深層学習支援遺伝的アルゴリズムを使用した翼空力形状最適化

Aerodynamic Wing Shape Optimization via Deep Learning-Assisted Genetic Algorithm

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Gradient-free population-based optimizers such as a genetic algorithm (GA) are criticized for their inefficiencies in solving high-dimensional optimization problems. However, GA features a global search capability that increases the likelihood of finding the global optimum. Efforts have been made by coupling GA in surrogate-based optimization (SBO) to increase its efficiency. However, the conventional SBO method suffers from difficulty achieving sufficient surrogate model accuracy. Surrogate models with low accuracy might degrade the optimization performance. A large-scale aerodynamic wing shape optimization is characterized by its high dimensionality, making SBO with GA an unpopular choice of the optimizer in the field. Hence, this paper addresses this issue by incorporating a deep convolutional generative adversarial network (DCGAN)-based sampling and a convolutional neural network (CNN)-based geometric filtering to speed up optimization convergence by producing more accurate models. We demonstrate the methods by solving a lift-constrained drag minimization of the Common Research Model (CRM) wing with 193 design variables. The results show that our proposed methods could produce more accurate models than the conventional SBO method. The optimal design by our method has lower drag than the conventional SBO method and the baseline CRM wing while maintaining the same lift and ensuring feasibility.

Key Words : DCGAN, CNN, Aerodynamic design, Surrogate-based optimization, Genetic algorithm, CRM wing

1. Introduction

The applications of population-based methods such as genetic algorithms (GAs) to aerodynamic wing shape optimization have been around for the last two decades. For example, Oyama et al. [1] performed a transonic wing optimization by directly coupling a CFD solver with an adaptive range GA. The optimization costed 4160 CFD evaluations with 87 design variables. The optimization would not have been possible without the presence of parallel computing since it would sequentially have taken more than nine months to evaluate the 4160 design candidates. One effort to reduce the number of evaluations is to replace the CFD with analytical models and perform the search on them, referred to as surrogate-based optimization (SBO). Zhang et al. [2] applied an SBO method based on a Kriging model coupled with a combination of GA and local optimizers to optimize the Common Research Model (CRM) wing with 39 design variables. They explained that it is challenging to construct surrogate models with sufficient accuracy in high-dimensional problems.

To overcome that, we introduce a deep convolutional generative adversarial network (DCGAN)-based sampling to produce synthetic wing designs as the initial samples, as opposed to the Latin hypercube sampling (LHS) that is often used in the conventional SBO method. We also train a convolutional neural network (CNN)-based geometric filter to quickly detect the geometric abnormality applied in the infill sampling process of the SBO method. As for the surrogate model, we train a multilayer perceptron (MLP) to analytically map the design variables as the inputs to the expensive aerodynamic performances (obtained by CFD) as the outputs. A variant of GA called NSGA-II [3] is used as the optimizer.

To demonstrate the advantages of our methods, we solve a lift-constrained drag minimization of a CRM wing with 193 design variables, subject to geometric and moment constraints. We then compare our methods with the conventional SBO method with LHS regarding the surrogate model’s accuracy and optimization performance. We will also discuss how the first might affect the latter. Finally, the obtained optimal design is compared with the baseline CRM wing.

2. Problem Formulation

We started with the CRM wing extracted from the CRM wing-body configuration proposed by Vassberg et al. [4] as our baseline model. The baseline is already a good-performing design, making it a complex optimization problem to find better-performing designs. The Free Form Deformation (FFD) is used to parameterize the geometry. Fig. 1 shows the baseline geometry embedded in the FFD volume that consists of 192 control points. These points are allowed to move only in the z-direction. The change in the z-direction Δz is treated as the design variable with the design boundary of $[-0.35t, 0.35t]$, where t is the local thickness between the FFD volume. However, all trailing edges (TEs) and the leading edge (LE) of the root section are fixed. The objective is to minimize the drag coefficient at the cruise condition with a fixed lift coefficient $C_L = 0.5$. The moment coefficient constraint is also introduced. The entire problem formulation is summarized in Table 1.

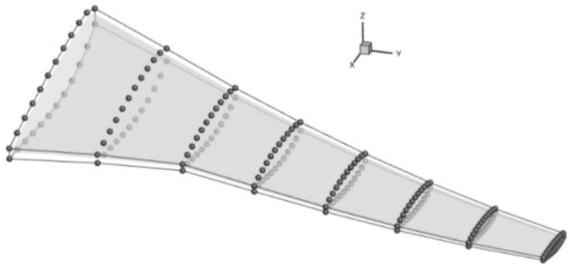

Fig. 1 The baseline geometry embedded in the FFD volume

Table 1 The aerodynamic wing shape optimization problem formulation

	Function/variable	Description	Quantity
Minimize	C_D	Drag coefficient	1
With respect to	α	Angle of attack	1
	Δz	FFD control point displacement	192
		Total design variables	193
Subject to	$C_L = 0.5$	Lift coefficient constraint	1
	$C_{My} \geq C_{My,base}$	Moment coefficient constraint	1
	$V \geq 0.8\, V_{base}$	Minimum FFD volume constraint	1
	$\Delta z_{TE,upper} = -\Delta z_{TE,upper}$	Fixed trailing edge constraint	8
	$\Delta z_{LE,upper} = -\Delta z_{LE,upper}$	Fixed leading edge constraint	1
		Total constraints	12

3. Methodology

An initial sampling must be done to construct the initial surrogate model. The conventional SBO method is usually done using LHS and directly perturbing the design variables. Here, we introduce a DCGAN-based sampling. DCGAN is a generative model that could produce synthetic samples from training samples given noisy inputs. This paper trains the DCGAN using 77 transonic airfoils from the UIUC airfoil database. The synthetic airfoils are used as the wing sections of the initial wing designs. An inverse FFD procedure is done to obtain the corresponding FFD points that match the wing sections.

200 initial wing designs are evaluated using CFD to obtain an initial dataset and thus construct an initial MLP-based surrogate model. This model maps the FFD displacements to aerodynamic performance measurement, i.e., drag and moment coefficients. Sub-optimization is carried out using the NSGA-II algorithm on the MLP model. In this phase, we introduce a CNN-based geometric filtering method to filter out poor-performing designs. The MLP model is only a data-driven model without any idea about physics. Hence, there might be cases when the model underestimates the drag coefficient of a design with an abnormal shape simply due to the lack of data. The CNN is trained using a separate set of DCGAN and LHS samples. The former is

labeled as realistic shapes, while the latter is labeled as abnormal. After the training, the CNN model can give a score to measure the abnormality of the shapes. This score is used as an analytical constraint in the sub-optimization. The optimized solution is directly appended to the dataset without doing any CFD. The evaluation by the MLP model is used as temporary labels in the next surrogate model construction, called a believer sub-iteration, and is repeated five times. In this way, 5 new designs can be obtained and evaluated using CFD in parallel. The whole process is repeated until we reach 1000 CFDs.

To demonstrate the efficacy of the DCGAN and CNN techniques, we solved the optimization problem via three methods:

1. Do the above procedure using LHS initial samples and without the geometric filter, called the LHS method.
2. Perform the procedure using the DCGAN initial samples and without the geometric filter, called the DCGAN method.
3. Combine the techniques, i.e., utilizing both the DGCAN initial samples and the CNN-based geometric filtering method, called the DCGAN+GF method.

4. Results and Discussion

4.1 LHS vs DCGAN Samples

The initial wing sections are produced by both LHS and DCGAN methods. The former directly perturbs the local FFD control points of the baseline, while the latter uses the generative DCGAN model to produce synthetic airfoils given noise inputs. Fig. 2 shows the UIUC transonic airfoils used to train the generative model, the DCGAN, and the LHS airfoils. The UIUC airfoils are normalized before training since they have different thicknesses and camber characteristics. It is observed that the DCGAN-based sampling produces smoother airfoils than the LHS airfoils that have irregular shapes.

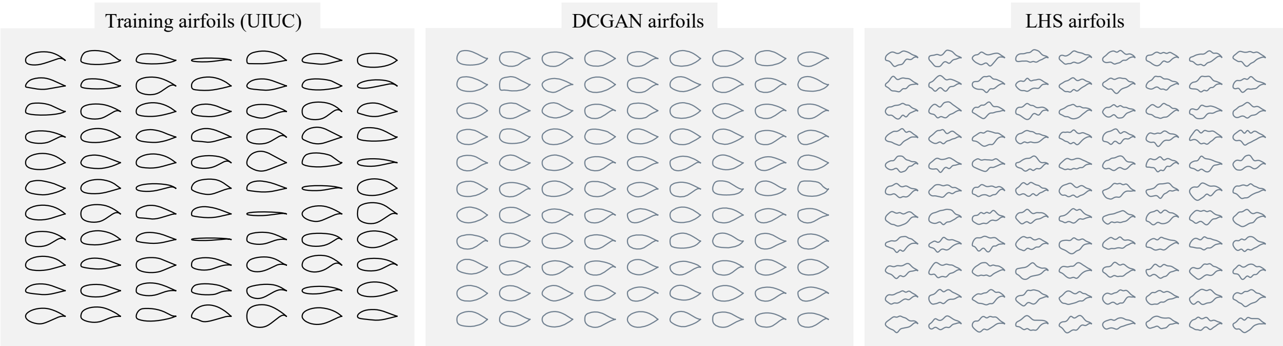

Fig. 2 The UIUC transonic (left), DCGAN (center) and LHS (right) airfoils.

The CNN-based geometric filter is trained using a separate set of 500 DCGAN and 500 LHS samples (not from the initial samples). We refer the former as the samples with realistic shapes and hence given a score of 1, while the latter as the samples with abnormal shapes with a score of 0. After training, we test the filter on the UIUC, the DCGAN, and the LHS initial samples. The score density distribution is shown in Fig. 3. It is observed that the filter can distinguish samples with abnormal shapes from realistic ones. To include this filter in the SBO method, the sub-optimization by NSGA-II considers an additional constraint $S \geq 0.4$. It is since all realistic shapes have a geometric score higher than 0.4.

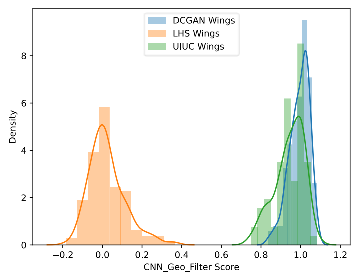

Fig. 3 The CNN-based geometric filter can separate abnormal airfoils from realistic ones.

4.2 Optimization Performance

We define a penalized objective function for plotting convenience as follows:

$$Penalized\ objective\ (count) = 1000 \times C_D + 1000 \times |0.5 - C_L| + 1000 \times |min(C_M - C_{M.base}, 0.0)| \qquad (1)$$

We plotted these objectives for all samples in Fig. 4 (left). For the 200 initial samples, it is clearly observed that the DCGAN-based method produced samples with relatively lower penalized objectives than the LHS samples. For the infilling samples, the DCGAN+GF is observed to have the fastest convergence among the three methods. The LHS and the DCGAN sometimes produced infilling samples with low performance (high penalized objective). The geometric filter in the DCGAN+GF managed to filter out these poor-performing samples. This behavior will be apparent when discussing the surrogate model's accuracy. To further compare the performance, we traced the history of the minimum feasible drag coefficient, excluding the initial samples in Fig. 4 (right). The DCGAN method could find solutions better than the LHS method at the 310th iteration. However, with 1000 CFDs, both methods failed to find any solutions better than the baseline, while the DGCAN+GF found a slightly better design with only one drag count improvement, demonstrating the difficulty of the problem.

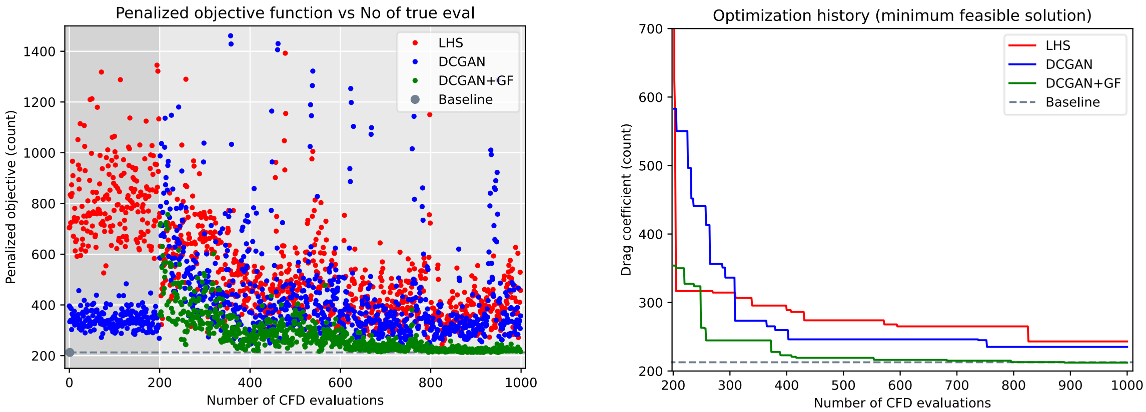

Fig. 4 Penalized objective functions (left) and minimum feasible drag coefficients (right).

4.3 Surrogate Model's Accuracy

We calculated the surrogate model's accuracy using the root mean square error (RMSE) of the modeled functions (drag and moment coefficients), shown in Fig. 5. The RMSE measures the distance between the predicted value by the model and the ground-truth by the CFD. The LHS and the DCGAN (without geometric filter) have several spikes at specific iterations, demonstrating low model accuracy. At these iterations, the model underestimates the modeled functions, creating infilling samples with irregular (or abnormal) shapes. That is why we could observe infilling samples with high penalized objectives in both methods. However, this can be alleviated by the geometric filter (GF), shown in the RMSE history of the DCGAN+GF method. The GF could filter out abnormal shapes, increase the model's accuracy, and speed up convergence.

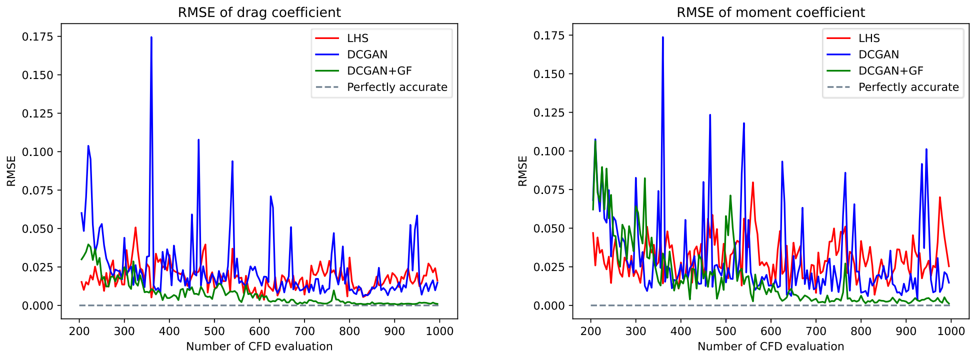

Fig. 5 The RMSE of the drag (left) and moment (right) coefficients.

4.4 Optimized Design

The CFD result for the baseline and the optimized design found by the DCGAN+GF method is presented in Fig. 6. Both designs have quite similar wing sections. However, the shock surface of the optimized design is less intense at 0 - 45% spanwise location, but not at the 45 - 95%. Some pressure oscillations are still spotted for the optimized design, indicating that there are still tiny bumps on its surface. However, the optimized design has a drag of around 0.5 counts less than the baseline while maintaining the same lift and meeting the given constraints.

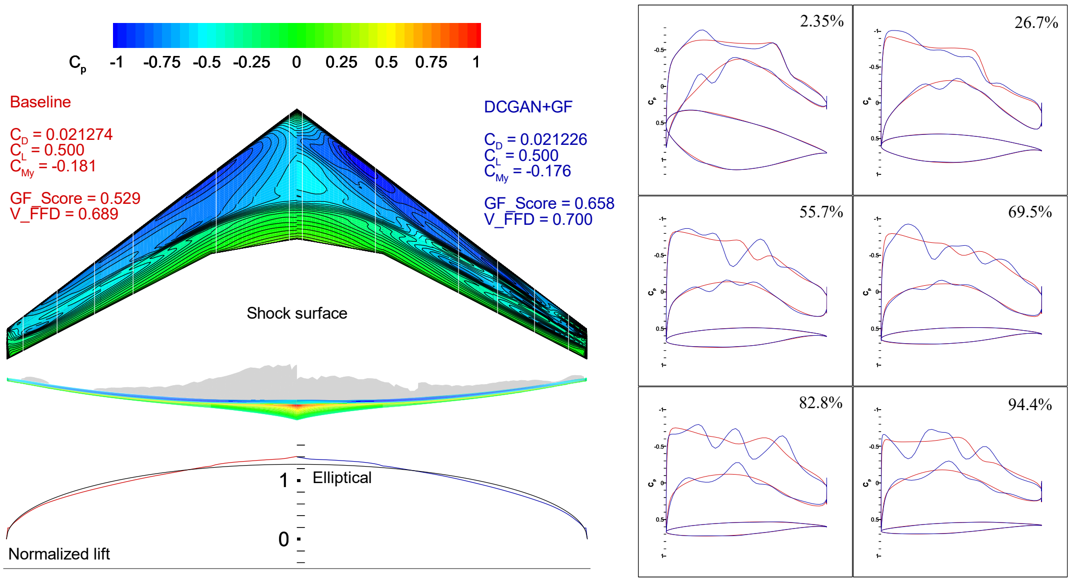

Fig. 6 CFD comparison between the baseline and the best feasible design by the DCGAN+GF method.

5. Concluding Remarks

This paper introduced two recent deep learning techniques: DCGAN-based sampling and CNN-based geometric filtering, to help solve high-dimensional aerodynamic wing shape optimization. The DCGAN-based sampling could produce smoother wing sections than the LHS-based sampling. The CNN-based geometric filter could separate realistic airfoils from abnormal ones. Used together, both techniques could speed up the optimization convergence of the conventional SBO method with LHS-based sampling by producing more accurate models. The optimized design found by the DCGAN+GF method has a lower drag compared to the one by the DCGAN method, the LHS method, and the baseline. No huge drag improvement from the baseline was obtained since we started with an already good-performing design: the CRM wing. To improve the optimized design, one might increase the computational budget (more iterations) or reformulate the problem to include more FFD points, although this will introduce more complexities.

References

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