Application of a convolutional neural network to classification of swell noise attenuation

Bagher Farmani, Morten W. Pedersen, PGS, Oslo, Norway*

Summary

Swell noise attenuation is an important part of a seismic processing flow and is often subject to extensive testing. The optimal parameters will often not only vary between surveys, but also within a survey. An automatic classification process based on deep learning can be used with a traditional noise suppression algorithm to pick the optimal noise attenuation result even if the best parameterization varies throughout the survey. We show how extending the classification from purely differentiating between noise and signal to also include an additional mixed class helps to identify regions of visible signal with residual noise. Similarly, we show the same mixed class approach helps to identify areas in the attenuated energy with traces of signal leakage. The improved classification will make the automated QC procedure more robust.

Introduction

Noise attenuation is an important and recurrent step in the seismic signal processing sequence. Deep learning-based noise attenuation approaches are becoming an increasingly popular signal processing methodology. Random and swell noise are two of the most typical seismic noises targeted by deep learning methods (e.g. Si and Yuan, 2018; Liu et al., 2018; Zhao et al., 2019). Swell noise in marine seismic data is generated by waves and turbulence and is usually characterized by high amplitude, low frequency waveforms. Typically, swell noise is attenuated by statistical detection and reconstruction method with a conservative attempt to keep the signal unharmed (e.g. Bekara and Baan, 2010). Even though the whole process of swell noise attenuation can be replaced by deep learning methods (e.g. Richardson and Feller, 2019, Zhao et. al., 2019), large-scale studies are required to verify the global performance of these methods.

Martin et al. (2015) and Bekara and Day (2019) both suggested automated quality control (QC) methods that calculate attributes based on statistical measures of similarities between the signal and noise estimates and perform a classification based on these attributes to find shot records with residual noise or signal leakage. Farmani and Pedersen (2020) showed how a similar classification approach could be performed at a sample level by using deep learning. They also proposed to use this technique to facilitate automatic guiding of the noise attenuation process. In their method, the engine for the noise attenuation does not change but the classification model will tune the selected parameters in the noise attenuation algorithm to produce a better result than could be achieved using a single set of global parameters. With the current size of the most exploration surveys, it is often found that fixed parameters for the noise attenuation algorithm may not be optimal for the whole survey and, therefore, automatic adjustment of the noise attenuation parameters can improve the results.

Farmani and Pedersen (2020) also showed that such a classification model can directly classify the seismic records in the QC step after the noise attenuation. Their classification model has three classes: signal, noise and mask. This might appear to be a natural way of defining the model for this purpose; however, in practice, the input to the model is neither pure signal nor pure noise. Seismic records always contain a combination of these two elements. Depending on which of the signal and noise is strongest at a given sample location and its surroundings, the sample will be classified as either signal or noise with their model. Consequently, if there are areas dominated by signal but containing residual noise, they are wrongly classified as signal. Similarly, if there are areas in the attenuated energy that are predominantly noise but containing residual signal, they are also wrongly classified as noise. Such mislabeling could be a drawback in the performance of automated noise attenuation.

To improve the performance of the model we introduce a fourth class, which is a combination of signal and noise. In this study, we compare the performance of the four-class model with the three-class equivalent model in a classification of shot records after the noise attenuation. We demonstrate that the four-class model gives superior performance in identifying both residual noise and signal leakage. In addition, the four-class model naturally performs better when it is used in the automated noise attenuation method presented by Farmani and Pedersen (2020).

Method

We use U-Net as our image segmentation classification model, which automatically labels the seismic samples. U-Net is a convolutional network originally developed for the classification of medical images (Ronneberger et al., 2015). The input to the model is a seismic tile with 336x336 samples. The model has 21x21 samples in the lowest resolution layer, and there are 16 filters for the first encoder. Our model has three or four output classes: signal, noise, mask and signal-and-noise. For both models, supervised training was conducted using labelled tiles. Tiles were extracted from shot gathers after noise attenuation using the output of the noise attenuation algorithm as signal and the attenuated energy as noise. Areas outside the shot gather defined the mask class. For the four-class model, a combination of signal and noise was used to train the signal-and-noise class. Models were trains with over 5000 tiles for each class. Tiles were split into 70% for training, 20% for verification, and 10% for testing. The accuracy of both models was above 98% after dozens of iterations. Models were trained in a python based machine learning environment but classification was performed in a production environment.

Both the three-class and four-class models are capable of classifying the noise attenuation process. If the shot record after noise attenuation is input to the model, any sample classified as noise or signal-and-noise is considered a sample containing possible residual noise. On the other hand, if the attenuated energy is input to the model, any sample classified as signal or signal-and-noise is considered a sample containing possible signal leakage. In the examples section, we will show that the four-class model can identify both residual noise and signal leakage more accurately than the three-class model. However, signal leakage can be better classified if the classification is carried out between incremental noise removal steps.

Examples

Figure 1a shows an acquired shot gather with three different levels of noise attenuation. This particular shot gather was severely contaminated by swell noise. Figures 1b and 1c show the results of the classification with the three-class model for signal and noise, respectively. Figures 1d, 1e and 1f show the results of the classification with the four-class model for signal, signal-and-noise and noise, respectively. The color scale shows the probability of a sample belonging to the class with blue equal to zero and red equal to one. When the remnant swell noise is strong, such as the noise contained in the yellow box, both models are able to classify the noisy samples as noise or signal-and-noise. However, when the noise is visible but not as strong, such as in the green box, the three-class model fails to spot it. This is expected because the seismic image in the green box looks more like signal than pure noise. At the bottom of the image in the green box for the noise attenuation level 1, the three-class model has picked up parts of the noise. As the signal-to-noise ratio drops in the seismic records with increasing recording time, remnant noise becomes more dominant and the three-class model is able to classify some noise samples. By contrast to the three-class model, the four-class model has picked up noisy samples in the green box as signal-and-noise. In the middle of yellow box in Figure 1f, the four-class model starts to pick up some samples as pure noise because the noise level in this area is close to the characteristic of the pure noise. Therefore, four-class model prediction matches a geophysicist interpretation better than the three-class model and gives us a chance to understand the severity of the remnant noise.

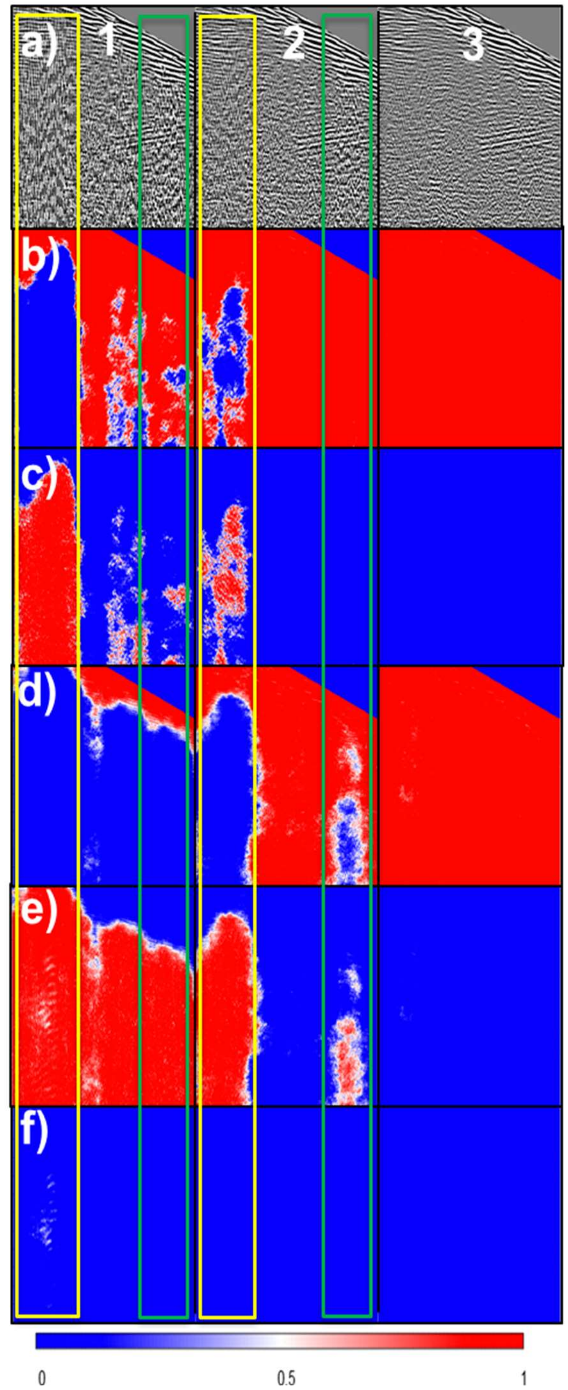

Figure 1: (a) Shot gather with three different levels of noise attenuation. (b, c) Probability of signal and noise classifiied with the three-class model. (d, e, f) probabilty of signal , signal-and-noise and noise classified with the four-class model.

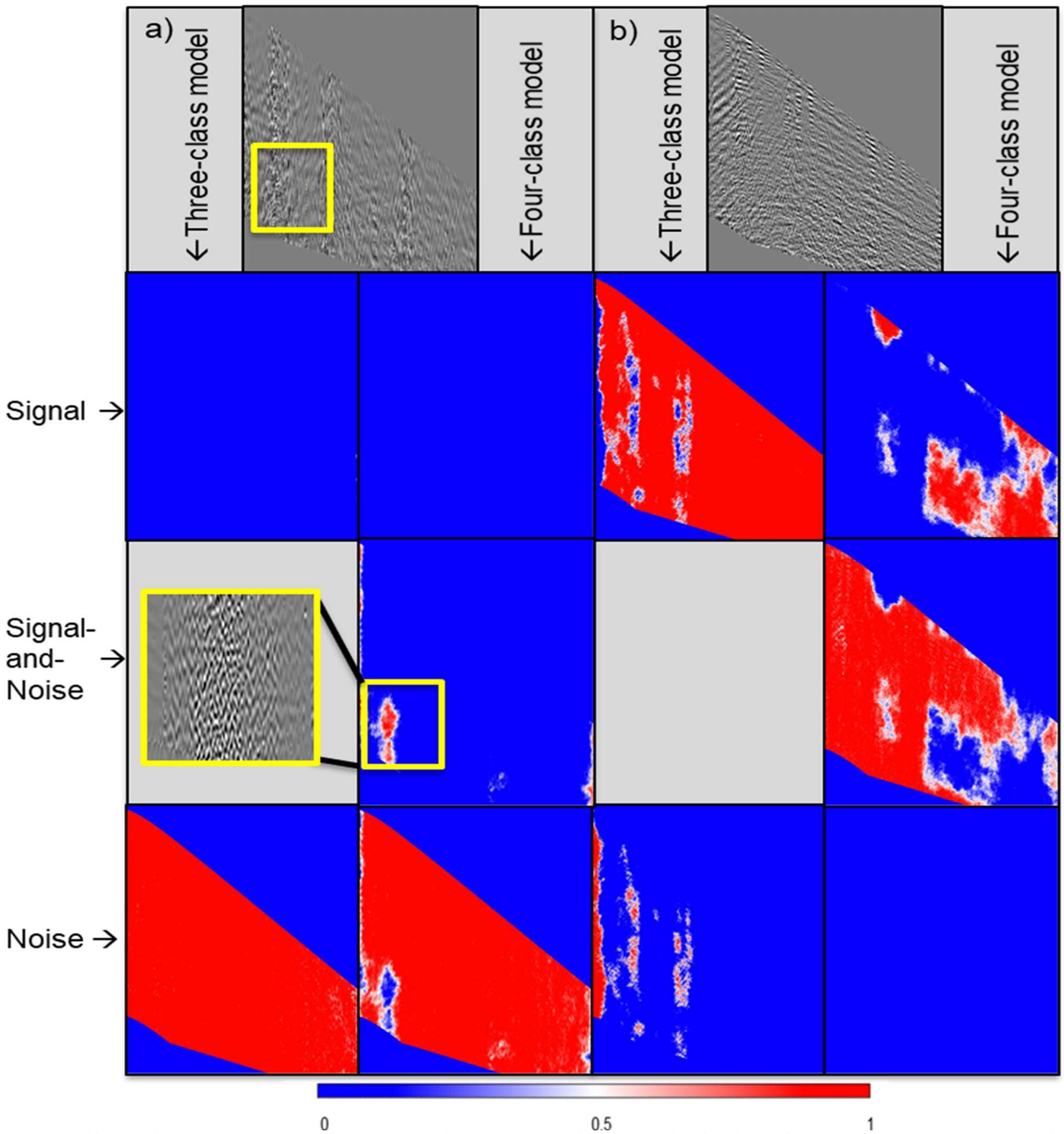

Figure 2: Difference between noise attenuation level 2 and level 1 (a) and level 3 and level 2 (b). Columns under the seismic images show the results of classification for the three-class and four-class models. The first, second and third classification rows show the probability of classes signal, signal-and-noise and noise, respectively. The yellow boxes show the area with possible signal leakage where no signal leakage was expected.

The classification models can also naturally detect signal leakage if the attenuated energy is given as input to the classification. However if the amplitude of the noise is very high compared to the signal leakage, both models are not able to detect the signal leakage. In such cases, stepwise noise attenuation can be used in a way that the noise attenuated would not fully mask the possible signal leakage below it. Stepwise noise attenuation can for example start with a parametrization that leads to mild noise attenuation and, if needed, the level of attenuation is increased by changing the selected parameters in the next step. The energy that is removed in each step is mainly noise;

however, if signal leakage occurs, there is a better chance to spot it. This is demonstrated in Figure 2. Figure 2a shows the energy attenuated between noise attenuation level 2 and level 1. The three-class model classifies all the energy as noise (first column in Figure 2a). However, the four-class model classifies the energy in the yellow box as signal-and-noise. This signal leakage is only visible if one zooms the section and removes the very low frequency background noise (see the inset seismic image in the signal-and-noise row). This is very encouraging because even an experienced geophysicist might miss such leakage when viewing the thousands of displays used for QC. Figure 2b shows the attenuated energy between noise attenuation level 3 and level 2. Noise attenuation level 3 was intentionally made harsh to damage the signal. Signal leakage exists all over the gather. Both models are able to detect the leakage with a high level of accuracy even though the three-class model has classified some samples as noise. The main difference is that the three-class model can only tell us there is signal leakage. However, the four-class model not only tells us there is signal leakage but also how much of the leakage is severe leakage (last image in the signal row).

Both the three-class and four-class models were used to classify a full line from the same survey (Figure 3). This line had a considerable amount of swell noise and, after the initial noise attenuation process, it still had an unacceptable level of residual noise. Therefore, an additional noise attenuation process was applied to the line to further attenuate the residual swell noise. Both classification models detect residual swell noise after the initial noise attenuation (Figure 3a, left images). However, the four-class model detects more residual swell noise in the added signal-and-noise class, which the three-class model classifies as signal. There is a further discrepancy between the outputs of the two models for the additional noise attenuation job. The three-class model suggests that the additional job was sufficient to attenuate the residual swell noise. However, the four-class model suggests that there are two areas with a considerable amount of residual swell noise. Further QC of the shot records, confirm the existence of the residual noise. Two shot gathers after the additional noise attenuation marked with the yellow stars in Figure 3a are displayed in Figures 3b and 3c. The shot gather in Figure 3c contains a considerable amount of residual swell noise. The four-class model was also tested successfully using data from another survey without re-training . We plan to re-training the model with seismic records selected from different surveys to improve the global performance of the model.

Conclusion

We have shown that, by extending the deep learning classification with a mixed class, we can improve the classification of the areas in a seismic shot gather that predominantly comprise signal with some residual swell noise. The same mixed class approach also improves the classification of signal leakage in the corresponding attenuated noise. The improved classification of swell noise improves the overall result of an automated noise attenuation approach where deep learning is used as an internal QC tool to choose the best from different noise attenuation results.

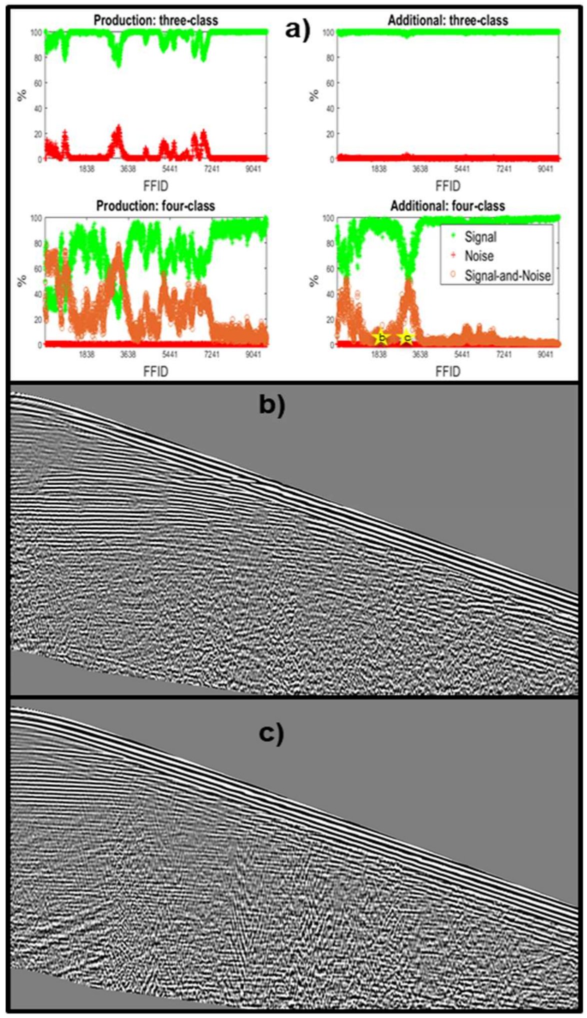

Figure 3. (a) Full shot line classification with three- and four-class models after the initial and additional swell noise attenuation. (b) and (c) shot gathers marked with stars in Figure 3a after the additional noise attenuation. A high-cut filter was applied to the shot gathers to display only the frequency range that is affected by the noise attenuation

Acknowledgements

We would like to thank PGS for the permission to publish these results.

REFERENCES

Bekara, M., and M. van der Baan, 2010, High-amplitude noise detection by the expectation-maximization algorithm with application to swell noise attenuation: Geophysics, **75**, V39–V49, doi: https://doi.org/10.1190/1.3428749.

Bekara, M., and A. Day, 2019, Automatic QC of denoise processing using a machine learning classification: First Break, **37**, 51–58, doi: https://doi.org/10.3997/1365-2397.n0055.

Farmani, B., and M. W. Pedersen, 2020, Application of convolutional neural network in automated swell noise attenuation: 82nd Conference and Exhibition, EAGE, Extended Abstracts.

Liu, D., W. Wang, W. Chen, X. Wang, Y. Zhou, and Z. Shi, 2018, Random-noise suppression in seismic data: What can deep learning do?: 88th Annual International Meeting, SEG, Expanded Abstracts, 2016–2020, doi: https://doi.org/10.1190/segam2018-2998114.1.

Martin, T., C. Saturni, and P. Ashby, 2015, Using machine learning to produce a global automated quantitative QC for noise attenuation: 85th Annual International Meeting, SEG, Expanded Abstracts, 4790–4794, doi: https://doi.org/10.1190/segam2015-5826237.1.

Richardson, A., and C. Feller, 2019, Seismic data denoising and deblending using deep learning: arXiv:1907.01497, https://arxiv.org/abs/1907.01497v1.

Ronneberger, O., P. Fischer, and T. Brox, 2015, U-Net: Convolutional networks for biomedical image segmentation: arXiv:1505.04597, https://arxiv.org/abs/1505.04597.

Si, X., and Y. Yuan, 2018, Random noise attenuation based on residual learning of deep convolutional neural network: 88th Annual International Meeting, SEG, Expanded Abstracts, 1986–1990, doi: https://doi.org/10.1190/segam2018- 2985176.1.

Zhao, X., P. Lu, Y. Zhang, J. Chen, and X. Li, 2019, Swell-noise attenuation: A deep learning approach: The Leading Edge, **38**, 934–942, doi: https://doi.org/10.1190/tle38120934.1.