Shape-Informed Dimensional Reduction in Airfoil/Hydrofoil Modeling Approaches

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Parametric models have been widely used in pertinent literature for reconstructing, modifying and representing a wide range of airfoil and/or hydrofoil profile geometries. Design spaces corresponding to these models can be exploited for modeling and profile-shape optimization under various performance criteria. Accuracy requirements, along with the need for modeling local features, often lead to high-dimensional design spaces that hinder the process of shape optimization and design through analysis.

Keywords: shape-informed parametrization ; dimensionality reduction ; airfoils ; hydrofoils

1. Introduction

Free-form functional surfaces, such as wings, rudders, turbine blades, ship hulls, etc., play a vital role in the performance of a wide range of engineering products. Consequently, they have a significant impact on energy efficiency, the environmental footprint, along with structural integrity, safety, durability, and the financial viability of such endeavors. Such surfaces commonly possess complex geometries, which go far beyond simple primitive shapes, and therefore require advanced modeling techniques, e.g., parametric modeling, to efficiently represent and handle their free-form nature. Recent advancements in geometric modeling techniques, pioneered by mathematicians, computer scientists, and engineers, have significantly enhanced the capabilities of parametric modeling. This state-of-the-art technology effectively represents intricate shapes encountered in diverse fields such as naval architecture, ocean engineering, turbo-machinery, and automotive design [1][2].

To meet the need for cutting-edge designs, there is an increasing need for global optimization across increasingly wider design spaces with an ever-increasing number of design variables. However, such attempts are commonly hampered by the curse of dimensionality, which degrades the performance of optimization techniques as the dimension of the design space increases [3][4]. The first steps in design space dimensionality reduction involve methods which identify significant factors and variables and eliminate the remaining ones by assigning appropriate constant values; see [5]. However, this approach is obviously simplistic and may fail to yield optimal results as it overlooks the potential importance of variables' interdependency and their effect on optimization; see also [6]. Variance-based sensitivity analysis, employing Sobol indices [7], allows a more nuanced evaluation of the significance of the variables, but requires a statistically significant number of samples and becomes computationally intensive as dimensionality increases. To address such challenges, dimensionality reduction techniques, ranging from principal component analysis to unsupervised learning and feature extraction techniques, that capture essential design space directions while preserving critical features, have been employed [8]. The last family of methods uncovers the underlying structures, enabling efficient optimization and knowledge acquisition.

Similarly, in the context of functional-surface design, high-dimensional simulation-driven design optimization problems can greatly benefit from the application of offline/upfront, design-space dimensionality reduction methods. Such contemporary methods assess the variability present within the design space and subsequently reduce its dimensionality accordingly. Hence, these techniques enable effective dimensionality reduction to be performed prior to initiating the optimization process. Diez et al. [9] introduced a method based on the Karhunen-Loève expansion, also known as proper orthogonal decomposition, to assess shape modification variability and establish a latent space with a reduced dimension for the shape modification vector; see also [10]. Despite the effectiveness of such approaches, they are not without drawbacks. One such drawback pertains to their failure to fully maintain the shape complexity and its underlying geometric structure. As a result, the resulting latent subspaces lack the ability to generate sufficiently diverse and/or valid shapes efficiently when used in shape optimization. This lack of representational capacity and compactness (i.e., shape validity) can hinder the success of the optimizer by spending the majority of the computational budget exploring infeasible or invalid shapes. In addition, these techniques often rely purely on geometric features and lack information related to performance criteria and the physics involved in the design assessment. Therefore, it is pivotal to employ more sophisticated representations that encompass high-level information regarding the shape's structure and physics.

2. Shape-Informed Dimensional Reduction in Airfoil/Hydrofoil Modeling Approachs

Locality preserving projection (LPP) [11] is a well known unsupervised dimensionality reduction method based on feature extraction. It is a linear approximation of another common method known as Laplacian Eigenmaps (LE) [12]. The goal of LPP is to use a linear transformation to project the original data onto a lower-dimensional space while retaining links between the nearest neighbors. In other words, LPP attempts to preserve local relationships and a neighborhood structure during the dimensionality reduction process.

Several variants of LPP have been proposed to address the specific limitations of the original method. One such variant is the *ILLP-L1* [13], where the $L2$ norm is replaced with the $L1$ norm to enhance robustness. Despite LPP's demonstrated effectiveness across various datasets, it is noteworthy that projection directions in LPP are highly sensitive to the coordinate system used for data points. Surprisingly, a mere rigid translation of data points, i.e., without altering their relative positions, can lead to significant changes in the projection directions determined by LPP. This indicates that LPP lacks the essential property of translation invariance, which is very significant.

Generative adversarial networks (GANs) have also been used in pertinent literature to model forms of airfoils/hydrofoils. For example, in Chen et al. [14], the authors demonstrated that their approach allowed them to achieve better optimization results with GAN mode shapes than they could with other parameterization techniques. At around the same time, Du et al. in [15] combined a B-spline representation approach with GANs, leading to the creation of BSplineGAN modes for foil design. However, the lack of prior knowledge regarding the proper number of modes to be used is a frequently voiced criticism against such dimension reduction strategies. Shape optimization with these reduced design spaces may fail to produce appropriate results when only a low number of modes is incorporated. On the other hand, using too many modes undermines the benefits gained by dimensionality reduction.

Using validity functions, which successfully eliminate aberrant foil designs, is another method to narrow the design space. This strategy depends on computationally efficient models to constrain the design space rather than reduce the number of design variables. Kedward et al. [16] presented a unique design constraint, based on curve derivatives/curvature, with the goal of ensuring smooth aerodynamic/hydrodynamic shapes during the shape design optimization process. This constraint significantly improved both the optimization's convergence rate and the resulting optimized designs. Li et al. [17] developed a set of marginal functions to represent the link between dominant foil modes and higher-order modes derived from the UIUC [18] database airfoils. These functions effectively eliminated unwanted airfoils from the design space. However, defining acceptable boundaries for curvature-based constraints ahead of time is frequently difficult, and there was no guarantee that the margin-based validity functions did not also eliminate perfectly valid foil designs by accident. Hence, an ideal validity model should be an accurate discriminator of geometric irregularities without the rejection of plausible foil designs.

Li et al. in [19] employed deep learning techniques, including a deep convolutional generative adversarial network (DCGAN) for sampling realistic airfoils and a convolutional (CNN) discriminator to identify abnormal shapes, within a surrogate-based optimization framework for effective aerodynamic shape optimization. However, it is worth noting that the CNN-based validity function may have limitations when it comes to exploring geometric innovation beyond the scope of the UIUC airfoils. This is because the CNN model is trained using the airfoil GAN model, which itself is exclusively pre-trained on UIUC airfoils. Moreover, if the GAN model encounters modal collapse, the geometric filtering model could potentially exclude conventional airfoil shapes. Consequently, the deep-learning-based filtering model has faced criticism regarding its ability to hinder the discovery of optimal designs with innovative aerodynamic shapes. Jichao Li and Mengqi Zhang [20] introduced a GAN based on the Wasserstein metric (WGAN) to overcome the problem of model collapse observed in the airfoil GAN model. The WGAN-generated synthetic airfoils not only accurately represent the training airfoils but also extend into regions where there is a scarcity of training samples. As a result, the WGAN model demonstrated extrapolation capabilities, enabling it to capture additional geometric information beyond those present in the training set.

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