Physics-Informed Machine Learning in the Context of Seismic Imaging

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In 2019, Raissi et al. demonstrated how it is possible to combine machine learning approaches with more traditional physical approaches (Physics-Informed Neural Networks, PINN) [2]. Applications are related to the resolution of partial differential equations (i.e. direct problems) as well as the resolution of inverse problems (determining the main parameters controlling physical phenomena, for example wave propagation, from a set of observations). The later approach will be developed in my thesis.

On one hand, deep neural networks are able in theory to describe any function. Learning is usually a complex task and, in physics-related problems, observations are rare and expensive to acquire. On the other hand, machine learning does not usually consider physics-based equations, a very useful source of information. As proposed in [2], a modified loss function in neural networks contains several terms to ensure that the data predicts the available observations and that laws of physics are fulfilled. This second term can be seen as a regularisation term, essential in practice to avoid any over-fitting in the case of noisy data. Auto-differentiation (back-propagation of the errors), within neural networks, provides a way to estimate the optimal parameters which minimize the loss function.

This approach is very attractive and will be extended and modified to be applicable in the context of seismic imaging. Seismic acquisition consists of activating a seismic source and recording acoustic / elastic waves from the surface. The objective is to determine seismic velocity wave fields and any other parameter controlling the wave propagation within the sub-surface (Figure 1).

In contrast with the first PINN applications, seismic imaging offers some particular aspects to be properly considered:

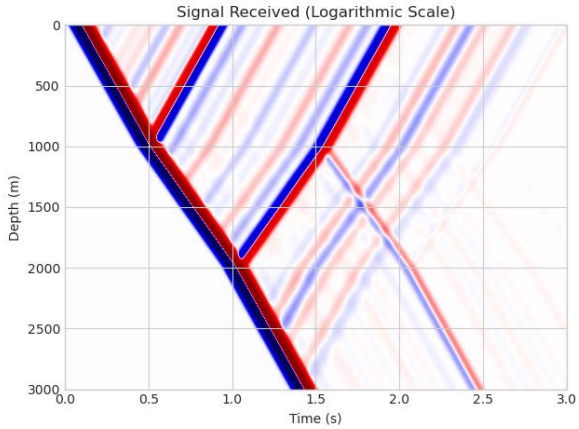

Figure 1: Seismic wave propagation.

- Seismic waves are mainly propagative waves, meaning that the wave field is not so smooth. In order to check that the wave field respects the wave equation, the number of controlling points is a priori much larger than for a diffusive problem with a more regular solution;

- The traditional loss function in seismic imaging contains a large number of local minima. How does the PINN approach behave in this case? How is it possible to take advantage of the frequency content of the data?

- Finally, the number of unknowns (number of parameters to be estimated) is potentially very large. How to play with the neural network to address this issue?

The objective of the PhD thesis is to develop a novel Physics-Informed Machine Learning approach in the context of seismic imaging.

References

[1] Chauris, H., 2019, Full waveform inversion, Seismic Imaging: a practical approach, J.-L. Mari and M. Mendes (Eds.), EDP Sciences, 123–145.
[2] Raissi, M., Perdikaris, P., Karniadakis G.E., 2019, Physics-informed neural networks, J. Comput. Phys. 378, 686–707.