

<u>Title:</u> Graph Centrality Analysis of Feature Dependencies to Unveil Modelling Intents

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Introduction:

CAD model reuse boosts product development process [5]. However, most of the CAD models are not well reusable. Even with the visually the same resulting CAD geometry, the modelling procedures and operations applied might be quite diverse. Without standard way of model construction, it is hard to modify CAD models to cater to new design requirements. In some cases, even a single alteration of certain value in the model could render the whole part unusable, which is even worse if it is not visually identifiable. The reason behind it, the authors believe, is that the non-optimal and implicit modelling strategy. In order to reach a more robust CAD modeling strategy, a better understanding of the nature of the CAD model construction is necessary. The authors believe the key lies in the understanding of modeling intents. Modeling intents are what behind the CAD model construction, i.e., what users wish the model to be. There are two levels of modelling intents, i.e., the reasons why models are constructed in certain ways to, firstly, conform to the physical structure, and secondly, comply with the functional design considerations. One of the generally-expected structural modeling intents is that minor (auxiliary) features should be built on top of major features that contribute to the general shape of the product. Understanding modelling intents is critical. If changes are to be made to the model, it is better to know how and why the model has been constructed such that when the changes are carried out the model will at least be able to regenerate. If the intents of model construction are unknown, it would be difficult to change the model properly due to its inner parametric and geometric associations [11-12]. Moreover, by inspecting modelling intents, engineers can see whether the model has been constructed robustly.

Main Idea:

In order to unveil modelling intents in CAD models, the analysis of applied features is a way to go, more specifically, analysis of feature dependencies [1]. Modeling intents are reflected through the way how features are applied in the model construction process. Users might apply the same set of features to construct visually identical product geometry with different modelling procedures, which results in the differences of feature dependencies. So it is not enough to analyze the shape information. The approach in this research is to retrieve implicit feature dependencies from a CAD model to construct its feature association graph from which further analysis is carried out. An algorithm is developed to retrieve feature information and to construct the graph automatically. The graph provides a more organized view towards the applied modelling procedures.

It is observed that the feature association graph is directed and acyclic, which is called Acyclic and Directed Feature Dependency Graph (ADFDG), where the set of nodes, or vertices V, are the features and edges E depict the feature dependencies. Moreover, due to the nature of feature modeling, feature dependencies in ADFDG have other characteristics; they are *non-reflexive*, i.e., a feature cannot

Proceedings of CAD'17, Okayama, Japan, August 10-12, 2017, 232-236 © 2017 CAD Solutions, LLC, <u>http://www.cad-conference.net</u> depend on itself, feature dependencies are *nonsymmetrical*, i.e., two features cannot mutually depend on each other. Further, feature dependencies are *transitive*, i.e., if feature c depends on feature b and feature b depends on feature a, then feature c also depends on feature a [1],[10].

There are multiple aspects of the ADFDG that can be analyzed to unveil modeling intents. Current research focusses on finding the critical features in ADFDG to provide engineers with a starting point to examine the rightfulness of modeling intents reflected by the model construction. Centrality related metrics, assessing each node's involvement in the walk structure of a graph [2],[4], are applied to characterize the properties of feature dependency graphs. There are local measures, e.g., degree centrality, and global measures, in the sense that they measure the centrality of the specific node relative to the rest of the network, e.g., closeness, betweenness, and eigenvector centrality [2],[4],[8]. Degree centrality measures how many edges are connected directly to each node in the graph. In a direct graph, degree centrality could be further categorized into in-degree and out-degree centrality. The larger the number of in- or out-connecting edges is, the bigger the in- or out-degree value is. The value could be normalized by dividing by the maximum possible number of the connections. Betweenness centrality is a measure to quantify the number of times a node acts as a bridge along the shortest path between two other nodes, the value of which can also be normalized. Closeness centrality of a node in the graph is the reciprocal of the length of the total shortest path between the node and all other nodes in the graph. Eigenvector centrality [3] measures the importance of a feature node by considering its neighbors' connectivity (or influence) as well as their subsequent downstream neighbors. The values of interests are contained in the eigenvector corresponding to the largest eigenvalue. The formulas for calculating the above mentioned centralities could be found in [2-3],[8-9]. Another variation of eigenvector centrality, which has been applied in link analysis using hubs and authorities in information networks and World Wide Web [7] and in determining the design domination weights and design subordination weights in the dependency analysis of the design elements in product development [6], is to calculate the dominant eigenvector, instead of the adjacency matrix of the graph, of the multiplication of adjacency matrix with its transpose.



Fig. 1: General framework of current research

The general framework of current research is presented in Fig. 1. It starts with a constructed featurebased CAD model with all the model history and feature information. Then feature information is extracted from the model with API programming to construct the ADFDG based on the algorithm introduced in Fig. 2. With the ADFDG at hand, visualization and centrality analysis of the graph could be carried out. The algorithm in Fig. 2 is designed based on how feature information is stored in the CAD models. A map, a type of associative container that stores key-value pairs, is used as the adjacency list representation for the graph. Note that some features are created automatically by the

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CAD system during the model construction. The resulting graph might show more feature nodes than in the part navigator, where only explicitly applied feature operations are presented.

Algorithm to create adjacency list representation of ADFDG Initialization: Given a feature-based CAD part p, an empty set $V = \{\emptyset\}$, and an empty map $A = \{\emptyset\}$ for each feature f in the part padd feature f ID f^* to the set Vfor each feature f_i^* in the set V, do create an empty list $L = [\emptyset]$ for each immediate child feature cf belonging to the feature f, do insert the child feature ID, cf^* , into list Linsert the pair $\{f^*, L\}$ into the map A AFig. 2: Algorithm to construct ADFDG from feature-based CAD model

In this paper, a connection rod model in an inner combustion engine design is taken as an example to illustrate our proposed method. Fig. 3 gives the geometry of the connection rod (b), its modelling history (a), and the corresponding visualization of its ADFDG (c).



Fig. 3: A connection rod case study with (a) model history, (b) CAD model, (c) visualization of its ADFDG.

The results of different centrality analyses are provided in Fig. 4. Fig. 5 gives the correlations of different centralities, where some key features are numbered and their correlation values are given as c. It is found that the connection rod model has a few dominant features. Except for the betweenness

Proceedings of CAD'17, Okayama, Japan, August 10-12, 2017, 232-236 © 2017 CAD Solutions, LLC, http://www.cad-conference.net centrality, other three centralities agree that the most critical features are the datum feature 1, and the extrusion feature 4. It is reasonable for those three agreeable centralities because these two identified features are constructed in the beginning of the model history and they generate the overall shape, on top of which many other features are built. This can be seen as a characteristic of the connection rod, i.e., one dominant shape. It is predicable that for some other mechanical parts one might found more dominant features upon which smaller features are built. Hence, the resulting ADFDG and centrality analyses would be totally different. It could be said that on the one hand centrality analysis helps to reveal critical features in the model construction, on the other hand helps to identify the characteristics of the model.



Fig. 4: Centralities of the connection rod case study.



Fig 5: Correlations for the centralities of connection rod case study.

The graphical representation of the feature dependencies provided by ADFDG offers engineers a more organized view toward the model construction, where feature dependencies are easily seen. Many Proceedings of CAD'17, Okayama, Japan, August 10-12, 2017, 232-236 © 2017 CAD Solutions, LLC, <u>http://www.cad-conference.net</u>

graph properties are exploitable to give insights in understanding modeling intents for individual model. Centrality analyses of ADFDG reveal the information of which features are critical from the perspective of network topology. By looking at the identified critical features, engineers can ponder whether it is reasonable based on their engineering judgements, i.e., whether they match the expected major features. As far as the connection rod case study is concerned, the identified major features are aligned with expectations.

Conclusions:

This work proposes an intelligent knowledge discovery scheme to unveil engineering modelling intents in CAD models via centrality analysis with a type of automatically-generated feature dependency graph. An algorithm has been developed to retrieve feature dependency information from CAD models, instead of consulting designers or engineers to build up the network for product features, and to generate an ADFDG for both visualization and analysis purposes. Posterior examination of the modelling intents could also reveal engineering constraints applied in those CAD models by analyzing the ADFDG. Current research focuses on one important aspect of the graph properties, i.e., centrality analysis. Potentially much more exploitable engineering knowledge can be revealed through this approach; this prospect warrants more future research. For example, more discoveries can be expected in the direction of merit comparison of different feature embodiment solutions. In addition, more effective parameterization of engineering modeling can be derived by comparing different feature structural-trees even when the visual geometric models seem to be the same.

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