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Geometric Analysis to Automate Design for Supply Chain

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Abstract

This paper presents a method for using geometric algorithms to characterize CAD models for the purpose of automated design for supply chain. Improvements in computing allow for fast manufacturability analysis of the 3D geometry found in CAD files. For example, designers can determine the percentage of a 3D model that can be machined, or how many cores would be required to produce a sand casting of the model. Traditionally, this kind of information has been used for process planning or reducing cost via design for manufacture. However, market pressures and product complexity cause firms to outsource fabrication to external suppliers. It is therefore necessary to understand how early design decisions will impact the *sourceability* of a design, which encompasses cost, quality, and lead time in the supply chain. The goal of this research is to use geometric characterizations and production requirements of a conceptual design to automatically predict sourceability, and provide feedback that enables proactive design changes. This paper works toward this goal by providing a correlation analysis of geometry-based metrics of models classified by manufacturing process.

Keywords
Design for supply chain, geometric analysis, manufacturability, concurrent engineering, sourceability

1. Introduction

Complex products such as consumer electronics, aircraft, and military systems are no longer created by a single, vertically integrated company. Firms that sell these products have started to specialize in large scale systems integration rather than piece part fabrication. Top level integration and assembly requires management of a global network of suppliers in order to meet demand. Supply chain management has arisen as a systematic method for managing these supplier networks. Traditionally, supply chain management occurs after the product has been designed. Once designs from new product development (NPD) are finalized, the schematics are "passed over the wall" to supply chain management. Supply chain analysts then seek to optimize the supply chain with respect to part cost, lead time, and expected on time quality performance. However, it has been shown that up to 80% of the avoidable cost of a product is determined solely by the design of the product [1]. Over half of this cost is determined by the general scheme of the design as opposed to detailed specifications such as geometric dimensioning and tolerances (GD&T). This scheme is determined early during the conceptual design stage of NPD, which consists of defining concept models and determining the relationship between subsystems and parts. The final bill of materials (BOM) to be manufactured or sourced is based off the conceptual designs. It is therefore important to understand how early design decisions impact the downstream costs of production.

Traditionally, design for manufacture (DfM) has been used to understand how the design of a part affects manufacturing processing and cost [2]. DfM methods provide feedback to the designer regarding the *manufacturability* of a part, which is an indicator of the ease of manufacturing the given design. However, if the firm is purchasing rather than manufacturing the part, there is a need to understand how the design affects the *sourceability* of a part. We define *sourceability* as the ease at which a firm can procure a quality part in the desired quantity within the desired amount of time at a reasonable price. Design for supply chain (DfSC), therefore, is a systematic approach to concurrent engineering where forward looking design decisions are made in order to satisfy performance requirements while maximizing sourceability.

There are many ways to characterize the manufacturability of a part. For example, in the machining process, a part may be highly manufacturable if the surface area of the part is completely visible from multiple setup orientations [3].

With respect to casting, however, a more important measure of manufacturability might be the presence of tapered features for easy separation of the mold from the pattern. During the conceptual design stage, it can be useful to explore the manufacturability of a design with respect to multiple manufacturing processes as production requirements may be uncertain. Like manufacturability, there are many ways to characterize the sourceability of a design. While average unit price is an obvious measure of sourceability, the impact of design on the supply chain extends beyond price. The lead time and quality acceptance rate, among other metrics, are also critical to the functioning of the manufacturing system, and can provide useful measures of sourceability [4]. It is important to note that the sourceability of a single design is different for different firms. For example, a company that is located centrally to suppliers will be able to source parts faster than a supplier located further away, simply because of transportation costs. In addition, societal factors such as relationships with suppliers and varying business processes mean that some firms will be able to source the same design more effectively than other firms. Therefore, robust methods for design for supply chain need to incorporate data specific to the firm procuring the part. Similar to manufacturability, optimal design decisions are made when multiple aspects of sourceability are considered early on in the conceptual design stage, allowing designers to make proactive changes that result in parts that are more sourceable.

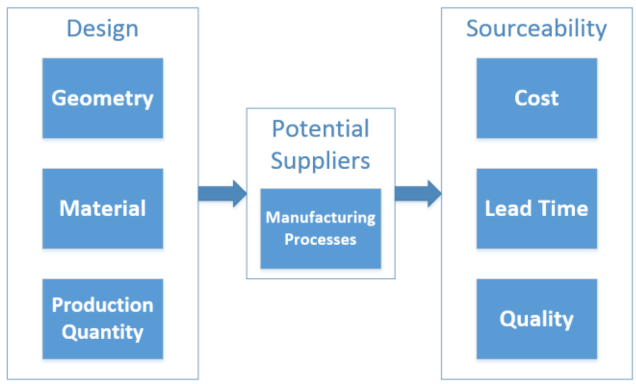

Figure 1: The connection between design, manufacturing, and sourceability

During the conceptual design stage, early geometric designs of the part are created in the form of CAD files. The geometry contained in the CAD files will dictate which manufacturing processes can produce the design. For example, parts with hollow internal cavities may be inaccessible to a machine tool and may require a casting process to create the required geometry. The manufacturing process has a significant impact on multiple aspects of sourceability (Figure 1). Part suppliers often specialize in a subset of manufacturing processes, so the geometry of a design will eliminate certain candidate suppliers. Manufacturing processes have different dimensional capabilities, material availability, and surface finishes which can affect product performance and quality. In addition, varying processing times, required labor skill, and capital investment between manufacturing processes impact the cost and lead time of a sourced part.

In addition to the geometry, other design requirements such as material and expected production quantity are driving factors in process selection, and therefore impact sourceability. It is expected that this information can be found in a company specific enterprise resource planning (ERP) or product data management (PDM) database [5]. ERP systems also contain information such as purchase orders and quality reports that would allow for the generation of sourceability metrics for each historically sourced part. By drawing a connection between the conceptual design and the expected sourceability of a part, it is possible for designers to make iterative proactive decisions that improve the expected sourceability before the design scheme is finalized. The overall goal of this research is to create an iterative method for automated sourceability prediction during conceptual development using machine learning (Figure 2). The machine learning model learns from historical geometric and supply chain data, characterizing how geometry and production requirements affect sourceability. The estimated sourceability of new designs can then be evaluated, allowing for improved redesigns.

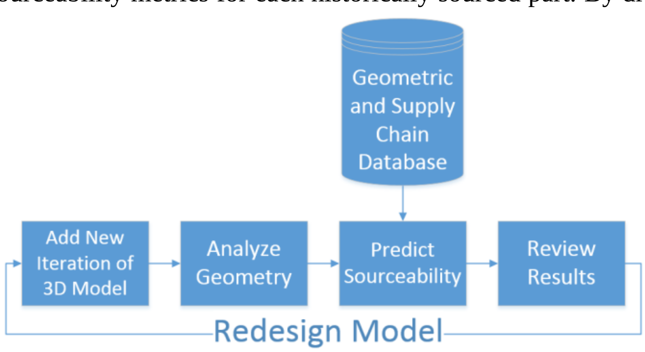

Figure 2: An iterative design for supply chain feedback loop utilizing geometric analysis

To accomplish this, four major research problems need to be addressed. First, new geometry metrics that accurately characterize CAD models need to be developed to serve as explanatory variables in machine learning algorithms. Second, measures of sourceability need to be defined using data from existing ERP databases. These sourceability metrics will serve as the response variables in the machine learning algorithms. Third, effective machine learning models need to be developed that combine CAD geometry and expected production requirements such as material and quantity, in order to predict the sourceability of part. Algorithms such as decision trees, random forests, and support vector machines are likely candidates for effective prediction of sourceability, and are the topic of current research efforts. Lastly, software packages need to be developed and integrated with ERP/PDM systems to provide a user-friendly interface for designers to use.

This paper contributes to the first research problem by providing an analysis of new, facet-based metrics that can effectively characterize conceptual design geometry in order to automate design for supply chain. As a proof of concept, the analysis methods are applied to the National Design Repository [6] and the generated metrics are shown to be significantly different between parts categorized as machined and cast-then-machined.

2. Related Work

2.1 Design for Supply Chain

Although DfSC during product development is an emerging field, companies have already begun to benefit from implementing DfSC practices [7]. Hewlett-Packard estimates savings of over $100 million by creating a formalized DfSC program that encourages design reuse and delayed product variety [8]. While case studies indicate DfSC is valuable, relatively few automated methodologies have been developed and implemented. Most efforts are focused on high level assembly BOM combinations. A database driven tool was developed that selects the optimal BOM for a product based on design for assembly, and evaluates the best designs using a supply chain index [9]. Other methods focus on managing risk, and have developed a mix-integer programming framework for choosing BOM alternatives [10]. There is currently no design for supply chain method that estimates the sourceability of a design of individual parts. In addition, the inclusion of geometry metrics into sourceability analysis has not yet been attempted.

2.2 Geometric Characterization of Models

While the geometry of the part designs contains information that can be used to predict the sourceability, this data is not easily accessible. Geometric analysis is necessary to extract meaningful information about the geometry in a CAD file. Much of the work regarding geometric characterization of 3D models in manufacturing comes from the field of group technology (GT), which focuses on grouping parts into similar batches for manufacturing to reduce cost. Most GT methods rely on feature-based CAD formats, such as STEP, which contain parametric descriptions of discrete features such as holes or extrusions. Methods have been developed to automatically assign an Optiz GT code to STEP files for CAD retrieval and design reuse [11]. Software has been written to analyze assemblies of parts based on mating geometries [12]. In contrast to feature-based methods, feature-free analysis uses a facet based approximation of the model's surface. Feature-free measures of curvature have been used to classify the National Design Repository, often used as a 3D manufacturing benchmark, with over 80% accuracy [13]. Other work shows distance based similarity measures have been used to effectively classify other feature-free models [14]. The work in this paper presents new facet based geometry metrics that are correlated with manufacturing processes, as a proxy for sourceability.

3. Methods

3.1 Approach

There are many possible measures of sourceability. Supply chain metrics have been defined on topics such as environment, logistics, quality, cost, and lead time [4]. This study uses the classification between machined and cast-then-machined parts to represent the sourceability of the part. Knowing which process a conceptual design will be manufactured with can provide useful information about the cost, lead time, quality, and other supply chain aspects. For example, cast parts often require part-specific tooling to be fabricated before manufacturing, which would indicate a longer lead time compared to a machined part. The approach of this analysis is to generate geometry metrics for a group of machined and cast parts, and compare the metrics with the manufacturing classification.

3.2 Experimental Evaluation Method

The data for this analysis comes from the National Design Repository, which classifies 97 geometric models as either machined (55) or cast-then-machined (42) [6]. Some models were not available as a surface based representation (VRML format), and other models had non-manifold surfaces. Removing these resulted in 47 machined models and 36 casting models. These parts were analyzed to generate machinability focused metrics for each facet in each model. The metrics, described in the following section, are visibility angle range, reachability depth, tool accessibility, best angle, and assigned angle. The average facet scores were calculated for each model, weighted by surface area to account for variability in facet size. The summative metrics were then averaged across the machined and cast-then-machined groups. A two-sample t-test with Welch-Satterthwaite correction was performed for each metric, testing the null hypothesis that the group means of machined and cast-then-machined parts are equal, resulting in documented t-statistics and p-values. In addition, the distributions of the metrics were visually analyzed.

3.3 Geometry Metrics and Hypotheses

3.3.1 Visibility Angle Range

Each facet was assigned a visibility range from 0-540 degrees. The highest possible score of 540 degrees, represents a facet that can be seen from three axes from a complete 180 degrees. This score represents the sum of angles defining cross sections of the visibility cone for the facet, similar to the method used in [15]. Figure 3 shows surfaces that have a range of visibility scores, ranging from zero in the hidden pocket (no visibility) to 540 on the outer surfaces (complete visibility). In addition to the average facet visibility, the 75% quantile was calculated for each model, which represents the visibility of the most visible surfaces of the model. While facet visibility is necessary for machining, it is also expected that cast parts will have high visibility scores. Casting designs require directional visibility in order to remove the mold from the pattern or to remove the cast part from the mold.

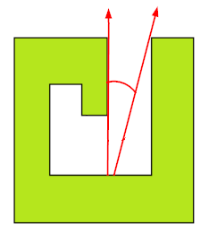

Figure 3: 2D representation of the visibility angle

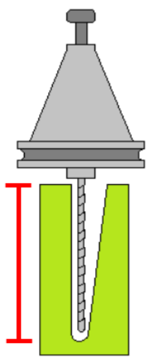

Figure 4: 2D representation of the reachability depth

3.3.2 Reachability Depth

Reachability depth represents the length of tool necessary to reach the facet from the top of the part. Each facet was assigned a reachability depth, in inches, that corresponds to the tool length required to reach the facet (Figure 4). Parts with deep pockets will have significant areas with high required reachability depth. Machining with longer tools results in tool deflection and requires slower machining speeds. For this reason, it is likely that parts requiring long tools will be classified as cast parts.

3.3.3 Tool Accessibility

Sharp corners and small features can be difficult to machine with standard tools (Figure 5). The tool accessibility metric is a binary value that is true if the facet is accessible by a common commercially available tool (in this case, a 1/4” end mill) without causing a collision. Current work involves determining a range of possible tool diameters for each facet rather than a Boolean value. The per-facet Boolean value was aggregated as a percent surface area accessibility metric for the model. Parts with features in tight spaces will result in less accessible surface area. Poor tool accessibility may push the design away from machining, but tight features could also pose difficulties for the casting process when removing the part from the mold.

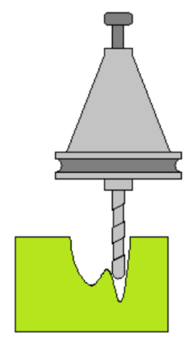

Figure 5: 2D representation of inaccessible surfaces

3.3.4 Facet Orientation

Each facet has a unit normal vector, which is perpendicular to a plane defined by the three points of the facet, and is facing away from the solid body of the model (Figure 6). Two metrics regarding facet orientation were created; best angle and assigned angle. Best angle is the angle closest to 90 degrees between the facet normal and any of the three primary axes. A value of 90 degrees represents a facet that is completely perpendicular to the axis of rotation and therefore parallel to a machine tool for common three and four-axis machine setups. The angle between the facet and the axis, A_{fa}, is transformed to the best orientation score, O_{best}, using Equation (1) which will standardize the values from zero to 90 degrees.

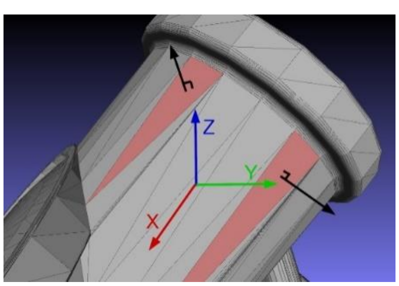

Figure 6: A cast-then-machined part showing highly variable facet orientations

$$O_{best} = 90 - |90 - A_{fa}| \quad (1)$$

In addition to weighted average, the best angle standard deviation is calculated to represent the complexity of the design. The assigned angle metric is derived from the method presented in [15], which performs a visibility set cover optimization and assigns each facet to one of the three primary axes, originally intended to determine the setup orientations for machining. The assigned angle is defined as the angle between the unit normal and the assigned axis of rotation. Once standardized using Equation (1), the best possible value for this metric is also 90 degrees. Machined parts tend to be designed using 90 degree angles, oriented along the three primary axes for easy machine setup. It is therefore expected that machined parts will have a higher best angle and assigned angle. Additionally, machined parts will likely have a lower standard deviation, as the facets on machined surfaces tend to be co-planar. Cast parts, however, are likely to have more complex and curved geometry, which would result in higher variability in facet orientation. The curved geometry of a cast part, such as draft, allows for directional solidification and easy removal from the mold. Lastly, product requirements may dictate curved geometry and encourage casting, instead of costly ball milling in machining.

4. Results and Discussion

The surface area weighted metrics are summarized below in Table 1, followed by a discussion of the results.

Table 1: Geometry metric values by group. Significance levels: *significant P<0.05, **highly significant P<0.001

Metric	Units	Machined Mean (N=47)	Cast-then-Machined Mean (N=36)	T Score	P Value
Average Visibility	Degrees	401.4	377.4	1.626	0.1086
75% Visibility Quantile	Degrees	534.5	507.3	2.882	0.0061*
Average Reachability	Inches	0.135	0.284	-4.161	<0.0001**
Percent Area Accessible	Percent	94.70	92.69	1.700	0.0943
Average Best Angle	Degrees	89.72	87.93	4.111	0.0002**
Best Angle Std. Dev.	Degrees	0.913	3.942	-5.404	<0.0001**
Average Assigned Angle	Degrees	75.14	68.68	4.026	0.0001**

4.1. Visibility and Reachability

While there is no statistically significant difference between the machined and cast mean for average visibility, there is a significant difference in the 75% quantile mean. Machined parts generally have outer planar surfaces that are commonly used as datums, which results in a significant portion of the surface area having high visibility. The average reachability for machined parts is significantly less than that for cast parts. Figure 7 indicates that machined parts have low average reachability depths. Cast parts have a higher average, and show greater variability between parts. This may indicate that reachability is not a great measure of castability, but machined parts will likely have low reachability.

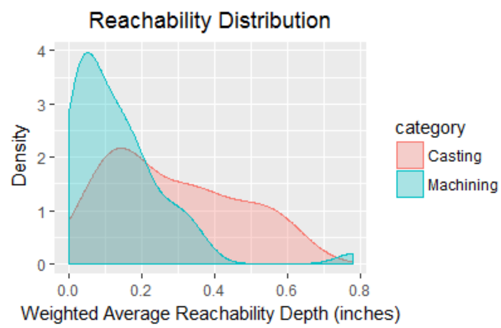

Figure 7: Reachability distribution

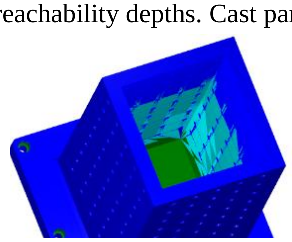

Figure 8: The machined tooling block with poor reachability

The outlier in the machining distribution is the tooling block, shown in Figure 8 with a teal and green colored deep pocket. While machining is a feasible process for this part, manufacturing engineers may recommend fabricating individual plates of the block and assembling the pieces via welding or fasteners. The tooling block highlights an issue with binary manufacturing classification, in that most geometries can be created using a variety of different processes. This issue could be handled by using a dataset containing weighted manufacturability scores for many processes.

4.2 Accessibility and Facet Orientation

While machined parts have a slightly higher percent accessibility than cast parts, both categories have high accessibility values as predicted. Accessibility may prove to be a more useful metric when the algorithm provides a range of tool diameters instead of the current binary value. Both assigned angle and best angle are highly significant between machined and cast models. Machined models have higher weighted average best angles, meaning a large percent of the model's surface is parallel to a primary or assigned axis of rotation. In addition, machined parts typically have a low standard deviation of facet orientations compared to cast parts (Figure 9). This agrees with our hypothesis that machined parts are designed to minimize the number of setup orientations, while castings can contain more complex geometry with a variety of facet orientations.

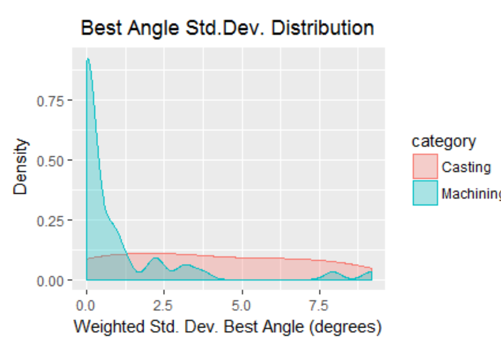

Figure 9: Best angle standard deviation distribution

5. Conclusions and Future Work

This paper describes a method for automated design for supply chain by using geometric data mining to characterize CAD models. While there are many research questions left to be answered, this paper contributes to the understanding of how the geometry of conceptual designs relates to sourceability. The facet based metrics presented have statistically significant differences between machined and cast parts, and these differences cohere with real manufacturing process constraints. Future work will involve using machine learning algorithms to create a model that can accurately learn from geometry alongside enterprise databases to predict measures of sourceability. To truly evaluate the relationships between conceptual design and final product sourceability, there is a need for a CAD database that contains data on production information in addition to the geometric models. A realistic dataset containing price, lead time, supplier capacity, and quality acceptance rates, along with the geometric models, would allow for researchers in academia and industry to experiment with new DfSC methodologies. This study used the manufacturing process classification as a proxy for sourceability, but there are many additional supply chain metrics that need to be examined. These automated methods also need to be implemented into user friendly tools that provide real-time, iterative feedback to the designer. By accessing the valuable geometric data hidden inside CAD files, companies can enable designers to make proactive decisions that improve sourceability during conceptual design and new product development.

Acknowledgement

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