Physics Informed Deep Learning in Predicting 2D Unsteady Flows = Applikasi Deep Learning berbasis fisika dalam memprediksi aliran 2D tidak stabil

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Abstrak

In this project, Physics-Informed Neural Networks (PINNs) will be used to predict 2D unsteady flows. PINNs is a deep learning application to solve partial differential equations where neural networks learn from data and from physics. In this project, PINNs will be used to predict the velocity and pressure fields of a 2D unsteady flow by learning from the pressure and velocity data from flow simulations and fitting the output velocity and pressure data and its derivatives to the Navier-Stokes equations (NSE) as the governing equations. PINNs learns from data by developing a model that performs nonlinear regression on a set of training velocity and pressure data to produce a predicted output velocity and pressure values that is close to the training pressure and velocity data values. To learn from physics, the derivatives of the output velocity and pressure fields are computed which will be fitted into the Navier-Stokes equations. This becomes an optimization problem where the neural network needs to minimize the error of the predicted and training data and the error from fitting the data and the derivatives to the Navier-Stokes equations.
PINNs will be implemented in 3 different scenarios, which are super resolution, data noise- filtering and pressure gradient prediction, and finally, time series prediction. In super resolution, the neural network will be trained with low resolution pressure and velocity field data to reconstruct accurate high-resolution velocity and pressure fields. In data noise- filtering and pressure gradient prediction, the neural network will be trained only with data from noisy velocity fields and no pressure data, mimicking data processing of Particle Image Velocimetry (PIV) measurements which will produce an accurate noise free velocity field and pressure gradient data. In time series prediction, the network will train with velocity and pressure fields at a limited time range and must predict the velocity and pressure data beyond the time range.
The result of this project shows that PINNs make excellent tools to the field of experimental and computational fluid dynamics. PINNs can reconstruct accurate high- resolution velocity and pressure fields with less than 0.01 normalized error even if training data has a resolution 10 times smaller than the validation data. PINNs can also remove noise with a normalized error of less than 0.02 despite the noisy data having a 0.25 mean squared error. PINNs are however not effective enough to predict flows in a domain without training data or boundary conditions.