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An investigation and evaluation of computer-aided design model complexity metrics

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ABSTRACT

Computer-aided design (CAD) tools are vital to the modern product commercialization process. CAD models and modeling activities are evaluated for various industrial, educational, and research purposes. However, there are no standard objective complexity metrics to use when evaluating these models or modeling procedures. Researchers and educators are often forced to use ad hoc quantities to normalize or account for CAD component variability. This work uses both quantitative and qualitative subjective assessments of CAD model complexity to evaluate objective geometric complexity metrics for CAD. These geometric complexity metrics are then compared to CAD model attributes related to CAD model complexity and modeling procedures. Modeling procedure includes the amount of time spent engaging in particular modeling activities. Curved and irregular surfaces are deemed difficult to model. Subjective quantitative assessments are found to be significantly correlated with objective geometric complexity metrics. Certain geometric complexity metrics are found to be related to computational processing time. Geometric metrics normalized by the number of features in a component are found to be significantly negatively correlated with modeling time. These results provide evidence of the relationship between the use of fewer features and modeling efficiency for components of a given complexity.

KEYWORDS

Model complexity; geometric complexity; design intent; CAD modeling procedure

1. Introduction

Computer-aided design (CAD) tools are vital to the modern product development and commercialization process. As some companies move towards a model based enterprise (MBE); their role becomes more critical. In the MBE, the CAD model is at the nexus of design and development activities; various professionals in the MBE will access the digital representation of the part to complete numerous tasks (e.g., finite element analysis or computer-aided manufacturing) [18]. CAD assists in improving the development process through virtual development [4]. The combination of these various computer-aided design tools is known as CAx and has become an integral part of product commercialization [15]. This requires the ability to share data across the enterprise [25]. Given the role of the CAD model in the development process, it is important to understand how various aspects of the model may impact its use in some of these tasks. One important aspect of CAD models that impacts numerous functions is the complexity of the model or component. There is no standard objective complexity metric used to assess a component in CAD [1].

An objective assessment of CAD model complexity can be useful in assessing case studies, evaluating the results of experiments, or evaluating student projects [36]. Braha and Maimon [6] also note the importance of these metrics for research and practical purposes. Camba, et al. [9] examine the ease of alteration for alternative modeling strategies; this is done for models with varying complexity. The complexity of a component can affect numerous aspects of the design process as well as particular engineering activities. It should be noted that while *geometric complexity* and *CAD model complexity* are likely highly related, they are not the same. As defined here, *geometric complexity* refers to the overall geometric complexity of a component. *CAD model complexity* refers to the complexity of the CAD model used to represent the component and incorporates the features and the relationships among those features. As an example, a cube could be created from the intersection or combination of numerous interrelated complex features in a CAD model. In this unlikely and stylized example, there would be a divergence between the geometric complexity (simple cube) and the CAD model complexity (numerous

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complex features). Given the likely relationship, it is important to understand geometric complexity and its effects on model complexity and modeling procedure.

Several authors have noted the likely effects of CAD model complexity. Amadori, et al. [1] note there is no widely accepted metric for CAD model complexity; however, in their experience increased CAD model complexity results in less model robustness and flexibility. Bodein, et al. [3] also report that complex models can make it difficult to determine design intent or alter CAD models. Bodein et al., [4] highlight the role of part complexity on various stages of model alteration; in their analysis complexity is captured by using the number of surfaces of the modeled component. In this case they are using geometric complexity as a proxy for CAD model complexity. Salehi and McMahon [34] also discuss the need to reduce model complexity to allow the reuse potential of product lifecycle management (PLM) systems to be used to their fullest.

Another area where geometric complexity can have a significant impact on time and cost is in finite element analyses (FEA) [39]. One of the most time consuming aspects of FEA is the generation of the mesh required for the analysis. White et al. [38] develop a meshing complexity metric based on the number of surfaces, edges, and the "sweepable" nature of the component. Osada, et al. [31] propose developing a probability distribution of 3D shapes to evaluate how dissimilar the shape under consideration is to evaluate its complexity.

In addition to the direct quantifiable aspects of complexity that can be easily related to manufacturing or analysis, complexity can also affect the design process. Understanding how geomteric complexity affects model complexity and design processes can allow for both a better understanding and assessment of the CAD modelling process. In Hamade, et al. [24], design skill is measured as using fewer features to create given geometry; a geometric complexity metric could help normalize this assessment. Another assessment example could evaluate the alteration time for models and if that is more dependent on geometric or CAD model complexity; this would be an extension of Camba et al., [9]. These assessments could be taken into account when assessing development timelines. General metrics of component and/or CAD model complexity might also be used to evaluate the number of design annotations necessary to explain it or the quality assurance plan necessary to evaluate it. As opposed to a purely quantitative assessment of component complexity, any valid measure should also be well correlated to the subjective assessment of complexity by CAx tool users. To evaluate the relationship among objective metrics, subjective assessments, model attributes, and modeling procedures, the paper is organized as follows. In the next section, previous work in this area is detailed. Next, the methods are presented; these are followed by results and the discussion. Finally, limitations, future work, and conclusions are detailed.

2. Previous work

Rossignac [33] identifies five types of complexity related to 3D CAx type components: algebraic, topological, morphological, combinatorial, and representational. Algebraic complexity is related to the complexity of the polynomials required to represent the component. Topological complexity refers to the non-regular and internal complexity (e.g., self-intersections) of a component. Morphological complexity is related to feature size and "smoothness"; those components having more and smaller features would be deemed more complex. Combinatorial complexity refers to the number of vertices in a polynomial mesh. Representation complexity is a measure of data structure and file size. These types of complexity are informed by both the design intent as well as its geometric representation of the component. Design intent can be defined as the way in which design decisions influence the way in which the final CAD model representation is formed [14]; this also includes any constraints imposed on the design [7]. As mentioned previously, CAD model complexity and geometric complexity are related, but not the same.

2.1. Design and CAD model complexity

There are several complexity metrics with respect to design. In Axiomatic Design, Suh [35] defines complexity as the uncertainty in meeting the functional requirements. Given the main functional requirement of a CAD model is to convey the design intent, a CAD-specific version of this complexity metric would be the uncertainty in conveying that design intent. Bhaskara [2] notes that model complexity makes it difficult to understand design intent and proposes the use of the design structure matrix to reorganize features and make the model less complex. Summers and Shah [36] propose several alternative complexity metrics. Those related to CAD include: the amount of information required to describe something, the amount of effort required to design it, and the number of operations needed to solve the problem. The information analog could be related to metrics for geometric complexity. Camba et al., [9] note the number of features, dependencies, and leaf nodes as metrics of CAD component complexity. The amount of time required to create a CAD model has been reported and used as a metric for CAD modeling [17, 21, 24] and alteration [9, 26] quality. The number of operations is a proxy for the number of features or operations required to create a specific piece of CAD geometry. This work examines the relationships among these various types of complexity.

2.2. Geometric complexity metrics

Several researchers have used objective metrics of geometric complexity to assess components or assign some quantitative value to the complexity of a component for differentiation purposes. Bodein et al., [4] examine parts of various complexity based on the number of surfaces a component has (55 – low complexity; 369 – high complexity). Denkena et al., [16] also use the number of surfaces as a proxy for complexity, but in their case it is to determine die casting mold costs. Boothroyd, et al. [5] also use the number of surfaces to determine the complexity, and thus cost, of injection molding tools.

Another metric for geometric complexity is the number of stereolithography (STL) file triangles required to represent an object. Valentan et al., [37] used the number of triangles (and that number normalized by component envelope volume) along with expert opinions to evaluate complexity. This was done with a goal of determining the preferred manufacturing process. Rossignac [33] also discuss triangle meshes and associate the complexity of an object with the number of vertices.

Other geometric metrics include those based on a components area or volume, usually in relation to some other shape. Joshi and Ravi [27] evaluate a sphere volume related measure of complexity as well as an area related measure of complexity (along with other component metrics) to assess their relationship to the manufacturing costs of cast parts. They also propose the volume of a part as compared to the volume of its bounding box as a complexity metric. Chougule and Ravi [11] use a cube based volume ratio (and other component attributes) to also evaluate casting costs. While alternative metrics exist, two aspects are missing from the existing literature: 1) an assessment of these alternative metrics as an assessment of the geometric complexity of CAD models and 2) a comparison of these metrics to other aspects of complexity such as the number of feature or the effort required to create the CAD model. This work aims to address these gaps in the literature.

3. Methods

To assess the relationship among objective component complexity metrics, subjective complexity assessments, model attributes, and the time spent modeling, the following data collection and assessment methods were used. A set of 10 test components is used to solicit subjective assessments of complexity. A group of 47 experimental components is used to evaluate the relationship among objective metrics of complexity, model attributes, and modeling time.

3.1. Complexity survey, test components, and experimental components

To examine the relationship between objective geometric complexity metrics and subjective assessments of component complexity, a survey was presented to 169 students of varying expertise. This survey asked them to list the number of CAx courses they had taken; these included both traditional CAD courses as well as CAM or CAE courses. It then asked them: "what shapes do you think are difficult to model with respect to CAD" as a free response. Next the students were asked to evaluate 10 components based on their assessment of that component's geometric complexity; these 10 items used are shown in Figure 1 and consist of a range of simple, stylized, and actual manufactured components. This was done using a 5-point Likert [30] scale. The scale consisted of: 1-very simple; 2-simple; 3-moderate; 4-complex; and 5-very complex. It should be noted that the parts did not have titles when provided as part of the survey.

The experimental components were part of a project assessing CAD education practices. As part of that project, students were asked to bring a component from their home and model it in class. This modeling exercise occurred at the end of the semester after the students had received approximately 20 hours of CAD instruction and practice in a third year college course. Students were given a maximum of one hour and 15 minutes to model the component. Components modeled by 47 students over the course of several semesters comprise the experimental data. Examples of the experimental components (CAD models and photos) are shown in Figure 2. All components (both test and experimental) were modeled in PTC Creo (or its predecessor Pro|Engineer).

3.2. Geometric complexity metrics

To evaluate the geometric complexity of the components several metrics were selected based on the existing literature. These consisted of: the number of surfaces, the number of triangles in the STL file (as well as normalized by part and bounding box volume), a part volume ratio, the cube area ratio, and the sphere area ratio. As noted in the literature [4, 9, 16], the number of surfaces of a component can be a measure of its geometric complexity. To determine the number of component surfaces, the components were imported into AutoDesk Inventor Professional 2015; surfaces were calculated using the BIM Exchange Check Design feature. This tool returned

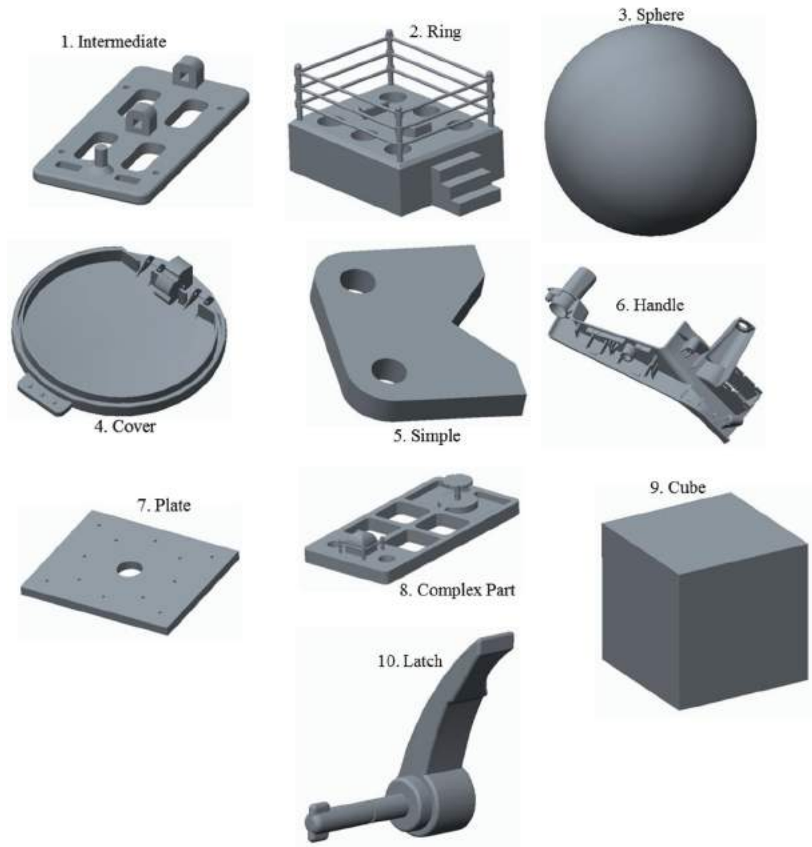

Figure 1. Test components for complexity survey.

the number of surfaces of the component as well as the length, width, and height of a box bounding the component. The sphere and cube test components were used to check the validity of the returned data.

The PTC Creo Parametric program's analysis tool was used to determine the surface area and volume of the components. This program was also used to create the STL files and determine the resultant number of triangle; the number of STL file triangles can be used as a metric of complexity [33, 37]; The deviation control factors used consisted of a chord height of 0.002 cm and an angle of 0.5. The number of triangles was noted, and like Valentan et al., [37] the number of STL file triangles were normalized by the volume of a bounding box of the component.

Other calculated metrics of complexity are based on the geometry of the component; these take the form of a ratio defined by the component's area or volume as related to another shape. The volume ratio [27] is calculated as:

$$R_{Vol} = 1 - \frac{V_P}{V_B} \tag{3.1}$$

where V_P is the volume of the component and V_B is the volume of the bounding box of the component. The sphere ratio [27] is calculated as:

$$R_{Sphere} = 1 - \frac{A_{Sphere}}{A_{Part}} \tag{3.2}$$

where A_{Sphere} is the surface area of a sphere of equal volume to that of the component and A_{Part} is the surface area of the component. The cube ratio [11] is calculated as:

$$R_{Cube} = 1 - \frac{A_{Cube}}{A_{Part}} \tag{3.3}$$

where A_{Cube} is the surface area of a cube of equal volume to that of the component and A_{Part} is the surface area of the component.

3.3. Feature and model attribute data

The feature and model attribute data for the experimental components were calculated and tabulated using the methods detailed in the works of Diwakaran and Johnson [17, 26]. The quantities tabulated included those thought to be related to CAD model complexity; these included: the number of features in the model, the reference geometry in the model (e.g., datum planes or axes), and the number of mirror and pattern features necessary

Figure 2. Representative experimental components from the modeling exercise.

to replicate the necessary geometry. Another key attribute thought to be related to CAD model complexity would be feature complexity as defined by the number of sketch segments per revolve or extrusion feature. Sketches serve as the basis for geometry that is manipulated through features (e.g., extrusions or revolves) in most modern CAD tools. Therefore, the number of sketch segments is noted as a complexity proxy. The product of these segments per feature and the total number of features is defined as the total number of segments. It is also proposed that more complex models will be more difficult to properly constrain. This would lead to constraint errors, namely the number of incorrect feature termination (e.g., a hole extruded an excessive distance as opposed to a defined through hole) and the number of weak dimensions (those not explicitly defined by the user or constraints generated by the modeling software).

3.4. Time usage data

As noted above, the experimental component data are part of a larger project. As part of that project in addition to students bringing components into class to model, their modeling procedures were recorded using the screen capture software Camtasia. These videos were analyzed using a running log that tabulated which activity was taking place as the participant worked. Five distinct activities were catalogued: doing, searching, thinking, trial and error, and regeneration or waiting. Doing is defined as the participant engaging in productive modeling activities (e.g., creating a feature). Searching is defined as the participant trying to locate or assess how to use a particular aspect of the software; this is identified by non-productive cursor movement or clicks. Thinking is identified by a lack of cursor movement or panning (or rotating) without purpose. Trial and error encompasses the creation or a feature or some geometry and its subsequent deletion. Regeneration or waiting time is defined as the user waiting for the program to complete some process. Both the absolute time spent engaging in these activities as well as their percentages of the overall modeling time are tabulated.

To examine the validity of the time usage categorizations, inter-rater reliability tests were used to examine the agreement of two raters using three sample videos. Results of these three samples are shown in Figure 3.

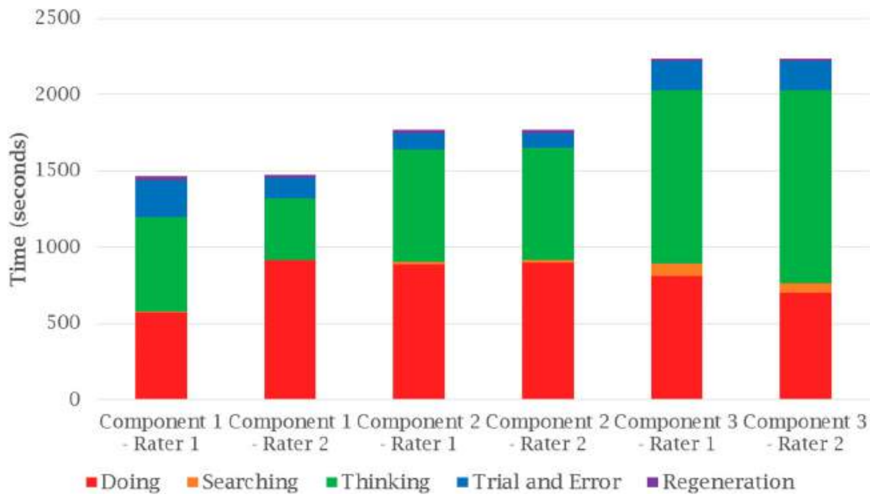

Figure 3. Time usage data as tabulated by alternative raters.

Table 1. Coefficients of agreement for video analysis.

	p_0	p_c	k	k_M	sig.
Component 1	61.4%	34.3%	0.412	0.604	0.022
Component 2	81.8%	43.0%	0.681	0.987	0.035
Component 3	84.1%	41.1%	0.730	0.903	0.035

Representative examples of the item from home (Component 1), a model from a stylistic drawing (Component 2), and a model from a 3D printed part (Component 3) were analyzed. The time usage overlap coded for the same category was deemed as agreement. The Cohen Kappa [12, 20] was used to account for chance agreement. Kappa (k) shows the chance adjusted agreement and the maximum Kappa (k_M) takes into account the differing marginal ratings for the raters. The agreement between the raters (p_0), the agreement expected due to chance (p_c), the Kappa calculations, and significance of Kappa are shown in Table 1. The lowest agreement was for Component 1; this can be seen in the difference between the thinking and doing categories in Figure 3. The amount of agreement in the other Components are much higher. Overall, the average k is 0.61 which is deemed “substantial” agreement by the Landis-Koch benchmark [28].

3.5. Modeler skill assessment

As part of the above mentioned CAD modeling course, a laboratory practical is administered near the end of the semester. As part of the laboratory practical students are given a drawing or physical component and asked to recreate the solid model geometry over the course of an hour. The practical requires students to use various modeling skills that have been introduced over the course of the semester; these include major feature creation methods (e.g., extrusion) as well as geometry replication methods (e.g., patterns). The practical is graded on a 20 point scale according to a scoring rubric that accounted for the major model geometry and other required features. In the case of this work, the laboratory practical also serves as an overall proxy for CAD modeling skill.

4. Results

The test components were used to compare subjective views of complexity with objective complexity metrics. The experimental components were used to examine the relationships among geometric complexity metrics, model attribute data, and modeling time usage. The results are as follows.

4.1. Complexity survey results

The survey data was taken from 169 students ranging from freshman level to senior level college students that had taken at least one CAD modeling course. These students ranged in experience from having taken between 1 and 4 courses with a significant CAx (e.g., computer-aided design or manufacturing) component. The mean number of CAx related courses was 1.72 (with a standard deviation of 0.99). The first step in the analysis of the results was to compare the free responses of difficulty and ratings of CAD complexity. Figure 4 shows a Word Cloud of the free responses to the question regarding shapes that are difficult to model. As can be seen in Figure 4, irregular, curved, and surfaces were the three aspects that stood out.

Table 2 shows the mean complexity ratings and standard deviation from the survey data as well as geometric quantities and complexity metrics for both the test parts and representative experimental components.

Figure 4. Word cloud of responses to modeling difficulty questions.

Table 2. Data for test components and representative experimental components.

#	Name	Surfaces	STL	L (mm)	W (mm)	H (mm)	Volume of Box (mm^3)	Volume of Part (mm^3)	Surface Area (mm^2)	Part Volume Ratio	Cube Ratio	Sphere Ratio	Mean Comp.	SD Comp.
1	Intermediate Part	103	992	254	38	127	1229030	341097	74891	0.722	60.89	0.685	2.917	0.960
2	Ring	144	6788	127	107	229	3097155	1058796	104939	0.658	40.60	0.521	3.450	0.925
3	Sphere	1	10148	508	508	508	131096512	68641970	810734	0.476	−24.07	0.000	1.393	0.819
4	Cover	128	7102	93	19	111	198332	20395	21659	0.897	79.32	0.833	3.805	0.84
5	Simple Part	13	464	305	51	381	5899343	4934784	284005	0.164	38.76	0.506	1.593	0.641
6	Handle	485	9678	220	165	105	3811174	74201	61804	0.981	82.86	0.862	4.799	0.431
7	Plate	19	496	330	19	279	1757513	1711662	210529	0.026	59.22	0.671	1.834	0.721
8	Complex Part	117	2588	155	25	75	290625	73648	29328	0.747	64.05	0.710	3.657	0.868
9	Cube	6	12	254	254	254	16387064	16387064	387096	0.000	0.00	0.194	1.124	0.348
10	Latch	107	1406	29	54	45	69975	6948	3128	0.901	30.16	0.437	3.728	0.792
11	Comb	346	7012	346	45	1	18519	6966	12777	0.624	82.87	0.862		
12	Brush	213	25734	114	48	127	696860	38278	18613	0.945	63.39	0.705		
13	Plug	40	308	25	45	25	28759	17461	5036	0.393	19.81	0.354		
14	Guard	186	2742	54	19	64	65416	8322	11261	0.873	78.12	0.824		

The component deemed the simplest, with an average complexity rating of 1.124 was the cube; the component deemed the most complex with an average complexity rating of 4.799 was the handle. As a test, the parts deemed simple, intermediate, and complex maintained the appropriate ordinal ranking of complexity with average ratings of 1.593, 2.917, and 3.675, respectively. The qualitative and quantitative responses were in agreement. The handle, complex part, and cover had more irregular surfaces and curved features; these were rated as more complex. The cube, plate, and simple part did not have these types of features and were generally rated with lower complexity.

Next the subjective complexity metrics were compared to calculated objective complexity metrics for the test components. These correlation are shown in Table 3. The upper number in each cell is the Pearson's correlation coefficient and the lower parenthetical number is the p-value (this is also the case with all similar tables in this work). With the exception of the STL triangle metrics, all other geometric complexity metrics were statistically significantly ($\alpha = 0.05$) correlated (henceforth denoted by significantly correlated) with the subjective mean complexity rating. The highest correlation was for the volume ratio metric. There were also significant correlations among the various complexity metrics. The number of surfaces was significantly correlated with the volume ratio. The cube and sphere ratio are perfectly correlated; this is as to be expected, given they are both based on the component surface area.

Table 3. Correlations of complexity metrics for test components and survey data.

	2	3	4	5	6	7	8
1. Surfaces	0.296 (0.407)	0.026 (0.944)	0.130 (0.72)	0.674* (0.033)	0.601 (0.066)	0.601 (0.066)	0.822** (0.004)
2. STL		0.042 (0.908)	0.082 (0.823)	0.466 (0.174)	−0.279 (0.435)	−0.279 (0.435)	0.244 (0.497)
3. STL/Box Volume			0.990** (0.000)	0.470 (0.171)	0.033 (0.927)	0.033 (0.927)	0.389 (0.266)
4. STL/Part Volume				0.499 (0.142)	0.058 (0.874)	0.058 (0.874)	0.431 (0.213)
5. Volume Ratio					0.473 (0.167)	0.473 (0.167)	0.903** (0.000)
6. Cube Ratio						1.000** (0.000)	0.723* (0.018)
7. Sphere Ratio							0.723* (0.018)
8. Mean Complexity							

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

4.2. Geometric complexity, model attributes, and modeling time usage results

To assess the relationships among geometric complexity metrics, model attribute data, and modeling time usage, a set of experimental components modeled by students were used. These experimental components had ranges for the various geometric complexity metrics that were generally wider than those of the test components; the one exception was that of the cube ratio which had an anomalous result in the test set due to the sphere component. These data are shown in Table 4. Also shown are the descriptive statistics for the laboratory practical that evaluates modeler skill, model attribute data, and time usage data (both absolute and as a percentage of the total).

Table 5 shows the correlations for the various complexity metrics among themselves for the experimental components as well as with the model attribute data. In the case of the experimental data, the surfaces metric was significantly correlated with the various STL metrics (unlike in the test component data). However, in this case, the number of surfaces was not significantly correlated with the volume ratio. The volume ratio was significantly positively correlated with the cube and sphere ratios. The volume ratio was also negatively correlated with the number of pattern features and both the cube and sphere ratios were positively correlated with the number of incorrect feature terminations.

Table 6 shows the correlations between the various geometric complexity metrics and the time spent engaging in the various categories of modeling activity. To assess if there was a relationship between complexity and modeling behavior, these correlations compared the complexity metrics to the modeling time usage categories as well as overall modeling time. The premise was that component complexity would be correlated with either the direct modeling (doing and trial and error) or planning (searching and thinking) related time categories. There were no significant correlations between any of the complexity metrics and the direct modeling or planning categories. The surfaces and normalized STL metrics

Table 4. Descriptive data for experimental components.

	Minimum	Maximum	Mean	Std. Deviation
Modeler Skill				
Practical Score	0	20	13	5
Complexity Metrics				
Surfaces	14.0	3790.0	287.6	651.8
STL	308.0	25734.0	3714.2	4924.8
STL/Part Volume	39.0	106189.1	5429.1	15965.7
STL/Box Volume	19.6	23700.8	1439.5	3843.9
Volume Ratio	0.1	1.0	0.6	0.2
Cube Ratio	11.3	91.0	50.8	22.5
Sphere Ratio	0.3	0.9	0.6	0.2
Model Attributes				
Number of Features	5.0	31.0	14.3	6.0
Reference Geometry	0.0	9.0	2.1	2.4
Incorrect Terminations	0.0	6.0	0.7	1.2
Patterns	0.0	6.0	1.3	1.5
Segments/Feature	0.7	8.7	3.2	1.7
Weak Dimensions	0.0	39.0	11.4	11.2
Total Segments	12.0	100.0	43.3	22.7
Modeling Time Usage				
Doing (s)	471	2496	1414	588
Searching (s)	0	642	130	122
Thinking (s)	286	2016	991	437
Trial and Error (s)	67	2222	665	490
Regeneration (s)	2	371	45	69
Total (s)	1464	4319	3244	761
Doing (%)	14.2%	70.2%	44.0%	15.5%
Searching (%)	0.0%	17.4%	3.9%	3.5%
Thinking (%)	10.1%	57.4%	30.9%	12.0%
Trial and Error (%)	1.9%	60.4%	19.8%	12.2%
Regeneration (%)	0.1%	8.9%	1.4%	2.2%

Table 5. Correlations of complexity metrics with model attributes and derived quantities.

	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Surfaces	0.510** (0.000)	0.780** (0.000)	0.706** (0.000)	0.105 (0.483)	0.195 (0.189)	0.195 (0.189)	−0.030 (0.842)	0.030 (0.842)	−0.176 (0.237)	0.124 (0.408)	−0.146 (0.327)	−0.208 (0.161)	−0.128 (0.392)
2. STL		0.435** (0.002)	0.386** (0.007)	0.188 (0.206)	0.232 (0.116)	0.232 (0.116)	0.001 (0.997)	−0.148 (0.322)	−0.107 (0.476)	0.221 (0.136)	0.080 (0.595)	0.197 (0.185)	0.148 (0.32)
3. STL/Part Volume			0.968** (0.000)	0.172 (0.248)	0.285 (0.052)	0.285 (0.052)	−0.025 (0.869)	0.125 (0.402)	−0.147 (0.323)	0.139 (0.35)	−0.107 (0.473)	−0.127 (0.394)	−0.090 (0.549)
4. STL/Box Volume				0.071 (0.636)	0.255 (0.084)	0.255 (0.084)	0.035 (0.816)	0.160 (0.283)	−0.146 (0.327)	0.175 (0.238)	−0.147 (0.323)	−0.158 (0.288)	−0.101 (0.500)
5. Volume Ratio					0.568** (0.000)	0.568** (0.000)	−0.199 (0.181)	0.134 (0.371)	−0.071 (0.637)	−0.301* (0.04)	0.066 (0.658)	0.272 (0.064)	−0.073 (0.626)
6. Cube Ratio						1.000** (0.000)	0.038 (0.799)	−0.013 (0.932)	−0.137 (0.357)	0.065 (0.666)	−0.095 (0.524)	0.292* (0.046)	−0.021 (0.889)
7. Sphere Ratio							0.038 (0.799)	−0.013 (0.932)	−0.137 (0.357)	0.065 (0.666)	−0.095 (0.524)	0.292* (0.046)	−0.021 (0.889)
8. Number of Features								0.372* (0.01)	−0.038 (0.798)	0.267 (0.069)	−0.250 (0.09)	−0.099 (0.510)	0.516** (0.000)
9. Reference Geometry									−0.154 (0.3)	−0.164 (0.272)	−0.322* (0.027)	−0.095 (0.527)	−0.081 (0.587)
10. Incorrect Terminations										−0.362* (0.013)	−0.044 (0.77)	0.176 (0.237)	−0.061 (0.684)
11. Patterns											−0.158 (0.29)	−0.197 (0.184)	0.098 (0.511)
12. Segments/Feature												0.349* (0.016)	0.667** (0.000)
13. Weak Dimensions													0.215 (0.147)
14. Total Segments													

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

were all positively significantly correlated with regeneration time. This is an expected result; geometric complexity is related to the level of detail and thus processing requirements [32]. The correlations for the time usage percentages are shown in Table 7. Again, the premise being that complexity would be correlated in some way to a larger percentage of planning or direct modeling time. However, these results were similar to those of the absolute data; the only significant correlations were those of the surfaces and the normalized STL metrics with the portion of regeneration time.

To control for modeler skill, the lab practical variable was "nullified" [19] using a first order partial correlation for the complexity metrics and the time usage data. The proposition here being that the skill level of the various modelers would be a significant contributing independent variable. By controlling for this variable, any relationships between the complexity metrics and the modeling procedure data might become more evident. These results are shown in Table 8. Again, even when controlling for modeler skill, there were no significant correlations between the complexity metrics and the time usage categories. The one exception was regeneration time, which maintained a significant positive correlation with the surface and STL normalized metrics.

To assess the role of feature complexity, the objective complexity metrics were normalized by the number of features in each of the components. The premise here being that for a given level of complexity, if fewer features were used the quicker the modeling could be completed. This is in line with the work of Hamade et al., [23] who equate fewer features for a given model with modeler skill. These results are shown in Table 9. For a model of given complexity, an increase in the number of features used is associated with greater modeling time; this is evidenced by the negative correlations for each of the complexity metrics normalized by the number of features. However, only the volume ratio normalized metric is significant.

Table 6. Correlations of complexity metrics with time usage data.

	2	3	4	5	6	7	8	9	10	11	12	13
1. Surfaces	0.510** (0.000)	0.780** (0.000)	0.706** (0.000)	0.105 (0.483)	0.195 (0.189)	0.195 (0.189)	−0.213 (0.151)	−0.102 (0.495)	−0.046 (0.756)	−0.116 (0.438)	0.362* (0.013)	−0.249 (0.092)
2. STL		0.435** (0.002)	0.386** (0.007)	0.188 (0.206)	0.232 (0.116)	0.232 (0.116)	0.017 (0.912)	−0.036 (0.809)	−0.187 (0.208)	−0.151 (0.312)	0.132 (0.375)	−0.185 (0.213)
3. STL/Part Volume			0.968** (0.000)	0.172 (0.248)	0.285 (0.052)	0.285 (0.052)	−0.106 (0.477)	0.085 (0.569)	−0.045 (0.766)	−0.105 (0.482)	0.351* (0.016)	−0.130 (0.384)
4. STL/Box Volume				0.071 (0.636)	0.255 (0.084)	0.255 (0.084)	−0.037 (0.806)	0.168 (0.26)	−0.063 (0.673)	−0.116 (0.436)	0.320* (0.028)	−0.084 (0.576)
5. Volume Ratio					0.568** (0.000)	0.568** (0.000)	0.018 (0.903)	0.091 (0.545)	−0.176 (0.238)	−0.240 (0.105)	0.184 (0.215)	−0.210 (0.157)
6. Cube Ratio						1.000** (0.000)	0.147 (0.324)	0.205 (0.167)	−0.008 (0.959)	−0.173 (0.245)	0.106 (0.478)	0.040 (0.789)
7. Sphere Ratio							0.147 (0.324)	0.205 (0.167)	−0.008 (0.959)	−0.173 (0.245)	0.106 (0.478)	0.040 (0.789)
8. Doing (s)								0.462** (0.001)	−0.323* (0.027)	−0.274 (0.063)	−0.058 (0.698)	0.480** (0.001)
9. Searching (s)									−0.118 (0.428)	−0.254 (0.084)	−0.013 (0.931)	0.284 (0.053)
10. Thinking (s)										0.184 (0.216)	0.098 (0.513)	0.432** (0.002)
11. Trial and Error (s)											0.062 (0.677)	0.502** (0.000)
12. Regeneration (s)												0.140 (0.348)
13. Total (s)												

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

5. Discussion

This work examined the relationships between subjective assessments of CAD model complexity and objective geometric complexity metrics as well as the relationships among complexity metrics, model attributes, and modeling time usage. Two sets of components were used to examine these relationships: the first was a test set of components that consisted of 10 stylized and actual industry produced components. The second set of 47 experimental components consisted of CAD models created by students of physical items with their modeling procedure recorded using screen capture software and subsequently analyzed to categorize time usage into particular categories.

To determine the ability of objective geometric complexity metrics to properly account for the perceived complexity of CAD components, a comparison was made between these metrics and a survey of student CAD users. There were statistically significant positive correlations between the subjective complexity metrics and the number of surfaces in a component, the volume ratio, the cube ratio, and the sphere ratio. The highest and most significant of these correlations was the volume ratio. The quantitative assessments of complexity were also consistent with the qualitative survey data collected in the survey; those components that had attributes associated with perceived modeling difficulty (irregular surfaces and curved features) were rated as more complex that those that did not. The combination of objective metrics and subjective metrics is analogous to the procedure used by Valentan et al., [37]. These objective complexity metrics have the ability to add to several aspects of CAD research and education. These complexity metrics allow for the evaluation of different components and the comparison of cases and experiments [6, 36]. For example, in the work of Company et al., [13], quality assessments are proposed to improve CAD education and promote preferable modeling strategies; including the volume ratio complexity metric could allow for instructors to ensure that these rubrics are appropriate for that level of complexity. Similarly, the annotations required to help understand the design intent of CAD models as highlighted in Camba et al., [8] could be checked against a geometric complexity metric to ensure that a model has a reasonable

Table 7. Correlations of complexity metrics with time usage percentage data.

	2	3	4	5	6	7	8	9	10	11	12
1. Surfaces	0.510** (0.000)	0.780** (0.000)	0.706** (0.000)	0.105 (0.483)	0.195 (0.189)	0.195 (0.189)	−0.127 (0.394)	−0.072 (0.632)	0.150 (0.315)	−0.049 (0.743)	.471** (0.001)
2. STL		0.435** (0.002)	0.386** (0.007)	0.188 (0.206)	0.232 (0.116)	0.232 (0.116)	0.136 (0.361)	0.002 (0.987)	−0.102 (0.495)	−0.103 (0.491)	0.162 (0.276)
3. STL/Part Volume			0.968** (0.000)	0.172 (0.248)	0.285 (0.052)	0.285 (0.052)	−0.084 (0.574)	0.137 (0.357)	0.066 (0.661)	−0.075 (0.616)	0.439** (0.002)
4. STL/Box Volume				0.071 (0.636)	0.255 (0.084)	0.255 (0.084)	−0.032 (0.833)	0.224 (0.13)	0.013 (0.933)	−0.106 (0.476)	0.396** (0.006)
5. Volume Ratio					0.568** (0.000)	0.568** (0.000)	0.130 (0.382)	0.119 (0.425)	−0.054 (0.717)	−0.180 (0.225)	0.189 (0.204)
6. Cube Ratio						1.000** (0.000)	0.081 (0.588)	0.197 (0.184)	0.022 (0.882)	−0.189 (0.204)	0.042 (0.778)
7. Sphere Ratio							0.081 (0.588)	0.197 (0.184)	0.022 (0.882)	−0.189 (0.204)	0.042 (0.778)
8. Doing (%)								0.354* (0.015)	−0.694** (0.000)	−0.675** (0.000)	−0.092 (0.541)
9. Searching (%)									−0.327* (0.025)	−0.414** (0.004)	0.007 (0.965)
10. Thinking (%)										−0.009 (0.952)	0.015 (0.921)
11. Trial and Error (%)											−0.079 (0.599)
12. Regen (%)											

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

amount of annotation for its complexity. This evaluation of objective complexity metrics for CAD modeling fills a gap in the existing literature. While this does not provide the missing "universal" CAD complexity metric [1], these results do provide promising candidates that can be further studied and used in future work.

The assessment of geometric complexity metrics with relation to other CAD model attributes (i.e., those related to CAD model complexity) and modeling effort also provide insights. The geometric complexity metrics for the experimental data set were correlated CAD model attributes and derived quantities. The only significant correlations were the volume ratio being negatively correlated with the number of incorrect feature terminations (an unexpected result) and the positive correlations between the cube and sphere ratios and the number of weak dimensions. More complex models did not lead to more features or more complex features as identified by more feature segments or segments per feature. The feature correlation could be explained by the variation of modeler skill; as seen in Table 4, some participants were unable to create any significant geometry as part of their laboratory practical and scored a zero on the exercise. Hamade et al., [23] note that more skilled modelers use fewer features. This lack of correlation also underscores the variability with which the same geometric can be created and thus further underscores the possible divergence between geometric complexity and CAD model complexity.

While several researchers [17, 22, 23, 26] have examined the interaction of modeling time and certain aspects of CAD models, this is usually done for a component of the same geometry and does not take into account how the modeling time is spent. A notable exception is the work of Chester [10] which used screen capture techniques to examine CAD modeling procedures. In this work screen capture videos were analyzed and the modeling activities were categorized into 5 categories: doing, thinking, searching, trial and error, and regeneration. It would be expected that more complex models would take longer to model and/or that complexity would be positively correlated with particular time usage categories. As seen in Table 6, the only time usage category significantly correlated with the complexity metrics was regeneration time; it was positively correlated with the surfaces and normalized STL metrics. This was an expected result; geometric complexity is related to processing requirements [32]. More complex components required more

Table 8. Correlations of complexity metrics with time usage data controlling for lab practical performance.

	2	3	4	5	6	7	8	9	10	11	12	13
1. Surfaces	0.482** (0.001)	0.771** (0.000)	0.697** (0.000)	0.009 (0.953)	0.150 (0.321)	0.150 (0.321)	−0.192 (0.202)	−0.124 (0.411)	−0.025 (0.871)	−0.097 (0.52)	0.315* (0.033)	−0.219 (0.144)
2. STL		0.412** (0.004)	0.365 (0.013)	0.119 (0.431)	0.197 (0.19)	0.197 (0.19)	0.041 (0.785)	−0.052 (0.73)	−0.173 (0.251)	−0.136 (0.367)	0.081 (0.593)	−0.157 (0.296)
3. STL/Part Volume			0.967** (0.000)	0.111 (0.462)	0.256 (0.086)	0.256 (0.086)	−0.088 (0.562)	0.074 (0.626)	−0.029 (0.85)	−0.091 (0.547)	0.319* (0.031)	−0.104 (0.493)
4. STL/Box Volume				0.011 (0.941)	0.229 (0.126)	0.229 (0.126)	−0.019 (0.898)	0.159 (0.292)	−0.050 (0.743)	−0.104 (0.491)	0.292* (0.049)	−0.060 (0.692)
5. Volume Ratio					0.540** (0.000)	0.540** (0.000)	0.066 (0.665)	0.069 (0.646)	−0.154 (0.308)	−0.225 (0.134)	0.093 (0.537)	−0.164 (0.276)
6. Cube Ratio						1.000** (0.000)	0.175 (0.244)	0.195 (0.194)	0.012 (0.94)	−0.159 (0.291)	0.053 (0.725)	0.076 (0.617)
7. Sphere Ratio							0.175 (0.244)	0.195 (0.194)	0.012 (0.94)	−0.159 (0.291)	0.053 (0.725)	0.076 (0.617)
8. Doing (s)								0.474** (0.001)	−0.336* (0.022)	−0.286 (0.054)	−0.030 (0.843)	0.471** (0.001)
9. Searching (s)									−0.113 (0.455)	−0.250 (0.094)	−0.033 (0.829)	0.300* (0.043)
10. Thinking (s)										0.177 (0.238)	0.127 (0.402)	0.425** (0.003)
11. Trial and Error (s)											0.089 (0.557)	0.497** (0.000)
12. Regeneration (s)												0.191 (0.204)
13. Total (s)												

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

regeneration time. The same was true when assessing the portion of modeling time for each category: the same three complexity metrics were positively correlated with regeneration time. Given the relationship between modeling skill and modeling time [22, 23], a first order partial correlation was used to control for modeling skill using the laboratory practical score. Again, only the regeneration time usage category was significantly positively correlated with the surfaces and normalized STL metrics.

Finally, given the interaction between the number of features, the complexity of the component, and the modeling time, the complexity metrics were normalized by the number of features and correlated with time usage data. As noted in Hamade et al. [24], fewer features can result in less modeling time. For a component of given complexity, if it has fewer features, it should be modeled more quickly. As seen in Table 9, this was the case; the volume ratio was negatively correlated with the overall necessary modeling time. The volume ratio, cube ratio, and sphere ratio were all also significantly negatively correlated with trial and error time. Given the skill required to model a complex component with minimal features, the participants likely needed to try alternative modeling solutions prior to completing their component. This result along with the high correlation between the subjective complexity survey and the volume ratio make this a useful objective complexity metric that combines both geometric and CAD model attributes. When the geometric complexity metrics were normalized by the total number of feature segments, there were no significant correlations of note (with the exception of regeneration time).

These results should be viewed in light of the study's limitations. First and foremost, both the survey data and the modeling data were generated by a sample population comprised totally of students. While some of them were senior-level students surveyed just prior to graduation, they do not have the same modeling experience as practicing CAD using professionals. However, given the significant correlations between their assessments and the objective complexity metrics this might be of limited concern. Some of the lack of significant correlations between any of the complexity metrics likely stems from the limitation of the experimental data set. Students were asked

Table 9. Correlations of complexity metrics normalized by features with time usage data.

	2	3	4	5	6	7	8	9	10	11
1. Surfaces/Features	0.874** (0.000)	0.113 (0.451)	0.170 (0.252)	0.158 (0.288)	−0.222 (0.133)	−0.062 (0.681)	−0.035 (0.817)	−0.144 (0.333)	0.393** (0.006)	−0.259 (0.079)
2. STL/Part Volume/Features		0.154 (0.301)	0.262 (0.076)	0.238 (0.108)	−0.134 (0.371)	0.091 (0.544)	−0.023 (0.879)	−0.119 (0.425)	0.355* (0.014)	−0.146 (0.327)
3. Volume Ratio/Features			0.812** (0.000)	0.863** (0.000)	−0.127 (0.396)	0.030 (0.839)	−0.097 (0.517)	−0.369* (0.011)	0.027 (0.856)	−0.384** (0.008)
4. Cube Ratio/Features				0.986** (0.000)	−0.009 (0.952)	0.175 (0.24)	−0.014 (0.924)	−0.369* (0.011)	0.006 (0.97)	−0.224 (0.13)
5. Sphere Ratio/Features					−0.050 (0.737)	0.148 (0.322)	−0.016 (0.917)	−0.398** (0.006)	−0.012 (0.938)	−0.281 (0.055)
6. Doing (s)						0.462** (0.001)	−0.323* (0.027)	−0.274 (0.063)	−0.058 (0.698)	0.480** (0.001)
7. Searching (s)							−0.118 (0.428)	−0.254 (0.084)	−0.013 (0.931)	0.284 (0.053)
8. Thinking (s)								0.184 (0.216)	0.098 (0.513)	0.432** (0.002)
9. Trial and Error (s)									0.062 (0.677)	0.502** (0.000)
10. Regeneration (s)										0.140 (0.348)
11. Total (s)										

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed).

to bring a component that they thought they could model in one hour; there was likely selection bias in the data set. There was a significant positive correlation between the participant lab practical score and the volume ratio complexity metric of the component they modeled (N = 47, r = 0.379, p = 0.009). There were also no alternative variables related to the assessment of different types of complex features (e.g. lofts or sweeps). While there was no reported use of such features, a method to tabulate them and their associated complexity could be useful. The data also only includes completed models; so students that might have been more ambitious (and less skilled) in their choice of component may not have finished and thus would not be included in the data set. The participants also did not receive any additional credit for modeling their component quickly. This may have reduced the pressure to model quickly, even for those students that could have done so.

Future work will attempt to rectify some of these limitations. Possibly having students model components of varying complexity with corresponding time limits and incentives for quickness might provide a wider range of data for a given skill level. This work is also limited to the initial modeling of single components. As highlighted by several researchers [4, 13, 17, 29, 34], one key concern with respect to complexity is the ability to alter a component. A similar methodology to that detailed here can be used to assess the effects of component complexity on alteration processes. This would be similar to the work by Diwakaran and Johnson [17], but incorporate model complexity as an independent variable to be correlated with model perception and alteration time. Rarely do complex products consist of single components. Again, building on the methods defined here, future work will aim to derive analogous complexity metrics for assemblies and incorporate the effect of component and assembly complexity on assemblies.

6. Conclusions

No universally accepted metric of CAD model complexity exists [1]. However, there are numerous cases where a CAD complexity metric could be used for educational, practical, and research purposes. These include assessing student work, normalizing case data, and ensuring that the necessary information is presented to help others understand a given model. This work examined several objective quantitative geometric CAD complexity metrics. The first portion of this work used a test set of 10 CAD models of both stylized and actual industry components along with a survey of 169 participants to examine the relationship between perceived complexity and objective metrics. The second part of this work used a set of 47 experimental CAD models; complexity metrics for these components were compared with model attribute data and time usage data from the screen capture of the modeling procedure.

The qualitative portion of the survey indicated that components with irregular or curved features were difficult to model. This was also shown in the quantitative ratings of complexity; those components in the test data set with curved or irregular features were deemed more complex. There were statistically significant positive correlations between the subjective complexity ratings and the objective geometric complexity metrics. These included the number of surfaces, the volume ratio metric, the cube ratio metric, and the sphere ratio metric. The highest correlation with the greatest significance was the volume ratio.

The experimental data set was used to examine the relationships among complexity metrics, CAD model attributes, and modeling time usage. There were no expected significant correlations between the geometric complexity metrics and the CAD model attributes. When examining the relationships between the geometric complexity metrics and time usage (both absolute and proportional), the only significant correlations were between the surfaces and normalized STL metrics and required regeneration time. This was an expected result given the relationship between geometric complexity and required processing [32]. To account for the role of modeler skill a first order partial correlation was used to remove the effect of the lab practical score variable (a proxy for modeler skill); this did not produce any additional significant correlations between the geometric complexity metrics and the modeling time usage categories.

To account for the role of efficiency afforded by using fewer features, the complexity metrics were normalized by the number of features. When normalized by the number of features, the volume ratio was significantly negatively correlated with the overall modeling time. This is an expected result given the role that fewer features plays in modeling efficiency [24]. The feature normalized volume ratio, sphere ratio, and cube ratio metrics were also significantly negatively correlated with trial and error time. The modeling of complex features using few features likely required some trial and error.

Overall, this work has presented an assessment of objective geometric complexity metrics. The volume ratio was found to be significantly correlated with subjective assessments of model complexity. The volume ratio when normalized by the number of features was also found to be significantly negatively correlated with modeling time. This metric could be used as a tool for various research and educational purposes to normalize the CAD models under consideration.

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