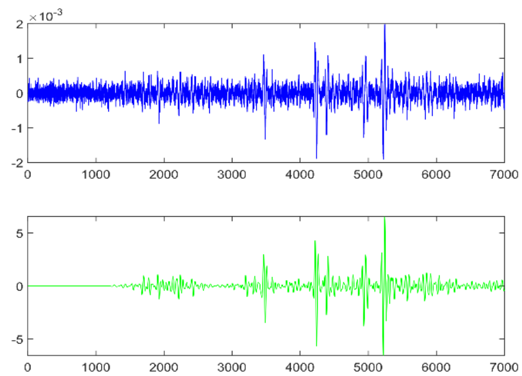

Fig. 8 noisy seismic signal and denoised seismic signal

DENOISING OF SEISMIC SHOT GATHERS

Based on results of one-dimensional signal, we used the trained CNN network to denoise 1000 seismic signals with 3dB Gaussian noise different from the training and validation sets. Figure 9 is the seismic signal before denoising, and the results after denoising are shown in Figure. 10.

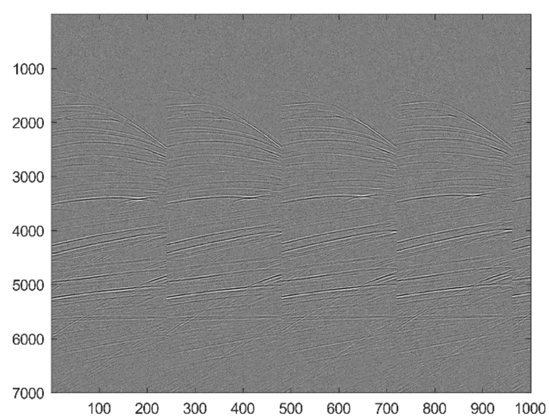

Fig. 9 seismic signal with noise

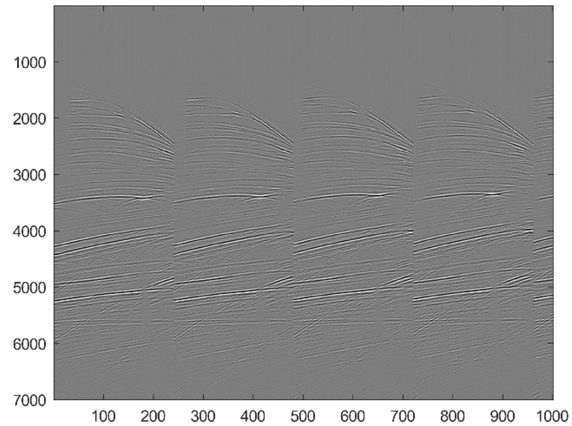

Fig. 10 seismic signal after CNN denoising

Comparing Figures 9 and 10, it can be found that much noise is removed. In order to quantify the denoising performance, we use introduce two parameters, peak signal-to-noise ratio (PSNR) and structural similarity (SSIM), and compare them with the classical median denoising filtering and our proposed CNN method. The higher the two parameters, the better the denoising performance. We normalized the PSNR of the results for a clear comparison.

As shown in Figure 11, with the increase of noises, SSIM is continuously decreasing, both our proposed CNN method and median filtering method, but our proposed CNN method is superior to median filtering method. We can have the same conclusion for PSNR in Figure 12.

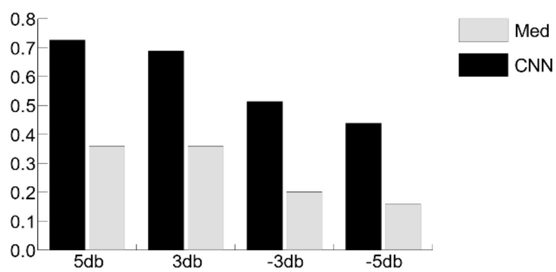

Fig. 11 Estimated SSIM by using different denoising methods with different noise intensities. Med and CNN present the median denoising and our proposed CNN methods, respectively.

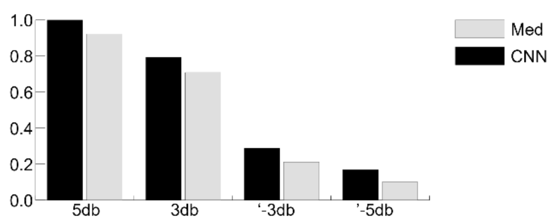

Fig. 12 Estimated PSNR by using different denoising methods with different noise intensities. Med and CNN present the median denoising and our proposed CNN methods, respectively.

CONCLUSION

This manuscript presents a denoising method for seismic signal processing by using a S-transform based CNN method. In this method, the one-dimensional seismic signal is first transformed into a two-dimensional matrix by S-transform. Then the amplitude part of the matrix is taken as the training set to train the network of u-net structure. After that, the trained network is used for seismic signal processing. The method in this paper has achieved outstanding performance in suppressing Gaussian white noise, and the denoising performance is better than the traditional denoising methods. However, there are still some problems, such as the network denoising performance decreases rapidly with the increase of noise. In the future, the method may be improved by increasing the network complexity. The influence of increasing the network complexity and using other networks on the denoising effect needs further study.

REFERENCES

Dai, H., and C. MacBeth, (1995). Automatic picking of seismic arrivals in local earthquake data using an artificial neural network: *Geophysical Journal International, 120,* 3, 758-774, doi: 10.1111/j.1365-246X.1995.tb01851.x.

Jifara, W., F. Jiang, S. Rho, MW. Cheng, and SH. Liu, (2019). Medical image denoising using convolutional neural network: a residual learning approach: *JOURNAL OF SUPERCOMPUTING, 75,* 2, 704-718, doi: 10.1007/s11227-017-2080-0.

Krizhevsky, A., I. Sutskever, and G.E. Hinton, (2017). ImageNet classification with deep convolutional neural networks: *Communications of the ACM, 60,* no. 6, 0001-0782, doi: 10.1145/3065386.

LeCun, Y., L. Bottou, Y. Bengio, and P. Haffner, (1998). Gradient-based learning applied to document recognition: *Proceedings of the IEEE, 86,* no. 11, 2278-2324, doi: 10.1109/9780470544976.ch9.

Li, Y., B. Yang, Y. Li, and Q. Zeng, (2008). Combining SVD With wavelet transform in synthetic seismic signal denoising: IEEE, doi: 10.1109/ICWAPR.2007.4421752.

Lilly, J. M., and S. C. Olhede. "Generalized Morse Wavelets as a Superfamily of Analytic Wavelets." *IEEE Transactions on Signal Processing.* Vol. 60, No. 11, 2012, pp. 6036–6041.

Liu, C., D. Wang, T. Wang, F. Feng, H. Cheng, and G. Meng, (2014). Random seismic noise attenuation based on the Shearlet transform: *Acta Petrolei Sinica, 35,* no. 4, 692-699, doi: 10.7623/syxb201404009.

Mitra, Sanjit K. *Digital Signal Processing: A Computer-Based Approach*. 2nd Ed. New York: McGraw-Hill, 2001.

Othman, A., N. Iqbal, S. M. Hanafy, and U. B. Waheed, (2021). Automated Event Detection and Denoising Method for Passive Seismic Data Using Residual Deep Convolutional Neural Networks: *IEEE Transactions on Geoscience and Remote Sensing, 1*-11, doi: 10.1109/TGRS.2021.3054071.

Romeo, G., F. Mele, and A. Morelli, (1995). Neural networks and discrimination of seismic signals: *Computers and Geosciences, 2,* doi: 279-288, 10.1016/0098-3004(94)00072-3.

Ronneberger, O., P. Fischer, and T. Brox, (2015). U-net: Convolutional networks for biomedical image segmentation: *Lecture Notes in Computer Science, 9351,* 234-241, doi: 10.1007/978-3-319-24574-4_28.

Scarpetta, S., F. Giudicepietro, E. C. Ezin, S. Petrosino, E. D. Pezzo, M. Martini, and M. Marinaro, (2005). Automatic Classification of Seismic Signals at Mt. Vesuvius Volcano, Italy, *Using Neural Networks: Bulletin of the Seismological Society of America, 95,* no. 1, 185-196, doi: 10.1785/0120030075.

Sid-Ali, O., and L. Aliouane, (2014). Random seismic noise attenuation data using the discrete and the continuous wavelet transforms: *Arabian Journal of Geosciences, 7,* no. 7, 2531-2537, doi: 10.1007/s12517-013-1005-3.

Thomas, E., B. A. P. Reif, and Ø. Andreassen, (2008). Flow and swell noise in marine seismic data: *Geophysics, 74,* no. 2, Q17–Q25, doi: 10.1190/1.3078403.

Titos, M., A. Bueno, L. Garcia, and C. Benitez, (2018). A Deep Neural Networks Approach to Automatic Recognition Systems for Volcano-Seismic Events: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11,* no. 5, doi: 10.1109/JSTARS.2018.2803198.

Wang, F., and S. Chen, (2019). Residual Learning of Deep Convolutional Neural Network for Seismic Random Noise Attenuation: *IEEE Geoscience and Remote Sensing Letters, 16,* no. 8, doi: 10.1109/LGRS.2019.2895702.

Wu, H., B. Zhang, T. Lin, F. Li, and N. Liu, (2019). White noise attenuation of seismic trace by integrating variational mode decomposition with convolutional neural network: *Geophysics, 84,* no. 5, V307-V317, doi: 10.1190/geo2018-0635.1.

You, J., Y. Xue, J. Cao, and C. Li, (2020). Attenuation of seismic swell noise using convolutional neural networks in frequency domain and transfer learning: *Interpretation, 8,* no. 4, T941-T952, doi: 10.1190/INT-2019-0303.1.

Yang, L., W. Chen, W. Liu, B. Zha, and L. Zhu, (2020). Random Noise Attenuation Based on Residual Convolutional Neural Network in Seismic Datasets: *IEEE Access, 8,* 30271-30286, doi: 10.1109/ACCESS.2020.2972464.

Zhang, M., Y. Liu, and Y. Chen, (2019). Unsupervised Seismic Random Noise Attenuation Based on Deep Convolutional Neural Network: *IEEE Access, 7,* 179810-179822, doi:10.1109/ACCESS.2019.2959238.

Zhang, Y., H. Lin, Y. Li, and H. Ma, (2019). A Patch Based Denoising Method Using Deep Convolutional Neural Network for Seismic Image: *IEEE Access, 7,* 156883-156894, doi: 10.1109/ACCESS.2019.2949774.

Zuo, W., K. Zhang, and L. Zhang, (2018). Convolutional Neural Networks for Image Denoising and Restoration: *Advances in Computer Vision and Pattern Recognition,* 93-123, doi: 10.1007/978-3-319-96029-64.