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Physics-Informed Neural Networks for Material Parameter Identification in Quasi-Real Problems

MSc. Ing. Christian Díaz-Cuadro*[1] and MSc. Ing. Mauricio Vanzulli Pena[1]
[1]Universidad de la república - Uruguay
cdiaz@fing.edu.uy

Abstract

Physics-Informed Neural Networks (PINNs) have emerged as a promising approach for solving scientific and engineering problems that involve partial differential equations or physical constraints. PINNs are a type of Neural Network (NN) that incorporates physical laws or governing equations into its learning process. By combining the strengths of deep learning and physics-based modeling, PINNs can learn complex patterns and relationships from data while simultaneously satisfying the physics of the problem.

In this work, we explore the capabilities of PINNs to solve physical problems while identify material properties simultaneously. The validation example is a three-dimensional rectangular prism with a Neo-Hookean material, submitted to a compressive load. In this example, the estimated parameters were the first and second Lame's parameters. The reliability of the results was assessed by comparing them against the ground truth displacement data, which were obtained from the analytical solution. These values were used as input to evaluate the loss data function, while the remaining loss functions were derived from the physics of the problem.

With this validated PINN, two more realistic cases were studied. The first case attempts to simulate a simplified femoral cartilage, which is loaded with a known force, resulting in the deformation of the cartilage. The second case aims to simulate a breast undergoing compression in a mammography study, where the compression force is also known. Both cases were simulated using FEBio software to obtain displacements data.

The PINN, as implemented in the validation example, failed to accurately identify the material parameters for realistic cases. Consequently, the incorporation of new strategies into the PINN are studied. A loss function was implemented to balance the forces on the loaded faces based on the integral of the stress tensor. Additionally, independent networks were used for displacements and the parameters to be identified. Alongside this, a regularization loss function was implemented to incorporate prior knowledge about the material parameter constraints.

The results of this study suggest that PINNs have the potential to be an effective tool for both material identification problems and real-time prediction of the physical solution. However, it is important to note that further research and dedicated efforts are required to fully explore and harness the capabilities of PINNs in these domains.