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Architecture and realization of a self–learning engineering assistance system for the use within sheet–bulk metal forming

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Abstract
Substantial efforts have been taken in the past to integrate manufacturing related and design–relevant knowledge into the product development process. A common approach is to provide this knowledge to the designer by implementing a knowledge–based system (KBS), an expert system or, as it is referred to in this submission, an engineering assistance system. Keeping the knowledge base of this KBS up to date is a central issue and the necessary knowledge acquisition the bottleneck within the development and maintenance process of a KBS. This applies especially for KBS applications were the knowledge can be considered as dynamic, that is the design– and engineering–relevant knowledge changes within short periods of time. In this paper the emerging manufacturing technology sheet–bulk metal forming (SBMF) is taken as the background for the development and application of an engineering assistance system. To overcome the bottleneck of knowledge acquisition the architecture of the presented assistance system is equipped with a self–learning component, based on knowledge discovery in databases applications

Keywords: engineering assistance system, knowledge discovery in databases

Introduction

In recent years, the requirements on technical products in automobile sector increased regarding userspecific flexibility, functionality, space– or weight–savings and will still increase. This fact represents a growing challenge for the manufacturing engineering which will be intensified by simultaneous demand for cost–effective and time–efficient production as well as for economization of energy and resources. This challenge will be met by the development of a new manufacturing technology called sheet–bulk metal forming (SBMF) which will unite the advantages of sheet and bulk metal forming processes to go far beyond the limitations of each process [5].

Precondition for the fast realization of this new manufacturing technology in industrial practice is that design engineers know the process limitations of this technology early to make full use of its potential. Today´s state of the art is to acquire design relevant knowledge only after the completed development of manufacturing process or technology, respectively. But the objective has to be to realize acquisition and maintenance of design–relevant knowledge contemporaneous to the development of the manufacturing technology to enable design engineers to integrate new design possibilities resulted from the new technology. This objective will be pursued with the development of a self–learning engineering assistance system that will support design engineers during a design process regarding production–

oriented design. For the analysis of a product regarding its manufacturability, corresponding knowledge has to be acquired and implemented in the assistance system. Furthermore, this knowledge must be maintained to avoid aging of the assistance system. The demand for the maintenance of knowledge implicates that knowledge acquisition has to be carried out at each stage of further development of sheet–bulk metal forming. In summary, the development of the self–learning engineering assistance systems addresses the well–known challenge of knowledge acquisition in the field of expert systems.
This paper reports about the development and application of an engineering assistance system for the early knowledge acquisition and provision within sheet-bulk metal forming. Due the implemented automatic knowledge acquisition tool it is referred to as *SLASSY*, the **s**elf-**l**earning **a**ssistance **sy**stem. At first a brief description of sheet-bulk metal forming is given. Then the general architecture of knowledge–based system in the domain of engineering design is highlighted. The methods of knowledge acquisition are presented and discussed. Afterwards the overall architecture of SLASSY is presented. The paper closes with an application of SLASSY for the synthesis and analysis of a single part that is to be manufactured with sheet-bulk metal forming and presents a conclusion and an outlook.

Sheet-bulk metal forming

The manufacturing technology sheet–bulk metal forming (SBMF) will be developed within the transregional collaborative research centre 73 (SFB/TR 73), funded by the German Research Foundation (DFG). This technology will unite the advantages of sheet and bulk metal forming processes to manufacture geometrically complex parts with variants and functional elements from thin sheet metal through forming. The objective is to manufacture these high–precision elements with close geometrical tolerances in which the geometrical details of the variants are in the range of the sheet thickness. The variants to manufacture are carriers and gearings derived from synchronizer rings and seat slide adjusters. The manufacturing of such variants out of sheet metals requires the overlapping or the sequence of 2– and 3–axis strain and stress states. To realize this, various sheet and bulk metal forming processes have to be combined [5]. For the development of SBMF processes, the process combinations “deep drawing – upsetting “, “deep drawing – extrusion“ and “cutting – deep drawing” will be investigated within (SFB/TR 73). In this paper, the process combination “deep drawing – extrusion” will be used as an application example. This combination aims at the manufacturing of a part similar to synchronizer rings (Figure 1).

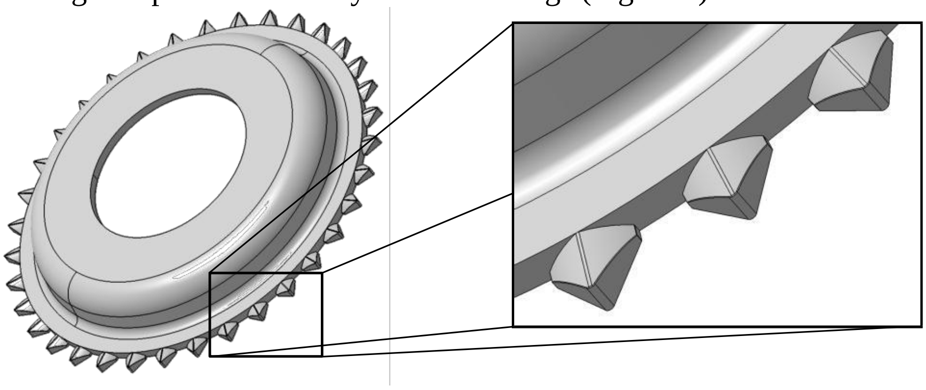

Figure 1: Demonstrator for sheet–bulk metal forming: a cup (deep–drawing) with attached ratching teeth as secondary form elements (extrusion).

Assistance systems in the engineering design domain

Knowledge-based assistance systems have been an extensive field of research in different domains and still are. Although developed for various areas the common idea is to map and store the knowledge of at least one expert in a computer and emulate the problem solving behaviour of this expert in a computer aided application [2]. Speaking of engineering design the computer aided design (CAD) has been the center of attention. The engineering assistance systems fulfil especially “design–for–manufacturing” related purposes such as design for assembly [3], [4].

General architecture of an engineering assistance system

Since they are related to the field of expert systems engineering assistance systems show a similar design regarding their core elements as they are depicted in figure 2.

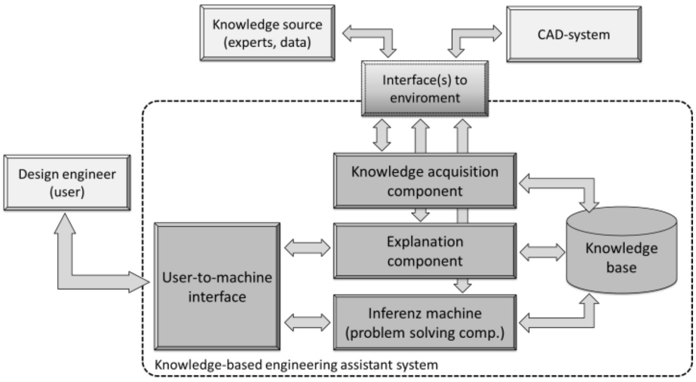

Figure 2: General architecture of an assistance system for use within engineering design.

Main parts are the knowledge base, the knowledge acquisition component, the explanation component, the inference machine (or problem solving component) and the user-to-machine interface. The system is embedded in the environment which consists of the user, in this case the design engineer, the knowledge source, mostly experts and data, as well as the interface to further IT-applications like a CAD-system. An assistance system equipped with those elements tries to solve a specific problem with the inference machine by getting the requested knowledge in agreement with the knowledge in the knowledge base. Missing knowledge will be enquired with the user input/output interface until inferences and deductions result in a problem solving. This problem solving can be finally checked via the explanation facility. [2]

Choosing a suitable method for knowledge acquisition

The development and maintenance of knowledge based systems is described as knowledge engineering. The knowledge acquisition as the initial phase represents the bottleneck of this process ([1, 2]) and is discussed controversially all over the literature. Depending on the reference it is sometimes merely equated with knowledge elicitation, whereas other authors regard knowledge acquisition as a process consisting of knowledge elicitation, knowledge interpretation (or analysis) and knowledge implementation. However, the common idea of these approaches is that knowledge acquisition methods can be classified either as direct, indirect or automatic (see figure 3). The direct knowledge acquisition is based on a dialogue between the experts and an intelligent knowledge acquisition tools, whereas the indirect knowledge acquisition is a knowledge engineer driven method and bases on the dialogue between a knowledge engineer and an expert. Automatic knowledge acquisition methods extract knowledge from different types of data such as documents, instructions, diagrams and so on, without the intervention of experts or knowledge engineers. The methods usually originate from fields like artificial intelligence, statistics or machine learning [10]. Since they are able to discover unknown knowledge from data the term “knowledge discovery in databases” (KDD) can also be found in the literature [6].

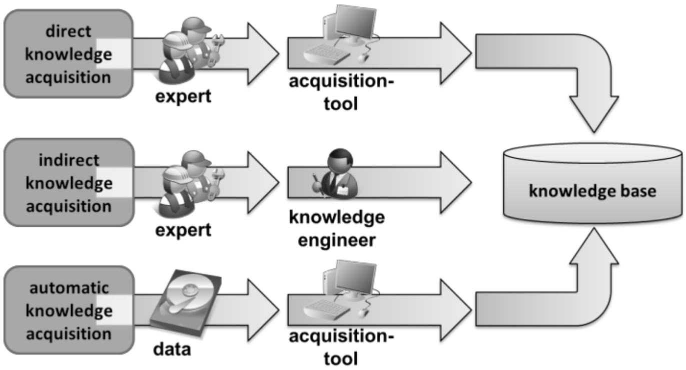

Figure 3: Methods of knowledge acquisition in the kontext of knowledge engineering.

Choosing a suitable knowledge acquisition method always depends on the context of a specific knowledge engineering problem in this case the emerging manufacturing technology of SBMF. In this case the objective is on the one hand to acquire design-relevant knowledge already in the early phases of process development and on the other hand to update or to maintain this knowledge simultaneously to the further development of the process. This intention intensifies the great challenge of knowledge acquisition owing to the resulting increase of time pressure. As a consequence of this increased time pressure the methods of the direct and indirect knowledge acquisition won't be applied during the development of SBMF. The reason for this is that its methods compared to the methods of automatic knowledge acquisition can be considered as time-consuming as well as cost-intensive due to the necessity of one or more knowledge carriers. Moreover, this time- and cost-factor increases during the process of indirect knowledge acquisition due to the need of one or more knowledge engineers. Furthermore, these methodologies will not be used within SFB/TR 73 because of the difficulty regarding the verbalization and formularization of knowledge as well as the influence of the knowledge engineer on the acquisition result. Furthermore the carrying out of an automatic knowledge acquisition is justified by the fact that the development of a new manufacturing technology requires the performing of numerical and experimental series of experiments.

SLASSY - The self–learning assistance system

SLASSY is an engineering assistance system developed for the purpose of helping the product developer to design parts that are to be manufactured by sheet-bulk metal forming. The synthesis step is supported by offering feature elements both for the primary design elements (PDE) and the secondary form elements (SDE) to the designer. It furthermore enables him to analyse a part, consisting of a primary form element (e.g. cup, plate, ring) and at least one secondary form element (tooth, strap, rib), that is to be manufactured with a sheet-bulk metal forming process. The knowledge needed for this analys is acquired through a processs of knowledge discovery in data bases whereas the data is derived from SBMF simulations or experiments with input-parameter variation studies. The explicit form of the design-relevant knowledge is represented by metamodels, a result of the KDD process [9].
The overall architecture of SLASSY is suitable to support the described aspects including the management of the simulation data and the design-relevant knowledge derived from this data. It is depictured in figure 4 and explained in detail in the following subparagraphs.

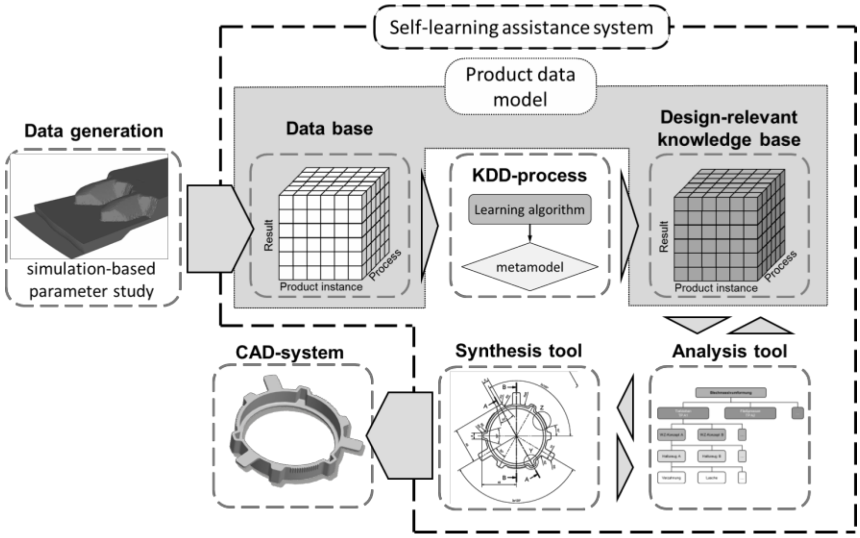

Figure 4: The overall architecture of SLASSY with product data model, KDD-process based knowledge acquisition tool, synthesis and analysis tool and interface to the CAD-system.

Product data model: Managing product data and design-relevant knowledge

The data within the SFB/TR73 is created in several sub-projects that are focussing on different research issues within SBMF that are not discussed in detail in this contribution. However, this leads to a heterogeneous and multi-dimensional character of the overall data that is to be managed. The basis for an efficient data management is a suitable product data model. It consists of several entities aggregated in classes and implemented in a relational data basis framework. With this framework the relevant information are stored such as: Geometric and process-related parameters of the different tool concepts and specific manufacturing processes (deep-drawing, extrusion, incremental forming etc.), geometry information about a part with its PDE and SDE. Each instance of the mentioned input- parameter variation studies is stored in the product data model with each single simulation run and is linked to a specific instance of a part (e.g. a “cup with attached ratching teeth” as depictured in figure 1). Each metamodel (the design-relevant knowledge) is also linked to a specific instance of a part and thus is related to the according parameter variation studies.

KDD-based self-learning component for automatic knowledge acquisition

In literature the term “self-learning” or “intelligent” can refer to the fact that a specific machine learning method such as artificial neural networks is used to implement human-like learning and inference behaviour in a knowledge-based system. Within this research project many learning algorithms have been analysed [8]. They have been compared with previously derived requirements for a knowledge acquisition component within a self-learning assistance system [7].

The result was that several machine learning methods are suitable for such purpose: The *linear and the polynomial regression, M5P regression tree learner* as well as the *M5Rules regression rule generator*. For detail information on these algorithms please refer to [10]. However, the potential of using different learning algorithms and thus making the knowledge acquisition component more flexible could only be revealed if SLASSY was able to choose the best fitting learning algorithm by itself without the intervention of the designer or a third party. The idea of “self-learning” was thereby seen from an essential different point of view. A KDD-process model for that purpose was not available so it was developed within this research project and implemented in SLASSY.

The starting point is the data that has been derived from sheet-bulk metal forming simulations or experiments. As described this *input-data* is stored in the data framework of the product data model. The implemented KDD-process filters the input-data set (e.g. deletes missing values) and performs different learning algorithms by using the input-data as training data. Every learning algorithm is performed with settings according to values of “good practice” [10]. Furthermore different optimization sub-processes are performed:

- stepwise forward attribute selection
- stepwise grid optimisation of algorithm settings
- grid optimisation of the settings paired with stepwise forward selection
- evolutionary optimisation of algorithm
- evolutionary optimisation the settings paired with stepwise forward selection

This results in 24 different metamodels (explicit form of design-relevant knowledge) that are all capable of predicting the manufacturability of a part but only one model offers the most dependable design-relevant knowledge. Every metamodel is evaluated independently from the others and its performance is determined [9]. Due to the limited simulation or experimental data the risk of outliers is mitigated by performing a stratified ten-times tenfold cross validation. This also increases the reliability of the performance estimate to assess the quality of the design-relevant knowledge. For more information about this strategy please refer to [9]. Now the challenge is to let SLASSY choose the metamodel with the best prediction performance automatically i.e. the most reliable design-relevant knowledge. Just choosing the model with the least error estimator might work on first sight. However, this leads to the problem that also a prediction error estimator is distorted by an error. The solution was to perform a statistical hypothesis test known as the *t-test*. Because same cross validation schemes for all metamodels have been used, the more sensitive *paired t-test* [10] was implemented in the code of SLASSY’s knowledge acquisition component. After this process the metamodel with the most reliable design-relevant knowledge is stored in the product data model and linked to the specific instance of a part (e.g. a “cup with attached ratching teeth” as depictured in figure 1) whereas it is only applicable for this instance. In order to derive a metamodel for another instance (e.g. “disk with flaps”) the KDD-process has to be performed again.
In order to enable continuous knowledge base updates the KDD-process is initiated automatically every time the input-data for a specific metamodel is updated, too. This can be the case when new developments of a sheet-bulk forming process lead to new simulations or experiments. The updated design-relevant knowledge is hidden in this new data and revealed by the developed KDD-process.

Synthesis and analysis tool

As mentioned the synthesis step is supported by offering feature elements both for the primary design elements (PDE) and the secondary design elements (SDE) to the designer. Depending on the CAD-system (in this contribution CATIA V5R19) these elements are designed as user defined features (UDF). Within the graphical user interface (GUI) for the synthesis step the designer selects the PDE of his choice. The availability of a design element had been checked with the product data model during the boot process of SLASSY. The selected UDF is loaded into the CAD-system and displayed. The design for the PDE is adopted in the corresponding context menu if needed. Afterwards the SDE are attached to the PDE. Due to reference elements (planes, lines, points) within the geometry of an SDE is always positioned correctly and changes its position if the shape (e.g. the diameter) of the PDE is changed. Like the PDE the geometry of a SDE can be adopted according to requirements that are to be met. All geometrical values (tooth width, strap length, flank angle, etc.) are stored in the product data model for further use. Figure 5 shows the synthesis tool.

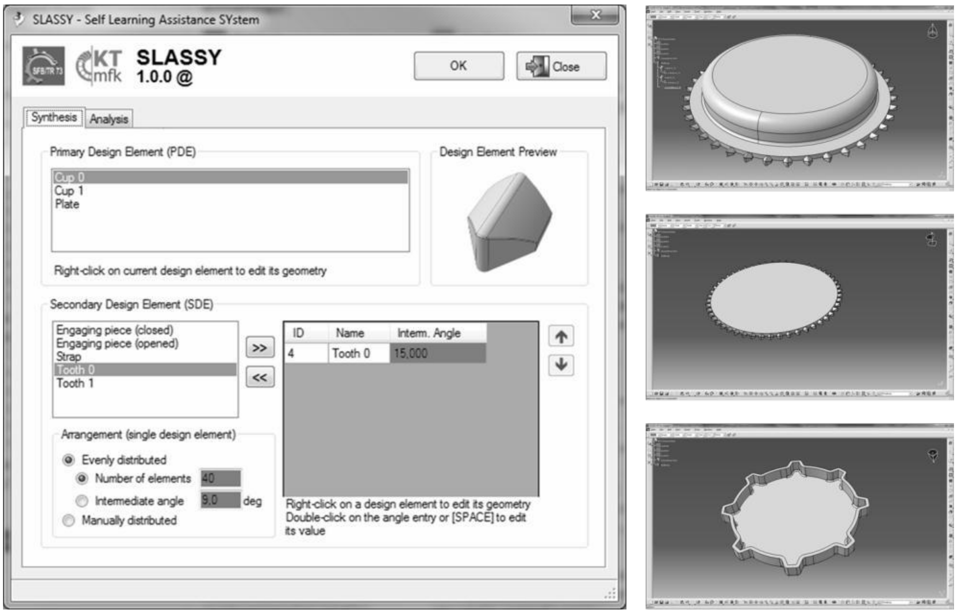

Figure 5: The graphical user interface of SLASSY with the synthesis tool for designing a sheet-bulk metal formed part consisting of PDE with SDE and exemplary parts (right, from top to down: cup with locking teeth, disk with teeth, cup with carrier elements).

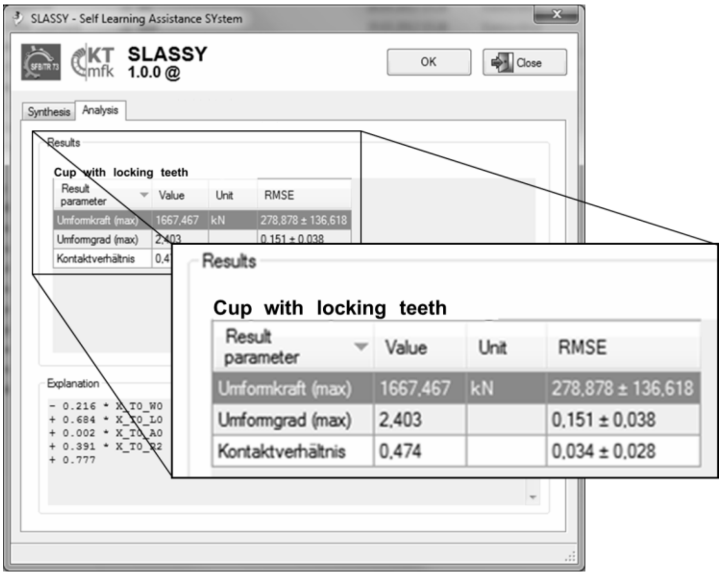

Figure 6: The graphical user interface of the analysis tool with the result values predicted via the metamodel. The explanation view at the bottom shows the corresponding metamodel.

After the synthesis step the designer can open the analysis tool in order to analyze the geometry regarding its manufacturability. SLASSY checks the product data whether a specific metamodel for the designed instance of a sheet-bulk metal formed part is available. The inference component of the analysis tool determines the actual geometrical values from the product data model, applies them to the metamodel and the results are displayed to the designer. Depending on the product instance different result values are of interest. For the “cup with locking teeth” the *total equivalent plastic strain* and the *forming force* are to be evaluated in order to assess the manufacturability whereas for the “cup with carrier elements” the *sheet thinning ratio* is of higher interest. The synthesis tool is shown in figure 6

Conclusion and outlook

This paper reports about the development of the self-learning assistance system, referred to as SLASSY. The purpose of SLASSY is to help the product developer to design parts that are to be manufactured by sheet-bulk metal forming, a new emerging manufacturing technology. It is shown that this leads to a situation where the established direct and indirect methods of knowledge acquisition are to time- and cost-consuming as well as to error-prone. An automatic KDD-based knowledge acquisition process that has been developed and implemented is presented. Furthermore the overall architecture of SLASSY that ensures its self-learning functionality and the management of the input-data and the design-relevant knowledge are described. Beside these components the graphical user interfaces for the synthesis and the analysis of a sheet-bulk metal formed part are highlighted.

Further developments will inter alia enable the assistance system to propose a part design that is suitable for manufacturing to the designer in case that a first geometry is not designed for manufacturing (i.e. “it is out of the process window”). In the near future SLASSY will also enhance the information exchange between product design and process engineering by deriving potential directions of process window expansion from the metamodels.

Acknowledgement

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