Towards understanding what makes 3D objects appear simple or complex

Sreenivas R. Sukumar, David L. Page, Andreas F. Koschan and Mongi A. Abidi
Imaging, Robotics and Intelligent Systems Lab, The University of Tennessee, Knoxville.
Website: (http://www.imaging.utk.edu) Email: {ssrangan, dpage, akoschan, abidi}@utk.edu

Abstract

Humans perceive some objects more complex than others and learning or describing a particular object is directly related to the judged complexity. Towards the goal of understanding why the geometry of some 3D objects appear more complex than others, we conducted a psychophysical study and identified contributing attributes. Our experiments conclude that surface variation, symmetry, part count, simpler part decomposability, intricate details and topology are six significant dimensions that influence 3D visual shape complexity. With that knowledge, we present a method of quantifying complexity and show that the informational aspect of Shannon's theory agrees with the human notion of shape complexity.

1. Introduction

The cognitive study of 3D shape perception has helped computer vision researchers try and emulate activities like object recognition [3] and scene analysis [5]. However, in the interface between cognitive science and computer vision, an observation that has not received much attention is that some objects are easier to learn, memorize and recollect compared to others. If we are shown a series of unseen objects and then asked to recollect them, we realize our tendency to memorize and recollect simpler objects better and faster. This happens because the human brain intuitively and swiftly classifies objects as simple or complex, memorizes the simpler ones easily, and develops better and intricate feature descriptions for representing complex objects. Attneave [1] noted this aspect of visual cognition and stated that the complex visual objects are not only harder to reproduce from memory than simpler ones but also harder to learn by name and match.

Attneave's observation extends to applications involving search in 3D virtual spaces using computers also. Complex objects require a detailed feature description as compared to simpler ones. This makes identifying simple objects an interesting problem to investigate from a feature dimensionality perspective. Our paper addresses such a motivation to quantify judged complexity and documents the experiments conducted to establish the domain knowledge of attributes that make 3D surfaces appear complex. Our results will be useful in applications spanning CAD/CAE engineering model database search [11] to automatically learning the gist of a 3D scene [15].

2. What is complexity? – Related work

The literal meaning of the term complexity refers to the quality or the state of being complex, the word complex referring to intricate and interconnected, hence not easy to understand and analyze. Our goal is to quantify the qualitative notion of shape complexity. Hence, in this section, we present the interpretation of the word "complexity" from several disciplines that we hope to leverage towards formulating a scalar index for perceived complexity with 3D shapes.

Shape complexity from a perceptual perspective: The seminal work with perceived or judged complexity dates back to Attneave [2]. Attneave had concluded that many aspects of object perception varied in difficulty with the complexity of the visual stimulus. But in spite of the complexity and the difficulty to memorize, humans still learn to encapsulate shape information in the associated complexity of the shape towards recognizing the object. Towards that end, Attneave's extension in [1] listed the dimensions and physical determinants of judged complexity of 2D shapes and studied the perceptual complexity of 2D curves and line drawings as a function of angular variation, symmetry, curvature and many such factors to derive a regression equation for complexity along those variables. His study revealed the relationship between judged complexity and informational content, and concluded that aspects of perceptual complexity closely relate to Shannon's information theory [24].

Study of perceived complexity has also been of research interest from a scene analysis standpoint. Heaps and Handel [9] studied the perception of visual complexity along different variables such as connectedness, depth, orientation and structure on texture images. With the definition of complexity as "the degree of difficulty in providing a verbal description of an image" their results correlated with existing domain knowledge of symmetry and similarity simplifying a visual pattern. Recently, Oliva from the MIT Cognitive Vision Lab [16] listed clutter, symmetry, openness, organization, quantity of objects and variety of colors as six significant dimensions of perceptual complexity with 2D scenes. Her experiments in classifying real world scenes as simple or complex indicated the preferences of the human brain along those dimensions. Our work is centered on the definition of complexity from Heaps and Handel [9] and is motivated towards listing dimensions of perceived complexity with 3D surfaces with the focus only on shape geometry.

3D shape complexity from a computational perspective: The notions that computer scientists associate the term complexity with are quite different from the vision perspective. Rossignac [23] defined different types of complexity that can be associated with a 3D object. He introduces algebraic complexity as the degree of polynomials needed to represent a shape in its implicit form, topological complexity as the existence of non-manifold singularities, holes or self-intersections, morphological complexity as the measure of smoothness and feature size, combinatorial complexity as the measure of the vertex count in polygonal meshes and representational complexity as a measure based on ease-of-use of a data structure, or the storage size of a compressed model. Furthermore, he discussed computational methods to approximate these shape complexity metrics. Rossignac's definitions of shape complexity are computationally motivated and do not have a perceptual proof. Additionally, we would like for shape complexity metrics of 3D surfaces, especially in search applications, to be independent of computational storage, resolution of digitization etc. with focus mainly on the encapsulated geometric shape.

Complexity from a statistical perspective: The statistics literature provides a system theoretic definition of complexity [4] as a measure of the degree of interdependency between the whole system and a simple enumerative composition of its subsystems. Several measures exist based on slightly different definitions of the aforementioned complexity. Shannon complexity [22], Kolmogorov complexity [6] and stochastic complexity [21] are some examples that derive out of information coding theory in being able to send a message as compactly and correctly as possible. The underlying concept with these definitions is the ability to quantify the distribution of local properties of the data as a measure (scalar index) of the interaction, predictability or dependency between its components. Relating Bozdogan's definition [4] to 3D geometry of shapes, we visualize an analogy to associate aspects or physical attributes of shape and geometry whose interaction leads to the overall perceived complexity associated with the object. For example, if we consider a mesh representation of a 3D surface, the sub-components of the 3D surface would be the vertices and triangles, and the factors that influence the local shape variability integrate over the context of the entire object.

In this paper, we essentially follow the spirit initiated by Attneave in understanding the different informational aspects of visual complexity with 3D surfaces. The significant difference from Attneave being that we study perceived complexity from the geometry of 3D objects and surfaces compared to 2D line drawings of Attneave while still drawing inspiration for our heuristics and dependent variables from seminal papers such as [8] and [1] on 2D shape analysis. Our effort also differs from studies of visual perception of 3D shape as in [26] with focus only on 3D geometry rather than 3D shape cues from color, texture and shading. Our goal is towards the comprehension of a psychophysical basis that we present in Section 3, and list the different interacting components that build towards the overall complexity of the object.

3. The psychophysical experiment

3.1. Subjects

We had over 300 volunteers all over the world, as participants in our survey. The survey website link was posted on several forums within the University of Tennessee at Knoxville and science groups that reach people all around the world. Requests to fellow researchers and colleagues that were interested in our results were also sent out through electronic mail and encouraged to participate. We also had a separate population of 35 vision research students at the University of Tennessee, Knoxville that were explained the purpose and motivation of our survey before their participation. The introduced bias in that small population of participants did not seem to statistically influence their response to the questions compared to the unbiased population. The underlying density of the biased sample and the total population did not show concerns for the inference using the analysis of variance (ANOVA) procedure. At this point, we would also like to note, all our statistical analysis wherever applicable and reported in this paper correspond to 95% confidence. We have reported observations in this paper only if they were found to be significant at $p < 0.01$.

3.2. Apparatus and stimuli

We constructed a web-based psychophysical experiment. With simple HTML (Hyper Text Mark-up Language) forms as the front-end interface and back-end database processing, we designed the survey to infer about perceived complexity along several variables. The web design enabled us to embed 3D virtual reality models of real world objects into the stimulus interface viewable using different computer platforms with minimal requirements from the participant. The survey questions were built over the knowledgebase of several papers in the 2D domain [19] and some new heuristics that we wanted to study for 3D shapes. Our implementation followed the guidelines of conducting a psychophysical experiment detailed by Martin [14]. Being a web-based survey, we implemented filters for discarding incomplete and thoughtless responses based on the number of questions answered and the time taken to answer each question. The web interface required a minimum monitor resolution of 800 by 600 which was verified before the experiment began with the stimuli. The stimuli were also chosen to minimize any kind of apriori bias about the object.

3.3. Method

Our survey had three different types of questions: (1) "2 alternative forced choice (2AFC)" (2) perceptual rating, scoring and sorting (3) Multiple choice questions. With the Type 1 questions, two pictures or animated images of 3D objects would be shown and the participant would be forced to choose one of the two pictures as a response to the question. We had included Type 3 multiple choice questions to explore new variables with additional flexibility of reporting answers if the participant considered the listed choices inappropriate. The participants were encouraged to use this "comments" feature at the beginning of the survey. The Type 2 perceptual rating and scoring questions were used to verify correlation between human perception and existing shape measures.

These rating and scoring questions validated the difference between what humans actually thought and how they responded. For example, a person would have answered that the unfamiliarity of a 3D object did not influence the perception of complexity on a multiple choice question but their response on the rating or 2AFC question would imply otherwise. The average time taken by participants to complete the survey was 20 minutes. In the following paragraphs, we will describe the experiments that lead to conclusions about the different dimensions of perceived surface shape complexity. We will describe the stimuli and the inference from the different responses in understanding the physical determinants of perceived complexity.

Our experiment was designed to evaluate the relationship between the following attributes as different dimensions that contribute to the judged complexity of a 3D surface: symmetry, surface variation, unfamiliarity, part count, presence of holes and protrusions, intricate details, relative size, scale and simpler part decomposability. These dimensions are listed from existing domain knowledge about influential aspects of object recognition. Without revealing these parameters, the participants were shown several 3D surfaces and 3D models of real-world objects. The participants were asked to choose between two shapes, and/or asked to sort and rate these objects based on their judged complexity in a scale of 1-10. Then, we evaluated different hypothesis about a physical parameter contributing to perceived complexity using the ANOVA procedure for statistically valid inferences. We will reveal our observations in the Section 4 and document the impact of each one of the dimensions on perceived complexity.

4. Experiment Results

4.1. Experiment 1 – Effect of surface variation

Synthetically generated deformable superquadrics [12] were chosen as a good test bed of varying surface shape while maintaining symmetry using shape parameters in a controlled manner. Based on the responses on a set of superquadrics similar to examples shown in Figure 1a, we observe that perceived complexity is directly related to the variation in the curvature; with sharper and unexpected variation contributing to increased complexity. We also observe that the average rating and the mode rating for hyperbolic surfaces increase with increase in variation of surface curvature. We are able to draw similarity with "surface curvature" as Attneave's "number of turns" with 2D contours. We show the trend in Figure 1b and 1c based on the average rating for different hyperbolic surface patches and superquadric shapes with a few examples.

4.2. Experiment 2 – Effect of part count and simpler part decomposability

In this experiment, the 3D objects were manually segmented into a number of perceptual parts, the definition of perceptual parts following Hoffman's work [10] on part decomposition. Then, we associated the judged complexity response from the participants with the part count. We observed that people label objects with more number of parts as complex. We show the trend between number of parts and the judged complexity with complexity directly proportional to the part count as in

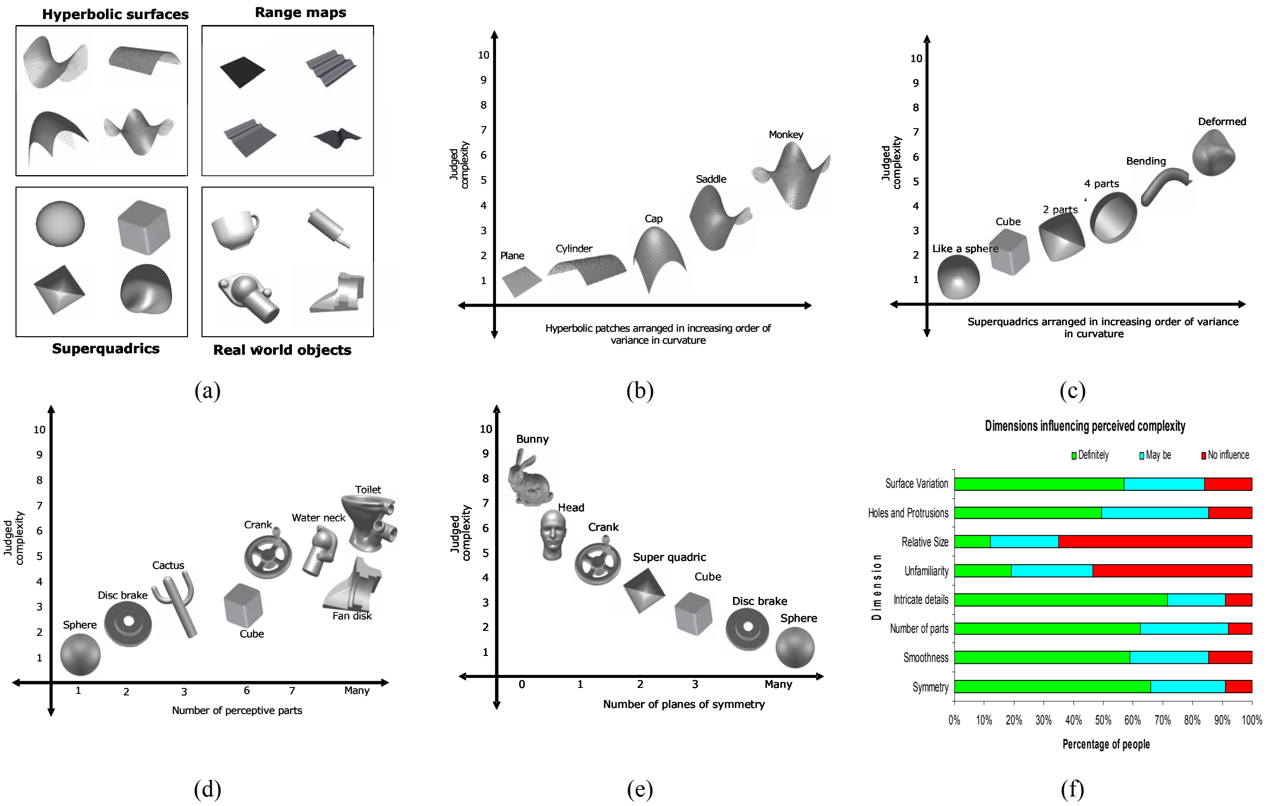

Figure 1: Attributes contributing to perceived complexity of 3D shapes. (a) Examples of stimuli used in the experiment. (b) Judged complexity on hyperbolic surface patches. (c) Judged complexity on superquadrics (d) Influence of part-count on judged complexity. (e) Effect of symmetry on perceived complexity (f) Feedback collected from participants at the end of the survey.

Figure 1d. We show the general trend observed with our sample of real-world objects in that figure. This observation not only reminds us of the statistical definition of complexity, but also relates to Rossignac's structural complexity. The variance seen in the box plot for some of the objects forced us into investigating what physical attribute was reducing an expected exponential or linear trend.

Our analysis revealed that some objects in our database are made up of simpler 3D surfaces like cylinders, planes, hemispheres and such smooth simple surfaces. This phenomenon is observed with two objects in Figure 1d, the cube and the fan disk. Though the cube is known to have six faces and the fan disk contains 17 distinguishable surface patches, most of these patches have smoothly varying curvature or are planar and hence possess very little visual complexity. This implies that such simple surfaces that make up the object are reducing the overall perceived complexity. Hence, the conclusion that we draw is that though the number of parts is significant and directly proportional to the overall judged complexity of a 3D object, the simplicity of parts in the decomposed form plays a significant counter-intuitive role.

4.3. Experiment 3 – Effect of symmetry

We evaluated the effect of symmetry in objects as well as surfaces. The symmetry was quantified by the number of axes of symmetry and studied as a parameter contributing to perceived complexity. As shown in Figure 1e, objects and surfaces with lesser or no symmetry had high complexity ratings indicating that perceived complexity is in fact inversely proportional to symmetry in the 3D surface.

4.4. Experiment 4 – Effect of protrusions, holes and intricate details

The evaluation of these factors was performed by displaying 3D objects on the screen and requesting the participants to label an object as simple or complex. This experiment was performed in a hierarchical fashion. Each participant was shown close to 50 objects, some of which that had protrusions, holes and some with intricate details and some models with smooth surfaces. The participants would label objects as simple or complex and create two classes based on perceived complexity. This process of classification was then repeated for three levels of complexity. We show the trend with 14 objects in Figure 2. We see that objects like the crank, the toilet with holes and protrusions, the dragon and the bunny with intricate details classified as complex. We are also able to gather support for the inference on the number of parts influencing judged complexity from this experiment also. The objects classified as the simplest either are made up of simpler parts, have very minimal variation in curvature and have multiple axes of symmetry. In the next class, there is not much symmetry with the objects, but factors like number of holes, number of discernable parts seem to be significant. In the most complex class of objects, we observe intricate details, very little symmetry and high surface variation.

5. Informational aspects

Having studied different dimensions that influence the judged complexity of 3D objects, and concluding with observations that appear to agree with Attneave, we note that of the six important dimensions that we inferred, surface variation and symmetry are the two factors not considered by Rossignac [23]. His list of computational methods already includes part count, holes and protrusions and the feature smoothness that relates to intricate details. Our work now has added a perceptual inspiration to those definitions (Figure 1f).

Additionally, the effort to include this perceptual aspect to Rossignac's definitions motivated our investigation of an information-theoretic method towards quantifying the perceptual characteristics of 3D geometric complexity using curvature variation. The observation that shapes with smoothly varying curvature attributed less to the judged complexity, and that objects with minimal or no surface variation appear less complex than shapes with significant variation in curvature helped us tread Attneave's path with 2D contours.

Also, we have observed that surfaces with repetitive curvature patterns have lower shape information than the surface with no patterns. These observations also agree with Attneave's theory [2] about how the probability of accidental occurrence contributes to visual significance. Thus, we begin relating notions of Shannon entropy [24] as suggested by Attneave and fore thought by Palmer [19] for 3D shapes. Although, the concept of Kolmogrov complexity, best suits the definition of 3D shape complexity as the difficulty for verbal description, we note that Kolmogrov complexity is not a computable scalar index.

5.1. Shape measure to quantify complexity

The shape measure that we formulate based on the perceptual inspiration can be implemented as three simple steps in sequence: (1) Curvature computation on a 3D mesh (2) bandwidth optimized density estimation (3) entropy computation from the kernel density estimate in Step 2. In the following paragraphs, we provide equations and a concise description to implement a simple shape complexity measure.

We now explain the Gauss-Bonnet curvature estimation algorithm in the umbrella neighborhood of a given vertex in the triangle mesh. Consider a vertex v and its immediate neighborhood vertices and define α_i as the angle at v between two successive edges vv_j and vv_k. The Gauss-Bonnet theorem from differential geometry can be simplified to digitized data towards computing curvature as shown below:

$$\kappa = \frac{3\left[2\pi - \sum_{i=0}^{nv-1} \alpha_i\right]}{A} \tag{1}$$

where A is the accumulated area of triangles around the vertex v and nv is the number of neighboring vertices of v. We compute the curvature using the formula in Equation 1 at all vertices in the mesh leaving out only the boundary vertices.

Next, we compute the kernel density function $\hat{p}$ of the curvature values over the entire mesh. Consider Equation 2 where n is the number of vertices in the mesh, h is the bandwidth of interest, G is the kernel function and κ_i is the curvature at vertex v_i. We visualize KDE as a series of 'bumps' placed at each of the n estimates of curvature in the density space. The kernel function G determines the shape of these bumps while the bandwidth h determines their extent. With large data sets (n is large), the choice for G does not have a strong influence on the estimate. We use the Gaussian kernel in our implementation.

$$\hat{p}(x) = \frac{1}{nh}\sum_{i=1}^{n} G\left(\frac{x-\kappa_i}{h}\right) \tag{2}$$

$$G(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \quad \text{such that} \quad \int_{-\infty}^{\infty} G(x)dx = 1 \tag{3}$$

We use the plug-in method in Equation 4 for optimal bandwidth selection as this method provides useful results without the selection of user parameters though commonly used cross validation methods can also be used.

$$h_{opt} = \left[\frac{243 R(G)}{35 \mu_2 (G)^2 n} \right]^{\frac{1}{5}} \hat{\sigma} \tag{4}$$

where $R(G) = \int G(t)^2 \, dt, \mu_2(G) = \int t^2 G(t) \, dt$ and $\hat{\sigma}$ is the absolute deviation of the curvature data κ_i.

We have used curvature estimates at each vertex to generate probability density curves [25]. With these curves, we now formulate an information theoretic approach based on entropy to define the shape complexity measure. We argue that the amount of information that the curvature conveys about the surface can be quantified as a measure using Shannon's framework. His definition of entropy for communication systems as a measure of uncertainty is the minimum number of bits required to encode a message. We apply Shannon's definition of entropy to measure the predictability of curvature considered as a random variable. Furthermore, we also have to deal with resolution and normalized measure space. The number of vertices in the mesh decides the quantization of curvature—the larger the number of vertices, the better the approximation to the infinitesimal curvature. We counter the asymptotic exponential interaction between the resolution and curvature by normalizing the Shannon's entropy measure as shown in Equation 5.

$$SCM = -\sum \hat{p} \log_n \hat{p} \tag{5}$$

We have chosen to normalize the SCM based on the resolution n (which is the number of vertices at which we have computed curvature). The normalization factor indirectly corresponds to the number of curvature quantization levels one expects from a triangulated model and decides the resolution of the SCM as a measure. The normalization lets us compare the SCM measures of two different surfaces at different levels of mesh resolution in addition to the convenience of [0, 1] feature space.

5.2. Correlation with human perception

As part of the psychophysical experiment, we had asked the participants to rate the perceived complexity of several surfaces (nearly 50) with a number in the scale 1-10. The statistical analysis on the SCM values with the human responses provided a high correlation of $\rho = 0.85$ with significance ($p < 0.01$) in support of the SCM capturing perceived complexity. We compared other shape metrics like shape index [27] ($\rho = 0.45$) and the variance of curvature ($\rho = 0.58$) also, before concluding the information-theoretic essence of judged complexity. Further, we conducted two more experiments for real world application. The first one was to classify 3D objects based on its judged complexity and the second towards identifying visually significant parts of 3D objects. We present a discussion of our observations in the following sections.

5.3. Classification of objects based on complexity

In CAE and CAD databases, classification is a major requirement and good features can fasten 3D database pruning. We present results on different 3D models as classified automatically using the curvature-based shape measure and verify the human response in close agreement. The participants in the survey classified 3D objects into different levels of complexity. The first one was to classify them into two groups and then into three and then rate each object based on perceived complexity. We also performed this experiment automatically using our shape complexity measure (Figure 2) and observed that the SCM based hierarchical ordering followed the majority opinion (> 90% support in a sample population of 300). In the next, level of classification however, SCM's performance dropped to 80% within each class of sub-divided complexity.

We attribute this to the fact that SCM does not encapsulate the interaction and the strength of contribution to observed complexity across the different dimensions. For example, we have not studied at what threshold a dimension like surface variation will over ride the number of parts towards judged complexity. These interactions are hard to quantify or understand and are potential bottlenecks in being able to quantify visual complexity using our proposed measure. Hence, we would like to note that with a larger database the classification rates may drop.

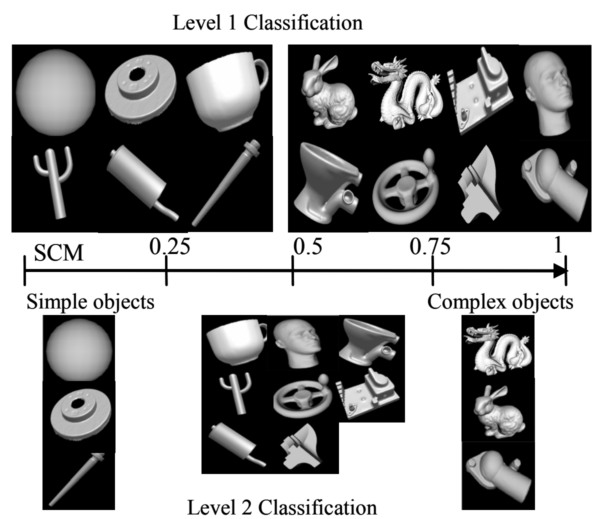

Figure 2: Classifying objects using the shape complexity measure agrees with how humans would do it. A simplified sample result with 14 objects.

5.4. Application: Object description towards identifying informative parts

The next application with the SCM is with identifying informative parts in 3D objects. Humans perceive 3D objects as a network of parts, some parts more significant and informative compared to others [7]. We intuitively tend to identify, label and memorize such salient structural information that we use for recognizing the object when observed in a different context. More so, the complexity of a part or an object helps is rejecting simpler ones in the database search process. In fact, the process of learning about a particular object happens by decomposing the object into abstract definitions and representations in our memory [20]. Page et al. [18] try to impart such a capability to the computer by demonstrating perceptual part-based representation of digitized 3D objects segmenting objects along the lines of negative curvature following the minima rule established by Hoffman and Richards [10]. We have used the mesh segmentation implementation of [18] on the objects that we show in this section.

Our brain is believed to further categorize relative importance of these segmented parts that make up the 3D object and remember the informative components even if they are not easy to describe in a physical or a verbal sense [26]. With our shape measure, we are able to simulate the quality of the human brain to attach significance/salience that is proportional to the descriptive complexity and recollect the significance for recognizing an object. Our claim is based on the observations similar to the examples shown in Figure 3.

Participants labeled the part that they considered would help in uniquely identifying the object. We found that for the objects in our experiment, the shape complexity measure identified the visually informative part of the 3D object nearly 60% of the time, with at least 80% accuracy within the top 3 choices agreeing with the majority of people. By identifying such parts, we should now be able focus our attention towards describing those parts better for matching purposes.

6. Conclusions and future work

Palmer [19] had stated that information theoretic structural description is not going to be easy but probably the best approach to object description in the 3D world. Our attempts in this paper, have taken us a step closer. Though not solving the problem completely, our effort is best summarized as having conducted a psychophysical experiment for understanding perceptual complexity with 3D objects extending existing domain knowledge on 2D contours and 2D images to 3D shapes. We have listed several variables as important dimensions of observing perceptual complexity. We have concluded that the physical attributes that contribute to perceived complexity on 3D geometry are surface variation, symmetry, part count, simpler part decomposability, intricate details and topology. Furthermore, based on the perceptual basis established, we have explained a shape analysis algorithm

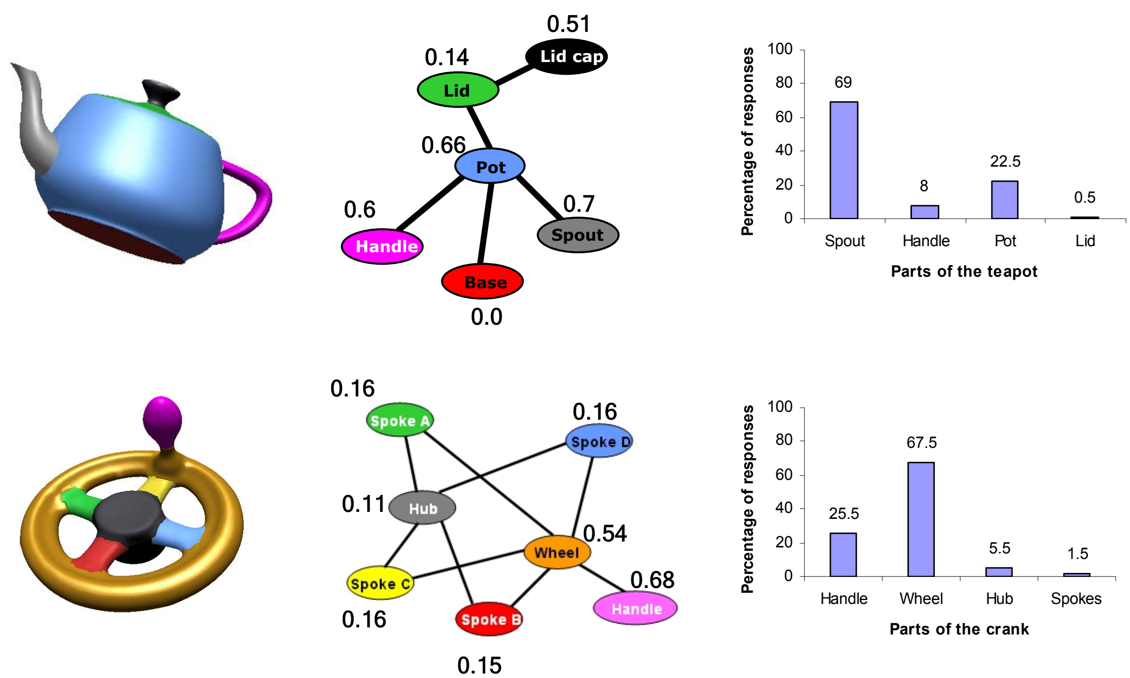

Figure 3: Identifying salient parts of a 3D object. The parts identified by the SCM mostly agree with the majority of human responses.

in the paper. The shape measure defined in the paper appears to quantify the perceptual aspect of descriptive complexity that can be associated with a 3D object. With the shape measure, we demonstrated the application on a database of 3D objects. We also extended the application to object description by quantifying the relative complexity of parts within the same object.

In future, we would like also like to implement our shape measure in 3D shape retrieval engines [17] to index objects based on perceptual principles, where the end user would specify the degree of complexity of the object and our shape measure could be used for reducing the model search space based on its magnitude. Further, the perceptual significance that our measure of complexity encapsulates can be used as an important feature towards object recognition and retrieval also. But, that will require more scale descriptive features to support the scale invariant SCM in an attributed graph in implementing a complete graph matching system for object recognition following Marr [13] and Biederman [3]. Our future efforts will target such applications.

Acknowledgements

The authors thank all the participants for their invaluable time in taking up our psychophysical survey and permitting us to publish the results. The authors are also grateful to the financial support through the University Research Program in Robotics grant DOE-DE-FG02-86NE37968, the DOD/ RDECOM/ NAC/ARC Program, grant Army-W56HC2V-04-C-0044, and the FAA/NSSA Program grant R01-1344-129/130 and R01-1344-088.

References

[1] F. Attneave (1957), "Physical determinants of the judged complexity of shape", *Journal of Experimental Psychology*, 53(4):221-227.

[2] F. Attneave (1954), "Some informational aspects of visual perception", *Psychology Review*, 61(3):183-193, 1954.

[3] I. Biederman (1987). Recognition-by-Components: A Theory of Human Image Understanding. Psychological Review, 94, 115-147.

[4] H. Bozdogan (2004), *"Statistical Data Mining and Knowledge Discovery"*, CRC Press.

[5] N. Bruce and J. Tsotsos (2007),"Attention based on information maximization ", *Journal of Vision*, 7(9):950, 950a.

[6] T. M. Cover, P. Gacs and R. M. Gray (1989), "Kolmogrov's contributions to information theory and algorithmic complexity", *Annals of Probability*, 17: 840-865.

[7] K. Denisova, M. Singh, E. Kowler (2006), "The role of part structure in the perceptual localization of a shape", Perception, Vol. 35(8): 1073–1087.

[8] E. V. Fehrer (1935), "An investigation of the learning of visually perceived forms", *The American Journal of Psychology*, 47(2): 187-221.

[9] C. Heaps and C.H. Handel (1999), "Similarity and features of natural textures", *Journal of Experimental Psychology: Human Perception and Performance*, 25:299-320.

[10] D.D. Hoffman and W.A. Richards (1984), "Parts of recognition", *Cognition*, 18:65-96, 1984.

[11] N. Iyer, S. Jayanti, K. Lou, Y. Kalyanaraman, and K. Ramani (2005), "Three-dimensional shape searching: state-of-the-art review and future trends", *Computer-Aided Design*, 37(5): 509-530.

[12] A. Jaklic, A. Leonardis, and F. Solina (2000), "Segmentation and recovery of superquadrics," Computational Imaging and Vision, Dordrecth, The Netherlands: Kluwer Publishers.

[13] D. Marr (1982), *Vision*, Freeman Publishers, New York.

[14] D.W. Martin (2000), *"Doing psychology experiments"*, Wadsworth Thomas Learning, Fifth Edition.

[15] A. Oliva and A. Torralba (2006), "Building the Gist of a Scene: The Role of Global Image Features in Recognition", *Progress in Brain Research: Visual perception*, 155:23-36.

[16] A. Oliva, M. L. Mack, M. Shrestha, and A. Peeper (2004), "Identifying the Perceptual Dimensions of Visual Complexity of Scenes", *in the Proc. of the 26th Annual Meeting of the Cognitive Science Society Meeting*.

[17] R. Osada, T. Funkhouser, B. Chazelle, and D. Dobkin (2002), "Shape distributions", *ACM Trans. on Graphics*, 21(4): 807-832, 2002.

[18] D. L. Page, A. F. Koschan, and M. A. Abidi (2003), "Perception-based 3D Triangle Mesh Segmentation Using Fast Marching Watersheds", *in Proc. Intl. Conf. on Computer Vision and Pattern Recognition*, 2:27-32.

[19] S.E. Palmer (1999), *"Vision Science: Photons to Phenomenology"*, MIT Press.

[20] M. Riessenhuber and T. Poggio (2000), "Models of object Recognition", *Nature America*, 1199-1204.

[21] J. Rissanen (1987), "Stochastic Complexity". *Journal of the Royal Statistical Society, Series B*, 49: 223-229.

[22] J. Rissanen (1989), *"Stochastic Complexity in Statistical Enquiry"*, World Scientific Publishing Company, Teaneck, NJ, 1989.

[23] J. Rossignac (2005), "Shape complexity", *The Visual Computer,* 21(12): 985-996.

[24] C. E. Shannon (1948), "A mathematical theory of communication". *The Bell System Technical Journal*, 27:379-423, 623-656.

[25] B. W. Silverman (1986), *Density Estimation for Statistics and Analysis*, London, UK: Chapman and Hall.

[26] J. T. Todd (2004), "The visual perception of 3D shape", *Trends in Cognitive Science*, 8:115−121.

[27] C. Dorai, and A. K. Jain (1997), "COSMOS - a representation scheme for 3D free-form objects", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 19:1115-1130.