An Architecture for Cultural Heritage Maintenance based on Data-Driven and Physics-Based Approaches

Francesco Colace
DIIN
University of Salerno
Fisciano (SA), Italy
fcolace@unisa.it

Dajana Conte
DIPMAT
University of Salerno
Fisciano (SA), Italy
dajconte@unisa.it

Giovanni Pagano
DIPMAT
University of Salerno
Fisciano (SA), Italy
gpagano@unisa.it

Beatrice Paternoster
DIPMAT
University of Salerno
Fisciano (SA), Italy
beapat@unisa.it

Federico Pichi
MathLab
SISSA
Trieste, Italy
fpichi@sissa.it

Gianluigi Rozza
MathLab
SISSA
Trieste, Italy
grozza@sissa.it

Carmine Valentino
DIIN
University of Salerno
Fisciano (SA), Italy
cvalentino@unisa.it

***Abstract*—Applying novel technologies to the cultural heritage field allows its enhancement by improving the user's cultural experience or guaranteeing a better preservation of cultural assets. This work introduces an architecture for cultural heritage maintenance based on data-driven and physics-based approaches. In particular, the architecture is composed by four layers taking care of the acquisition of data from sensors, the management of three-dimensional models, the storage of collected data, its elaboration, and the provision of services to expert users in the cultural heritage maintenance field. The elaboration phase exploits 3D geometries related to cultural assets and analyzes mathematical models based on Partial Differential Equations by employing collected data and Physics-Informed Neural Networks (PiNNs) or Finite Element Methods (FEM) strategies. In particular, the application of PiNNs, based on the package PINA, improves the efficiency of the architecture.**

***Index Terms*—Cultural Heritage, Physics-Informed Neural Networks, Partial Differential Equations, Maintenance**

I. Introduction

Cultural heritage represents a significant testing field for novel technologies by improving the enjoyment of cultural heritage and conserving cultural assets [1]. In particular, cultural heritage preservation requires the application of several technologies related to the digitalization of assets, their monitoring, and prediction techniques for understanding and preventing possible damages.

Therefore, this work aims to introduce an architecture for cultural heritage maintenance based on the analysis and the acquisition of 3D models of cultural assets, the integration of sensors for the comprehension of effects related to their environment, and the exploitation of mathematical models to make reliable prediction about future possible deteriorations.

The architecture consists of four functional layers: the Data Acquisition Layer, the Knowledge-Base Layer, the Inference Engine Layer, and the Application Layer. The Data Acquisition Layer exploits the Internet of Things [1] for acquiring data related to the environmental situation in which the cultural assets stay. Therefore, the layer requires several typologies of sensors to obtain temperature, air quality, movements by accelerometers, and all environmental conditions that can affect indoor or outdoor assets. The Acquisition Layer focuses on integrating 3D models related to cultural assets. This layer combines classical mesh-based approaches with mesh-free ones to guarantee architectural flexibility. The Knowledge-Base Layer takes advantage of a database storing structured and semi-structured data coming from sensor acquisitions together with significant information about the models. Moreover, this layer includes pre-processing strategies for preparing data for the elaboration phase. The Inference Engine Layer presents The Model Elaboration Module, the PINA Module, and the FEM Module. The Model Elaboration Module elaborates on information from the 3D geometries for acquiring points related to the analysis through mathematical models. This Module exploits classical mesh-based approaches by automatically generating a discrete representation of the cultural asset. This mesh constitutes the computational domain on which the PINA Module or the FEM Module will elaborate the predictions. Moreover, the Model Elaboration Module also integrates approaches for avoiding the creation of cultural asset mesh, speeding up the elaboration process regarding the PINA Module. The PINA Module employs Physics-Informed Neural Networks (PiNNs) [2], an unsupervised Scientific Machine Learning approach to solving Partial Differential Equations (PDEs). This Module takes advantage of the package PINA [3]. In particular, PiNNs exploit the ability of neural networks as universal approximators for identifying the function able to minimize the residual, boundary conditions, and initial conditions related to the PDE analyzed. In the literature, there is a significant interest in these approaches and a widespread effort for improving these solvers. Specifically, PiNN requires improvements for managing two issues: unbalanced losses [4] and causality [5]. The loss imbalance refers to cases in which the magnitude of losses for reducing residual, boundary conditions, and initial conditions are different, compromising the ability of the Neural Network to learn uniformly. Therefore, the PINA package includes several solvers to overcome this specific issue. Instead, the improvement of causality allows PiNN to handle time-dependent problems more consistently. The proposed architecture improves this issue by applying a novel approach by including numerical methods to semi-discretize the problem in time [6]. In particular, the proposed approach presents several advantages concerning the classical Time-Discrete PiNNs approaches. Finally, the FEM Module represents an alternative to the PINA Module and exploits the mesh created by the Model Elaboration Module for solving the PDE. The application of the FEM Module is less efficient with respect to the PINA Module, but it benefits from more interpretable numerical investigations. The last layer is the Application Layer, which allows the introduction of the elaborations made by the Inference Engine Layer to expert users by visualizing simulations.

REFERENCES

[1] Colace, F., Conte, D., Frasca-Caccia, G., Lorusso, A., Santaniello, D., & Valentino, C. (2023, June). An IoT-based framework for the enjoyment and protection of Cultural Heritage Artifacts. In 2023 IEEE 24th International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM) (pp. 489-494). IEEE.

[2] Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 378, 686-707.

[3] Coscia, D., Ivagnes, A., Demo, N., & Rozza, G. (2023). Physics-informed neural networks for advanced modeling. Journal of Open Source Software, 8(87), 5352.

[4] Saadat, M. H., Gjorgiev, B., Das, L., & Sansavini, G. (2022). Neural tangent kernel analysis of PINN for advection-diffusion equation. arXiv preprint arXiv:2211.11716.

[5] Wang, S., Sankaran, S., & Perdikaris, P. (2024). Respecting causality for training physics-informed neural networks. Computer Methods in Applied Mechanics and Engineering, 421, 116813.

[6] Colace, F., Conte, D., Pagano, G., Paternoster, B., & Valentino, C. (submitted). Step-by-step time discrete Physics-Informed Neural Networks with application to a sustainability PDE model