Fish-lateral-inspired pressure sensing neural networks for underwater object identification

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Abstract— **In the current project, we numerically study underwater object identification using a hydrofoil with pressure sensors. Using LilyPad, a boundary data immersion method (BDIM) viscous 2D solver, we simulate and generate a large dataset that describes pressure evolution over time around a constant speed moving foil passing by various objects at different distances (ellipses and rectangles of different geometries and orientations). A multivariate convolutional neural network is then constructed and trained on the dataset after the application of the POD dimensionality reduction, mapping the distinctive pressure information of the near body flow feature's distinctive pressure information to the objects close to the passing foil.**

I. Introduction

The ever growing research in the field of underwater world has led to its in-depth understanding. At the same time, the emergence of major problems such marine environmental pollution, ocean acidification require the need for equipment's that have the ability to explore the ocean widely and efficiently. Oceans are vast, and water being a special medium, makes it challenging to explore the unexplored. Equipment's for instance optical radar, can be deeply affected by the environment of the sea.

Nevertheless, nature provides solutions to some unanswered questions. A sensory mechanism inspired by the lateral line that runs along the side of the fish is used to locate predators or prey and underwater objects [1]. This system enables fishes to reconstruct the near-field three-dimensional flow around their bodies and hence interact effectively with their environment [2]. Researchers in their effort to replicate similar marine equipment and vehicles have created bio-inspired MEMS flow sensors [3]. These researches are proof-of-concept demonstrating engineering possibility and benefits of using pressure information as a near-flow/wake sensor for better control of ocean vehicles [4]. The lateral line consists of superficial neuromasts and canal neuromasts. Inspired by this, researchers attempt to create canal-type artificial lateral lines, which demonstrate excellent features that match the expectations [5]. Fish's organs enable them to sense the environment to avoid catching and tracking prey behind rocks, in murky deep waters, or without light. Studies indicate the value of imitating the mechanism fish's use as their flow sensing system.

Long strides have been put in order to replicate nature's greatness. In Micromachining and micro-electromechanical system (MEMS), a wide variety of transduction mechanisms can be used to convert real-world signals from one form of energy to another, thereby enabling many different micro sensors, micro actuators, and microsystems[6][7]. Many aquatic organisms exhibit remarkable abilities to detect and track chemical signals when foraging, mating and escaping, which inspires scholars to develop a sensory system that can detect local concentration and adjust its orientation accordingly[8][9][10]. In order to successfully imitate the ability of fish, qualitative sensing is required, considering underwater fluctuations. Many have contributed to the discussion of possibility and feasibility. It is still difficult to apply the ability to ships and marine vehicles. The ability to quantify the process using pressure like fishes has not yet been achieved.

In this work, we studied underwater object identification using a hydrofoil with pressure sensors to demonstrate that underwater objects' geometries and orientations are predictable using neural network the underwater pressure sensors. The rest of the paper is organized as follows, we first present in the section II the method and design to generate pressure data in simulated viscous underwater environment, including analysis of pressure data characteristics. Then we demonstrate in the section III that object can be predicted by the pressure data and display the neural network design and prediction accuracy.

II. NUMERICAL ENVIRONMENT AND MODEL

A. Boundary data immersion methods

In recent years, boundary data immersion methods (BDIM) [11] have been put forward as a viable alternative to conventional body-conformal grid methods especially in problems involving complex stationary and/or moving boundaries [12], [13]. Based on the incompressible Navier-Stokes equation. The analytic BDIM formulation allows the formulation of the near-boundary interaction between the fluid and solid domains in high order.

B. Numerical Model

In our model, we simulate the 2-D cases that a foil passing by a fixed object with different geometry. To be more specific, we design an experiment where five parameters of the object are free in the range as follows and two are fixed. In the randomization process, all of the free parameters are uniformly distributed, which is best appropriate in underwater conditions.

Abbreviation	Parameter Definition	Range
c	Length of the Foil	..
a_0	Length of the object	[0.25c, 2c]
a_1	Height of the object	[0.1c, c]
a_2	The angle of the object relative to the horizontal axis	[0, π]
a_3	The vertical distance between the object and the centre of the foil	[0, 0.7c]
a_4	The horizontal distance between the object and the highest point of the foil	2c
a_5	The shape of the object (Ellipse and Rectangle)	0: Rectangle 1: Ellipse

Table 1: The parameters used for the simulation on the LilyPad and implementation for the multivariate neural network

C. Simulation Environment and Improvement

Lily-Pad [14] is a solver for fluid-structure interactions based on BDIM. Referencing some classes in Lily-Pad, a new 2-D solver for this work is created. Totally, 5500 experiments with different parameters combinations, similar to the following picture, were conducted and we collected the time series data.

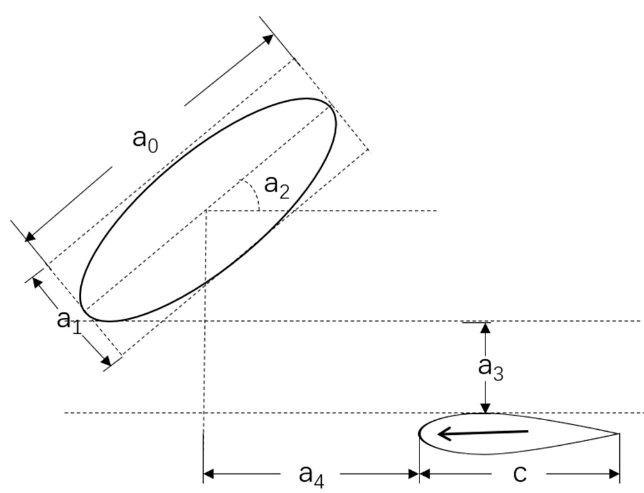

Fig 1: Sketch of this paper's simulation experiment. The parameters' meaning and range are explained in Table 1.

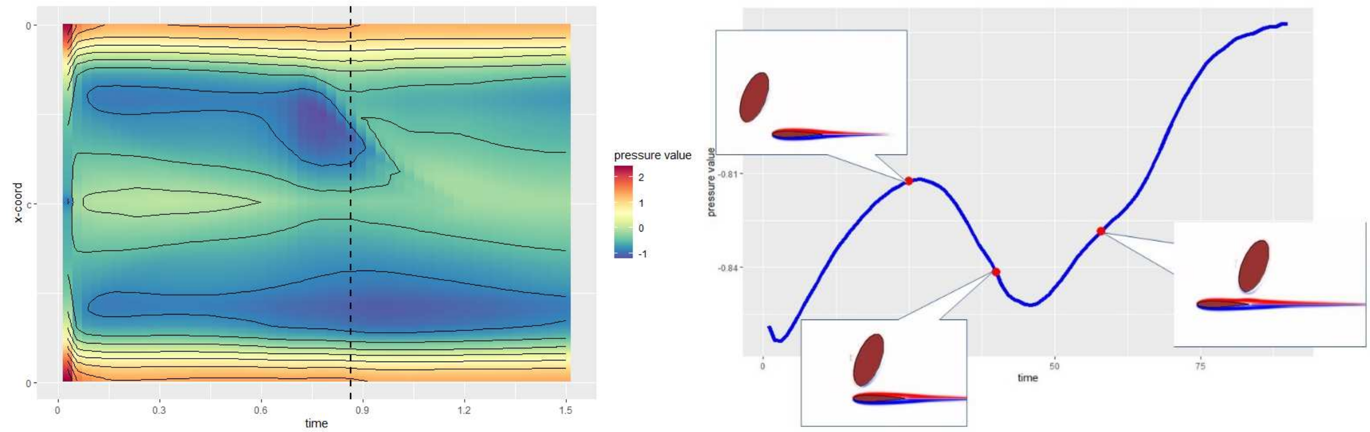

Fig 2: (a) The pressure changes of the foil's surface during the process that it passes by the object, in which the black dashed line is when the foil's center is right below the object's center. The dataset produced in one experiment is flattened so the foil's surface is flattened clockwise into a vertical line as the y axis. (b) The pressure change of a point on the upper surface of the foil during an experiment

During the process of foil approaching the object, its upper surface and lower surface are facing first small rise then descend in pressure, while there is no obvious pressure change on the head and tail. After passing the object, the pressure picks up as the foil moves away. This is demonstrated in the Fig 2(b) where we can see first up then down then up of the pressure on the point.

The simulations have been non-dimensionalized to use these variables when setting up our experiment more appropriately. For example, the geometries of objects and the speed of the moving foil are all expressed in units.

A sharp corner solver is provided as we avoid the misconvergence in by replacing corners with several small quadrants. Quadrants instead of sharp corners are more general in underwater environments, improving the speed of computation.

III. Learning Process and Prediction Result

A Creating the neural network

As illustrated in the image above, we plan to obtain an inverse of the LilyPad simulation that helps users to predict the various parameters such as length/ breadth of an object, angle of inclination, the distance between the object and fish etc. which were used in the first place for the simulation of our model.

We start y converting the received text files from the simulation into readable and inferable forms and removing the junk/**NaN** values to prevent its effect on the model while training. After receiving the cleaned data set for a single simulation, we calculate the SVD, i.e. Singular Value Decomposition, to receive the descending order of the Eigen energy for each dataset which helps us describe the simulation. We count the number of initial Eigenvalues in the descending array that amount to 98% of the total energy for the dataset that helps us in the dimensional reduction for each data set.

To find the ideal number of Eigenvalues required to represent the average of the DataFrame, we capture the accuracy up to 2 standard deviations. We use the formula below to calculate the ideal number.

$$\text{No of Components} = \text{Mean} + 2 * (\text{Standard deviation})$$

We continue the same process for all the 5500 datasets to receive a final DataFrame which consists of the corresponding Eigen energy values amounting to 98% of the total.

On this DataFrame, we apply the PCA (Principal Component Analysis) for further dimensionality reduction, which helps in projecting each data point onto only the first few principal components to obtain lower-dimensional data while preserving as much of the data's variation as possible.

Our model consists of 3 dense layers with the activation function as "relu" (rectified linear activation function), which is most commonly used for non-linear training and analysis. We use optimiser as "Adam" and the loss function as "mean squared error" for constructing the model. [15][17]

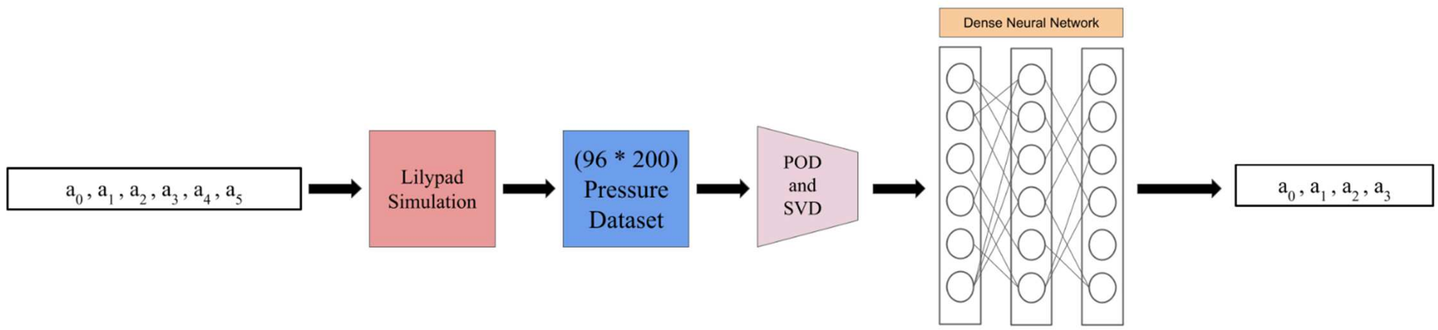

Fig 4: An illustration of data input for a particular simulation to understand the various steps to finally predict the parameter values. An example of data input for a specific simulation is understanding the multiple steps to finally predict the parameter values. In the final output, we do not calculate/train the parameter a_4 as it has a constant value of 2 for all the 5500 simulations, as stated in Table 1. [16]

B POD (Proper Orthogonal Decomposition)

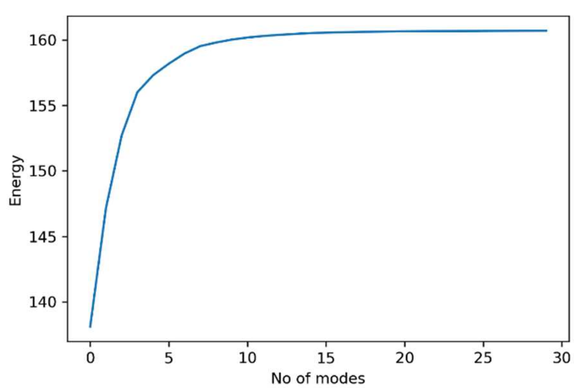

Fig 5: Energy VS Mode plot for a simulation using the POD dimensionality reduction method.

For a randomly selected simulation, the image above shows the efficiency of using the POD dimensionality reduction for the training model [18]. With very few modes ranging from 5-30, we are able to represent the Eigen Energy values of the pressure data sets making them suitable for reducing complexity.

For the 5500 pressure data sets, we have 22 modes (average +2 * standard deviation) representing 98% Eigen Energy summation for a particular simulation. Therefore, proving to be an effective way.

C *Training the neural network model*

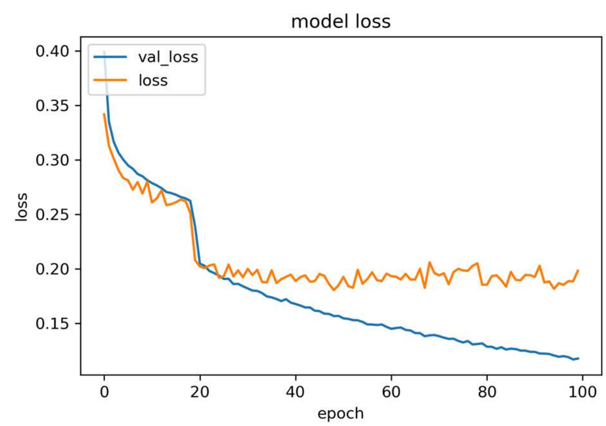

Fig 6: Training loss VS Model Loss

Our training data set consisted of 5000 datasets along with 250 datasets for validation of the neural network. As summarised by the image, it model was learning and training itself for the first 20 epochs but after that becomes stagnated in its loss parameter. Indicating that a better neural network model is required for better accuracy.

D Prediction of Results:

From a training dataset of 5000, we predict our model on datasets obtained from 250 simulations. Below are the results for 50 simulations differentiating between the prediction and the original values for the parameters namely a_0, a_1, a_2 and a_3.

To better understand the prediction we take up 4 random points (A, B, C, D) as depicted on all three graphs and run a simulation on LilyPad for these values. The images below provide a visual depiction of our prediction with the solid red figure being the original object and the translucent image of the object being the prediction from our neural network.

We also tried to predict the type of object i.e. (rectangle or ellipse) using the parameter a_5 for all 250 simulations. The accuracy of that prediction is 72.85 %.

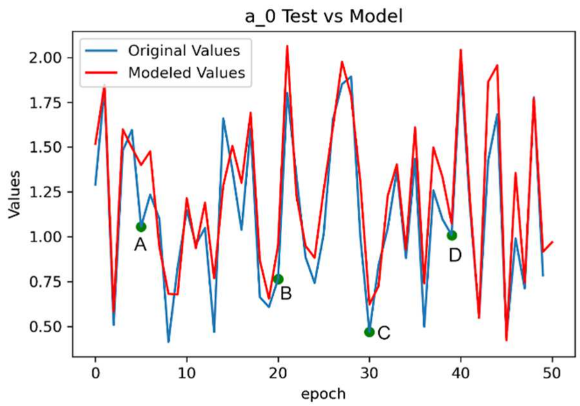

Fig 7: Prediction vs Original values for the parameter a_0

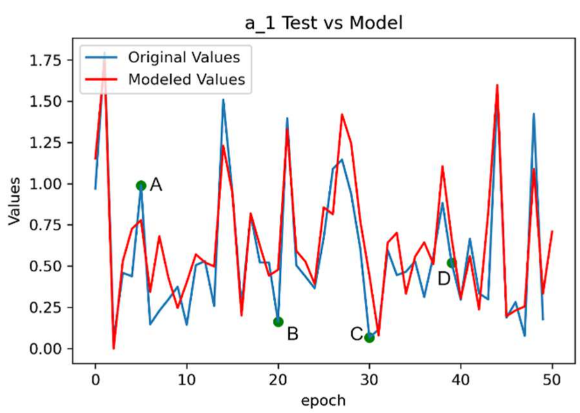

Fig 8: Prediction vs Original values for the parameter a_1

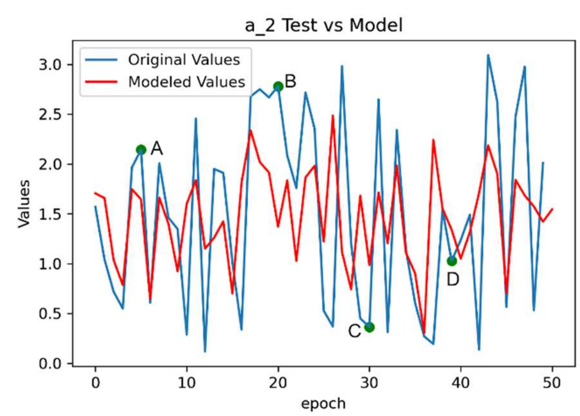

Fig 9: Prediction vs Original values for the parameter a_2

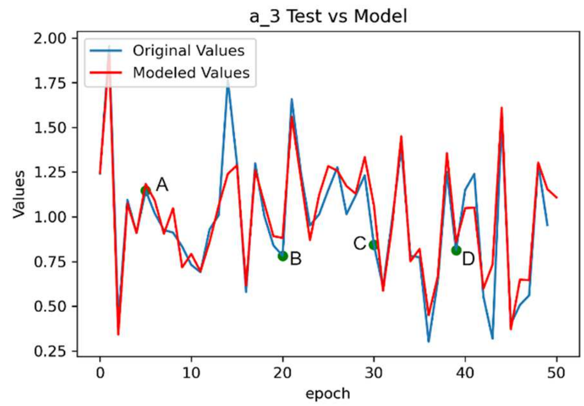

Fig 10: Prediction VS Original values for the parameter a_3

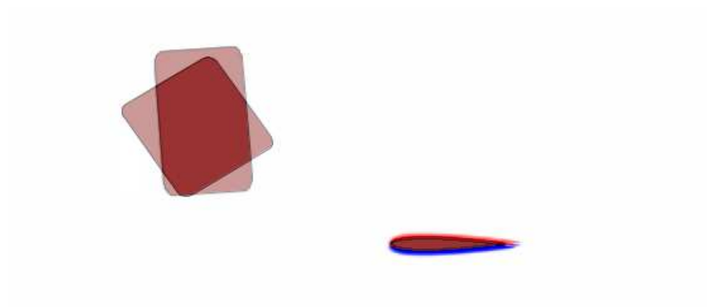

Fig 11: Model vs Prediction results for point A

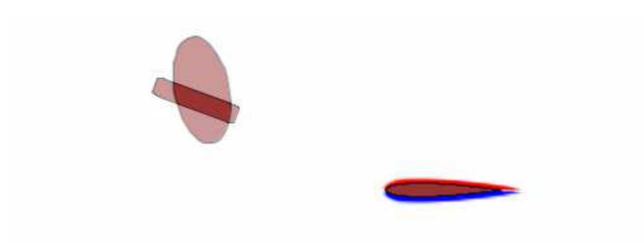

Fig 12: Model vs Prediction results for point B

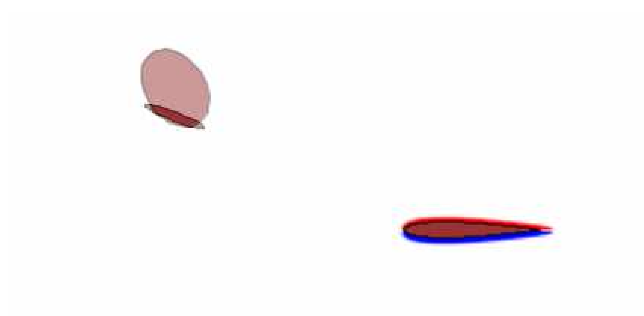

Fig 13: Model vs Prediction results for point C

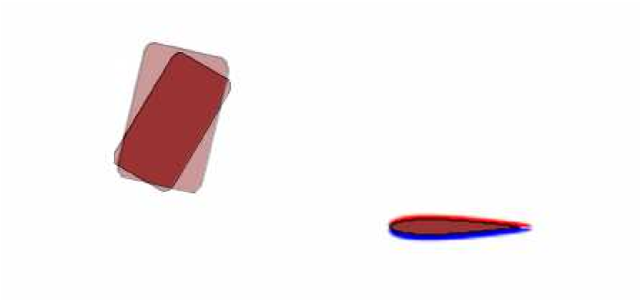

Fig 14: Model vs Prediction results for point D

IV. CONCLUSION

Inspired by nature we have created a simulation underwater environment for a fish to measure the pressure points on its surface and predict the nearby objects. The prediction of the vertical and horizontal distance between the fish and object was close to accurate but there was a significant lack in the dimension prediction of the passing object as visible in the above images from Fig: (11-14). One of our closest predictions corresponds to point D portrayed in Fig 14.

We believe a lot of work will be required on incorporating the non-linear movement of the objects with varying velocity and distances from the hydrofoil with different shapes and sizes. We would also work to convert the model for a 3-D simulation that would be an accurate conversion of the model for the real-life scenarios to be used for underwater flow sensing and detection.
This paper will be our stepping stone for more research to come on this topic.

V. ACKNOWLEDGEMENT

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