Abstract

Modeling of complex spatial structures using physics-informed neural network

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This study explores issues of modeling complex spatial structures appeared in various physical fields using Physics-informed Neural Network (PINN) where physical laws are integrated into deep learning model to enhance its performance. In this study, PINN models have been developed for the following two problems: non-invasive analysis of ancient documents through "virtual unfolding" and elastic analysis of plates with holes. The combination of CT imaging applications and the PINN deep learning model allows for high-precision text extraction from unopenable ancient documents by fitting the spatial structure of the CT data using deep learning models. Facing the requirements of computational resources for elastic analyses of plates with holes in complex situations, the use of PINN provides an advanced solution to quickly fit complex structures and predict stress distributions, even with limited data. This dissertation demonstrates the potential of PINN as a possible alternative while highlighting the shortcomings of traditional computational methods.

Chapter 1 begins with an introduction to the importance of accurate modelling of complex spatial structures in various scientific and engineering fields. Modelling is key to understanding and analysing the physical world. Traditional modelling methods often fail to achieve the expected results due to the fact that they can only handle simple objectives and the limitations of computational power. In this chapter, PINN model is explained, which is a novel deep learning model that is widely considered to be an effective way to address the above mentioned problems. The overviews of the two problems explored in this study are then described: One is the problem of extracting information from ancient documents, in a non-invasive way, using CT images. The other problem is the problem related to stress analysis of plates with holes, which has not been done well, since traditional methods are not able to analyse complex situations quickly. Related works are also explained in this chapter, which clarifies the current research problems and presents motivation for methods to be presented in this dissertation.

Chapter 2 introduces a new method for extracting pages from 3D booklet CT images. The proposed method directly fitting the 3D structure of the booklet by manually annotating and solving Laplace equation, overcoming the limitation of traditional 2D image detection which cannot be directly modelled on 3D. Specifically, the traditional methods all process 2D CT images by segmenting the pages of the booklet in one plane and then simply combining them in another dimension. This kind of method does not guarantee the

consistency of three-dimensional structure. The proposed method aims to directly modelling the booklet in 3D, by manually annotating it to roughly describe the 3D structure of the pages, and then using the annotated data to generate a scalar field using a 3D Laplace equation. The generated scalar field can be interpreted as a one representing 3D spatial structure of the booklet. The isosurfaces in the scalar field can be considered as the faces of the page, and the page information can be extracted by directly extracting the isosurfaces. A sample booklet has been prepared for experiments in this chapter. The page information extracted in the experiment has shown to be correct, which verifies the effectiveness of the proposed method and gives motivation for considering a more sophisticated method using deep learning instead of the Laplace equation fitting process.

Chapter 3 introduces a PINN-based page extraction method based on the foundation presented in Chapter 2. By combining PINN, the proposed method can adapt more cleverly to the complex structure of 3D booklet page distribution. Specifically, the idea of the proposed method originates from the principle of universal approximation, which holds that a neural network with a certain depth can approximate any continuous function. This is the theoretical basis for using deep learning models instead of Laplace equation. This does not mean the Laplace equation is useless for modeling. Physical law is still important for modeling spatial structure. PINN model provides us with a way to combine the laws of physics on the basis of deep learning techniques, and we cleverly use the PINN model that combines Laplace equation, successfully replacing the method in Chapter 2. Here the PINN model generates scalar field by fitting annotation data. We used the same CT image data and annotation data as in Chapter 2 for comparative experiments on page extraction. Experimental results shown in this chapter indicate that the PINN method can extract page information with higher accuracy for multiple sets of booklet samples, which provides a new feasible solution for exploring the hidden page information in ancient books by non-invasive CT scanning.

In Chapter 4, the analysis of stress distribution in plates with holes, another important structural modelling problem in materials engineering, is discussed. As a replacement for the traditional finite element method, a PINN-based surrogate model is proposed in this chapter. In general, traditional calculations require a lot of time and experience. At the same time, the commonly used finite element method is unable to model complex problems in real-world situations. Even the simple problem of stress distribution in a plate with holes requires significant time and computational resources to re-model when changing the size or position of the holes. To address this problem, the PINN-based surrogate model has been proposed which is supposed to efficiently and accurately predict stress distribution for plates with a hole of various size and position. Due to the properties of PINN, it is possible to train a PINN-based surrogate model that can predict the stress distribution in any case using only a small amount of simulated data, in addition the physical laws contained in PINN provide physical consistency in the predictions. This feature can greatly improve the engineering design process and optimize workflow.

This chapter additionally explains the shortcomings of PINN when faced with certain situations, such as the lack of accuracy in the details of the prediction results for changes in hole position, which shows that PINN which is a newborn deep learning model still needs to be optimized for specific situations.

The final chapter summarizes the insights gained throughout this study, positioning PINN as a powerful model, indicating to the potential of PINN by constructing models for analyzing complex spatial structures appeared in two specific problems. The chapter acknowledges the limitations of the current research, such as the fact that page extraction cannot be fully automated still requiring manual annotation of the data, the PINN is not able to predict the positional variations of holes in a plate with high accuracy, and the exiting PINN model is not further optimized for the particular task. Nevertheless of this problem, the dissertation states that PINN is promissing when considering further expansion of the research. The dissertation concludes with requirements for further research efforts aimed at fully utilizing PINN's capabilities to further extend the application and enable us obtaining useful models.

In summary this dissertation demonstrated the versatility and effectiveness of PINN in the modelling of complex spatial structures through two specific case studies, showing that computational science is shifting towards the integration of physical models with machine learning. In particular, PINN is promissing as an alternative to traditional methods in real-life complex situations where applicability is currently limited. The potential of this newborn deep learning model is huge but has not yet been fully explored.