TOWARDS COGNITIVE COMPUTER AIDED ENGINEERING

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SUMMARY

Computer Aided Engineering (CAE) methods such as finite element based simulation and optimization techniques have become invaluable for product development in the automotive industry. Due to the continuously growing computational power and the introduction of cloud infrastructures, CAE tools are becoming more powerful, faster and cheaper to deploy. However, they still require a lot of expert knowledge in order to be used correctly and effectively. This is why larger corporations usually employ specially trained simulation engineers who help design engineers to set-up, run and post-process simulation scenarios. In order to make simulation technology ubiquitous even in small and medium sized enterprises, it is necessary to develop CAE tools that are equipped with intuitive interfaces and that can be used by non-experts (CAE democratization).

Recent advances in artificial intelligence have sparked the development of novel computer-based assistance systems in many domains such as autonomous vehicles, robotics and medicine. These systems demonstrate how knowledge-based approaches can either augment the capabilities of human experts or even replace them. Currently, these methods have seen very limited use within the CAE community.

In this paper we outline a set of methods that pave the way for a computer-based Cognitive Simulation Assistant (CoSA). Such an assistance system can help design engineers to leverage the full power of CAE tools in the same way as a human simulation engineer. This includes in particular the construction of the whole simulation workflow by autonomously selecting the appropriate tools, solver types, boundary conditions, numerical parameters and required cloud resources.

1: Introduction

Most products are developed in product generations. Based on a reference product (e.g. predecessor or competitive product), a new product generation is developed with appropriate differentiation characteristics [1]. Therefore Computer Aided Engineering (CAE) methods such as finite element based simulation and optimization techniques have become invaluable. Due to the continuously growing computational power and the introduction of cloud infrastructures CAE tools are becoming more powerful, faster and cheaper to deploy. However, they still require a lot of time and expert knowledge in order to be used correctly and effectively. In order to make simulation technology ubiquitous even in small and medium sized enterprises, it is necessary to develop CAE tools that are equipped with intuitive interfaces and that can be used by non-experts (CAE democratization).

2: Cognitive Computer Aided Engineering

The idea to automate simulations using knowledge based systems has already been proposed in the 1990s [2]. However, as in many other domains, these rule based expert achieved only limited success. Instead of trying to build general purpose solutions, recent work focuses on the concept of simulation templates (simulation apps) in order to simplify the CAE user interface [3]. However, advances in artificial intelligence technologies (e.g. semantic web [5], deep learning [6]) have the potential to finally deliver on the original promise to make extensive expert knowledge computer readable and usable. These so called cognitive systems are highly successful in a range of applications such as autonomous vehicles, medical computing or robotics. In contrast, these methods have seen very limited use within the CAE community.

3: Computer Aided Engineering Modeling Language

Semantic web technologies such as the Web Ontology Language have been used by many groups to describe formal knowledge in the CAE domain. This includes data integration, collaborative engineering or geometric representations [4][5]. However, all these ontologies are not integrated into a top-level ontology. This prevents their combination and thus their re-use in a general cognitive framework for the whole simulation workflow. In order to achieve this goal we have developed the Computer Aided Engineering Modeling Language Ontology (CAEMLOnto), which is integrated into the Basic Formal Ontology (BFO). It not only relies on existing CAE standards (STEP AP 209), but also makes use of other established ontologies (e.g. Information Artefact Ontology). Furthermore, CAEMLOnto adds important simulation specific knowledge such as discretization methods, solver

TOWARDS COGNITIVE COMPUTER AIDED ENGINEERING

types, contact models etc. This knowledge about the different simulations properties is essential for a CoSA.

Although knowledge representation by ontologies offer great value in terms of flexibility and reuse, the usability of this approach is often limited. The necessary methods and software tools require a large amount of expert knowledge that a typical CAE developer does not necessarily have. That is why the current reference implementation of the Computer Aided Engineering Modeling Language (CAEML) translates the ontology into an object oriented class model in order to provide an easy-to-access Python programming interface (API).

4: Shape understanding through machine learning

However, not all information that is associated with simulation scenarios can be captured in a semantic (i.e. symbolic) representation. This in particular applies to all properties that are directly associated with the geometry such as boundary conditions or defeaturing operations. It has been notoriously difficult to make such sub-symbolic knowledge computer readable. In the realm of image understanding, deep learning approaches that mimic the human understanding have recently achieved extraordinary success in this regard [6]. Inspired by these results, we are developing a novel convolutional neural network (CNN) for shape understanding (i.e. classification and segmentation) from CAD meshes. In this context we extend the concept of the convolution to triangular meshes and use the resulting CNN architecture to filter a

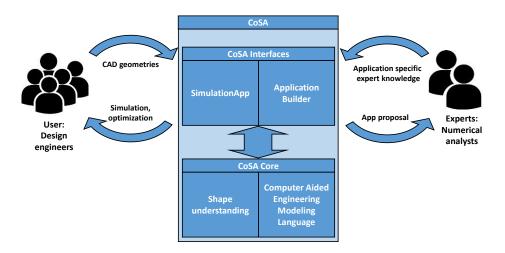


Fig. 1: A Cognitive Simulation Assistant (CoSA) helps numerical analysts to design cognitive simulation apps

large set of local mesh features.

5: Conclusions and Outlook

The methods outlined above can be used to implement a Cognitive Simulation Assistant (CoSA). As a first step towards a general CoSA, the technology can augment the current generation of simulation apps. In this context, the cognitive modules can be used to build cognitive simulation apps from simulation examples (see Fig. 1). The cognitive modules such as the shape understanding technology enable the system to generalize from the given input decks and also make the app geometry independent by automatically applying boundary conditions other geometry dependent data to new CAD input.

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