Two for one: A joint denoising and segmentation scheme for post-stack seismic data

Claire Birnie and Tariq Alkhalifah [KAUST]

Introduction

Neural networks-based algorithms are beginning to augment our arsenal of processing and interpretation methods, with a number of options being proposed for denoising, first break picking, inversion and horizon picking. One of the big challenges we face is the common requirement of a "ground truth" label for training, where we often do not know the ground truth for field data. For example, as we do not know the true elastic parameters in the subsurface, deep learning approaches struggle to produce high-quality seismic inversion results. Similarly, for denoising, we do not know the true, clean waveform data. The requirement for labelled data within denoising plagues multiple fields from natural images to medical imaging to remote sensing. To tackle this, in 2019 blind-spot networks were proposed which use the noisy input data as the label set, as well as the feature set (e.g., Krull et al., 2019; Batson and Royer, 2019). Birnie et al. (2021) recently illustrated the potential of such self-supervised approaches for the case of suppressing random noise in seismic data.

Despite often being treated as so, consecutive steps in our processing and interpretation workflows are not independent. Previously Ravasi and Birnie (2021), illustrated the power of coupling acoustic impedance inversion with a segmentation procedure, iterating between the two processes. This iterative scheme showed an overall improvement in the quality and resolution of the inversion product alongside providing a macro-structure of the subsurface. Similarly, within the computer vision field, Buchholz et al. (2020) combined the tasks of denoising and segmentation by adding additional segmentation channels to the output of their original denoising network. Not only do these approaches show improved performance in comparison to their sequential counterparts, they can also reduce the computational cost by optimising for both tasks concurrently. In addition to these benefits, with an on production, joint schemes such as these reduce the number of components within our toolbox, aiding debugging and maintenance operations.

In this work we show how coupling a self-supervised denoising scheme with a supervised segmentation scheme, results in an increased performance in both tasks.

Methodology

The loss functions for the individual segmentation and denoising tasks can be represented as,

$$\mathcal{L}_{segmentation} = -\frac{1}{N_s}\sum_{j=1}^{N_s} y^j \log(\hat{y}^j) + (1-y^j)\log(1-\hat{y}^j) \tag{1}$$

$$\mathcal{L}_{denoising} = \frac{1}{N_s N_p}\sum_{j=1}^{N_s}\sum_{i=1}^{N_p} |x_i^j - \hat{y}_i^j|^2 \tag{2}$$

respectively, where the segmentation loss is the standard Binary Cross-Entropy (BCE) Loss with N_s representing the number of training samples, y the true value of the class, and $\hat{y}$ the predicted probability of the class. Whilst the denoising loss is the L2 loss at the 'blind-spots' selected during the denoising procedure, where N_p denotes the number of blind-spots and x is the noisy input data. For more information on the blind-spot denoising, see Krull et al. (2019).

In the joint denoising scheme, the two tasks are evaluated together with a weighting factor, α, that determines which task is favoured during the loss calculation,

$$\mathcal{L}_{Joint} = \alpha\mathcal{L}_{denoise} + (1-\alpha)\mathcal{L}_{segmentation} \tag{3}$$

where we set α to 0.4. Following the approach of Buchholz et al. (2020), the input data is a single channel image containing the noisy data whilst the output data is ordered across the channels, with the first dimension containing the noisy data and the second dimension, the labelled segmentation map.

For comparative purposes, a sequential workflow is also followed by performing self-supervised denoising followed by training a separate model with the denoised results for the segmentation task. The training data and all hyper-parameters are kept consistent between the sequential and joint experiments.

Results

Trained over 50 epochs, Figure 1 illustrates the performance of the joint denoising and segmentation scheme when applied to a post-stack section contaminated with both White Gaussian and spatio-temporally correlated random noise. Within the image domain, the Peak Signal to Noise Ratio (PSNR) gain is 9.54%, compared to the 7.29% of the sequential approach. Whilst, for the segmentation predictions we can clearly see the joint denoising-segmentation scheme provides a much cleaner representation of the true segmentation map. This is also observed in the notable difference between the BCE loss value for the two segmentation predictions.

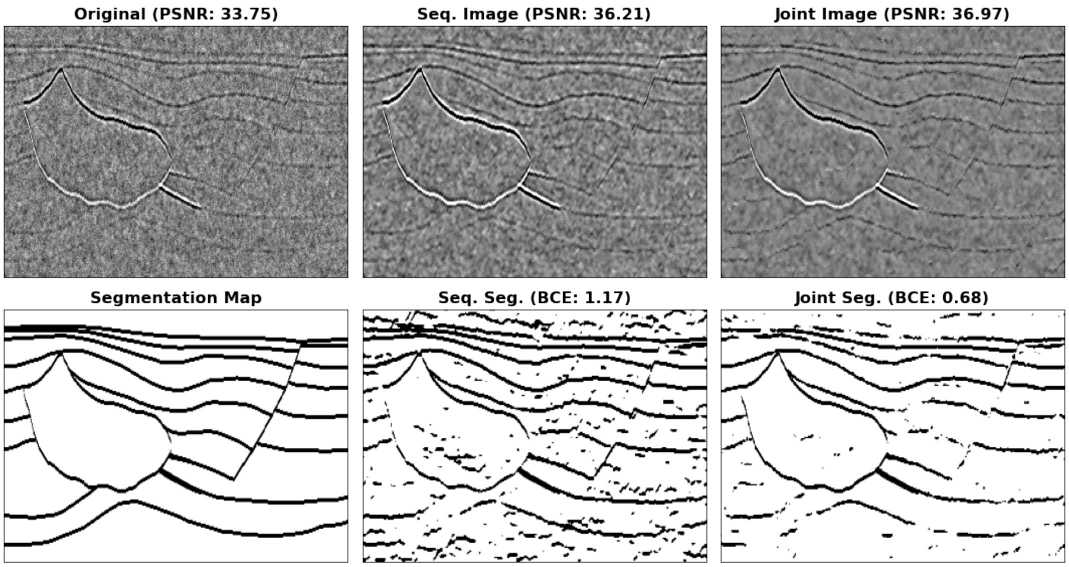

Figure 1: Analysis of the joint denoising-segmentation scheme (right) on synthetic data with correlated random noise, against a sequential denoising and segmentation scheme (middle). The first column represents the original noisy data (top) and the labelled segmentation map (bottom). The corresponding PSNR is included in the titles of the images whilst the BCE loss is included in the titles of the predicted segmentation maps.

Conclusion

Through a synthetic example with correlated noise we have illustrated the benefits of coupling the denoising and segmentation tasks resulting in both an increased performance and decreased computational cost overall. By leveraging blind-spot networks for denoising, the only data label required for training was that of the segmentation map. In this sense, the denoised image can be considered as an effort-free, by-product of the supervised segmentation procedure.

References

Batson, J., and L. Royer, 2019, Noise2self: Blind denoising by self-supervision: International Conference on Machine Learning, PMLR, 524–533.

Birnie, C., M. Ravasi, S. Liu, and T. Alkhalifah, 2021, The potential of self-supervised networks for random noise suppression in seismic data: Artificial Intelligence in Geosciences.

Buchholz, T.-O., M. Prakash, D. Schmidt, A. Krull, and F. Jug, 2020, Denoiseg: joint denoising and segmentation: European Conference on Computer Vision, Springer, 324–337.

Krull, A., T.-O. Buchholz, and F. Jug, 2019, Noise2void-learning denoising from single noisy images: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2129–2137.

Ravasi, M., and C. E. Birnie, 2021, A joint inversion-segmentation approach to assisted seismic interpretation: arXiv preprint arXiv:2102.03860.