SOLUTIONS OF FORWARD AND INVERSE PROBLEMS FOR INCOMPRESSIBLE VISCOUS FLUID USING A PHYSICS-INFORMED NEURAL NETWORK

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It is known that laminar and turbulent flows can be studied by solving the Navier-Stokes equations. Such currents include currents in the ocean, the movement of fluid in pipes and blood through vessels, the flow of air around the wing of the aircraft. Various computational methods and algorithms are used to simulate such phenomena, and modeling processes on modern servers and computing clusters takes considerable time. Recently, the direction associated with the development of the architecture of physically-informed neural networks (PINN) has been actively developing, which significantly reduces the estimated computer time. At the same time, the neural network is designed using basic physical laws and available observational data. In [1], the authors introduced for the first time the concept of PINN for solving forward and inverse problems involving consideration of various types equations (ODE, PDE). In this paper, we consider the issue of constructing the architecture of a physics-informed neural network for modeling the direct problem of 2D incompressible stationary Kovasznay flow at Re=40,100 and for solving the inverse problem of 2D laminar fluid flow around a cylinder at Re=100. Such PINN consists of three main blocks. A mesh-free Lagrangian method is used for such PINN, which includes setting the required number of calculation points in the study area, for initial and boundary conditions, as well as a procedure for calculating derivatives using the autodifferentiation procedure, which is available in TensorFow, PyTorch. To solve such problem, we must first set the size of numerical domain and the time range. The problem is defined for dimensionless quantities. A neural network with 4 hidden layers and 50 neurons per layer (4x50) and 7x50,10x100 was used to solve the Kovasznay flow problem, for which there is an exact analytical solution. The relative errors in the L2 norm could reach the order of 10^{-5}. For the inverse problem with cylinder flow at Re=100, the numerical data from Nektar spectral-element code were used and two unknown parameters lambda1, lambda2 were determined. These parameters were present in the initial equations of motion for the two velocity components for convective and diffusion terms. The training time ranged from 30 minutes to 4 hours, depending on the choice of hyperparameters. The value of MSE was chosen as a metric for evaluating the prediction results.

REFERENCES

1. *Raissi M., Perdikaris P., Karniadakis G.E.* Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations // Journal of Computational Physics, 2019, Volume 378, pp. 686-707.