Leveraging Neural Fields for Geophysical Inverse Problems

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Motivation

In computer vision/graphysics, some test-time learning methods such as deep image prior (DIP) and coordinate-based representations have shown that some ML models, without any prior learning, can produce good inversion results.

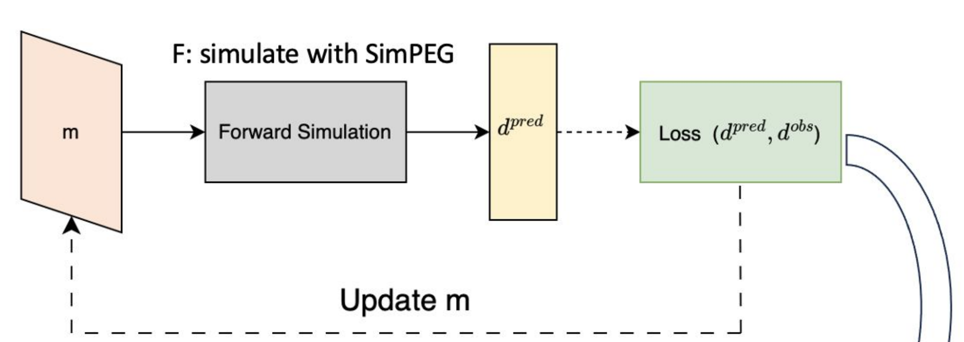
- Neural Fields (NFs) use neural networks (NN) to **map coordinates** to the physical property values
- Solving inverse problems in an **unsupervised manner** is feasible
- Parameterizing the inverse problems in a **continuous setting** naturally introduces **smoothing regularization effects**

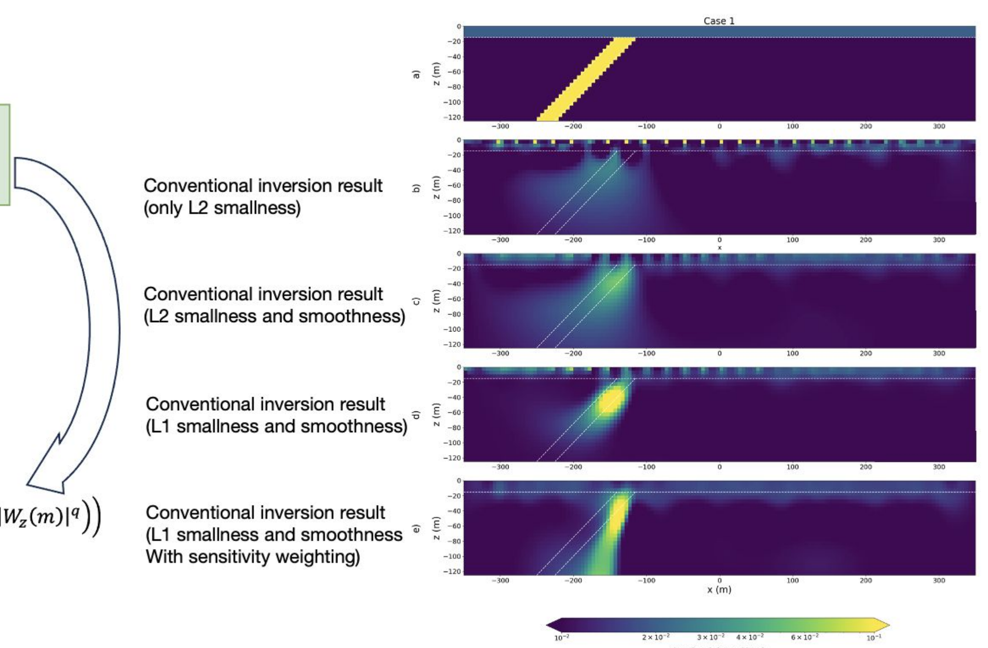
Geophysical Inverse Problems

The goal is to **recover the subsurface models** from the geophysical measurements such as arrival time (seismic tomography inversion) and voltages (direct current resistivity inversion)

- In a conventional inversion, it is common for **unwanted artifacts** (along ray-paths or near electrodes) to be recovered because of the sensitivity.
- The structures tend to concentrate near the electrodes since the sensitivity is high in the shallower region in this problem. These artifacts are geologically unreasonable and may **deteriorate the recovery of structures** in the region where the sensitivity is lower.

Conventional inversion results with different regularization methods



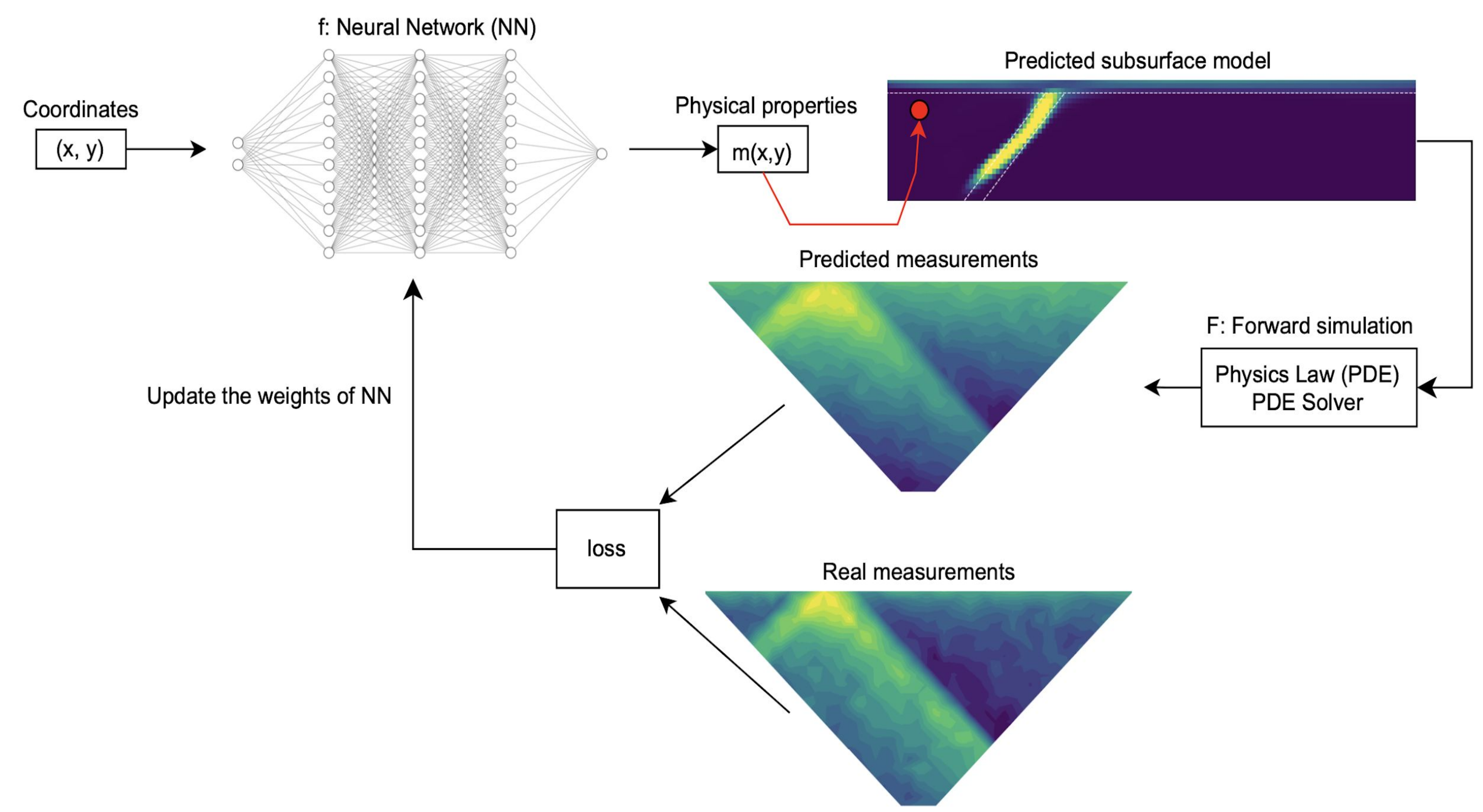


Conventional inversion:

$$\min_m(\phi_d(m) + \beta\phi_m(m)) = \min_m\left(|W_d(F(m) - d^{obs})|^2 + \beta\left(\alpha_s|W_s(m - m_{ref})|^p + \alpha_x|W_x(m)|^q + \alpha_z|W_z(m)|^q\right)\right)$$

Method

Proposed Method flowchart



coordinates coordinates

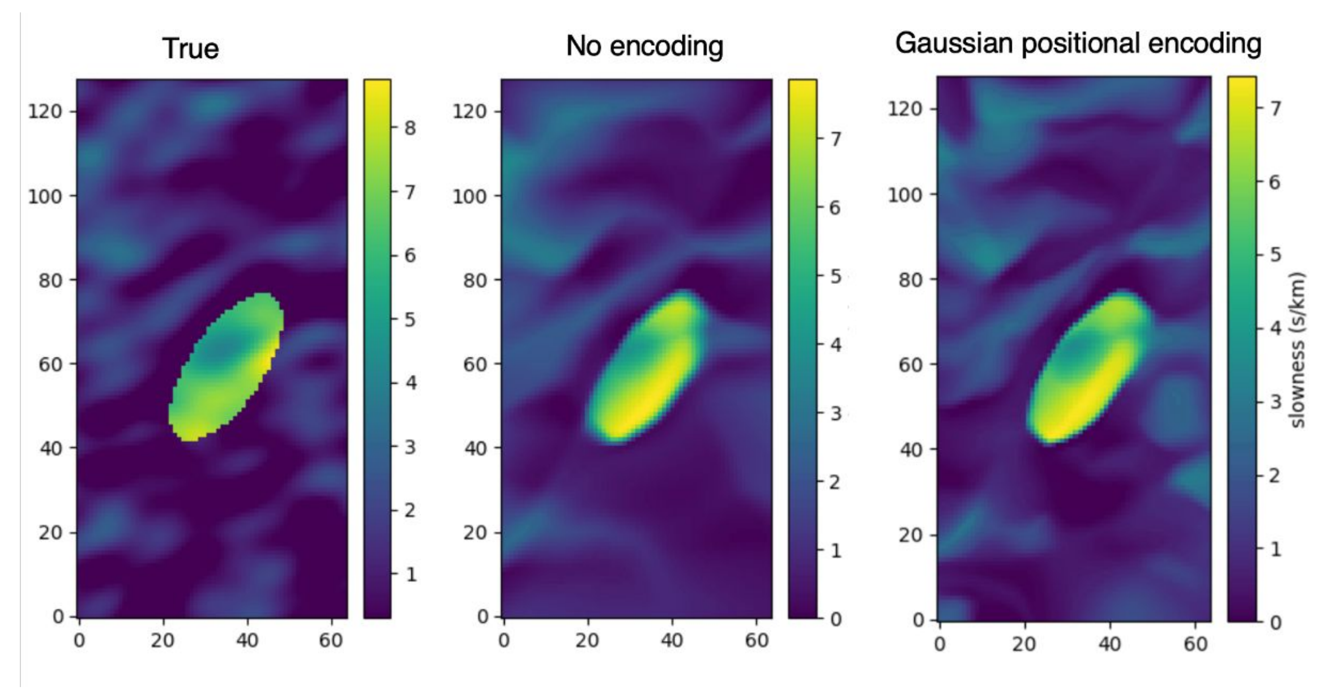
$$\min_\theta (1-\beta)|W_d(F(f_\theta(Z)) - d^{obs})|^2 + \beta|f_\theta(Z) - m_{ref}|^1, \text{ where } Z_{ij} = \gamma(x_i, y_i)_j$$

Positional encoding

- A transform function that maps (x, z) to a higher-dimension space.
- To capture high-frequency variations.
- Attempted: Basis encoding, Fourier positional encoding, Linear positional encoding, Gaussian positional encoding (proposed by Tancik et al.).

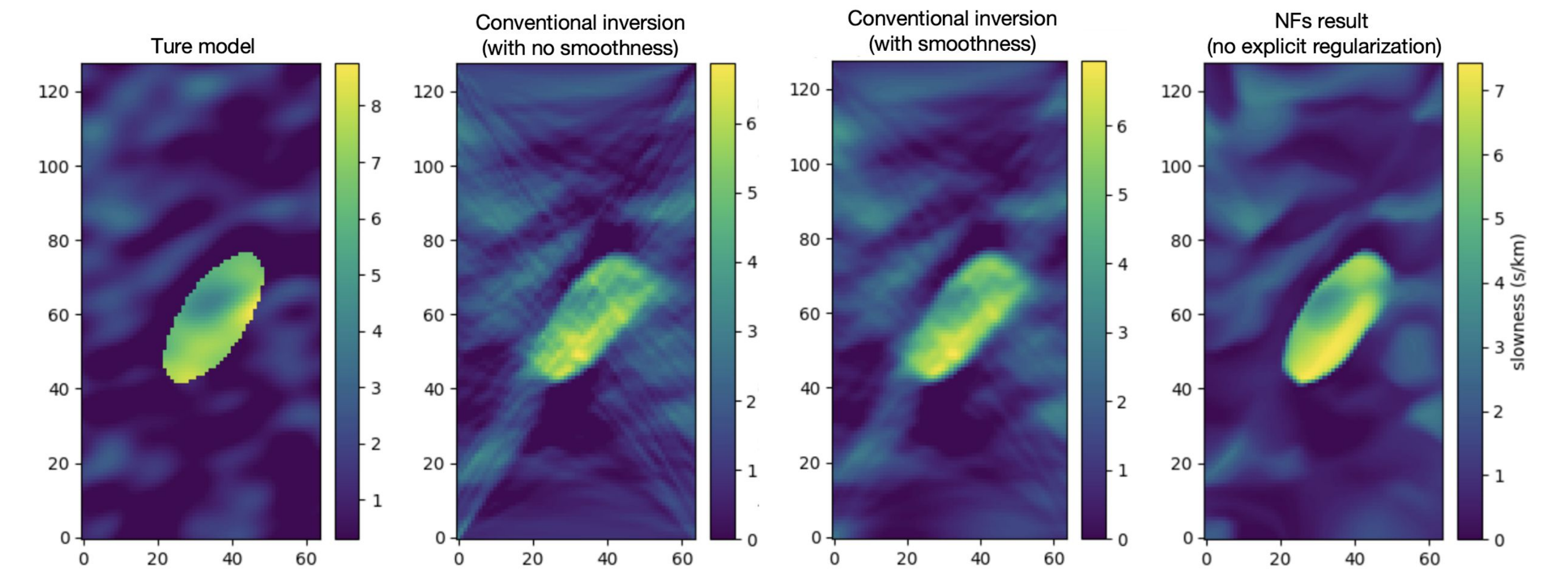
Gaussian positional encoding

$$\gamma(\mathbf{x}) = [cos(2\pi B\mathbf{x}), sin(2\pi B\mathbf{x})], \qquad \text{where } B \in R^{\hat{h}\times w}(h = 2\hat{h}).$$

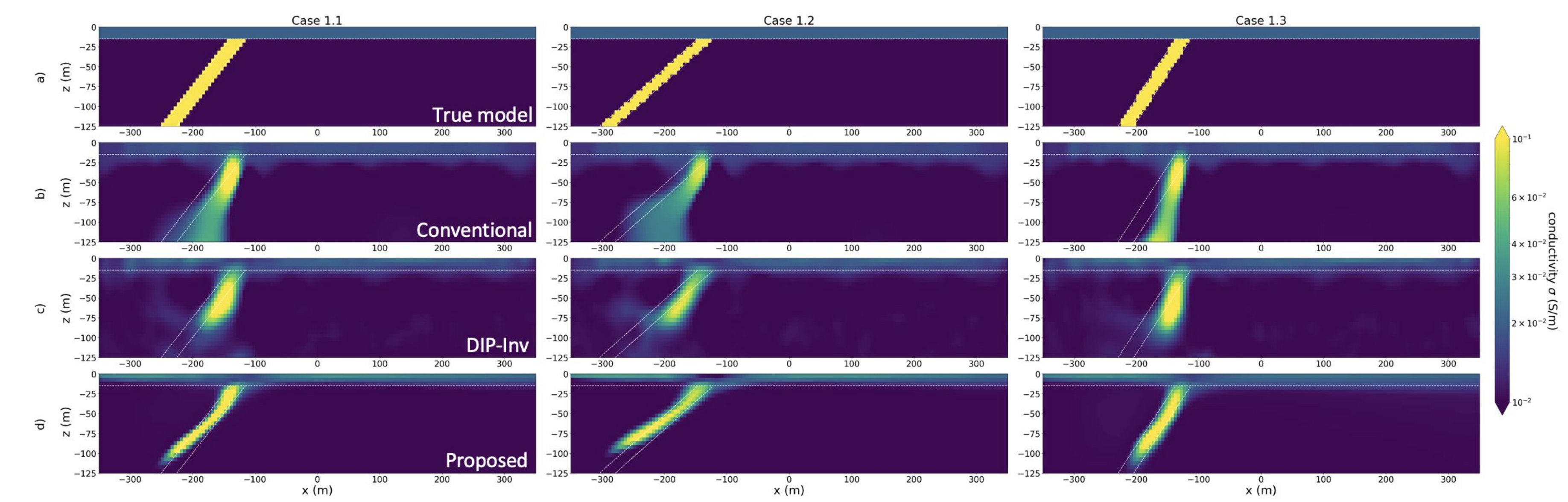


Results

Seismic cross-hole tomography inversion



Direct current resistivity inversion



By searching over a higher dimensional space using a coordinate-based neural networks, the geophysical inverse solutions can overcome the problem of predicting too many unwanted artifacts due to sensitivity.

- The seismic cross-hole tomography inversion and direct current resistivity inversion with/without heterogenous background are tested.
- The proposed method has a better recovery of the main targets

Future work: Need to **further explore the source of implicit regularization**: If we replace the NN in the proposed method by some other models but still search over a higher dimensional space, will we get comparable results? If not, what properties of the NN imposed this useful implicit regularization?

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Preprint can be found in https://anna1963.github.io/ once available or emailing the authors.

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