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PROCEEDINGS

High-Resolution Flow Field Reconstruction Based on Graph-Embedding Neural Network

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ABSTRACT

High resolution flow field results are of great significance for exploring physical laws and guiding practical engineering practice. However, traditional activities based on experiments or direct numerical solutions to obtain high-resolution flow fields typically require a significant amount of computational time or resources. In response to this challenge, this study proposes an efficient and robust high-resolution flow field reconstruction method by embedding graph theory into neural networks, to adapt to low data volume situations. In the high resolution flow field reconstruction problem of an NS equation, the proposed model has a lower mean squared error on the test set compared that of physics-informed neural network and classical neural network models. Among them, the low resolution data comes from 0.1% high resolution data. And the predicted results of the proposed model at time 10s is also closest to the direct numerical simulation results. The proposed model exhibits great advantages in robustness.

KEYWORDS

Flow field reconstruction; graph embedding; neural network; high resolution prediction

The flow field exists in all aspects of life and production. To explore the flow phenomenon, high-resolution (HR) data are generally needed. The acquired HR flow fields are important for guiding production and mechanism research. However, obtaining HR flow fields from experiments or simulations is generally time and resource-consuming. When the cost of these resources decreases, only low-resolution (LR) data can be acquired, which may not meet the research requirements. Studying how to reconstruct HR from LR data has become a worthwhile research topic.

The early research on flow field prediction was mainly based on the experimental methods. As a consequence of imperfections of measuring devices or instability of the observed scene, the obtained images may full of noisy and flawed in spatial and temporal resolution in the experimental environment. To address this challenge, direct numerical simulation (DNS) methods are adopted for the flow field prediction. The HR results obtained through DNS generally ask for high mesh refinement, but the calculation resource and time of numerical simulation may grow exponentially.

Considering the computation expense of the numerical simulations, one alternative is the mathematical approximation, i.e. surrogate models. The extraordinary capability of surrogate models is to extract deeper features and representations of data that could not be easily explored via the conventional shallow techniques in machine learning. Therefore, the surrogate models can capture the non-linear relationship between the variables of the flow field, and recover the HR from LR. Besides, these models are much faster than the numerical simulations in the prediction process and are implemented as a trade-off between precision and computation time. However, such surrogate models lack a physical explanation and usually require additional data from other temporal-resolved measurements to train the model. At the same time, physics-informed neural networks have been used for HR flow field reconstruction by combining the prediction error of the NN with the residual of the PDE loss function. Despite these deep models performing well in the precise prediction for the flow field, the current success of deep learning hinges on the ability to learn high-capacity models from large-scale data.

Ideally, the diverse experimental data and the DNS results promote a dramatic increase in data collection. This can majorly contribute to the development of a high-capability deep learning model in tandem with incremental data. However, in practical situations where data is scarce and boundary conditions are incomplete, the performance of the above methods also deteriorates. To address the above challenges, this research proposes a novel graph-embedding neural network (GENN) for HR prediction, as shown in Figure 1.

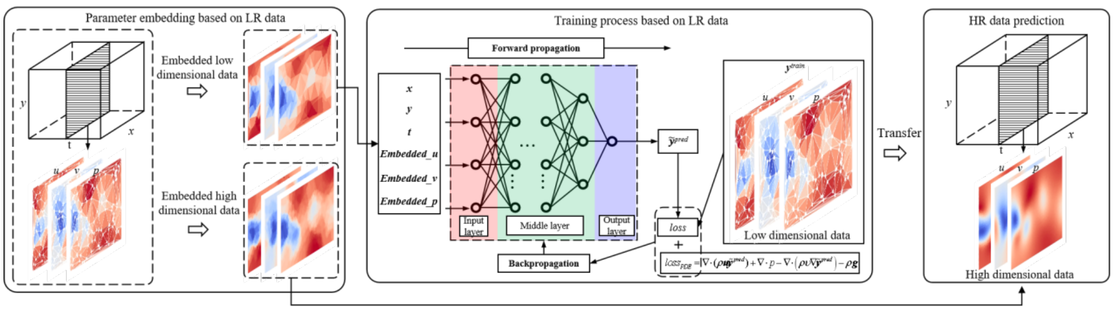
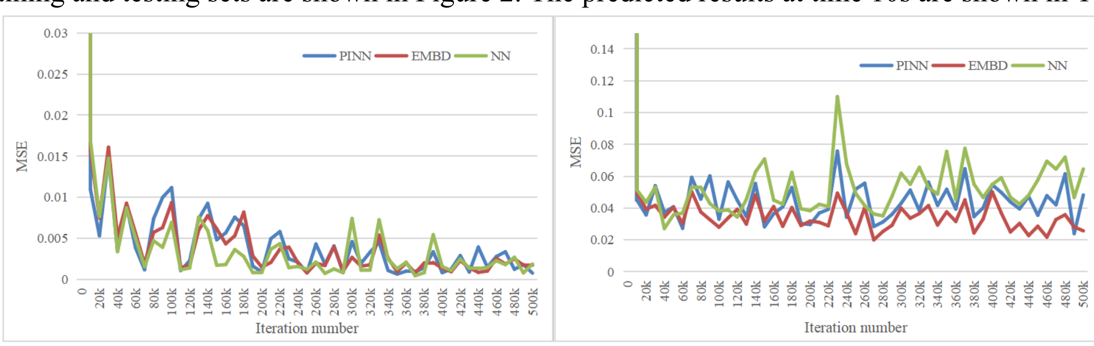


Fig. 1. GENN trained on LR data and used for HR data prediction

The performance of the proposed model is further compared with classic NN and PINN for an Navier-Stokes (NS) HR fluid reconstruction problem based on the LR results. This model is derived from LR flow fields and migrated to predict HR flow fields. For these models, the training set consists of randomly selecting data from 5 nodes (including pressure, x-direction flow velocity, and y-direction flow velocity) from the DNS results (5000 nodes) at each time layer. It can be seen that this study used a very small amount of data to validate the performance of the model (only 0.1% of the data was extracted from the DNS results).

The number of iterations, learning rate, node numbers of each layer, and number of hidden layers for the above model are 5 million, 0.001, 20, and 8, respectively. The prediction curves of the above model on the training and testing sets are shown in Figure 2. The predicted results at time 10s are shown in Table 1.

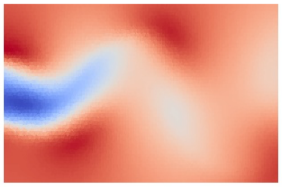
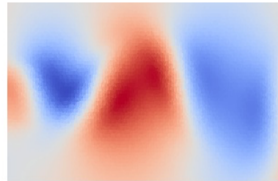
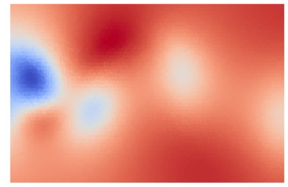
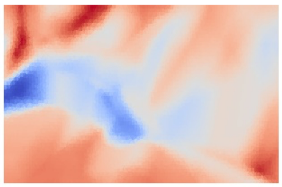
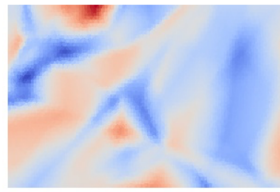
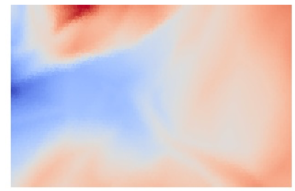
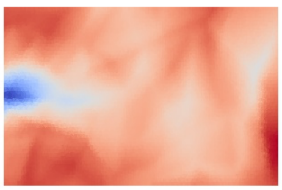
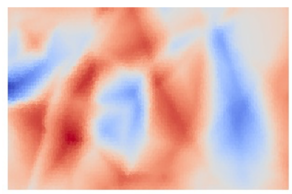
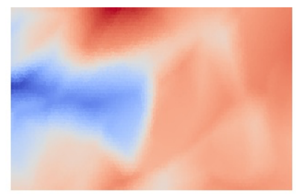
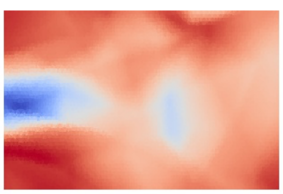
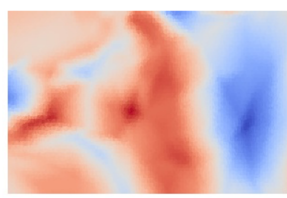
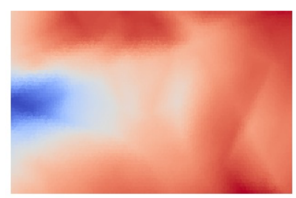


(a) Training set (b) Test set

Fig. 2. The MSE curves of different models for the training set and test set

Table 1. HR prediction results of different models at time 10s

	x-direction flow velocity	y-direction flow velocity	Pressure

DNS			
NN			
	Error:0.152	Error:0.266	Error:0.060
PINN			
	Error:0.130	Error:0.206	Error:0.057
EMNN			
	Error:0.117	Error:0.159	Error:0.048

Compared with other models, the proposed EBNN model has the highest prediction accuracy in reconstructing high-resolution data, even with a coarse to fine resolution ratio of 0.1%. Which means that the proposed model has high prediction accuracy in HR flow field prediction problems.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.