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Abstract. In large and complex aerodynamic systems the overall performance of a design is mainly defined by interactions between design areas rather than by single design regions. Therefore it is necessary to identify these interactions in order to be able to understand and improve the designs. However, detecting and modeling those interactive effects between distant design areas is a very challenging task which usually requires a detailed understanding of the flow patterns and dedicated expert knowledge.
In this paper we apply the information theoretic concept of interaction information to aerodynamic design data in order to detect and quantify interaction effects between distant design regions. Information graphs are suggested in order to provide the results to the aerodynamic engineer in a graphical form. In order to show the feasibility of this approach, the information theoretic quantities are applied to the data of a 2D wing assembly as well as to the 3D turbine blade design data.

Key words: Knowledge Extraction, Interaction Detection, Information Theory, Aerodynamic Design Data, Turbine Blade

1 Introduction

One of the most challenging tasks in aerodynamic systems is the understanding of the interplay between distant parts of a 3D design related to their joint influence on the overall performance. Especially for complex aerodynamic designs it can be observed that the influence of one part of the design on the performance strongly depends on the shape of another part due to the dynamics of the aerodynamic flow. Knowledge about the interactions of the aerodynamic flow and the highly non-linear relationship between design parts is usually captured in expert knowledge.

This paper aims at identifying interactions between design parts using computer aided methodologies. The identification is purely based on the observation of geometric changes and the change in the overall performance number. The overall performance numbers of a design (e.g. pressure loss, drag, lift or down-force) sums up the characteristic of the aerodynamic flow under stationary conditions. One can expect that different interactions between design parts are relevant for different performance numbers.

During the evaluation process of a design the flow around each design is either simulated using high-fidelity CFD (computational fluid dynamic) simulations, using wind tunnel experiments or by exposing the design to its real working condition. The results are a single or multiple performance numbers which are subject for optimization. The optimizer that drives the optimization process can either be a human, a machine or a sensible combination of both. During the optimization of an aerodynamic design a huge amount of design data with its related performance numbers is generated. It is important to note that among different optimization runs the parameters of the used representation or the representation itself which defines the shape of the geometry can change [12]. Different representations raise difficulties in extracting information from all designs. This includes the detection of interactions. A strategy to overcome this problem has already been presented in [4].

The information theoretic concepts for the identification of interactions are formalized in section 2. In practice highly complex designs can't be handled by one optimizer and thus design parts are distributed to different ones. The partitioning of the design is usually done based on expert knowledge. If important interrelations are not captured by the knowledge of the expert a final superposition of the optimized design parts might end up with unexpected results. Applying the information theoretic concepts for the detection of interaction effects to a 2D wing assembly in section 3.1 aims at making this issue apparent to the reader. Finally, the use for more complex aerodynamic designs given the example of a 3D turbine blade is demonstrated in section 3.2.

2 Interaction Detection

In order to increase the understanding on how certain parts of the design interact and how this interaction effects the flow and thus the performance number, first the interacting design parts have to be identified. Jeong [10] applied ANOVA techniques in order to extract information about the interaction effect of design variables related to the performance number(s). Therefore A Kriging model has been applied to approximate the relationship between the design variables and the performance numbers. The explained variance of the outcome of the model defines the importance of a single or multiple design variables. The main disadvantage of this approach is that the accuracy of the importance estimation and thus the detection of important interrelations between variables strongly depends on the reliability of the underlying Kriging model.

A different approach from statistics adds interaction terms to multiple regression models for detecting and modeling moderated causal relationships between variables, [8]. The interaction between variables will be significant if the influence of one variable on the outcome changes as a function of another one. An F-test can be used to test for significance. In multiple regression models a certain functional relationship between the related variables has to be asssumed which is usually not known.

We suggest to apply methods from information theory for analyzing the dependencies between design parameters. This approach is purely data driven and does not need any background knowledge concerning the kind of relationship.

2.1 Interaction Information

Without loss of generality we define $\Delta = \{\Delta_k | k = 1 \ldots N_\Delta\}$ as a set of N_Δ design parameters and $\Phi = \{\Phi_m | m = 1 \ldots N_\Phi\}$ as a set of N_Φ performance numbers. Mutual information is suggested for quantifying the correlation between a design parameter Δ_k and a performance number Φ_m:

$$I(\Delta_k; \Phi_m) = \sum_{\delta_k \in \Delta_k} \sum_{\phi_m \in \Phi_m} p(\delta_k, \phi_m) \log \frac{p(\delta_k, \phi_m)}{p(\delta_k) p(\phi_m)} \tag{1}$$

$$= H(\Phi_m) - H(\Phi_m | \Delta_k), \tag{2}$$

where δ_k and ϕ_m are discrete instances of the design and performance variables respectively, after e.g. binning has been applied, with $0 \leq I(\Delta_k; \Phi_m) \leq \min(H(\Delta_k), H(\Phi_m))$. An equivalent formulation of the mutual information in terms of the Shannon entropy is shown in equation 2. We term $I(\Delta_k; \Phi_m)$ the marginal information gain of parameter Δ_k on the performance Φ_m. Although the marginal information gain of one design parameter might be vanishing, thus the design parameter has no direct impact on the performance, the design parameter might be correlated to the performance in the context of another design parameter Δ_l.

McGill [11] has been one of the first who formalized the concept of mutual information for more than two attributes. Jakulin [9] summarized the concepts from the literature to the concept of interaction information. Following Jakulin, the interaction information for three attributes in terms of marginal and joint entropies is defined as follows:

$$\begin{aligned} I(\Delta_k; \Delta_l; \Phi_m) = {} & H(\Delta_k, \Delta_l) + H(\Delta_k, \Phi_m) + H(\Delta_l, \Phi_m) \\ & - H(\Delta_k) - H(\Delta_l) - H(\Phi_m) - H(\Delta_k, \Delta_l, \Phi_m) \qquad (3) \\ = {} & I(\Delta_k, \Delta_l; \Phi_m) - \big(I(\Delta_k; \Phi_m) + I(\Delta_l; \Phi_m) \big) \qquad (4) \end{aligned}$$

Writing the three way interaction in terms of mutual information easies the interpretation and understanding of this quantity, see equation 4, with $I(\Delta_k, \Delta_l; \Phi_m)$ being the joint information gain of two design parameters Δ_k and Δ_l. From equation 4 one can see that the interaction information for three attributes (Δ_k, Δ_l, Φ_m) equals the difference between the joint information gain and the sum of the marginals. On the one hand, if the joint information gain equals the sum of the marginal gains one can conclude that there is no interaction between the design parameters. If on the other hand the joint information gain is larger than the information gains from the single parameters, both parameters are said to interact. Unlike mutual information, the interaction information can be negative. That happens when the information gain from the marginals exceeds the joint information gain. A negative value can be interpreted as redundant information that one parameter adds about the performance.

Jakulin [9] generalized the information theoretic concepts of three-way interaction to the interaction information of multiple attributes. However the remainder of this paper focuses on the calculation of three-way interactions.

The interaction information like it is defined here is based on discrete instances of the design and performance numbers. Thus the continuous design and performance parameters have to be discretized. The discretization can be done e.g. using a simple binning approach. More sophisticated solutions exist where e.g. splines have been used for the generation of the marginal and joint distributions, see [2]. In this approach instances of an attribute are assigned to multiple bins depending on their value and on the used spline function. This approach is especially suited for small data sets and is used here.

2.2 Interaction Visualization

Information graphs [9] are used to visualize the calculated information quantities in order to facilitate the analysis of the interactions between variables. An information graph is an adequate tool for presenting the results of the interaction analysis e.g. to aerodynamic engineers. The graph contains one node for each design variable under consideration, see Fig. 1. The marginal information gain of a design variable on the performance is assigned to each node while the information that is gained from the interaction of two design variables is assigned to the edge between nodes. A negative interaction information is indicated by a dotted while a positive interaction information is indicated by a solid line between two nodes.

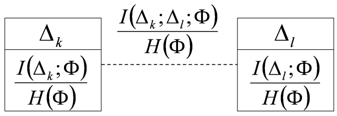

Fig. 1. Visualization of the information graph for two design parameters Δ_k and Δ_l.

Under the assumption that the maximum information gain is the information that we need to remove all uncertainty about predicting the performance, the information quantities are normalized by $H(\Phi)$. Fig. 1 illustrates an interaction graph for two design parameters.

3 Results

The information theoretic concepts have been applied to a test data set that stems from a 2D flap-wing profile as well as to a second more advanced data set that captures local design deformation data from the optimization of a 3D turbine blade.

3.1 Flap-Wing Test Case

The used test case is a 2D wing assembly which consists of two wings, a central wing and a flap wing. The shape of the wing assembly is controlled by two design parameters $\Delta = \{\alpha_{wing}, \alpha_{flap}\}$, the angle of the central wing and the angle of the flap wing, see Fig. 2*a*. In order to generate the design data set different wing assemblies have been generated: $\alpha_{flap} \in \{0.5°, 1.0°, 1.5°, 2.0°\}$, $\alpha_{wing} \in \{6.0°, 6.5°, 7.0°, 7.5°\}$. For each combination of the flap and central wing angle a 2D CFD mesh has been generated using Mesh2D [3]. Given the CFD mesh the flow has been simulated by solving 2D unsteady Navier-Stokes equations. From the resulting flow the mean drag coefficient has been calculated which determines the performance $\Phi = \{\bar{C}_d\}$ of each wing assembly. The resulting performance numbers of the generated wing assemblies are summarized in Fig. 2*b* that shows the influence of α_{flap} on the mean drag coefficient for constant angles of the central wing α_{wing}.

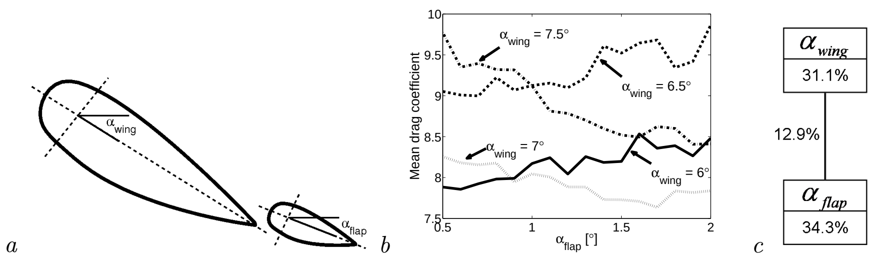

Fig. 2. *a*: Illustration of the wing assembly. *b*: The influence of the flap angle on the mean drag coefficient for different angles of the central wing. *c*: Visualization of the interaction graph for the wing-flap test case.

Assume that the wing assembly would be the target of optimization without having any knowledge on the interaction between the angle of the central and the angle of the flap wing. Further assume a given start design with $\alpha_{wing} = 7.5°$ and $\alpha_{flap} = 0.5°$. The mean drag coefficient for the start design configuration has been calculated with $\bar{C}_d = 9.75$. In the following scenario, the design is separated into two parts and distributed to two optimizers. The task of each optimizer is to find a value for the considered angle which minimizes the mean drag coefficient. In the described scenario the optimization of the central wing would probably result in an optimal solution with $\alpha_{wing}^{opt} = 6°$ (19% reduction of $\bar{C}_d$). The optimization of the flap wing will most likely result in an value $\alpha_{flap}^{opt} = 2°$ (14% reduction of $\bar{C}_d$). As can be seen from Fig. 2*b*, putting both solutions together will fail in further reducing drag. The reduction of the mean drag coefficient is about 14% which is less than what could be reached if both parameters would be optimized together.

Given the already evaluated wing designs we want to see whether the calculation of the three-way interaction information can be applied to get a hint on the relationship between both variables. Therefore the values of the angles and the performance numbers have been discretized using 10 bins and a spline function of order 2. The resulting information gain with respect to two- and three-way interactions is summarized in the interaction graph shown in Fig. 2*c*. As can be seen, the interaction information between both design parameters is positive. The aggregation of both parameters lead to 12.9% reduction of the uncertainty of the mean drag coefficient. This verifies that the assumed separation is suboptimal because the statistical dependency was ignored. Therefore, we conclude that our system set-up to extract dependencies between design variables show the expected results.

3.2 Turbine Blade

In the following application, the concepts for analyzing interactions are applied to a data set of 3D turbine blade designs. The reference blade geometry is from a high pressure (HP) turbine of the Honda HF118 turbofan engine. The considered data set consist of 200 different blade designs that result from several computational optimization runs where evolutionary strategies have been applied [6], [7]. A parallelized 3D in house Navier Stokes solver, called HSTAR3d [1] is used to simulate the fluid dynamics of the stator blade section. Based on the flow field the pressure loss is calculated and is used to quantify the performance of each blade. In order to analyse local design interactions the unstructured surface meshes of the 200 blade designs have been generated by uniformly triangulating the bounding surface of each blade, see [5] . The cross sections of the blade have not been triangulated because there is no flow at all. Each surface mesh comprises $N_V = 1200$ vertices which are used to sample the continuous surface of the blade. Based on the surface meshes and the related performance numbers, all pairwise design comparisons are generated. The displacement values of the corresponding vertices together with the performance differences between the blade designs are calculated, as suggested in [4]. This results in a set of displacements, $\Delta = \{\Delta_i : \Delta_i = \{\delta_{i,j}^{r,m} : i, j \in [1 \cdots N_V]; r, m \in [1 \cdots N_B]; r \neq m\}\}$ (where $N_B = 200$ defines the number of blades in the design data set) and a set of performance differences, $\Phi = \{\omega^m - \omega^r : r, m \in [1 \cdots N_B]; r \neq m\}\}$ (where ω defines the pressure loss of the blade).

The displacement values Δ and the performance differences Φ are the basis for the analysis of local design interactions. The set of displacement values for each vertex Δ_i as well as the performance differences are discretized using 10 bins and a spline order of 2. The brute force approach for analysing the interactions between vertices is to calculate all pairwise interaction information between all vertices. Especially for complex designs with a high number of vertices this becomes infeasible. In [4] an algorithm is suggested for reducing the considered vertices to a manageable number. The sensitivity of the vertices is calculated

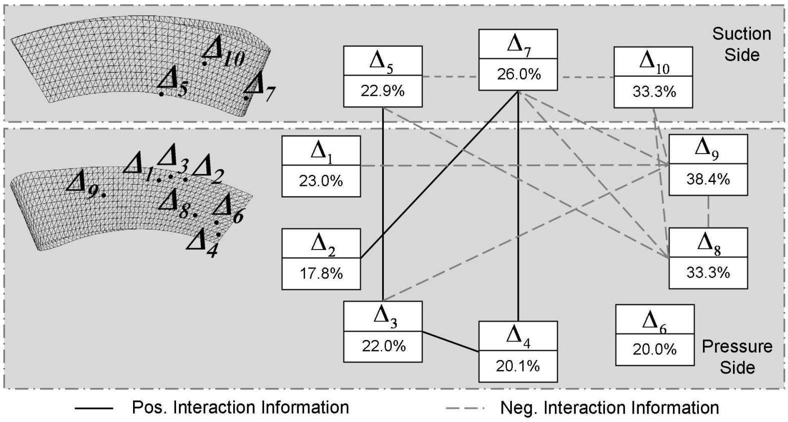

Fig. 3. Information graph which visualizes the two- and three-way interaction between the identified sensitive design regions and the change in the pressure loss are shown on the right. The cluster centers of the sensitive design regions are shown on the left.

and a pivot design has been chosen. After that, vertices are clustered based on the x, y, z coordinates and its sensitivity. Finally, vertices are selected that are closest to the emerged cluster centers. Given a fixed number of 10 clusters the resulting vertices are presented in Fig. 3 on the left. Thus instead of calculating the interactions between 1200 vertices only the 10 selected vertices are considered. The resulting interaction graph after calculating the information theoretic quantities for two and three variables is shown in Fig. 3 on the right. In order to increase the interpretability of the graph, weak pronounced interactions are not drawn in the graph. Edges where the normalized interaction information is between -6% and 2% have been removed. It can be seen that especially vertices Δ_{10}, Δ_9 and Δ_8 provide mainly redundant information on the performance. This indicates that those vertices can be removed from further optimizations. However, positive interactions are identified between vertices of the suction and the pressure side of the blade. Especially interesting is the interaction between the leading edge Δ_7 and the trailing edge Δ_4 and the interaction between the vertex close to the casing at the pressure side Δ_3 and the vertex close to the hub section at the suction side Δ_5. These are interactions that might not be obviuos for an aerodynamic expert. With the provided interaction graph the expert can get interesting insights into the interaction between design parts which can be target for a more detailed analysis with respect to fluid dynamic properties.

4 Conclusion

In this paper, we focused on the detection of interaction effects based on aerodynamic design data. The use of the information theoretic interaction information is suggested because no assumptions about the underlying functional relationship have to be made. By applying the concept of interaction information to a flap-wing assembly test case, we highlighted the discussion on the importance of interaction detection before splitting complex aerodynamic designs into parts for distributing the optimization process. The interaction quantities have been applied for detecting local design interactions between sensitive regions of a 3D turbine blade. Important relationships between design regions with respect to the overall performance have been identified as well as design regions which do not contribute to the performance at all. It has been shown that using displacement information that is calculated based on unstructured surface meshes and combining this representation with interaction information allows to detect interaction effects independent of the representation used during the optimization process. The use of interaction graphs is suggested in order to hand over the extracted information to aerodynamic experts.

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