Physics-informed neural networks with trainable weighted

loss using uncertainty: Applications to inverse analysis of

tunnel rings

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ABSTRACT

Recently, a class of machine learning methods called physics-informed neural networks (PINNs) has been proposed and gained great prevalence in solving various scientific computing problems. This approach enables the solution of partial differential equations (PDEs) via embedding physical laws into the loss function of neural networks. Many inverse problems can also be tackled by simply combining the observational data from real life scenarios with existing PINN algorithms. In this paper, we present a multi-task learning method to improve the training stability of PINNs for linear elastic problems, and the relative weights of different loss terms can be updated during back-propagation. The results of our benchmark problem show that the unbalanced gradients between tasks can be alleviated by introducing homoscedastic uncertainty as a basis for weighting losses. Moreover, we further demonstrate an application of PINNs to a practical ill-posed problem in tunnel engineering: prediction of external loading distributions of tunnel rings based on a very limited number of displacement monitoring points. To this end, we manage to reconstruct the whole displacement field with the help of the Kriging method, and then the reconstructed data are integrated into the loss function of PINNs to predict the external loads. Our results show that, although the reconstructed displacement field generated from gappy measurements is accompanied by noise, sufficiently accurate results can still be obtained from the PINN model due to the regularization of physics laws, which exhibits better robustness compared to traditional analysis methods.

**Key words:** Physics-informed neural networks (PINNs), Multi-task learning, Kriging method, Inverse analysis, Tunnel engineering