On the use of Physics Informed Neural Networks (PINNs) to solve inverse problems in heterogeneous materials

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1. INTRODUCTION & OBJECTIVE

Inverse problems are ubiquitous in subsurface mechanics, spanning applications from groundwater flow to geophysics. These problems involve deducing hidden material properties or sources from observed data. Traditional numerical methods [1-5] do not always yield expected results when applied to inverse problems due to several reasons such as, their sensitivity to noise in observed data, ill-posedness of inverse problems, poor convergence for nonlinear problems, and their inability to efficiently incorporate prior knowledge.

Physics Informed Neural Networks (PINNs) have emerged as a promising alternative for such problems. In their pioneering work, Raissi et al. [6] provided a PINNs framework that demonstrated good potential in addressing ill-posed inverse problems. The key idea behind their method is the integration of physical principles into the loss functionals that are optimized by neural networks. Although Raissi et al. focused on determining constant system parameters, subsequent research explored the determination of material properties that exhibit a spatial variation. However, PINNs in their most vanilla form are ineffective in capturing abrupt variation in the solution fields, like jumps in the field and its gradient at material interfaces in both forward and inverse problems.

For problems where the domain includes material interfaces, an Interface PINNs (I-PINNs) approach has been proposed recently [7-8]. The key idea of this method is that for distinct subdomains separated by material interfaces, separate neural networks must be utilized so that discontinuities in solution fields and their gradients are accurately captured. The distinguishing characteristic of I-PINNs is in the selection of distinct activation functions for each material region while maintaining consistency in all other parameters that define the neural network. This framework was initially crafted to proficiently address forward interface problems, which pose challenges for conventional PINNs. However, the application of I-PINNs to inverse problems with material interfaces is yet to be explored. As such, we study the application of I-PINNs to inverse problems.

2. RESULTS & HIGHLIGHTS OF IMPORTANT POINTS

In this work, we consider the values of field variables (such as temperature, displacements, and stresses) to be given at certain points in the computational domain and seek to deduce the material property distribution throughout the domain. We consider problems where the material properties exhibit a sharp variation across a material interface. We intend to explore two situations: one where the interface's location is known a priori, and another where the location is unknown. We create a new neural network to determine the variation of system parameters across the domain using the same method as I-PINNs, which discretizes the domain into as many neural networks as computational subdomains. When determining the properties of a material at a known interface position, we employ distinct neural networks for each domain while maintaining the same weights and biases. However, we utilize a single neural network to ascertain the material qualities in the scenario when the position of the interface is unknown. The location of the interface is inferred by looking for abrupt changes in the data. The proposed formulation is compared with the more conventional PINNs approach, and their relative strengths and weaknesses are identified in terms of cost and accuracy.

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