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Shape mining: A holistic data mining approach for engineering design

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ABSTRACT

Although the integration of engineering data within the framework of product data management systems has been successful in the recent years, the holistic analysis (from a systems engineering perspective) of multi-disciplinary data or data based on different representations and tools is still not realized in practice. At the same time, the application of advanced data mining techniques to complete designs is very promising and bears a high potential for synergy between different teams in the development process. In this paper, we propose shape mining as a framework to combine and analyze data from engineering design across different tools and disciplines. In the first part of the paper, we introduce unstructured surface meshes as meta-design representations that enable us to apply sensitivity analysis, design concept retrieval and learning as well as methods for interaction analysis to heterogeneous engineering design data. We propose a new measure of relevance to evaluate the utility of a design concept. In the second part of the paper, we apply the formal methods to passenger car design. We combine data from different representations, design tools and methods for a holistic analysis of the resulting shapes. We visualize sensitivities and sensitive cluster centers (after feature reduction) on the car shape. Furthermore, we are able to identify conceptual design rules using tree induction and to create interaction graphs that illustrate the interrelation between spatially decoupled surface areas. Shape data mining in this paper is studied for a multi-criteria aerodynamic problem, i.e. drag force and rear lift, however, the extension to quality criteria from different disciplines is straightforward as long as the meta-design representation is still applicable.

1. Introduction

The intensive use of computational engineering tools in the recent years and the transition from an experiment to a simulation based product design process, in particular in the automotive industry, has led to a significant increase of computer-readable design data relating design characteristics[1] to the design quality.[2]

In the context of Product Data Management (PDM) and Product Lifecycle Management (PLM), product related data is maintained and integrated through the whole design process or even through the whole lifetime of the product. Although PDM/PLM frameworks have been successful in managing CAD models and documents as well as in integrating CAD and ERP (Enterprise Resource Planning) systems, PLM solutions still need customization to the actual tools used in the design process [1]. Furthermore, the handling of multi-disciplinary processes, tools and data structures as well as a systems engineering or holistic interpretation of the design process remains to be challenging, e.g. see [1,2]. Industrial informatics in the domain of PDM and PLM still has not received the required attention in the literature, e.g. see [3]. As a result the application of data mining techniques to engineering data in practice is still often restricted to single design processes and individual design teams working on a certain CAE task, which we will call a sub-process in the following. The stronger the variation between the CAE tasks is (different representations, different disciplines, different tools and data structures), the more isolated is the data handling. Even though the data might be integrated into an overall PDM framework, it is not available for a holistic data mining approach from a systems engineering perspective. As a simple example different design teams might focus on the aerodynamics of the frontal part of the car, the rear part of the car, the noise generated or the cooling of the front brakes. However, the CAE results as well as the changes the teams proposed to the design are seldom independent from each other, since they are very likely to employ different representations of the design parts. This makes it difficult for data mining techniques to integrate data across teams and disciplines. On the one hand, the decomposition of the overall design problem (known as Simultaneous or Concurrent Engineering) is necessary

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[1] In the following, "design" refers to the 3D shape or topology of an engineering object, e.g., a car, and to the parameterization of the shape, e.g., a B-spline representation.

[2] In the following, "design quality" refers to one or several criteria that evaluate the performance of a design, e.g. based on the results of CAE simulations.

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for an efficient design process. On the other hand, we can expect that new important insight about the design can be gained only when we examine the data holistically and relate previously unrelated parts of the design process to each other.

In a more formalized way, the targeted approach is illustrated in Fig. 1. The engineering design process is considered to be best described as a goal oriented iterative decision making process [4]. In each iteration, engineers decide about individual or a sequence of design variations, which lead to a final design configuration fulfilling pre-defined constraints and design goals best. The overall design process is spatiotemporally decomposed into a number of (multi-disciplinary) sub-processes $\{1,\ldots,i,j,\ldots,P\}$. Based on the result of a decision making process (DMP), each sub-process defines design changes that contribute to the synthesis process (SP) for the finally submitted design. The aim of the paper is to propose an approach that allows cross-process design data management (DB) and that enables the analytics process (AP) to integrate knowledge and information gained from all sub-processes. Finally, the results of the holistic analysis can be fed back to the individual sub-processes to improve the individual decision making.

Apart from the problem of relating different design representations to each other in the overall design process, in general the application of data mining techniques to engineering data has been less explored than, e.g. to economic data. Literature related to the extraction of human readable knowledge in the field of aerodynamic and structural design is rare. The team of Obayashi [5,6] have addressed the extraction of knowledge from a given data set in order to gain insights into the relationship between geometry and multi-criteria performance measurements. The authors applied self-organizing maps (SOM) in order to find groups of similar designs for multi-criteria performance improvements and trade-offs, and used the analysis of variance technique (ANOVA) to identify the most important design parameters. Their methods have been applied to supersonic wing design. In [7] the use of methods from information theory have been studied to reveal higher order interrelations between design and flow field properties. Their methods have been tested in the domain of turbine blade and passenger car design.

In most of the literature, the extracted information is linked to a specific and well-defined representation being used in the design process. Thus, the usability of the extracted information beyond this particular design and optimization process is only possible to a limited extent. Therefore, Graening et al. in [8] started to study the use of data mining techniques on a unified object representation. However, data mining based on such a typically high dimensional representation goes beyond the application of individual modeling technologies. Furthermore, it requires the consideration of other data mining aspects like, feature extraction, feature reduction and post-processing. Wilkinson et al. [9] adopted the basic idea of Graening et al. and utilized unstructured surface meshes as unified object representation for the prediction of the local wind pressure distribution on tall buildings.

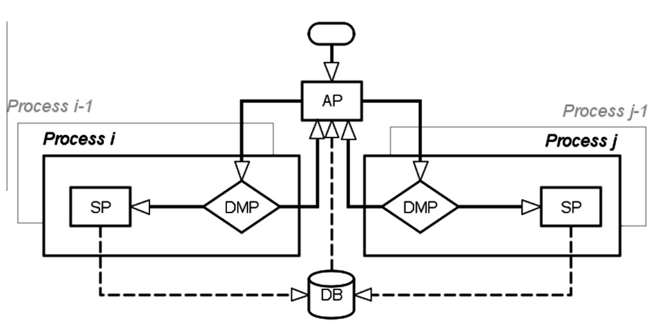

Fig. 1. A formalized view on the design process including the design synthesis (SP), the decision making (DMP) and the analysis (AP) process, see the text for a detailed explanation.

In this paper, we generalize the concept behind the analytics of design data based on a unified shape representation by introducing the shape mining framework. The remainder of the paper is organized in two parts. In the first part, we discuss different methods for shape mining and embed them into an overall framework. In the second part, the shape mining framework is applied to the analysis of passenger car design data.

The first part is divided into four sections. In Section 2, a unified design representation[3] is defined together with methods for the evaluation of local design differences. In Sections 3–5, methods for sensitivity analysis, for the extraction of design concepts, and for interaction analysis are introduced and discussed.

The second part of the paper is organized almost synonymously with the first part. Firstly, elements of different design processes that are the sources for the passenger car design data are described in Section 6. Statistical methods are applied to the meta design representation in Section 7, e.g. to investigate the course of design processes. In Sections 8–10 the methods from part one for sensitivity analysis, the extraction of design concepts, and the interaction analysis are applied to the data from the industrial design process. The aim is to model and understand the relation between shape variations of the car and changes in their aerodynamic quality.

Whereas part two of the paper is an application specific example, the approach presented in part one is generally applicable to all problems in the area of shape or topology mining. At the same time, some readers might find it useful to see the practical use of algorithms introduced in part one immediately; those readers are invited to read, e.g., Section 8 after Section 3. The paper closes in Section 11 with a conclusion and summary of the work.

Part I: shape mining

More recently, technologies from computational intelligence and data mining, e.g., see [5,6], have been adopted to exploit experimental design data and computational resources for the support of engineers in the decision making process. However, the multi-disciplinary characteristics of complex design processes and the huge variability in computational design representations hinders the analysis of design data beyond individual design configurations and processes. Especially the variation in the computational representations being used makes an efficient knowledge exchange between design processes difficult.

The shape mining framework, as illustrated in Fig. 2, targets the integration of technologies for the implementation of a holistic analysis processes. It requires the transformation of designs into a meta-representation, which facilitates the evaluation of design differences on a holistic basis. Just the transformation of the designs into such a unified meta-representation, together with the evaluation of design quality differences, allows a holistic modeling of the design data independently of the originating process. Depending on the stated problem, modeling techniques from data mining and machine learning are applicable to investigate design sensitivities, retrieve abstract design concepts and analyze the interrelations between distinct design parts with the focus to understand the interplay between local design differences and changes in their quality. The resulting knowledge from the analysis of the design data can be utilized to support engineers in decision making and to improve future design and optimization processes.

[3] In the following, we will use the terms "unified design representation" and "meta design representation" synonymously.