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Incorporation of Physics Informed Neural Networks (PINNs) for Gas Source Localization Task

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Gas leaks can pose severe risks to both humans and animals. For this reason, it is crucial to investigate quick and accurate algorithms to perform Gas Source Localization (GSL).

Despite technological advancements, GSL remains challenging because of the nature of gas dispersion. Indeed, both the air flow and the convection and diffusion of the gas in the environment follow a Partial Differential Equation (PDE). The former is governed by the Navier-Stokes equations while the latter is governed by the convection-diffusion equation. Because of the complexity of these equations, solutions are available only in the simplest situations.

For this reason, this work investigated Physics-Informed Neural Networks (PINNs) to solve the GSL task while leveraging the physics prior knowledge. PINNs are a deep learning framework incorporating the governing physical laws into their loss function.

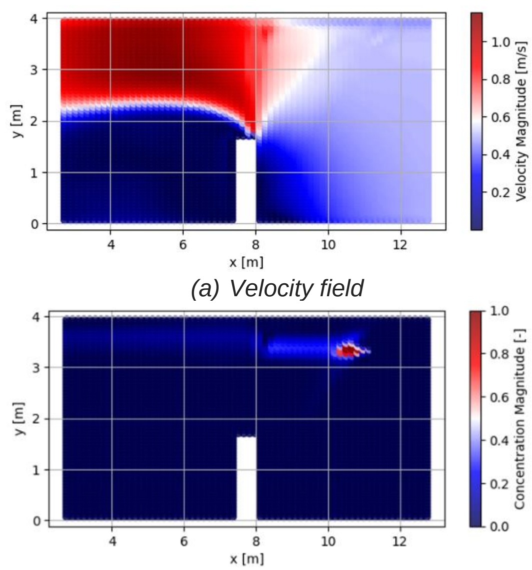
The goal was to assess the potential of this model in evaluating and reproducing both the velocity field and gas plume from scarce data.

Training data was generated in two steps. First, a wind map was computed by a highly accurate CFD solver. Then, it was fed into a robotic simulator which computed the gas plume thanks to a gas dispersion plugin.

The network was trained on points randomly selected inside of the computational domain as well as on its boundaries and points belonging to the obstacles in the environment.

Once trained, the network was provided with coordinates at which it had to estimate the velocity (horizontal and vertical) as well as the gas concentration.

Initially, the model was trained on three different maps (both with and without obstacles). The model proved to be able to accurately estimate both the velocity field and the gas plume in each configuration (see Figure 1).



(a) Velocity field

(b) Gas plume

Figure 1: *PINN model estimations*

Then, to align with a more realistic scenario, the robustness of the results was tested by varying the number of training iterations and training points. Ideally, both quantities should be minimized.

The model was able to successfully reproduce the velocity field using only 1.5% of the target resolution points during training. The gas plume was estimated accurately using only 7% of the target resolution points.

Finally, to mitigate the inability of PINNs to generalize to different sets of initial or boundary conditions, transfer learning was investigated. The model was pre-trained on a map containing an obstacle and further trained on a variation of this map (translated obstacle) and a different map.

The neural network was able to leverage the knowledge learned in the pre-training during the transfer learning. The number of training iterations could be hence greatly reduced without compromising result accuracy.