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2011

Preprint:

This is an accepted article published in Int. Conf. on Intelligent Data Engeneering and Automated Learning (IDEAL). The final authenticated version is available online at: https://doi.org/[DOI not available]

Modeling Design and Flow Feature Interactions for Automotive Synthesis

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Abstract. In the automotive industry Computational Fluid Dynamics (CFD) simulations have become an important technology to support the development process of a new automobile. During that process, individual simulations of the air flow produce a huge amount of information about the design characteristic, where mostly only a minority of information is used. At the same time knowledge about the relationship between design modifications and their aerodynamic consequences provides valuable insight into the entire aerodynamic system. In this work a computational framework is introduced, providing means to identify relevant interactions within the aerodynamic system based on existing design and flow data. For an efficient modeling, the raw flow field data is reduced to a set of relevant flow features or phenomena. Applying interaction graphs to the aerodynamic data set unveils interacting and redundant structures between design variations and observed changes of flow phenomena. The general framework is applied to an exemplary aerodynamic system representing a 2D contour of a passenger car.

Key words: Data Mining, Structural Modeling, Information Theory, Interaction Information, Aerodynamic Design, Flow Field Feature

1 Introduction

In the automotive industry computer aided engineering (CAE) tools have become an important technology for improving the design development process. Physical experiments are replaced by computational tools to reduce development costs, see [10]. Hundreds and thousands of different geometric models of the designs and flow fields are simulated before an actual physical model of a design is build. However, usually the resulting flow field is reduced to a single number, defining the performance of the design. In order to get a deeper insight into the aerodynamic system at hand, we developed a framework for identifying relevant interaction structures between shape, flow field phenomena and performance, based on these otherwise unused data.

After reviewing related research activities in the subsequent section, the detailed framework proposed is depicted in section 3, including details about data reduction, the modeling of the interaction structure and the visualization of the results. The general framework has been applied to an exemplary aerodynamic system modeling the 2D contour of a passenger car, depicted in section 4.

2 Related Work

In the domain of aerodynamics, computational approaches for data mining and knowledge extraction are rarely being reported. Nevertheless, most of the existing works approach the modeling of the relationship between design variations and performance only. As an example, Obayashi et. al [18, 1] utilized self-organizing map (SOM) and analysis of variance (ANOVA) techniques to identify relevant relationships between design and performance, and Graening et. al [4] introduced a knowledge extraction framework discovering a set of If-Then rules, which illuminate causal relations between design modifications and performance changes. Further, the need of a universal geometric design representation within the framework is stated. However, the flow field produces much more information about the design concept than kept in the performance number. Nevertheless, it is impossible to handle the whole flow field. Therefore we extract flow field features commonly used for the visualization of flow field data. An overview of the sate of the art in flow visualization are given by [19]. De-composition methods, like the proper orthogonal decomposition (POD) [14], are applied to reduce the dimensionality of the flow field while keeping the majority of the energy contained in the flow. Often, decomposition methods are used in a pre-processing step, e.g. before flow phenomena like vortices are extracted, see [6]. While decomposition methods come up with features that have no direct physical meaning, other researchers aim at explicitly quantifying the position, rotation and elongation of physical artifacts like vortices or attachment and detachment lines [11]. Due to the similarity to optical flow, some attempts are derived from the computer vision domain to detect flow patterns, e.g. see [20]. In the context of applying data mining technologies to flow field features, Depardon et. al [3] use multi-dimensional scaling (MDS) for the classification of flow topologies. However, the relationship between flow fields and design properties has not been considered.

3 Interaction Modeling Framework

Based on earlier work from Graening et al. [5], the authors aim at deriving a general framework for identifying interaction structures in aerodynamic systems. Given the design process (e.g. targeting the development of a new car design), various design shapes together with its related flow field data are generated. Each of the shapes is represented by a low dimensional geometric representation of the actual continuous surface. Spline surfaces like NURBS (Non-uniform Rational B-Spline) or FFD (Free-From Deformation) are exemplary representations often being used. In a pre-processing step the geometric representations have to be unified and reduced to managable number of design features. Given the surface

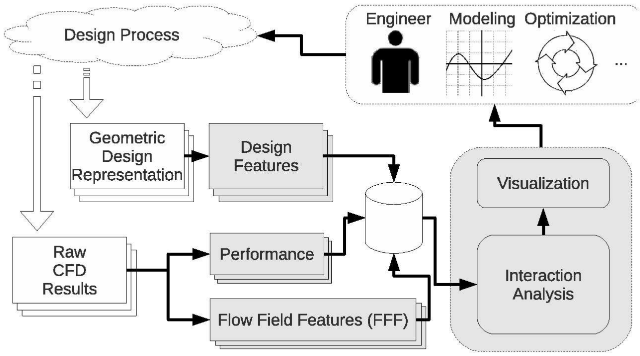


Fig. 1. Overall framework for the identification of structural interaction patterns with an aerodynamic system.

representation and the size of the computational area in which to model the flow, a discrete volume mesh is generated discretizing the computational area, with a typical mesh size in the order of 10^6 or more cells. The volume mesh together with the pre-defined wall conditions make up the initial setup for the CFD simulator. After simulation, detailed local information about the flow direction, velocity, pressure, temperature and so on is available. The resulting amount of data is too huge for an adequate analysis of flow effects and its relation to design parameter variations. A feature extraction step is introduced reducing the raw flow field to a low dimensional representation as depicted in Fig. 1. The choice of the flow field features strongly depend on the given task. Alongside the flow features, individual performance indicators are calculated, to quantify the overall quality of the shape.

After the pre-processing, interaction analysis is applied to identify the intrinsic structure of the aerodynamic system at hand. Based on a probabilistic attempt from information theory, described in the following section, the most relevant structures in the system of design features, flow features and performance are identified. Finally, interaction graphs are deployed to transfer the extracted information to the aerodynamic engineer, thus influencing the design process.

3.1 Information Theoretic Interactions

Following Krippendorff [12], we define interaction as *a unique dependency from which all relations of lower ordinality are removed*. Information theoretic attempts for quantifying interactions are founded based on the formulation of the Shannon entropy. Given a discrete random variable X_i, the Shannon entropy, denoted as $H(X_i)$, is a non-negative measure of uncertainty quantifying the amount of randomness contained in X_i. It is formally defined as: $0 \leq H(X_i) = -\sum_{n=1}^{N} p(x_n) \log p(x_n) \leq \log N$, with N being the number of discrete intervals.

The logarithm is commonly chosen with the base two, resulting in $H(X_i)$ being measured in bits.

For two variables X_i and X_j, the mutual information [2], $I(X_i; X_j)$, 2-way interaction or transmitted information can be considered as the amount of information shared among both variables. The mutual information can be written as the difference between maximum entropy, assuming independence among the variables, and the actual joint entropy [12] observed:

$$I(X_i; X_j) = H(X_i) + H(X_j) - H(X_i, X_j). \quad (1)$$

$I(X_i; X_j)$ is only equal to zero if X_i and X_j are statistical independent. In case that a dependency between X_i and X_j exists, $I(X_i; X_j)$ is always larger zero, bounded by the maximum of the marginal entropies $H(X_i)$ and $H(X_j)$. Based on the work of McGill [15], Jakulin and Bratko [7] defined the interaction information for multiple attributes. The interaction information for three variables X_1, X_2 and X_3 evaluates the information gain resulting from the 3-way interaction which is not present in any of the 2-way interactions:

$$I_J(X_1; X_2; X_3) = I(X_1, X_2; X_3) - I(X_1; X_3) - I(X_2; X3). \quad (2)$$

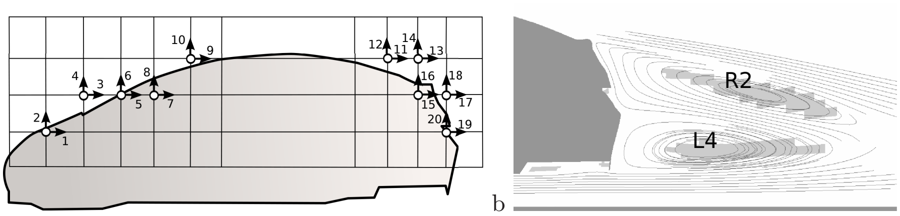
$I_J(X_1; X_2; X_3)$ quantifies the information shared among the variables X_1 and X_2 with X_3, reduced by the information shared between variable X_1, X_3 and X_2, X_3. It is important to note that in contrast to the mutual information the interaction information can have negative values. $I_J(X_1; X_2; X_3)$ gets negative if the joint information of X_1 and X_2 on X_3 is smaller than the product of $I(X_1; X_3)$ and $I(X_2; X3)$. This is the case if the information added to the system through interaction is smaller compared to the amount of redundant information in the system that e.g. X_1 and X_2 have in common about X_3, see [13]. In consequence, $I_J(X_1; X_2; X_3) = 0$ not necessarily reflects the absence of an interaction rather that information and redundancy cancel each other out. However, a positive I_J indicates a surplus of information due to interaction and a negative I_J indicates a surplus of redundancy. Higher order interactions (larger three), as defined by Jakulin [8], are not considered throughout this study.

3.2 Interaction Graph

An interaction graph [7] is a visualization of the identified interaction structure from observed variables characterizing the system. In this work we adopt supervised graph structures visualizing 2-and 3-way interactions relative to an a priori chosen dependent variable Y with the target to explain the uncertainty of the dependent variable. Thus, all information quantities are normalized by the uncertainty of the dependent variable, $H(Y)$. The graph consists knots labeled by the relative mutual information $I(X_i, Y)/H(Y)$ and edges between two nodes of X_i and X_j corresponding to the relative interaction information $I_J(X_i, X_j, Y)/H(Y)$. Edges with a negative relative interaction information are drawn with dashed lines and with solid lines otherwise. For the sake of readability, only the most significant 3-way interactions are drawn into an interaction graph.

4 Application to a Passenger Car Model

The introduced framework is applied to a two-dimensional model of a passenger car to unveil interactions between car shape deformations, flow field features and performance measures. A parametric Free-Form Deformation (FFD) [21] with 20 control point parameters (design parameters), see Fig. 2, is applied to model the design contour of the car. 1000 variations of the car design are generated by applying a latin hypercube sampling (LHS) [16] to the design parameters. The



a b

Fig. 2. a: Contour of the initial passenger car together with the FFD control point lattice, defining the position of the control point parameters used to vary the car shape, b: Visualization of the identified upper $R2$ and lower $L4$ wake vortex behind the car

computational fluid dynamics simulation of the passenger car is carried out by OpenFOAM®[1]. For each car, the stationary flow field is computed using the simpleFOAM solver, which iteratively computes the steady-state solution of the incompressible Navier-Stokes equations.

4.1 Flow Feature Extraction and Performance Evaluation

The resulting flow fields are reduced to a small set of flow features and performance indicators. A common objective in car design is to reduce the drag force D, acting opposite to the flow direction, while reducing lift force L, perpendicular to the drag force component. Beside drag and lift and without loss of generality our performance indicator is defined by a superposition of lift and drag:

$$Q = \frac{L}{\sqrt{\mathrm{var}L}} + \frac{D}{\sqrt{\mathrm{var}D}}. \tag{3}$$

The major part of drag on road vehicles (form drag) is the result of flow separations [9], especially at the aft section of the vehicle. The flow separation at the back of the car is always attended by an upper and lower vortex sheet behind the vehicle. Hence, the size and orientation of the emerging vortices is linked to an change of the drag value. Vortices are characterized by discontinuities observed

[1] OpenFOAM: open source CFD, http://www.openfoam.com/

in the vector field. To identify those discontinuities the vortex identification algorithm of Michard [17] has been adopted,

$$\Gamma_1(P) = \frac{1}{N} \sum_S (\theta_M) \tag{4}$$

The dimensionless scalar $\Gamma_1(P)$ integrates over the angles θ_M between the velocity vectors for each point $M \in S$, where S defines the neighborhood around P and the vector PM. $|\Gamma_1|$ becomes close to one in the range of vortex centers. Applying a threshold to the calculated values of $|\Gamma_1|$ allows to identify vortex regions as shown in Fig. 2b. Gray areas indicate the position of the upper $R2$ and lower wake vortex $L4$ behind the car. The results of Γ_1 are used to model the vortices with ellipses, estimating the orientation, the size and eccentricity of the vortices. For all 1000 generated flow fields the corresponding vortices between different flow fields are identified using the Euclidean distance between the vortex centers. Flow fields that have no correspondence in any of the generated flow fields have to be treated differently what is not considered in this work. We limit the following studies to the vortices $R2$ and $L4$, where a correspondence for any flow field is found.

4.2 Interaction Analysis

Given the data of all 1000 designs the interactions are modeled and visualized using interaction graphs. Only the design parameter modifying the design in y-direction have be considered in this study. The interaction graphs for modeling the relationship between a: design features and drag D, b: design features and Q, c: design features and the size of the upper wake vortex $R2$ as well as flow features and Q are depicted. Regarding the influence of the design parameters d_i on the drag D, Fig. 3a, variations of the rear part of the car have a stronger influence compared to variations on the frontal part. Especially parameter $d18$ and $d12$ share a majority of information with the drag. $d18$ already explains about 26% of $H(D)$. Further, the interaction between $d12$ and $d18$ seems to be relevant for explaining variations in drag. Interactions between the frontal and rear part of the car model seem to be negligible. The interaction graph concerning lift L, not presented here, provides qualitative similar results as for the drag. Concerning the influence of the flow field features on the drag, the size of the upper wake vortex $R2$ turned out to be most relevant. The interaction structure for the size of $R2$, Fig. 3c, is qualitatively the same as, Fig. 3a, what consolidates the importance of the flow feature. Interestingly, in all interaction graphs comprising design parameters, no strong redundant connections are observed, possibly due to the chosen representation, where the influence of individual design parameter on the shape does not overlap.

While usually the effect of design variations and flow phenomena is studied regarding aerodynamic properties like drag and lift, the influence on combined objectives like the performance measure Q is seldom be regarded. The graphs showing the interaction structure between design features and Q as well as between flow features and Q are depicted in Fig. 3b and d respectively. Comparing

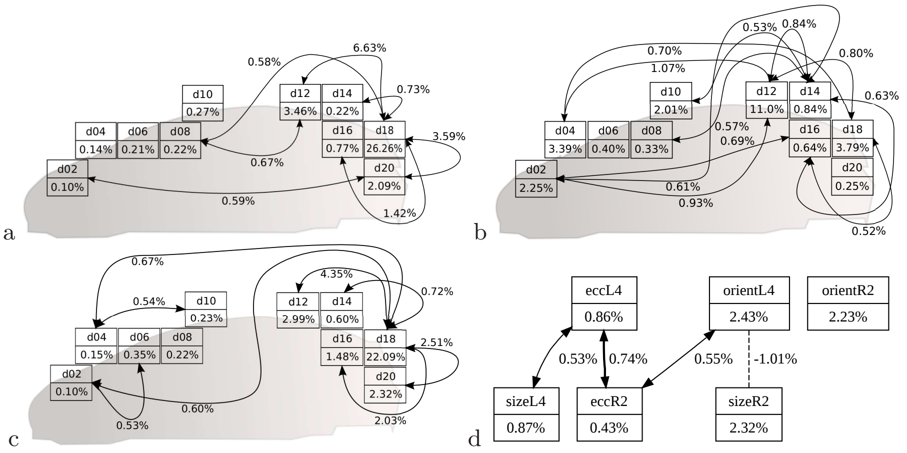


Fig. 3. Resulting interaction graphs modeling the interactions between a: design parameter and drag D, b: design parameter and objective Q, c: design parameter and the size of the upper wake vortex $R2$, d: flow features and the objective Q.

the interaction graph from Fig. 3a, showing the interactions between design parameters and D, with the interaction graph from Fig. 3b, interactions are of relevance which are not important for either of the individual objectives D or L. E.g. the influence of $d04$, located at the frontal part of the car, becomes more relevant. Please consider that the graph for L is not shown here but is qualitative similar to the interaction graph for D. Further, the frontal part and its interaction with the rear part of the car becomes more relevant concerning the combined objective Q. Finally, the interrelation between the flow features and Q are under investigation. Fig. 3d shows that the orientation of the lower wake vortex $L4$, the orientation of $R2$ and the size of $R2$ seemingly have a strong influence on Q. Redundancy between the orientation of $L4$ and the size of $R2$ are observed. This might be the result of interference between the lower and upper vortex for certain configurations of the size of $R2$ and the orientation of $L4$.

Overall, the interaction analysis results in hypothesis about the relationship between design-, flow properties and objectives valuable for the ongoing design process, once consolidated with real physical experiments. E.g. with the given knowledge, selected design parameters can be modified for manipulating distinct flow phenomena with respect to a given objective.

5 Conclusion

In this work we presented a general framework for identifying interaction structures in aerodynamic systems, by deploying techniques from information theory. For the investigation of aerodynamic systems that constitute high-fidelity flow simulations, the flow field data has to be reduced to a manageable amount of flow features before modeling interactions. As pointed out, the choice of flow features depends on the defined objective. The framework is applied to the automotive domain, exemplary to the 2D contour of a passenger car model. Investigating the interactions between design-, flow features and objectives provides valuable knowledge about the aerodynamic system. The knowledge can directly be utilized by the design process by filtering design parameters and interactions affecting distinct flow features relevant for a defined objective. The application of the framework to 3D non-stationary flow field data is considered for future work. This requires to discover different techniques for identifying and tracking flow field features and discrete information like the absence of a flow feature has to be processed properly. Finally, the result of the interaction analysis need to be consolidated by real physical experiments.

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