Reconstruction of flow field from sparse data using physics informed machine learning

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ABSTRACT Physics-informed machine learning is employed to resolve the flow field from sparse pressure observations from the experiments/computations. An Euler solver is used to find the supersonic flow of 1.35 over a wedge of 5 degrees. The pressure data from the computations are subsampled to mimic the sparse availability of the data in the real world and used to optimize the network weights. Without explicitly giving the data, the network has predicted all the field variables like density, x-component velocity, and y-component velocity.

1 INTRODUCTION

Studying the flow field in a high-speed regime is very laborious and expensive in terms of both experiments and computations. The mesh size in computations of a flow depends on the Reynolds number and the Mach number of the flow. Since the high-speed flow has the highest Reynolds number of 106, it demands a high mesh count to resolve or model the flow field using Direct numerical simulation (DNS) or RANS models. The direct numerical simulation of complex problems faced by industries will take several days to solve using high-power CPUs or GPUs, which cannot be affordable for industries that require faster design iterations. The comparatively cheaper simulation types like large eddy simulation or Reynolds average Navier-Stokes cannot resolve the flow; instead, they tend to model the flow field, rendering them inaccurate in real scenarios. Generally, high pressures are required to generate supersonic flow in wind tunnels, which demands larger and thicker storage facilities, increasing the experiment's cost. Until now, no measurement technique can give all the field variables like velocity, pressure, and density in one experiment. The density or gradient of the density measurements techniques like background-oriented Schlieren, laser interferometer, or Schlieren photography is challenging to compute or set up. Velocity measurement techniques like Laser Doppler or particle image velocimetry are expensive and difficult to set up. These measurement techniques utilize mathematical tools like filtering or cross-correlation to find the velocity, which inherently brings uncertainties that sometimes cannot be quantified. These techniques work in high-speed flow only if the flow is heavily seeded with the particle, which can scatter the laser light, making the flow a multi-phase. Another demerit of these techniques is that they are either poor in spatial resolution (in the case of PIV) or temporal resolution (like in LDV). Then, the cheapest and easiest flow variable to measure is the pressure using the wall tap. However, inferring the complete flow field using this wall static pressure alone is impossible. Recently, there has been tremendous growth in machine learning due to the advent of generative pre-trained transformers like ChatGPT and Gemini. The universal function approximation theorem [Cybenko (1989)] and universal operator approximation theorem [Chen & Chen (1995)] helped the researchers to apply machine learning to the non-linear fluid dynamics problem. The physics-informed Machine learning proposed by Raissi et al. (2019) can solve non-linear high-dimensional partial differential equations without mesh. The current paper investigates the effectiveness of extracting flow field data like velocity and density into a higher resolution using the sparsely available pressure field data obtained from experiments or low-fidelity computations using physics-informed machine learning.

2 METHODOLOGY

The supersonic flow of Mach number 1.35 over a wedge of 5 degree is simulated by solving Euler equation using a low fidelity industrial solver Fluent. This particular Mach number and wedge angle combination cannot be solved using a three-shock theory instead a four-wave theory is advised and result in Guderley Mach reflection. The pressures are sub sampled from the computational data for training the machine learning model. The deep learning model consist of 8 hidden layers and 20 neuron each in a layer. The tanh activation function used to add the non-linearity in the model. The model predicts x-velocity (u), y-velocity (v), density (ρ) and pressure (p). The least square error between the pressure predicted by the model and the pressure forms the computations is used to optimize the weights of the network. The Euler equations are used as the regularization term in the loss function of physics informed machine learning. More specifically, the residuals of Eulers equation are computed for locations corresponding to the sampled data from the computations using Automatic differentiation. The optimizer used for the backpropagation is Adam with learning rate of 1.0e-3. An adaptive weighting strategy is also used as proposed by Wang et al. (2020).

3 RESULTS AND DISCUSSION

The physics informed neural network is trained by optimizing the weights by performing the gradient descent of the loss due to the difference between the predicted pressure and the pressure data extracted from the points shown in the figure 1(a) and the residual from the Euler equations. The difference in the pressure field predicted by the neural network and the pressure from the computations is given in the figure 1(b). The flow field predicted by neural network such as Mach number, density, x-velocity and y-velocity is given in the figure 2(a) – (d), respectively.

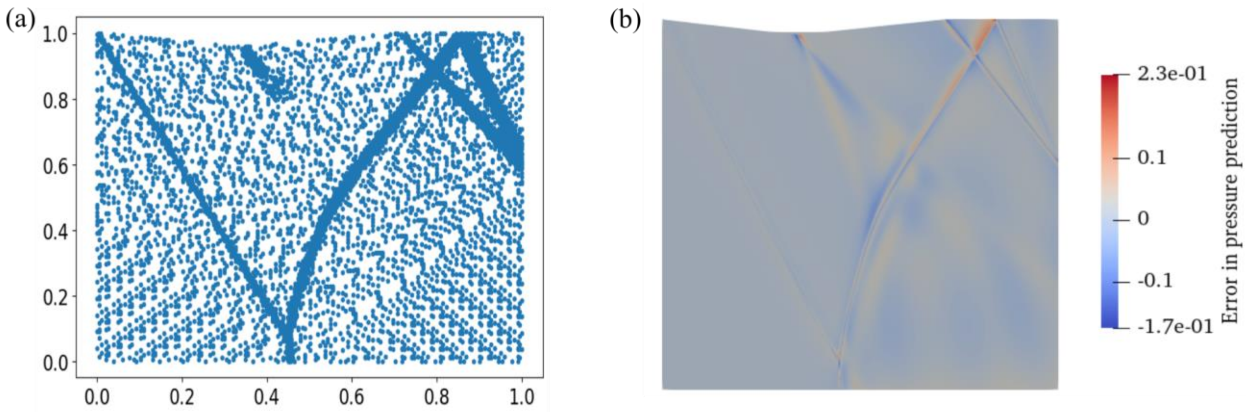

Figure 1: (a) Sub-sampled data points (b) Error in pressure prediction

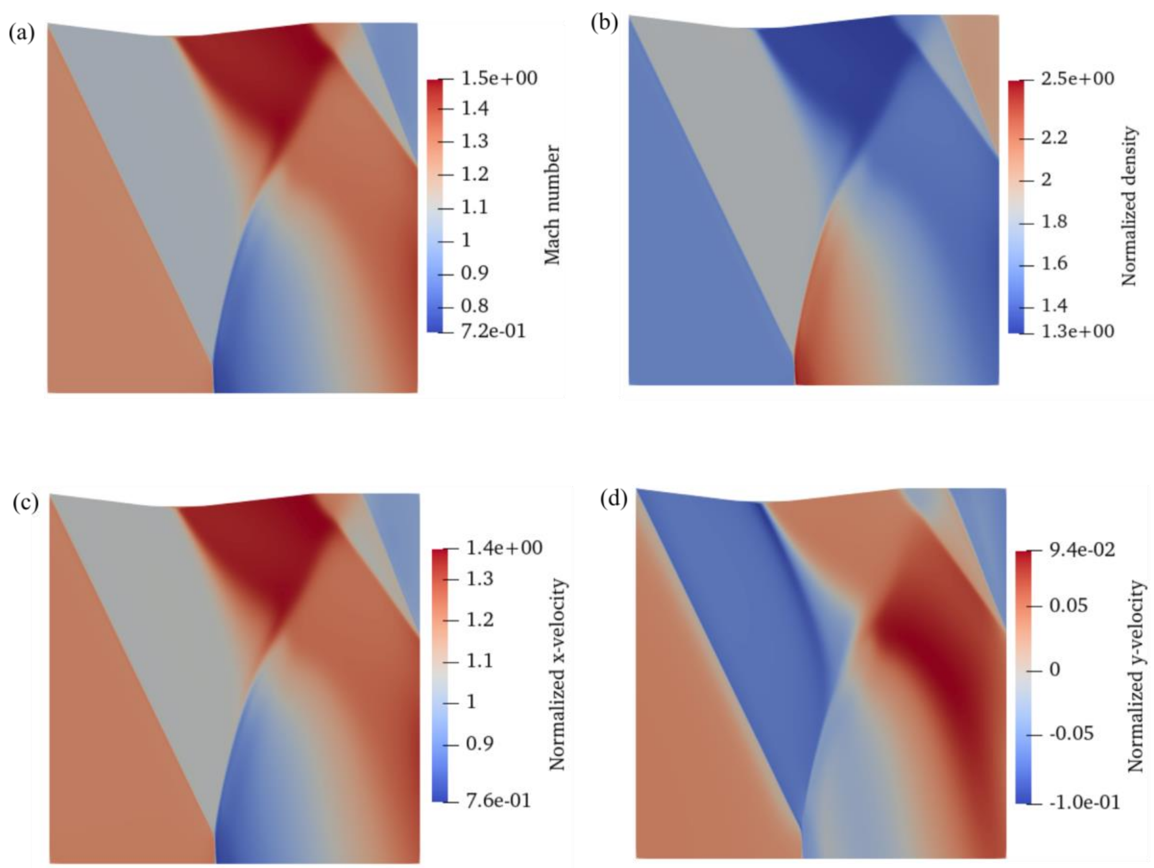

Figure 2: Flow fields predicted by the physics informed neural network (a) Mach number (b) Normalized density (c) Normalized x-velocity (d) Normalized y-velocity.

4 CONCLUSIONS

The physics informed neural network is successful in extracting the whole flow field data with sparse data on pressure alone from computations. This shows the potential of the physics informed network in helping experimentalist to generate flow field information from few experimental observations like pressure readings or density gradients. In the full paper the pressure or schlieren data will be used to generate the flow field information.

(1)

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