

Interactive comment on “A denoising stacked autoencoders for transient electromagnetic signal denoising” by Fanqiang Lin et al.

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Received and published: 15 January 2019

Author's Response for comments of review 3

Dear Anonymous Referee: Thank for you positive comments to our manuscript! We give below responses to some of these. Meanwhile, according to your comments, we revised this manuscript overhaul. All of the changes were made in the supplement files, which are a marked-up version and a revised version.

1. Comment from Reviewer: “The paper aims to denoise a signal with autoencoders (unsupervised manner). However, the authors did this by putting a theoretical signal as output. This is not an unsupervised manner to proceed. Why did the authors put an output? Is it a traditional way to proceed in geophysics?” Reply: We are very sorry

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that make you think that we put a theoretical signal as output because of our unclear expression in Figure 1 (in original manuscript). In fact, in Page 4 Line 14, we described that the theoretical signal is used to get the model loss with the output using the loss function, to realize back propagation. Meanwhile, we have replaced Figure 1 with a clear version. For another question, naturally, it is not a traditional way to proceed in geophysics. We have modify manuscript according to this comment.

2. Comment from Reviewer: “Page 2 line 3: can you please explain little bit why PCA is cumbersome and what could be the effect on the signal used as case study? Reply: According to the references (Wu et al., 2014), the process of PCA can be divided into 5 steps. (1) Normalize the obtained data (2) Calculate the covariance matrix for obtaining multidimensional data (3) Decompose the covariance matrix to obtain the eigenvalue matrix and eigenvector (4) Obtain the corresponding main components after dimensionality reduction according to the PCA calculation method (5) Selecting the representative principal components by the trend comparison method and the L-curve method, and performing reconstruction to obtain the denoised secondary field signal waveform. By using the PCA method, we do the experiment to verify the effect of noise reduction. But the process of programming is more complicated using mathematical derivation, so we use scikit-learn library to realize noise reduction. However, the underlying structure is not easy to modify resulting in scikit-learn library is unable to adjust parameters adaptively based on signal characteristics. Meanwhile, we found that the filtering effect is not ideal. More details can be find in revised manuscript.

3. Comment from Reviewer: “Page 3, in which the SELU activation function and the ADAM optimization algorithm are introduced, a justification of choice is needed.” Reply: The problem of too many nodes dying is a general disadvantage for RELU activation function and improved RELU activation functions like leaky RELU all consistently outperform the RELU in some tasks (Xu et al.2015). Therefore, it is necessary to apply the improved RELU function to reduce the impact of the shortcomings of the RELU function. We choose the SELU that have the preponderances of overcoming vanish-

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ing and exploding gradient problems in a sense and the best performing in full connection networks (Klambauer et al., 2014). Adam algorithm have the advantages of calculating different adaptive learning rates for different parameters and requiring little memory(Kingma et sl.,2014). Through Table 1(in original manuscript), we find that the combination of models using SELU is better than the combination of models using RELU in the MAE indicator. Similarly, we find that the combination of models using ADAM optimization algorithm outperform compared with not using ADAM in the MAE indicator. More details can be find in revised manuscript.

4. Comment from Reviewer: “Page 3 line 24: “SELU activation function is utilized to prevent too many of depth”: please put a reference for that? Same page line 12, authors said: SELU and ADAM optimization algorithm are used to solve the problem of over-fitting. How? Need references for this point or a good justification.” Reply: we are very sorry that the sentence of “SELU activation function is utilized to prevent too many of depth” has a spelling mistake (the word ‘depth’ should be replaced to ‘death’) to lead to an unclear and incorrect description. In fact, this sentence wants to express that SELU is utilized to reduce the impact of too many dying nodes problem(Xu et al.2015, Klambauer et al., 2014). For the second question in page 3 line 12, our description of function of SELU and Adam is unclear because of the poor grammar. In fact, we chose Adam algorithm, which have the advantages of calculating different adaptive learning rates for different parameters and requiring little memory(Kingma et sl.,2014). And SELU have the preponderances of overcoming vanishing and exploding gradient problems in a sense and the best performing in full connection networks (Klambauer et al., 2014). We changed the description of the part to a correct expression. More details can be find in revised manuscript.

5. Comment from Reviewer:“Please add other criteria in addition to the MAE” Reply: In fact, we analyzed and compared the selection of the two loss functions of MAE and MSE in the previous experiments as shown in figure 1. Meanwhile, according to the previous work and the secondary field signal denoising task of transient electromag-

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netic method, we think that MAE is a better choice. First, our task is to map the outliers affected by noise to the vicinity of the theoretical signal point, in other words, model should ignore the outliers affected by noise to make it more consistent with the distribution of the overall signal. We know that MAE is quite resistant to outliers(Rishabh, 2015), so we choose it. Second, the squared-error is going to be huge for outliers, which tries to adjust the model according to these outliers on the expense of other good-points(Rishabh, 2015). For signal that are subject to noise interference in the secondary field of transient electromagnetic method, we don’t want to over-fitting outliers that are disturbed by noise, but we want to treat them as noise interfered data. Finally, observing the secondary field signal of transient electromagnetic method, we found that the amplitude of the early track data points is very large, but the amplitude of the late track data is small, and the squared-error will inevitably give the early points of the abnormal points more weight to result in Ignoring the difference in late-channel data, this is very unfair. This question may lead to inaccurate model and late-channel signals will be ignored. We have modify manuscript according to this comment.

6. Comment from Reviewer:“The data splitting need more explanations. The experimental case study needs also some explanation with some exploratory analysis” Reply: In the previous experiment, we randomly collected 2400 periods of transient electromagnetic method secondary field signals from the same collection location and we collected 434 signal points per period. Meanwhile, 100 periods of signals are randomly acquired as a test and validation set. In the meantime, we accept the second suggestion to do some explanation with some exploratory analysis in reply 7 and we update the manuscript for adding more details. We have modify manuscript according to this comment.

7. Comment from Reviewer: “For choosing only 2 hidden layers, did you take into account the other hyper parameters. I suggest a grid search, which is possible to do using TensorFlow library or Keras in Python”. Reply: Thank the reviewer for this precious and professional comment about hyper parameters, and we’re so sorry that

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this paper doesn't list some important hyper parameters such as learning rate, regular parameter and so on completely. We have added those key hyper-parameters in marked-up manuscript. In the previous experiments, we set hyper-parameters (batch-size=8, learning-rate=0.1, regularization-rate=0, epochs=20) based on experience but we initially take the measure of a small number of epochs (epochs=2) according to experiment. We added the experiment as shown in Figure 2 to support our standpoint. The model oscillates quickly and converges. Training with fewer epochs can avoid useless training and over-fitting, maintaining the distribution characteristics of the signal itself. As shown in Figure 5(in original manuscript), the reconstruction error oscillates and converges as the training progresses. This phenomenon is similar to the tail of the actual signal. We try stopping training when the convergence occurs, the idea similar to early-stopping makes the model more robust(Caruana ,2000). At the same time, we got the result of stacking two AEs with good effect as shown in Figure 4(in original manuscript). We guess that the size of the AE hidden layer is too small after multiple stacks (for instance, the 4th AE only has 27 nodes because the size of latter AE is half of the previous AE in order to extract the better feature), and the representation of signal characteristics are not complete resulting in large reconstruction costs. If we want to get a better result, more iterations may be used but this tends to cause over-fitting. Meanwhile, we found that the reconstruction loss of the second AE is already very small shown in Figure 2. And it is not necessary to stack more AEs. We accept the reviewer's suggestion to do a grid search, and we get the good parameter combination of learning rate and regularization rate as shown in table 1 in revised manuscript (learning rate=0.001 and regularization rate=0.15).

8. Comment from Reviewer:" For the comparison with traditional methods, please add PCA." Reply: We have already added in the manuscript about the comparison of PCA algorithm in transient electromagnetic signal denoising. After the filtering test, and then the MAE corresponding to the calculation of the theoretical data, it can be seen that the effect of pca filtering is lower than SFSDSA. Please see the fifth part of the article for details.

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9. Explain how the traditional methods were applied (mother wavelet ...). Reply: A denoising algorithm utilizing wavelet threshold method and exponential adaptive window width-fitting(Ji et al.,2016). An exponential fitting algorithm was used to achieve the attenuation curve for each window, and the data contaminated with non-fixed electromagnetic noise was replaced by their results. Another algorithm utilizes multi-resolution analysis via a stationary wavelet transform of the data(Li et al.,2017).The measured data are decomposed into detailed coefficients and approximated coefficients. Then, the logarithmic slope of measured data and a threshold are calculated to identify the noise in the detailed coefficients; the corresponding detailed coefficients are processed to reduce the noise. Finally, the undisturbed data are reconstructed using inverse stationary wavelet transform. The third method presents an exponential fitting-adaptive Kalman filter to remove mixed electromagnetic noises(Ji et al.,2017), while preserving the signal characteristics. It consists of an exponential fitting procedure and an adaptive scalar Kalman filter. The adaptive scalar Kalman uses the exponential fitting results in the weighting coefficients calculation. Another wavelet-based baseline drift correction method for grounded electrical source airborne transient electromagnetic signals(Wang et al.,2013), through simulations, this method can improve the signal-to-noise ratio. Simulation results show that the wavelet-based method outperforms the interpolation method. All above were added in manuscript at the part of Related work.

Response for some remarks: 1. Put more explanation on the caption of figure 1 if possible. Reply: We accept this suggestion to put more explanation on the caption of figure 1. More details can be find in revised manuscript. 2. Equation 9: put bracket. In addition, explain it little bit (m , X , h ...) if possible. Reply: We are so sorry that we miss bracket on the right of 'x', and the input value of MAE should revised to 'x' and 'y'. x denotes the noise interference data, m denotes the number of sampling points, h denotes the model and y denotes theoretical data. The revised formula can be find in marked-up manuscript.

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3. Page 6 line 10: the authors used Tensorflow, please put a figure of the architecture of the used model. Reply: The figure is exporting from Tensorboard GRAPHS to show the architecture of used model. <https://github.com/tonyckc/SFSDSA/blob/master/The%20model%20structure%20.png>

4. Since the journal is open source, think to put your code on an open source platform (e.g. GitHub ...) Reply: Code can be find: <https://github.com/tonyckc/SFSDSA>.

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

References: Caruana R, Lawrence S, Giles L.: Overfitting in neural nets: backpropagation, conjugate gradient, and early stopping, International Conference on Neural Information Processing Systems. MIT Press, 2000.

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Rishabh.: L1 vs. L2 Loss function, <http://rishy.github.io/ml/2015/07/28/l1-vs-l2-loss>, 2015

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Xu B, Wang N, Chen T, et al. Empirical evaluation of rectified activations in convolutional network[J]. arXiv preprint arXiv:1505.00853, 2015

Wang, Y., Ji, Y.J, Li, S.Y., Lin, J., Zhou, F.D., Yang, G.H.: A wavelet-based baseline drift correction method for grounded electrical source airborne transient electromagnetic signals. Exploration Geophysics, 44, 229–237, 2013.

Wu, Y., Lu, C. D., Du, X. Z., Yu, X.D.: A denoising method based on principal component analysis for airborne transient electromagnetic data, Computing Techniques for Geophysical and Geochemical Exploration., 36(2), 170-176, DOI: 10.3969/j.issn.1001-1749.2014.02.08, 2014.

Please also note the supplement to this comment:

<https://www.nonlin-processes-geophys-discuss.net/npg-2018-39/npg-2018-39-AC3-supplement.pdf>

Interactive comment on Nonlin. Processes Geophys. Discuss., <https://doi.org/10.5194/npg-2018-39>, 2018.

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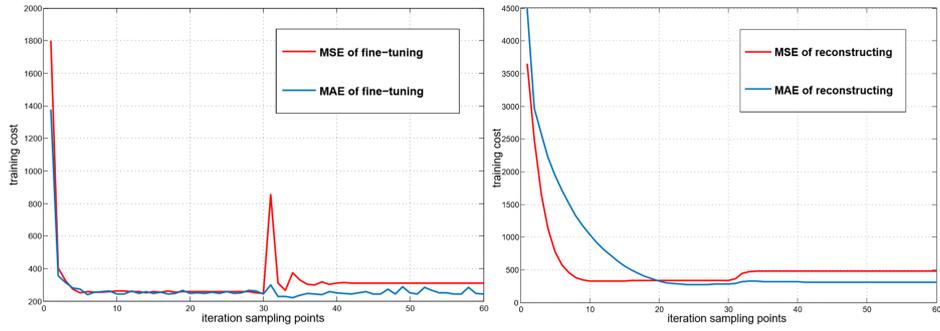


Fig. 1. training cost of MAE and MSE

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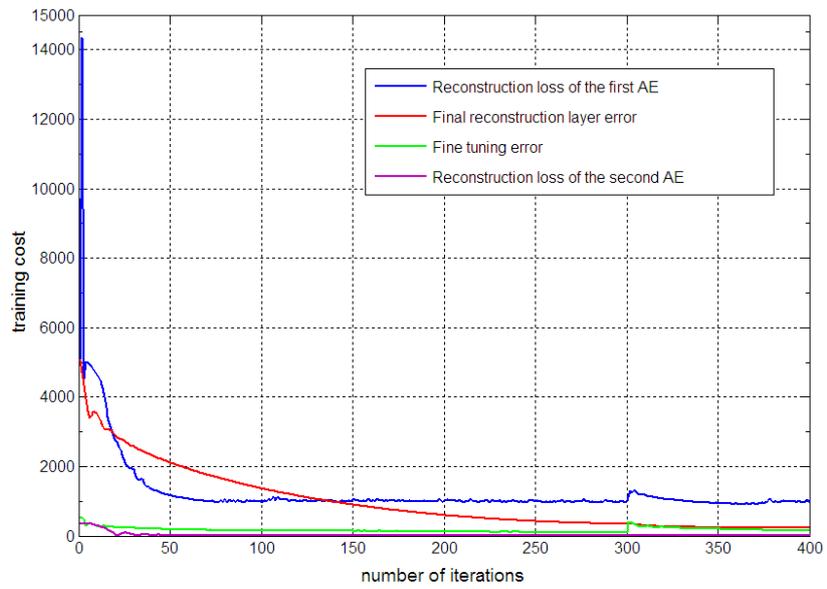


Fig. 2. training cost of each process

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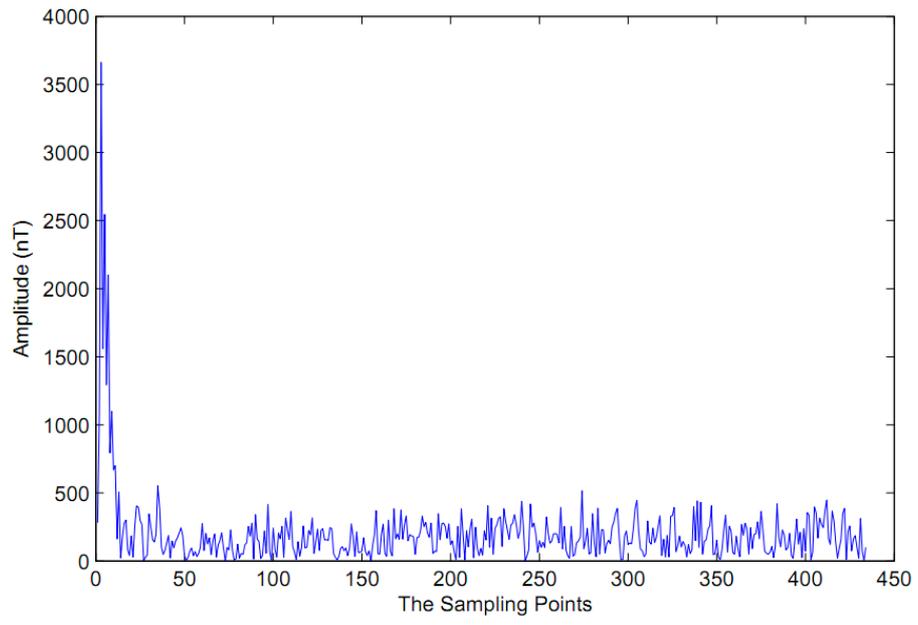


Fig. 3. PCA