Water Physics Simulation Using Fourier Neural Operators

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How can Fourier Neural Operators (FNOs) help us solve complex water simulations?

Introduction

This research leverages Fourier Neural Operators (FNO) to create faster, high-fidelity water simulations, enabling real-time fluid dynamics modelling for engineering, graphics, and environmental applications.

What are FNOs?

- Operates in the frequency domain, making it highly efficient for Partial Differential Equation (PDE) Solutions.
- Generalizes well across different resolutions and boundaries.
- Outperforms CNNs and Graph Neural Networks (GNNs).

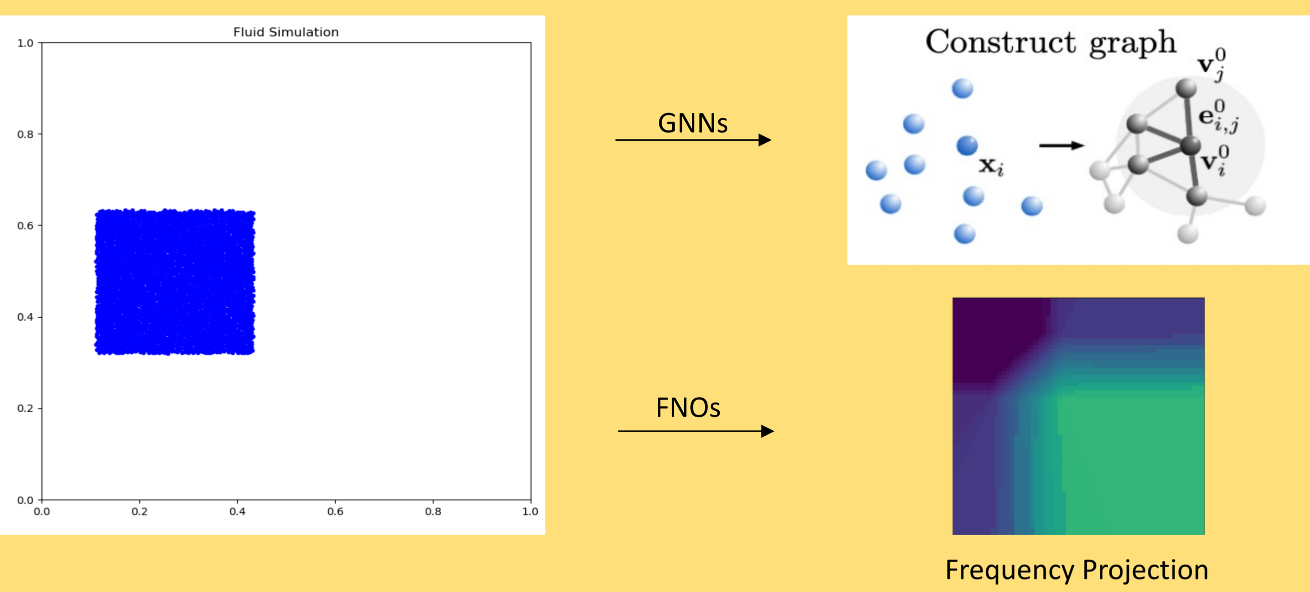

Fig 1: Comparison of GNNs vs FNOs initial frame processing

References

[1] - Learning to Simulate Complex Physics with Graph Networks
Alvaro Sanchez-Gonzalez, Jonathan Godwin, Tobias Pfaff, Rex Ying, Jure Leskovec, Peter W. Battaglia

[2] - Fourier Neural Operator for Parametric Partial Differential Equations
Zongyi Li, Nikola Kovachki, Kamyar Azizzadenesheli, Burigede Liu, Kaushik Bhattacharya, Andrew Stuart, Anima Anandkumar

Methodology

1. Data Source: This research used Deepmind's WaterDrop-XL dataset [1]. The data contained position, velocity, acceleration and time features of each particle.
2. Temporal Sampling: A fixed length temporal window was defined to construct sequences for the Model. Each sample consisted of T past interpolated frames as input and T+1 th frame as target output.
3. Model Architecture: A FNO2D model [2] was chosen for this research to learn temporal dynamics over the interpolated position fields. The model maps a spatio-temporal input sequence to the next predicted position field.

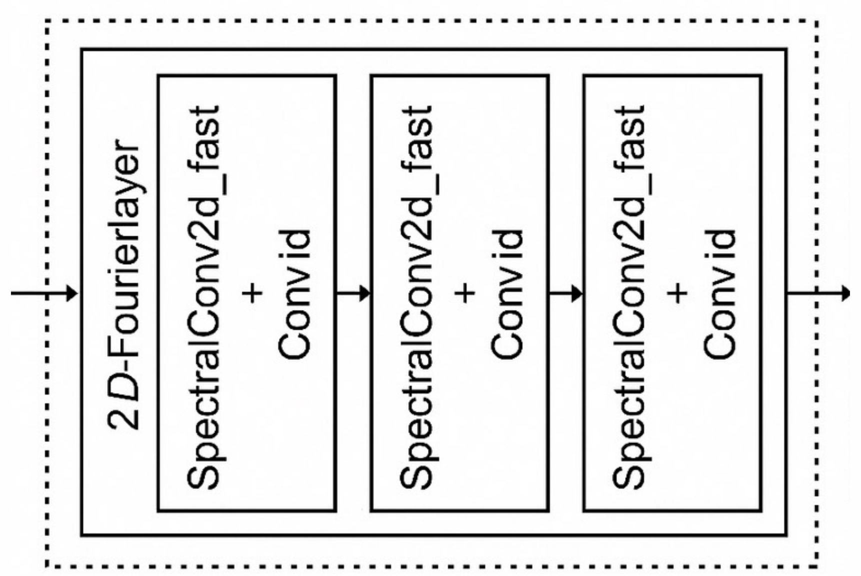

Fig 2: FNO2D model architecture

4. Training Objective: The model was trained to minimize the mean squared error between predicted and ground-truth position fields on the grid, encouraging accurate recovery of underlying physical dynamics.

Results

The figure 3 shows a comparison between the predicted particles (orange) and the true particles (blue) at different frames. Our model effectively captures the fluid boundary and dynamics over time.

Quantitative Metrics

Fig 4 shows the temporal error progression

- Mean Squared Error (MSE): 0.0008
- Mean Absolute Error (MAE): 0.0234
- Wasserstein Distance: 0.0225

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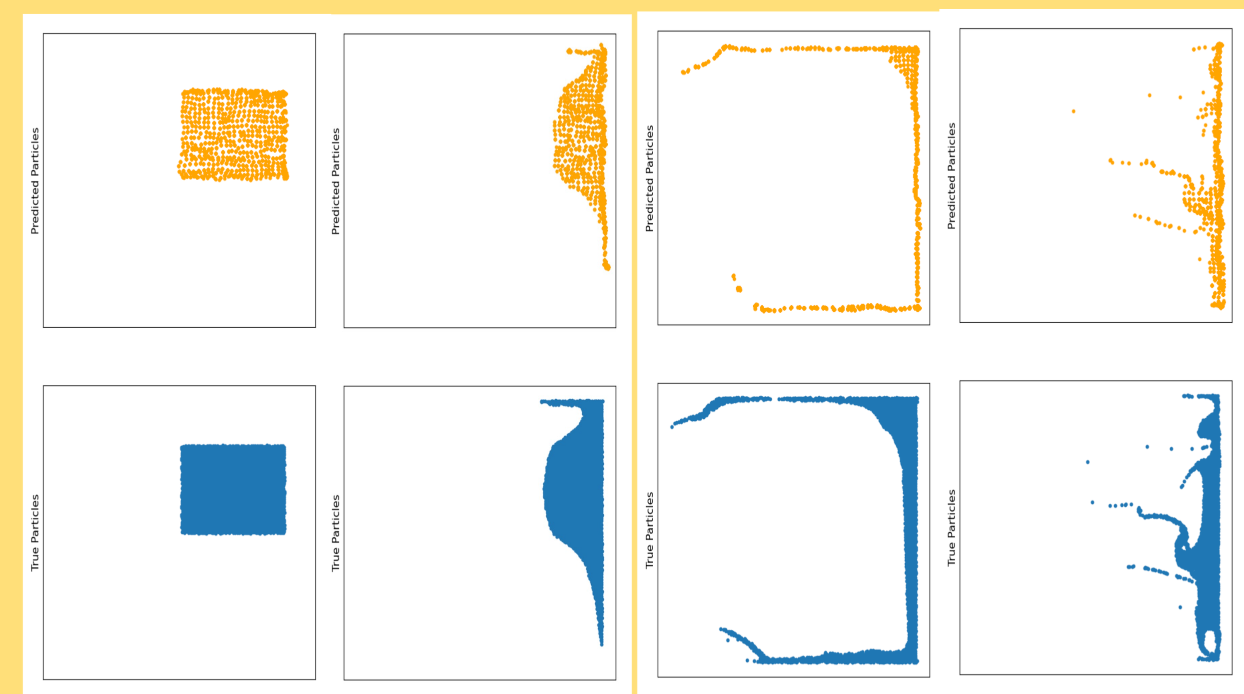

Fig 3 (inverted): Ground Truth (Blue) Vs Predicted Particles (Orange)

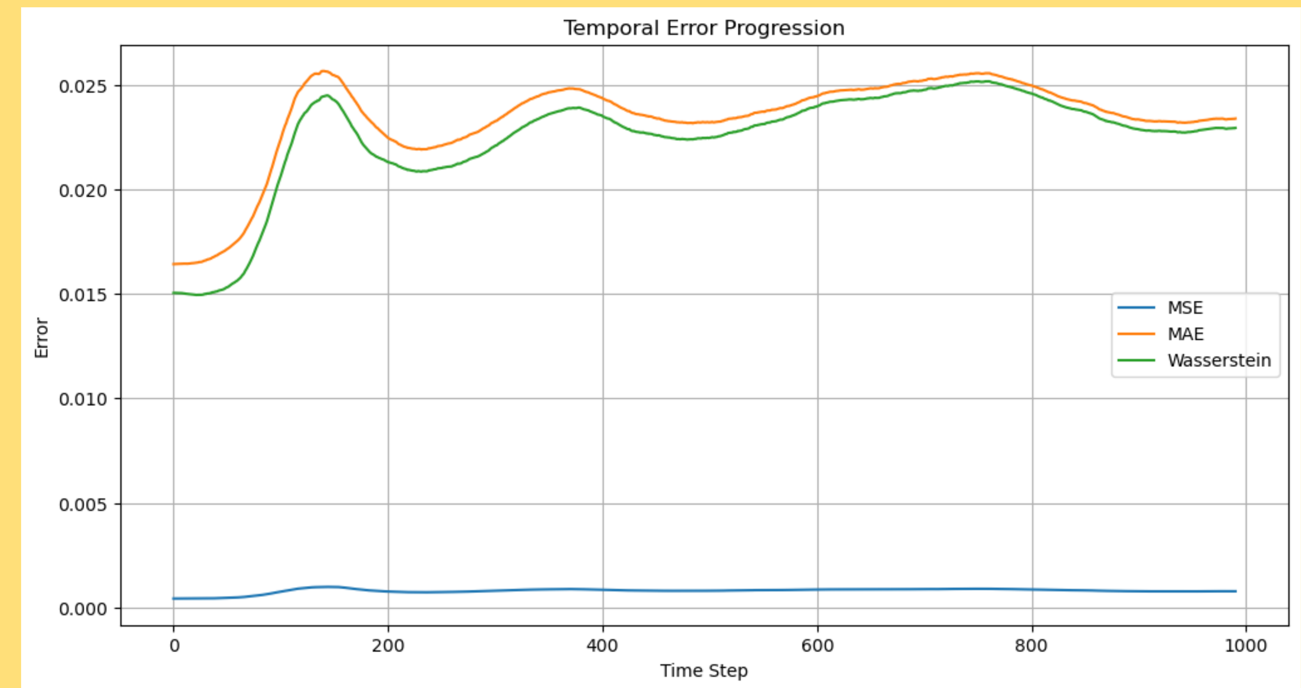

Fig 4: Temporal Error Progression