Stabilizing neural networks using iterated Graph Laplacian - a seismic impedance example

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The acquisition of training data is essential for the success of neural networks. This is a difficult task in many use cases. On the one hand, artificially created datasets can not accurately represent real world scenarios, on the other hand real data is often hard to acquire, noisy, and the ground truth is unknown. This leads to suboptimal reconstruction results due to data shifts or noise.

We propose an Iterated Graph Laplacian algorithm to stabilize the network output and improve the reconstruction. Consider the minimization problem

$$\tilde{x} = \arg\min_{x} \|Ax - y^{\delta}\|_2^2 + \lambda \|L(x')x\|_1 \tag{1}$$

where A is the measurement operator, y^{δ} are the noisy observations, and $L(x')$ is a Graph Laplacian matrix. The corresponding graph is constructed from an initial guess x' obtained by the neural network. As such, the regularizer in (1) is data adaptive and directly depends on the network. We solve (1) using an iterative gradient descend method with x' as starting guess. The result $\tilde{x}$ is less noisy and closer to the ground truth. This process can be iterated by setting $x' = \tilde{x}$ and updating the Graph Laplacian. However, to many iterations will lead to an oversmoothing effect.

Figure 1 demonstrates the method for seismic impedance inversion. We used a state-of-the-art neural network in our approach. The results are clearly improved by the new method. After 100 iterations we see oversmoothing effects.

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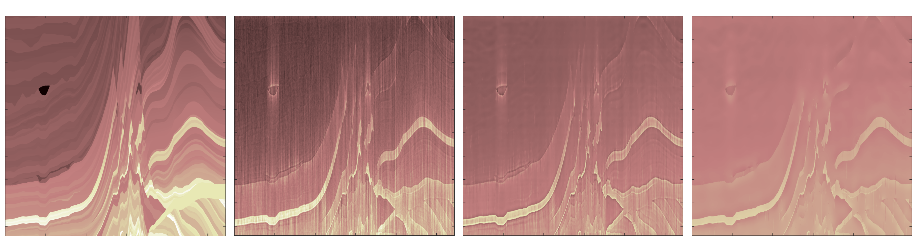

Figure 1: left to right: original impedance data, network reconstruction, denoising using Graph Laplacian after 1 and 100 iterations.