A Novel Approach for Hull Hydrodynamic Surrogate Models with Convolutional Neural Networks (CNNs)

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ABSTRACT

A novel approach for using artificial neural networks (ANNs) in the hull design problem is considered. Convolutional Neural Networks (CNNs), commonly used for image recognition tasks and other models that require spatial reasoning, are used to model the resistance of a hull form. The CNNs are given the (X,Y,Z) value of the hull control point coordinates instead of the traditional RGBA (Red, Blue, Green, Alpha) values of image pixels. The CNNs are trained to regress the non-dimensional coefficient of resistance of the hull form. This new method for generating surrogate models is compared to conventional surrogate model methods as a function of regression error and training sample size. This sensitivity shows that this new approach for generating surrogate models of hull form performance is comparable to existing methods but offers more functionality and flexibility. The CNNs offer an efficient computation of the partial derivative of the movement of each control point to the objective function, which is the coefficient of resistance in this study. Figure 1 is a heat map of these partial derivatives relating the suggested movement in the v-direction (beam) of each of the control points on the series-64 hull form to the coefficient of resistance at a Froude number of 0.28. This heat map can focus the hull form optimization process, resulting in more successful use of optimization tools. In addition, the efficient development of partial derivatives from the surrogate model supports the use of direct searching optimization methods. Finally, this paper investigates the memory of the CNNs and their ability to learn the entire design space and then optimize a subset of the design space. A small study is conducted training the CNNs on a larger, more variable design space and then using this CNN to optimize the hull with a subset of the trained design variables. Multiple methods for training and re-training the CNNs are tested for effectiveness with initial results suggesting this could be a functional use case for CNNs to improve hull form optimization efficiency.



Figure 1: Series 64 Hull Form Control Point Modification Heatmap, Froude Number = 0.28