Hyper-parameter selection for self-supervised seismic denoising

Claire Birnie, Matteo Ravasi, Sixiu Liu and Tariq Alkhalifah
King Abdullah University of Science and Technology

Representing a key component in any seismic processing workflow, noise suppression has recently experienced renowned interest with a number of new procedures being developed to leverage on the power of deep learning. A common denominator of such techniques lies in the fact that the majority are framed as supervised learning tasks. The requirement for pairs of noisy and clean images for training denoising procedures is however often unfeasible not just in the seismic domain but also across many other scientific disciplines such as computer vision, medical imaging, and microscopy.

To overcome the need for a clean data counterpart, Lehtinen et al. (2018) proposed Noise2Noise, which uses a second noisy image of the same scene as the training label. By assuming that the signal is constant between the two images, a network is trained to learn a mapping between the noisy image pairs. When the noise is independent between the images, it is not possible to learn a mapping of the noise therefore the mapping procedure acts as a natural denoiser. Whilst often possible for natural images, having access to two images with the same signal is still an unfeasible condition for many applications, in particular seismic. Therefore, Krull et al. (2019) proposed Noise2Void (N2V), which works on a single image by utilising so-called blind-spot networks. By assuming that the noise field is isolated and independent at the pixel level, the network uses neighbouring pixels to predict the central pixel's signal contribution. Once again, the portion of the central pixel's value that arises from random noise is unpredictable, therefore the blind-spot approach of N2V proves to be a powerful random noise suppressor.

N2V works by replacing a set of non-adjacent pixels $\mathcal{J}$ in an image x with randomly selected pixels $\mathcal{J}'$ that pertain to the receptive field of the chosen network. The corrupted image becomes the input to a standard NN architecture denoted as f_θ where θ refers to the trainable parameters (in our case a U-Net architecture – Ronneberger et al. (2015)), whilst the original noisy image is used as the target. Finally, contrary to standard NN image processing tasks, the loss function is here only evaluated at the blind-spotted pixels, i.e., those that were corrupted in the input image:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \frac{1}{N_s} \sum_{i=1}^{N_s} ||\mathbb{I}_{\mathcal{J}}(f_\theta(\mathbb{I}_{\mathcal{J}' \to \mathcal{J}}(x_i))) - \mathbb{I}_{\mathcal{J}}(x_i)||_1, \tag{1}$$

where $\mathbb{I}_{\mathcal{J}' \to \mathcal{J}}$ applies the blind-spot operation, $\mathbb{I}_{\mathcal{J}}$ extracts the values of the input image at the pixels $\mathcal{J}$, and N_s is the number of available training samples.

Whilst originally proposed for the suppression of i.i.d. noise in natural images and microscopy data, in this work we show that N2V can be adapted into an efficient suppressor of band-passed random noise in seismic data, i.e. data that has some degree of correlation along the time axis (Figure 1a). This however requires a careful consideration of the algorithm's hyper-parameters and their meaning with respect to the seismic scenario. More specifically, through our experimentation we found that:

- the mean-absolute error (i.e., L1 norm) showed superior performance to the originally used mean-square error (i.e., L2 norm) – see Figures 1c and d;
- a trade-off occurs between learning the signal's full contribution versus beginning to also learn the noise, to balance this the number of epochs is reduced by a factor of 6; and,
- to counteract the reduced number of epochs, a higher percentage of active pixels should be used during training.

The influence of these parameters when using the L1 loss is further illustrated in Figure 1b. Other parameters which have been shown to have less of an influence, such as batch-size, will be detailed further in the presentation. The presentation shall conclude by illustrating how N2V can be successfully applied to field data and how it compares against more traditional suppression procedures such as FX-deconvolution and the Curvelet transform.

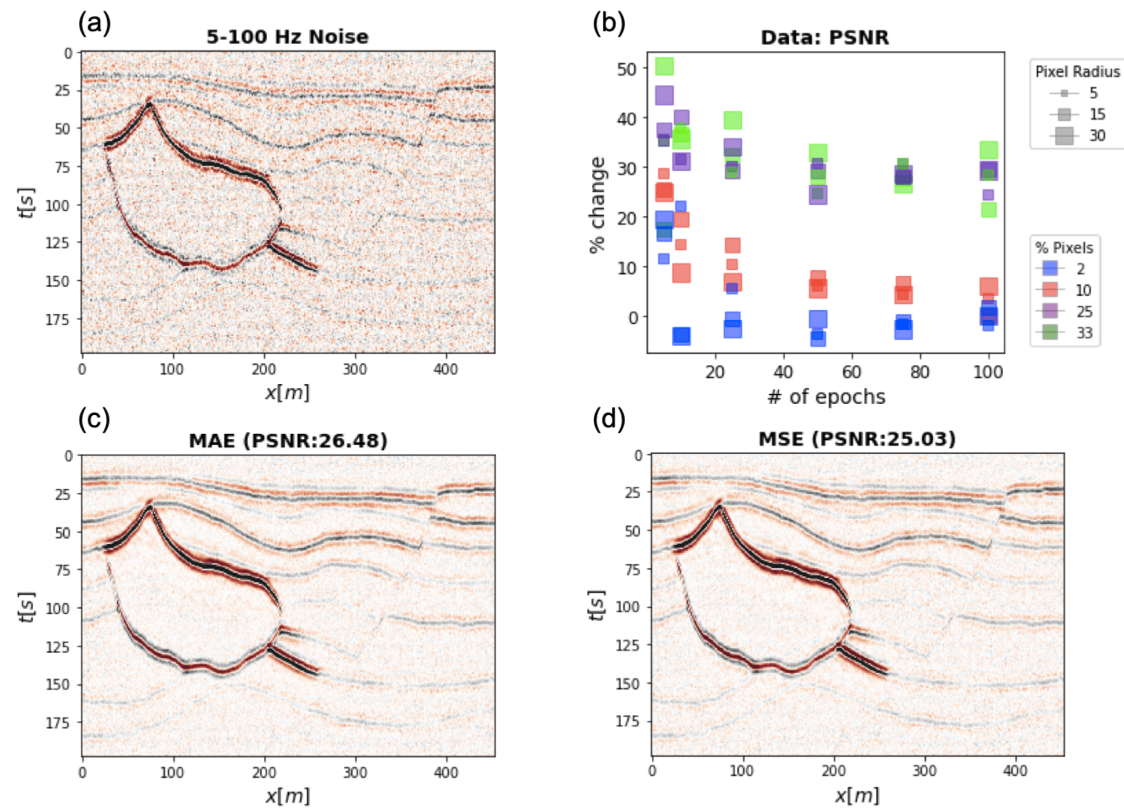

Figure 1: Hyper-parameters analysis in the application of N2V to band-passed seismic noise. (a) Noisy seismic section; (b) influence of the number of epochs, pixel neighbourhood radius, and the percent of active pixels on the PSNR of the denoising product; (c-d) Denoised sections trained with an L1 and L2 norm losses, respectively.

References

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