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Nonlinear Processes in Geophysics
Discussions
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Interactive comment on "A denoising stacked autoencoders for transient electromagnetic signal denoising" *by* Fanqiang Lin et al.

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Dear Anonymous Referee:

We very much appreciate the overall positive attitude of the referee to our manuscript and thank you for your time and very useful comments! We give below a first response to some of these. Meanwhile, according to your comments, we revised this manuscript. All of the changes were made in a marked-up manuscript version and a clear revised version.

1. Comment from Reviewer: How exactly you are planning to train the network on realistic geophysical problems?

Reply: We agree with your comment. We explained how to train the network on real-

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istic geophysical problems in the section 4 (Experiment and Analysis). However, we found that the explanation of this process was not clear after we carefully read the fourth part of the manuscript again. We briefly described the process: As described in the third part (Mathematical Derivation of SFSDSA), we can obtain an actual detection signal sample and a theoretical signal sample, and then we build a model for training. Meanwhile, Figure 1 shows the network structure and training process in a more vivid way. For realistic geophysical problems such as transient electromagnetic method secondary field signals, we carried out experiments in the fourth part according to the process proposed in the third part .We collect the actual detection signal of the secondary field, the dimensions are 1 * 434 (this dimension can reflect the attenuation process of transient electromagnetic method secondary field signal), the inversion theory signal and the actual detection signal of the secondary field has the same dimensions. Finally, we used two samples for training according to training process of the Figure 1(we added more details, such as training platform, hyper-parameters etc.). Meanwhile, inversion theory signals play a semi-supervisory role in the model. In the end, SFSDSA can map the signal points of the noise interference to the high probability points with clean signal as reference according to the deep characteristics of the signal, so as to realize the signal noise and reduce noise interference.

2. Comment from Reviewer: Is this method can be generalized in the sense that the training on one data can be used on different datasets?

Reply: Yes, this method has a good generalization in a certain sense. Our method has good generalization for different collection points of the same geological feature area. As shown in Figure 9, we use the same model for 7 collection points. However, if the acquisition areas of the two data have large differences in geological features, this will inevitably lead to different deep features of the forward and inversion signals that cause the secondary field. The model will perform noise reduction based on the geological features represented by the previous training dataset. Therefore, it is necessary to analyze the known geological features more carefully and apply the model according to the actual geological conditions before using our method. At the same time, this view is consistent with machine learning theory(Neyshabur et al,.2017). If the model will be well generalized, it must be built to varying degrees of similarity problems. If we do not analyze the principle of the problem and ignore the huge differences in features, it is unrealistic to try to achieve a high degree of generalization. According to this comment, we added this view to the part of conclusion the marked-up manuscript.

3. Comment from Reviewer: Any comments on using supervised learning since that seems work better than the unsupervised learningïij§

Reply: Recently, we have noticed that supervised learning performs well in classification problems such as image recognition and semantic understanding(He et al.,2016, Long et al.,2014). At the same time, unsupervised learning also has a good performance in clustering and association problems (Klampanos et al., 2018.), and the goal of unsupervised learning is usually to extract the distribution characteristics of the data in order to understand the deep features of the data (Becker et al.,1996, Liu et al., 2015). Both supervised learning and unsupervised learning have their own well-behaved areas, so we need to choose different learning styles and models for different problems. For the noise suppression problem of the secondary field signal in transient electromagnetic method, our goal is to extract the deep features of the secondary field signal, and map the data points affected by noise to the estimated high probability points according to their own signal features. We also found that the purpose of extracting the distribution characteristics of the secondary field signal data is similar to that of unsupervised learning. Meanwhile, unsupervised learning models are widely used in different signal noise reduction problems, some of which perform well such as gravitational waves, power transmission equipment status signals, etc. According to this comment, we added this view to the part of relate work in marked-up manuscript.

4. Comment from Reviewer: If noise is not random as shown in the examples, will this method still work?

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Reply: Yes, Our model can extract features of the secondary field signal, so as the signal points of noise interference are mapped to the estimated high probability points according to their own signal characteristics. From a very natural point of view, noise can be seen as an interference whether it is random or not. At the same time, the deep learning model has a good generalization feature to support our point of view (Neyshabur et al., 2017), we also added measures to improve generalization in SFS-DSA such as regularization (Nowlan and Hinton., 1992), so our method has a better performance in actual tests such as the results of Figure 8 and Figure 10. Therefore, this method is still work in a certain sense if the noise is not random.

5. Comment from Reviewer: What the runtime cost of the proposed method compared to other denoising methods?

Reply: Our runtime cost are less at the end of training compared to other denoising methods such as wavelet transform. We can use the data with noise to achieve end-to-end denoising (as described in the process of Figure 1) using the trained model, without having to spend a lot of time to adjust the wavelet threshold and wavelet base like wavelet transform. For small sample data sets, the time consumption difference between SFSDSA and other denoising methods is small, but when the number of data samples reach a certain quantity, the model has a higher advantage in time consumption after training.

We appreciate all the comments, which we will use to improve the manuscript.

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Please also note the supplement to this comment:
https://www.nonlin-processes-geophys-discuss.net/npg-2018-39/npg-2018-39-AC2-supplement.pdf

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