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SHAPE SPIRIT: DECIPHERING FORM CHARACTERISTICS AND EMOTIONAL ASSOCIATIONS THROUGH GEOMETRIC ABSTRACTION

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ABSTRACT

Understanding and tailoring the visual elements of a developing product to evoke a desired emotional response and aesthetic perception is a key challenge in industrial design. To date, computational approaches to assist this process have either relied on stiff geometric representations, or focused on superficial features that exclude often elusive shape characteristics. In this work, we aim to study the relationship between product form and consumer emotions through a visual deconstruction and abstraction of existing final products. In particular, we attempt to answer three questions: (1) Do observers' aesthetic judgments rely on the product as a whole, including fine geometric details, superficial surface features, and brand-revealing icons, or are large, prominent shape characteristics sufficient to make this determination? (2) Is it possible to isolate shape features that give rise to specific emotional responses? (3) Is there a relationship between consumers' ability to recognize a brand and the emotional attributes they associate with that brand. At the heart of our investigation is a shape analysis method that produces a spectrum of abstractions for a given 3D computer model. This produces a hierarchical simplification of an end product, whereby consumer response to geometric elements can be statistically studied across different products, as well as across the different abstractions of one particular product. The results of our study show that emotional responses evoked by coarse product "impressions" are strongly correlated with those evoked by final production models. This, in turn, highlights the importance of early aesthetic assessment and exploration before committing to detail design efforts.

INTRODUCTION

The ability to identify, engineer, and incorporate consumer preferences into a new product has a pivotal role in market success. Studies have shown that, among others, emotional factors play a critical role on how strongly a product captivates its user [1, 2, 3]. As part of this pursuit, designers spend a considerable effort to create appropriate stylistic rules and form languages that evoke a desired emotional response in the hands of its consumers [4,5]. Recent studies have identified several categories of key form factors influential in emotion [6] such as shape, characteristic curves, textures, colors and materials. However, the engineering of strictly geometric elements remains a highly elusive, labor intensive and iterative task, whose success depends largely on human skill and expertise [7]. We believe a lack of appropriate computational techniques in support of this task contributes directly to this challenge. Specifically, while our current knowledge includes vast anecdotal evidence supporting a strong coupling between shape and human emotion, we currently lack the means to digitally decipher and engineer such relationships. This, in turn, poses a great challenge to developing a brand identity across a family of products, as well as across temporally and geographically dynamic consumer markets.

This work aims to address this challenge through a new computational method that helps reveal the relationships between product geometry and emotional associations. In particular, we focus on the task of reverse-engineering geometric form features from production models in the form of a hierarchy, and study the effect of the identified features on consumer perception. A distinguishing characteristic of the proposed work is its ability to alleviate the dependency on canonical shape templates, over which parametric studies are typically conducted [8, 9, 10, 11]. Instead, our approach aims to reveal design-specific 3D geometric features that are not readily extractable from the surfaces of the final production models, yet form the perceived volumetric entities giving rise to the final shape.

Using this approach, we seek to answer the following questions:

1. *Do consumers' aesthetic judgments rely on the product as a whole, including fine geometric details, superficial surface features, and brand-revealing icons, or are large, prominent shape characteristics sufficient to make this determination?*
2. *Is it possible to isolate shape features that give rise to specific emotional responses?*
3. *What is the relationship between the ability to recognize a brand and the emotional responses associated with its distinguishing features? Does recognizing a brand cause a confirmation bias for articulated emotional responses, or are emotional responses solely tied to geometric features?*

Note that the proposed work currently provides a basis for analysis only. The more challenging task of how the outcomes of this work can be used for automatic or even human-guided shape synthesis is not addressed in this work, although our results help develop useful insights toward this higher goal.

Overview

To address the above questions, we conducted a three-stage user study. At the heart of this study is a geometric analysis method that produces a spectrum of *abstractions* of a given 3D model [12]. An abstraction is a geometrically simplified version of an original production model, where the level of abstraction (*i.e.* simplification) in the spectrum determines how much of the original details are preserved or removed. Specifically, starting from the most abstract version of the model, a geometric feature is added or removed from the abstracted model, until the working model matches the original 3D model. This approach allows geometric features to be studied in isolation and forms the basis for our user studies.

We chose to study a set of relatively well-recognized cars to illustrate our methodologies. In the scenarios easiest to our online participants, this choice enables an accurate brand recognition in nearly all cases, which forms a suitable benchmark for our analysis. This allows our participants to serve as suitable potential consumers of these products. **Study I** investigates the level of geometric simplification beyond which consumers fail to recognize the brand/model of the product. In **Study II**, we investigate the correlation between consumer emotional responses over a set of abstract car models and over a set of original car models. In **Study III**, we investigate how different geometric features extracted from a model influence consumers' perception of the product and whether there are prominent features responsible for evoking specific emotional associations. As will be described, these studies help answer the questions posed above. Figure 1 illustrates a hierarchy of 3D abstractions for a Mustang model and a sample set of car images employed in our user studies.

Contributions

Our work attempts to reveal how early design decisions regarding form may influence consumer perception. For this, we believe one must study consumer responses to approximate and abstract 3D geometries that are representative of a product's form, but are devoid of superficial revealing features such as icons, logos, and similar elements. The hierarchical abstraction geometries used in this work facilitate this task, in a way similar to how progressively detailed product sketches communicate design ideas at different levels of granularity [12]. In effect, the proposed work may help computationally reveal how much of the final consumer perception is tied to the decisions made early in the design process.

Additionally, the ability to add and subtract features progressively, enables specific geometric features to be studied in isolation. We believe this decoupling is critical in establishing a mapping between geometry and emotion. With such studies, design cues responsible for particular consumer emotions can be extracted, thus revealing the signature building blocks of a product's spirit, and further assist form language identification efforts [4].

Our technical contributions are:

1. A template-free study of the relationship between shape and consumer emotions that is applicable to a wide variety of products.
2. A geometric assessment of how individual shape features and product proportions impact consumer perception.
3. The ability to decouple consumer perception originating purely from geometry versus perception superficially associated with a recognized brand.
4. The ability to dissect a final model in ways that enable independent access to its features developed in different phases of the design process. To the best of our knowledge, this work is the first to attempt such a deconstruction, which facilitates the study of conceptual versus detail design decisions.

Our studies have resulted in the following main outcomes:

1. Geometric design features can be separated into two fundamental categories: (1) prominent bulk features, (2) brand-revealing features. Bulk features establish the core identity of a product and likely develop early in the design process. They are also influential in consumers' perception of certain attributes, and these perceptions may not change with added superficial features. This points out the importance of early design stages.
2. There is a strong correlation between consumers' relative assessments within a set of final products and within a set of abstracted models of the same products. This means comparative assessments in the early design cycle are almost as useful as the comparative assessments later in the design cycle.
3. Certain design features have a significant impact on particular consumer emotions. This mapping can be learned and reused so as to preserve desirable product qualities and brand identity.

FIGURE 1. (a) The 9-level simple-to-complex abstraction of a Mustang model. Note that several distinguishing characteristics of a Mustang such as the front bumper, grill and air intake on the hood start to emerge over abstractions. (b) Various real car images used in our user studies. The Mustang model in (a) corresponds to the top-left image in (b).

4. Certain emotional attributes exhibit strong and consistent associations with a recognized brand, but show major fluctuations when the brand cannot be recognized. Conversely, certain other emotional attributes are far less sensitive to an identified brand: they develop early in the design cycle, and are difficult to change with late geometric alterations or brand-revealing features.

RELATED WORK

Shape-emotion studies: Kansei engineering [13] aims to map style features and parameters to observer emotions. Recent studies have used geometric models and user surveys to uncover the mechanisms behind such design-evoked consumer emotions. Chen and Chuang [14] studied a large number of cellular phone drawings to identify the relationship between engineering performance and customer satisfaction. Luo *et al.* [15] studied bottle designs to identify the factors that make certain designs more successful than others. Luo *et al.* [16] later studied cars and wheel hubs to identify consumers' aesthetic preferences. In these studies, query designs are typically created manually as 2D side or front view proxy drawings. These interventions are both laborious, and lead to oversimplifications and information loss that may introduce perceptive biases.

In automotive aesthetics, recent works have relied on parametric templates to study shape variation (*e.g.* sedan, hatchback, SUV, etc.) and synthesis. Lai *et al.* [8] identified parameters that impact specific attributes, Orsborn *et al.* [9] focused on aesthetic preferences, Reid *et al.* [10] studied the perceived environmental friendliness, and later studied [11] the trade-offs using aerodynamic analyses. These studies have shown that a mapping from consumer emotions to a parametric model can be learned through user surveys. However, these approaches require a template geometry to be manually created, resulting in a limited space of shape variations spanned by the fixed topology model. Additionally, the 2D orthographic views often cause perceptually relevant voluminous features to be eliminated during consumer assessments.

Form language studies: Previous studies proposed methods to identify and reuse *form languages* from existing designs. In one group of studies, Chen and Owen [17] developed a generative system that can produce block-based structures with stylized transitions between the blocks. Chan [18] attempted to quantify style by comparing the similarities between repeating geometric features, then studied architectural structures [19] to embed artistic preferences within a form language. These studies are tailored toward repetitive geometric features, and hence may not be readily extendable non-repetetive aesthetic features.

Prats *et al.* [20] studied visual perception mechanisms from

2D drawings to identify a set of generative design rules similar to shape grammars [21, 22]. Karjalainen [23] studied car models for symbolic design cues that establish brand identity. Similarly, Cheutet *et al.* [24] identified G1 continuities as part of a commonly utilized form of stylization, and developed a computer aided design tool to semi-automatically apply such geometric rules. While powerful in their particular domains, these studies similarly rely on a manual identification of the perceptually salient design constructs. Moreover, since they are tailored for a limited set of geometric features and rules, such approaches do not generalize to form languages that originate from a product's overall shape, proportions, particular dimensions and geometric configurations.

Giannini and Monti [25, 26] aim to determine a relationship between geometric curve characteristics and resulting consumer emotions. Subsequent studies [27, 28] demonstrated the utility with a computer-aided modeling system that allows the control of geometric curves through semantically labelled attributes. While forming a promising map between emotion and geometry, these individual curve-based methods do not allow the detection of aesthetically relevant elements that appear through the synthesis of volumetric bulk features.

In this study, we aim to extend the boundaries of these previous efforts through a 3D hierarchical deconstruction method capable of producing a rich set of topologies and shape variations. This allows aesthetically salient 3D forms to be isolated, preserved, and methodologically manipulated throughout the human studies. Specifically, the domain-invariant, automatic shape decomposition enables final production models to be represented and visualized at a variety of detail levels, thereby helping isolate the effects of different geometric elements. We believe this property makes our approach suitable for studying a wide variety of geometric shapes and their variations, even though this work only focuses on a set of car models as a test-bed.

Terminology and Methodology

In the remainder of this work, the following terminology is used:

Full model: The original computer model of a car, containing all the details representing a production model.

Abstraction spectrum: Various abstractions of a full model, similar to those shown in Fig. 1a. All abstractions start with the simplest model, and moves toward higher complexity until the final, full model is reached. Different car models may have a different number of abstractions.

Feature (Geometric): A volumetric detail added or subtracted from a working abstraction model. The addition of such features moves the model from simple toward complex along the abstraction spectrum.

Attribute (Consumer response): The set of attributes that the participants of our user studies employ for evaluating the car models. In this work, we use the following six attributes: **fast**, **muscular**, **elegant**, **sophisticated**, **utility** and **compact**. These attributes are used to demonstrate the proposed analysis techniques. While they do not form a comprehensive basis to fully characterize the models used in our studies, they are nonetheless distinct, commonly well-understood by our participants, and form a small set that is not overwhelming to our participants. Note that the proposed techniques are amenable to the addition of new attributes or car models, without affecting the subsequent analysis methods.

Debranded model (DB): For a given car, the abstraction model containing the most amount of feature details, yet which cannot be reliably recognized by consumers. This represents the abstraction model from which all brand-revealing features have been removed. In Fig. 1a, our studies showed that Abstraction 2 is the DB model for the Mustang.

Volumetric Shape Abstraction

We utilize the volumetric shape abstraction method introduced by Yumer and Kara [12][1]. This approach views a product as a set of volumetric regions, whose unions and intersections produce the perceived surfaces and character lines of the product. The volume-based view and construction of objects is common in aesthetic form design, where conceptualization begins with rough volumetric elements such as scaffolds or inside/outside spaces [4]. The abstraction method initially uses volumetric constructs to decompose the original model into successively smaller volumes. In each step, the surfaces of the identified primitives are beautified to reproduce the form present in the original model. This formulation results in a compact representation of the original geometry as a set of implicit surfaces and blending functions. The method can operate on models containing many internal components, but still produce a representative outer form of interest.

This approach seeks to generate *beautified volumetric primitives*, which are bounded spaces that evolve from basic primitives. The abstraction method is based on a probabilistic primitive generation and scoring algorithm that, in each step, tries to identify the progressively smaller volumes of the model which have not been represented by the primitives of the earlier levels. After a basic primitive is fit, each face of the primitive undergoes a polynomial beautification, while maintaining its association with the primitive. Starting from the coarsest level of abstraction, *i.e.* model represented with the minimum number of primitives (Abtsraction 1 in Fig. 1a), the algorithm hierarchically identifies other primitives that progressively refine the initial abstraction. The refinement can add or subtract volumes, similar to the union and difference operations in conventional Constructive Solid Geometry (CSG) algorithms. This process iteratively continues until the volume of the smallest primitive falls below a user-specified threshold, thereby leading to the abstraction hierarchy of an input model. The following studies rely on this hierarchical structure of the resulting abstractions.

[1] A demonstration of this method, examples, and supplemental material can be found at: `http://vdel.me.cmu.edu/co-abstraction-of-shape-collections/`

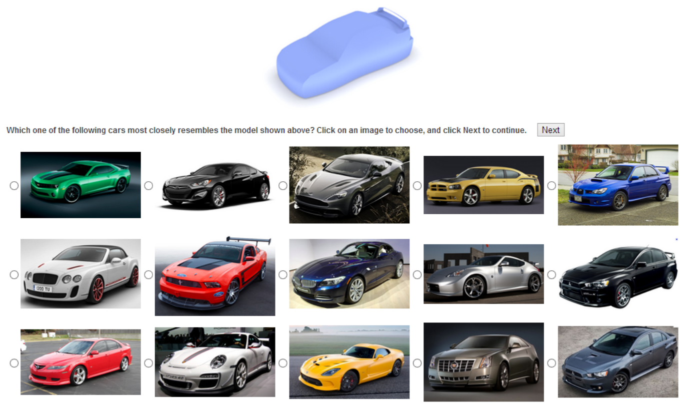

FIGURE 2. A typical survey question in Study I. The answer to this question is the Subaru at the top right.

Study I: Debranding - Isolation of Bias Toward Recognizable Brand and Design Features

This study aims to identify the debranded abstract model (DB) of an input car to the point where all the brand-revealing features are removed, and the viewers could no longer reliably identify the make of the car.

Procedure: We recruited 31 participants (18 male and 13 females) with $age = 24.6 \pm 2.5$ to an online survey on a voluntary basis[2]. We instructed the participants to answer a series of multiple choice questions to the best of their ability, and offered no monetary incentive. No time restriction was imposed. Figure 2 shows an example survey question. In each question, we showed the participants an image of a computer-rendered model that is either the full or one of the abstraction models of a car. We then asked them to choose, from a pool of 15 photographic images, the image that corresponds to the presented computer model. In each case, only one of the 15 photographic images was the correct match to the presented computer model. Aside from the true match for the computer model, the remaining 14 models were chosen randomly from a large database of car images, all approximately taken from the conventional 3/4 view. This random draw from a large pool was introduced to alleviate identification via elimination.

The set of cars we used in this and subsequent studies consist of 7 different models. Each car model had anywhere between 3 to 9 abstractions, which depended on the geometric complexity of the full models. In total, we have 36 abstraction models (*i.e.* , on average, 5.14 abstractions per car) plus the 7 full models as queries, leading to 43 total questions per participant.

Results: Figure 3 shows the average participant recognition accuracy of each car *versus* the abstraction level, together with the full models, and inferred debranded models.

As expected, the general tendency is that the accuracy for brand recognition increases as the abstraction moves from simple to complex. We rule a few exceptions, such as car 5 (Ford Mustang) at abstraction level 9, as incidental, because at such levels they lack small, but crucial details to be distinguished from similarly shaped "decoys" among the choice images.

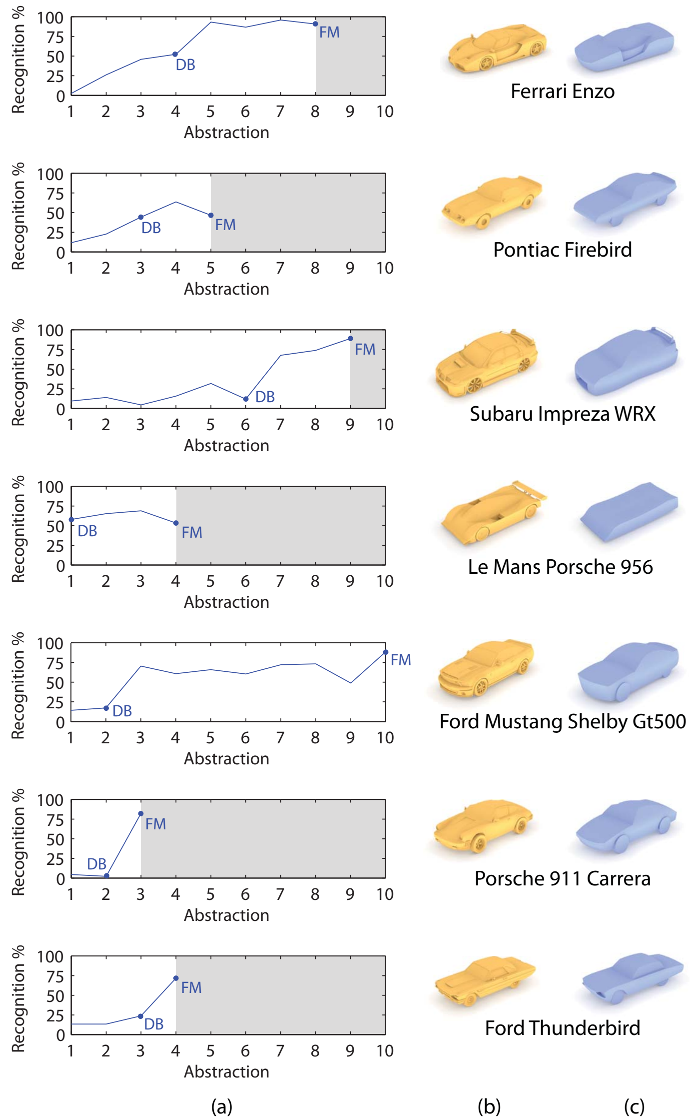

FIGURE 3. (a) Average participant recognition accuracies in **Study I** as a function of the abstraction level. For each plot, the left-most point corresponds to the simplest abstraction, while point FM corresponds to the full models, (b) Full models, (c) DB models.

This study sought to determine the highest level of abstraction at which the brand identity is not revealed (DB models). Toward this end, we start from the rightmost, full model end of the accuracy curve, trace the curve to the left towards the lower abstraction levels, and look for the largest drop in accuracy. The abstraction level corresponding to the lower end of this drop is declared the DB model. Note that a DB model does not represent an abstraction for which none of the viewers are able to discern the brand. Instead, it represents a threshold model such that, on average, the introduction of one additional feature causes a significant increase in the model's recognition. In our study, the DB models serve as a suitable simplification of the full models that enable a separation of geometry versus brand-driven user

[2] http://goo.gl/WfqFW

perception.

When Pearson's χ^2 test is applied to the accuracy drops, all but one of the drops are found to be significant with $p < 0.05$. The only notable exception, car 4 (Le Mans), exhibits a stable but low recognition rate of $\approx 60\%$. We attribute recognition stability to Le Mans' unique shape as a highly aerodynamic race car: its identity is deeply rooted in the base shape of a low and wide stance already prevalent in its simplest abstractions. However, we have found the low recognition rates to be due to the participants' frequent confusion of this model with two other incorrect "decoy" models that closely resemble the Le Mans. Figure 4 shows this peculiarity.

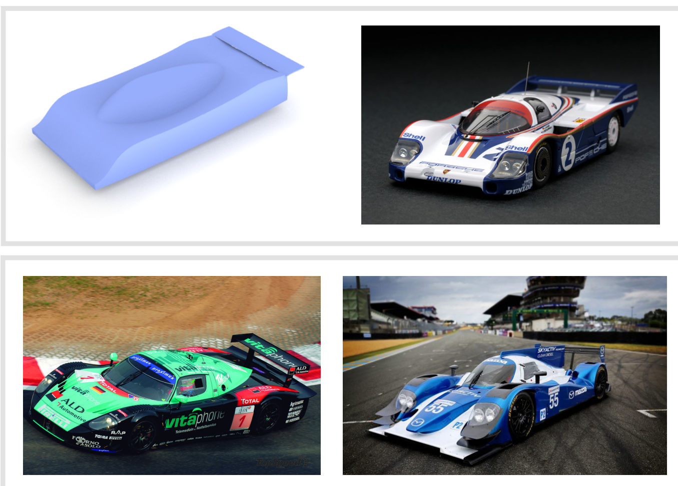

FIGURE 4. Top: One of Le Mans' abstractions and the true matching image. Bottom: Two decoy images in **Study I** that participants frequently selected.

Implications: The results provide support for the existence of brand-revealing features, whose introduction systematically contributes to the most significant boost in the consumers' recognition of brand identity. Such features develop relatively early in the design timeline, as reflected by their positions in the lower end of the abstraction spectrum. An inspection of the geometric features added after the DB levels indicates that further feature introductions such as spoilers, headlights and air intake cut-outs are often the most responsible for brand revelation.

Study II: Correlations Between Emotional Responses to Abstractions and Full Models

This study intends to measure and compare the emotional responses to debranded abstractions and full models of cars. It utilizes the debranded abstractions found in Study I. It aims to discover whether humans' relative assessments across a set of full car models are similar to their assessments across the debranded versions of the same cars.

Procedure We recruited 30 participants (19 males and 11 females) with age $= 35.6 \pm 14.2$ to an online survey[3] through Amazon Mechanical Turk. There was no overlap between the participants in Study I and this study. We instructed the participants to answer a series of questions to the best of their ability, and offered a monetary incentive of 25 cents upon completion. In each question, we first showed the participants a pair of computer-rendered models, and then asked them to compare and rate the two in terms of the 6 emotional attributes using a set of sliders. As introduced previously, these 6 attributes are [**fast**, **muscular**, **elegant**, **sophisticated**, **utility**, **compact**]. A typical survey question is shown in Fig. 5.

The set of cars we used in this study are the same seven used in Study I. We asked the participants to compare any two of them in a pairwise fashion. Hence there are $C_7^2 = 21$ such pairwise comparisons in total, corresponding to 21 survey questions.

We randomly assigned each participant to one of the following two conditions:

1. **Condition D** We showed the participant pairs of only *debranded* abstractions.
2. **Condition F** We showed the participant pairs of only *full* models.

With this, participants never compared a full model to an abstract model. The survey allowed the participants to advance to subsequent screens only if all the sliders have been activated/moved in the current screen. For some of the attributes, hovering over its name revealed a description of that attribute for the participants unsure about its interpretation.

For each attribute, the participants make their assessments on a semantic scale akin to "Left more, Both about the same, Right more". However, internally the scores are recorded in the range of $[-100, 100]$, where $-$ and $+$ signs denote higher scores for the car on the left and right, respectively. This allows for each pair of cars, each attribute to attain a unique quantitative value in $[-100, 100]$.

Results Given two brands, for each of the attribute comparison solicited, we compare the responses from condition D and condition F using Student's t-test, and summarize the resulting statistics in Table 1. Furthermore, we plot all the pairwise comparisons in Figure 6, using color-coded edges to represent the mean differences. In this figure, an edge between two numbers, say 2 and 6, represent a comparison between car 2 and car 6. For each attribute, say utility, we record the slider positions set by the participants in the range $[-100, 100]$. Note that multiple responses are typically recorded from different participants for the same comparison.

The edges in Figure 6 show the differences between the attribute values recorded for the comparisons across the full models (condition F) versus the comparisons across the debranded abstract models (condition D). Significant differences between the graphs of D and F (individual graphs not shown) are displayed in solid lines, while similar attribute values between the graphs of D and F give rise to faint dashed lines. Hence, faint

[3]http://goo.gl/87bUF

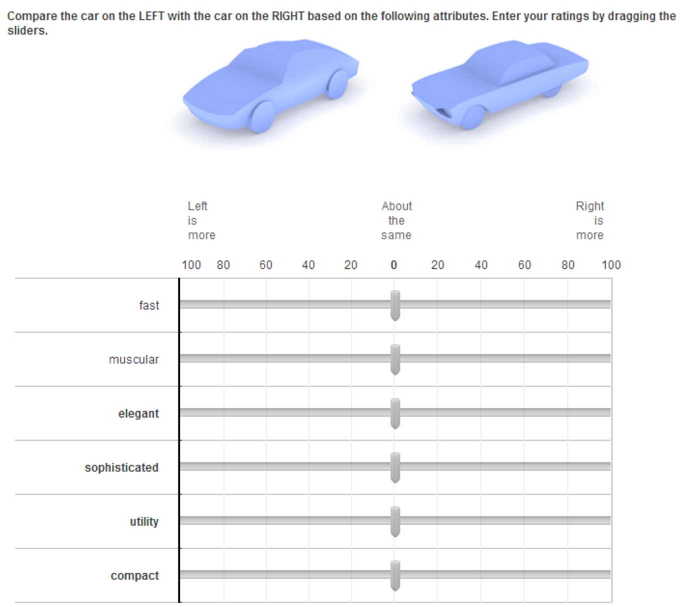

FIGURE 5. A typical survey question in Study II.

lines suggest a strong consistency between consumers' relative assessments of models when viewed in full models versus when viewed in abstract representations. Conversely, solids lines, whose colors represent the severity of the difference, indicate a discrepancy between the assessments in D versus the assessments in F.

For further interpretation of the results, we conducted an Analytic Hierarchy Process (AHP, [29]) analysis to infer *absolute* attribute scores from pairwise comparisons. Please refer to Appendix A for a brief summary. We convert the earlier attribute scores to a ratio scale, where one model can attain a score at most four times more than its competitor, in which case, the competitor's attribute score is four times less. We populate a matrix by taking the average scores from our survey and converting them into such score ratios. In the case of debranded abstraction and full model comparisons, we calculate a 7×7 AHP matrix for each attribute. Through an Eigenanalysis on these matrices, we calculate the eigenvector that corresponds to the highest eigenvalue. When unit normalized, this eigenvector yields the absolute scores of the cars specific to that attribute, similar to a 1D embedding of a high dimensional distance graph. Hence, for a given attribute, different cars can be rank-ordered if desired separately for condition D and condition F. When applied to all six attributes, this analysis results in a joint 6D embedding of each car. Figure 7 shows the absolute scores of abstracted (D, blue) and full (F, red) models as a set of 2D plots for each attribute pair. As shown, the embeddings of the cars in D and the cars in F exhibit a good correspondence, as evidenced by the relatively short edge links.

Implications: These outcomes suggest that humans' perception of a set of products may indeed be detail- and brand-neutral: their perception of fully developed products may be consistent with their perception of highly abstract, simple representations of the same products. For designers, this points to the importance of establishing a convincing base form before detail design efforts are undertaken. More specifically, it gives rise to informative early form-assessment opportunities, whose results are likely to remain valid even after seemingly unique, brand-specific details are added.

Study III: Design Features and Associated Emotions

The goal in this study is to compute the sensitivity of a geometric feature on the resulting emotional responses. The study is designed to systematically assess all the abstractions of one car model, using the set of 7 full car models as a basis.

Procedure We recruited 80 participants (53 males and 27 females) with age $= 38.3 \pm 14.7$ to an online survey[4] through Amazon Mechanical Turk. There was no overlap between the participants in Study I, II and this study. We instructed the participants to answer a series of questions to the best of their ability, and offered a monetary incentive of 25 cents upon completion. No time restriction was imposed.

In each survey question, we first showed the participants a pair of computer-rendered models, **one of which is an abstracted model while the other is a full model**. We then asked them to compare the two, and rate them in terms of the 6 emotional attributes introduced in Study II using a slider. The questions here were in a format similar to that in the previous study (Fig. 5).

In this study, the dataset contains a total of 36 abstraction models and 7 full models, which results in $36 \times 7 = 252$ pairwise comparisons. The pool of abstract models from which query screens were generated included the entire set of abstractions, instead of only the abstraction spectrum of the particular model being studied. The reason behind this choice is that we observed that when the participants were repeatedly presented with different abstractions of the same car in question (even in random order), they quickly became familiar with the car and responded with the same judgement score, regardless of the geometric variations present across the abstraction spectrum.

To alleviate such a bias, we solicited from each participant only 21 pairwise judgements, where the abstraction models could come from different car models. As a result, no participant was presented with the abstractions of solely a single model, but rather provided scores for randomly chosen 21 out of 36×7 possible pairwise comparisons. The 80 participants contributing to this study resulted in an average of 6.67 responses per comparison.

Results Similar to Study II, we use AHP to calculate absolute attribute scores of the abstractions. However, different from Study II, here we consider the full models of cars as a consistent basis for analysis. The seven links corresponding to the pairwise comparisons between a particular abstraction model and all of the full models are collected into a vector $\mathbf{v}_{1\times 7}$, and are com-

[4] `http://goo.gl/xYVgW`

TABLE 1. The t-test statistics for the comparison of the emotional ratings between debranded abstractions and full models

Comparison	Mean difference (in bold if **significant** at $\alpha = 0.05$)					
	Fast	Muscular	Elegant	Sophisticated	Utility	Compact
1 *vs.* 2	15.9	23.26	10.18	-0.9107	9.768	-2.554
1 *vs.* 3	12.66	5.946	31.05	10.46	-1.563	2.679
1 *vs.* 4	-36.69	-26.63	-36.92	-30.28	-10.18	-13.08
1 *vs.* 5	30.53	6.107	27.59	3.982	8.563	-5.813
1 *vs.* 6	-13.1	13.4	-29.98	-5.018	21.37	-21.45
1 *vs.* 7	25.28	36.2	20.29	5.366	-2.893	8.188
2 *vs.* 3	3.982	-25.21	10.05	-3.116	-7.071	13.66
2 *vs.* 4	**-85.02**	**-58.91**	-39.97	**-46.4**	-11.04	7.955
2 *vs.* 5	19.3	23.56	21.46	9.438	-2.143	-7.705
2 *vs.* 6	-16.06	-1.384	-29.24	-13.2	**30.2**	12.65
2 *vs.* 7	2.188	-8.518	-26.58	-24.88	-3.491	6.277
3 *vs.* 4	**-52.6**	-36.5	-15.67	-34.3	-14.96	-8.464
3 *vs.* 5	-3.116	21.37	12.01	12.87	**31.02**	-14.38
3 *vs.* 6	-31.01	25.71	-24.57	-10.96	4.321	-24.48
3 *vs.* 7	5.375	22.04	-33.28	-21.91	11.14	-6.884
4 *vs.* 5	**69.84**	**35.42**	39.87	**64.78**	-13.44	17.11
4 *vs.* 6	**62.07**	**50.5**	12.2	14.06	20.66	7.813
4 *vs.* 7	**55.63**	**69.97**	18.06	33.69	14.34	20.9
5 *vs.* 6	-13.63	-10.03	**-58.66**	**-45.13**	12.04	-0.5536
5 *vs.* 7	0.6607	11.13	-6.429	-9.58	25.57	5.384
6 *vs.* 7	13.4	1.214	-4.768	21.21	-31.74	8.08

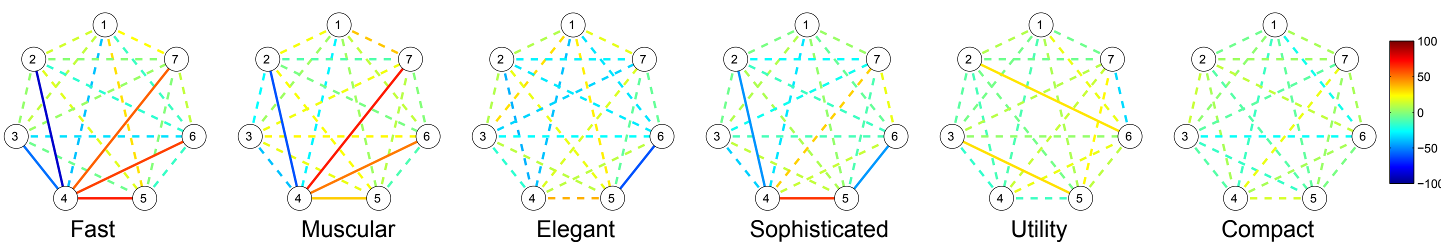

FIGURE 6. The differences between consumers' relative assessments within a set of final products (condition F) and that within a set of debranded abstracted models of the same products (condition D) for the 6 tested attributes. The numbers (1-7) in circles denote the brand. Each edge between two circles corresponds to a pairwise comparison. In each graph there are 21 such edges. The color of each edge represents the magnitude of the mean difference between the assessments of full models and that of the debranded abstractions. See the legend for the color map. Edges are drawn as solid lines if the mean difference is statistically significant, and dashed otherwise. The percentage of solid edges for each attribute is 24%, 19%, 5%, 14%,10% and 0% respectively.

bined with the full-to-full model comparisons that were encoded in Study II as a matrix $\mathbf{Q}_{7\times7}$. This allows an absolute score to be calculated for any abstraction model and any attribute with respect to the full models. The AHP comparison matrix in this case is 8×8, where the first column is $[1\ \mathbf{v}]^T$, the first row is $[1\ \mathbf{v}]$, and the rest of the matrix is $\mathbf{Q}$.

Figure 8 shows the AHP scores (blue with circle markers) with respect to the abstraction models of all cars. The figure also overlays the recognition rates (green) calculated from Study I, as well as their forward (red) and backward (black) cross-correlations with the AHP scores. As shown, the attribute scores exhibit interesting trends. For instance, car 4 is consistently rated fast throughout its abstractions despite its simplicity, whereas cars 1, 3 and 5 are perceived faster as more geometric details are added. In addition, the "fast" attribute for car 1 is strongly correlated with brand recognition accuracy. By contrast, the "compact" attribute for car 1 and 5 are strongly and negatively correlated with brand recognition rates. In both cases, these correlations reveal the coupled effect of brand and geometry on perceived attributes: as the participants begin to recognize the features associated with a brand, they alter their judgements in ways that reflect brand-specific notions and qualities. For instance, as soon as the brand is recognized, respondents reverse their opinions about the compactness of the cars, even though the geometric differences between the abstraction models might have been minor. However, these outcomes only point to the *joint* influence of geometry and brand; they do not suggest one influence outweighs the other. Additionally, the trend in "sophistication"

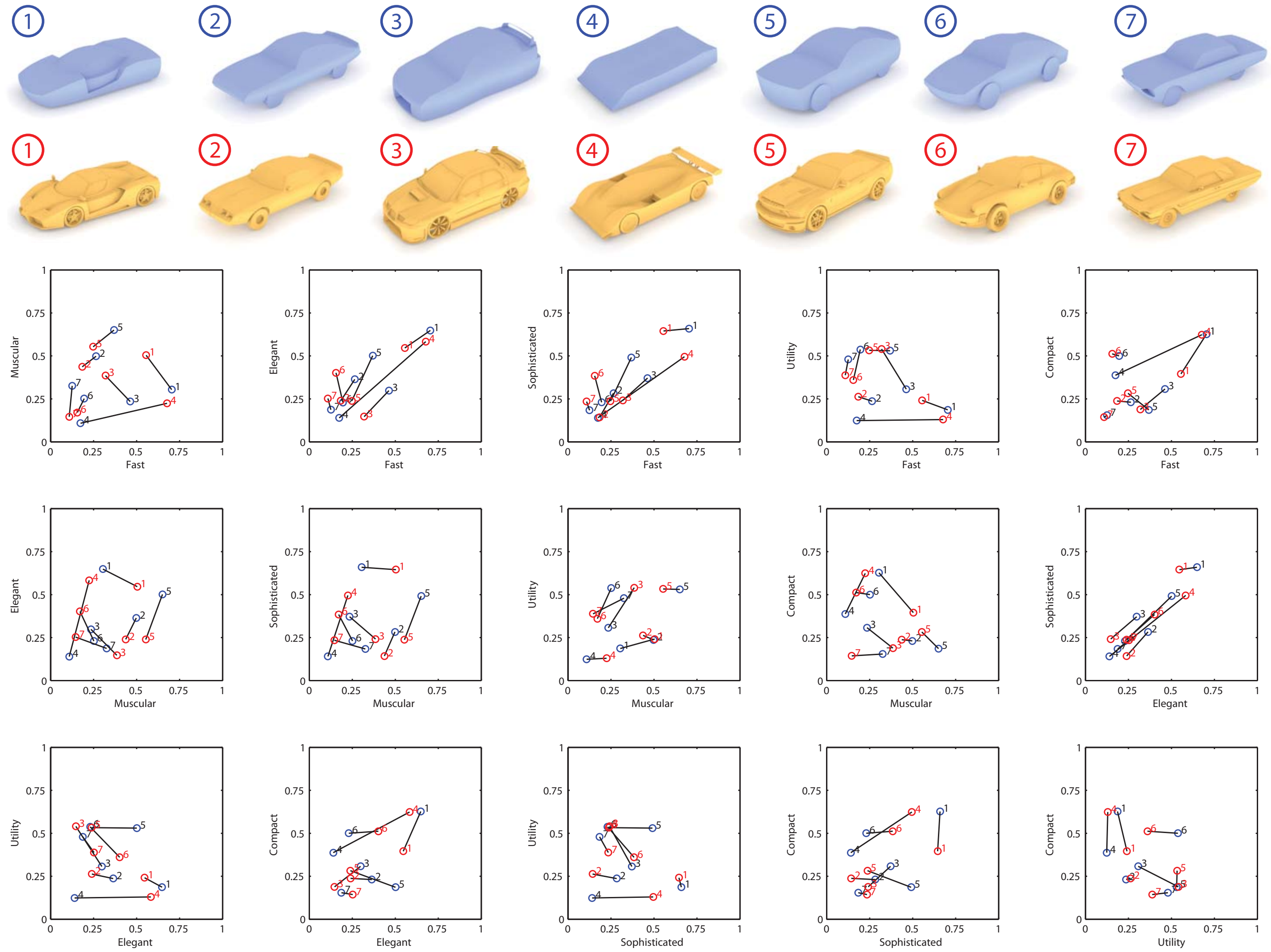

FIGURE 7. The positioning maps of the debranded abstractions and full models by their AHP scores in terms of two attributes. The numbers in or near the circles denote the brand. The **blue** circles in the plot represent the debranded abstractions. The **red** circles represent the full models. The solid lines connect the abstraction and the full model of the same car. The models, debranded and full, are shown at the top.

closely follows the trend in "elegance" for all the cars, suggesting a strong correlation between the two attributes.

Implications The results of this study suggest that geometric features may influence consumers' emotional responses through two parallel pathways. On one hand, bulk geometric features developed early in the design process may directly evoke particular emotional responses, and their effect seems invariant to the subsequent emergence or recognition of brand identity. Such features should be discovered through studies and reused so as to preserve fundamental product qualities.

On the other hand, brand recognition may act as a mediator between geometric features and certain emotional responses, and establishes an indirect pathway therein, as illustrated in Fig. 9. This second pathway is particularly interesting, because it suggests that brand identity is not an artificial notion, but carries strong emotional associations. Designers should therefore capitalize on such brand-revealing features to engineer desired emotional qualities into the product. "What's in a name? That which we call a rose by any other name[5]" perhaps would not always "smell as sweet".

FIGURE 9. The mediating effect of brand identity between geometric features and emotional responses.

To compare the statistic *strength* of the two pathways, future experiments should include paired brand recognition and emo-

[5]Shakespeare, Romeo and Juliet, Act II, Scene ii.

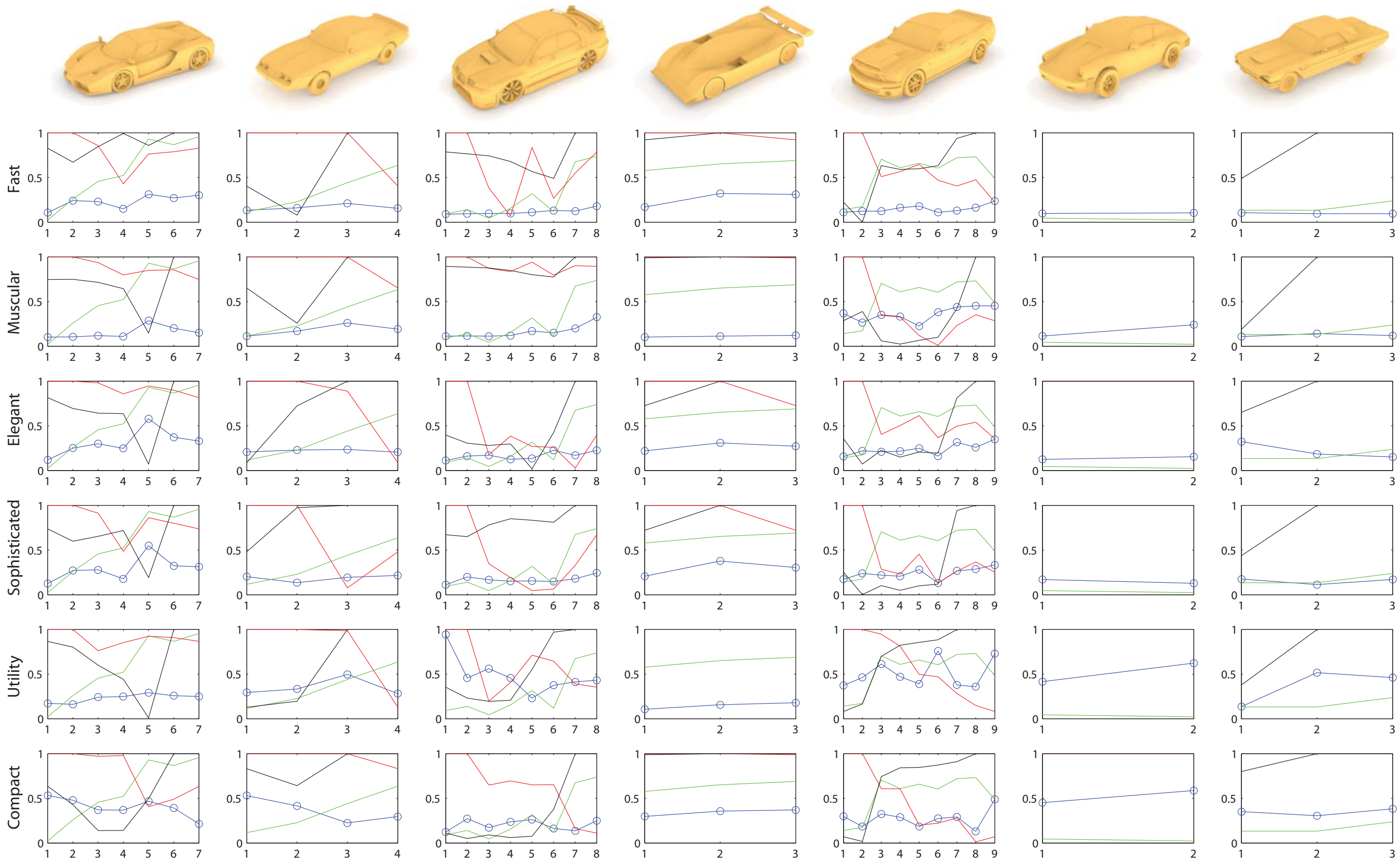

FIGURE 8. The AHP scores with respect to the abstraction levels for all cars and attributes. The **blue** lines with circle markers denote the AHP scores, the **green** lines show the recognition accuracy calculated in Study I, and the **red** and **black** lines show the correlation values between the AHP scores for attributes and the brand recognition accuracy in increasing and decreasing directions of abstraction levels, respectively. The two correlation values suggest potential connections between the bulk features or brand-revealing geometric features and the attribute scores.

tional ratings that are sampled from the same participant, which is not the case in the current studies. We leave this to future work.

Discussions on Implications

Our studies provide valuable insights into form characteristics and associated consumer emotions. We believe the answers to the questions raised earlier may guide the development of future synthesis methods.

Study I suggests that there exists brand-revealing features whose presence greatly enhance brand recognition. For certain products, such features may develop early in the design process, which highlights the impact of major volumetric constructs and proportions on brand identity. (Figure 10a,b illustrates the introduction of brand identity by geometric features on two example cases.) Our approach has shown that through similar computational analyses and human studies, designers can decipher the core geometric features making up a brand, and possibly engineer them to suite future endeavors.

The results of **Study II** point to an invariance in perception: humans' comparative assessments of a set of products may be detail- and brand-neutral. Our results suggest that the relative scores among a set of fully developed products are strongly consistent with the scorings among the highly simplified, coarse versions of the same products. This suggests that early form-assessments are as valuable as late stage assessments, and these results are likely to remain valid even after seemingly unique, brand-specific details are added.

Study III suggests that a mapping between geometric features and particular consumer emotions can be identified. The results show that the variations in emotional attributes can be explained by additional geometric features in the absence of a recognizable brand identity. Figure 10c illustrates an example. Certain emotional attributes are invariant to an identified brand and are instead ingrained in the core stance of the product. Such attributes may emerge early in the design cycle and are difficult to change with detailed shape manipulations. Conversely, certain other emotional attributes exhibit strong and consistent associations with a recognized brand, but show major fluctuations when the brand cannot be recognized. These observations suggest a two-path causal relationship between geometric features and consumer emotions (Fig. 9). In one path, the geometry can give rise to particular emotional responses, whereas on the other path, the variations in the emotional responses may be attributed to a joint effect of geometric features and brand identity.

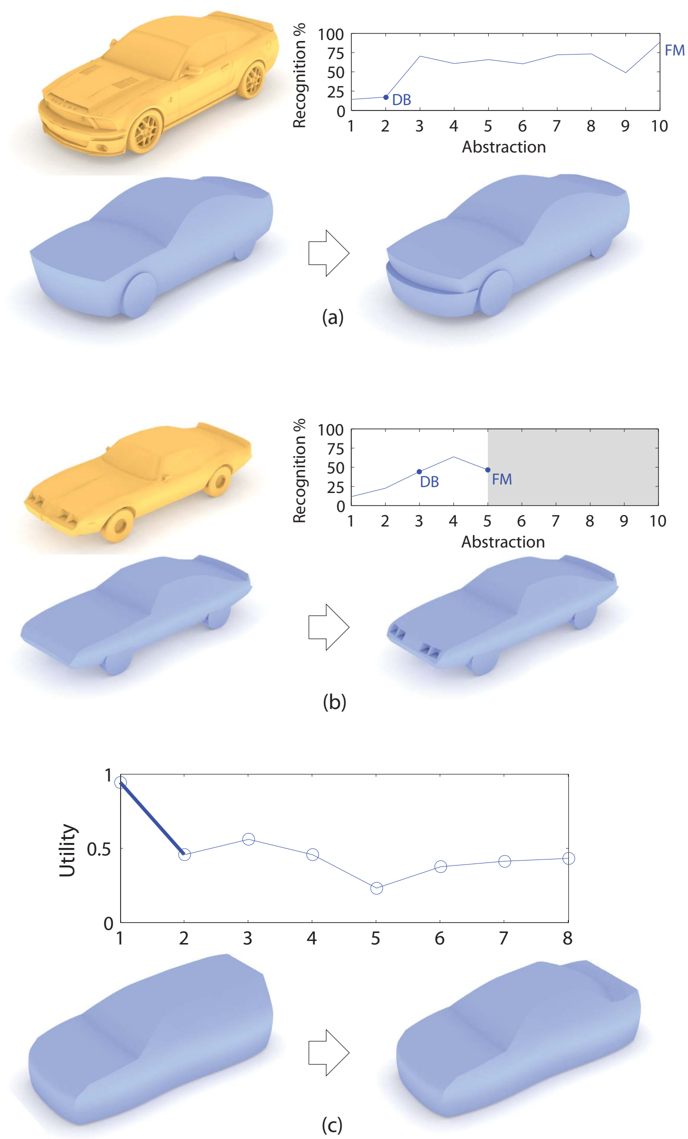

FIGURE 10. Our studies have identified brand-revealing features for all the models in our examples. Certain features impact brand recognition rates more than others. (a) The recognition of the Mustang by the majority was highly affected by the front bumper. (b) Similarly, headlight sockets were the most distinguishing details for the Firebird. In (a,b) the DB models and the next level in the abstraction spectrum are shown on the left and right, respectively. Our studies have also analyzed the sensitivity of consumer responses with respect to the geometric features: (c) The drop in utility scores for the Impreza can be explained by a class shift from an SUV to a compact sedan in the abstractions.

Limitations The participants consisted of college students and Amazon MTurk workers. We would ideally like to include a broader set of auto buyers. However, we believe that our participant pool is sufficiently representative for this initial study, and our findings herein should generalize.

The abstraction hierarchy obtained from our volumetric decomposition method may not accurately reflect the original construction hierarchy of the model being studied. Figure 11 shows the original Ferrari Enzo model alongside its fifth and sixth abstractions. One can argue that the subtracted volumes intend to represent the central piece of the hood as well as the air intakes and outlets simultaneously. A more meaningful decomposition, however, may involve an additional block for the central piece, followed by four subtracted blocks for the air inlets and outlets. Currently, our method cannot resolve such peculiarities.

In Study I, a correct response may be deduced by a series of pairwise comparisons between the query image and all the choice images. We took measures to discourage substituting recognition with comparison by making it laborious, such as randomizing the order of the choice images in every question, and show 15 choice images in each question. However, a tenacious participant might still exploit similarity comparisons.

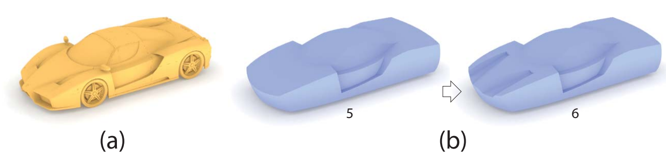

FIGURE 11. (a) The production model of Ferrari Enzo. (b) Our volumetric decompositions adds simultaneously adds the central piece of the hood, the air intakes, and the air outlets between levels 5 and 6.

Finally, consumers' brand associations and aesthetic judgments do not solely rely on shape. Color, texture, and material properties are also significant factors. While our focus on geometric features justifies the exclusion of these other factors from our studies, studying the conjoint effect of these factors in a similar framework would mark a step forward from the current study.

Conclusions

Our work puts forth a streamlined surveying and analysis approach that computationally identifies the relationships between shape and evoked emotions. We believe that our approach is a step toward a methodical analysis of form language and its impact on consumer reactions and can lead to integrated design approach where form and consumer emotions are strongly coupled.

The results of our studies show that emotional responses evoked by coarse product "impressions" are strongly correlated with those evoked by final production models. This, in turn, highlights the importance of early and frequent aesthetic evaluations. Moreover, we discovered that not all consumer attributes develop at the same rate through the design timeline. Certain attributes solidify much earlier in the design cycle and may be difficult to alter later. Certain other attributes are stronger functions of the brand, possibly due to historical associations. Product designers may benefit from distinguishing such attributes, and devising the means to preserve, improve, and consistently reuse this knowledge across their product portfolio.

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Appendix A: Analytic Hierarchy Process (AHP)

AHP [29] can be used in cases where the absolute significance of a number of paramaters needs to be determined solely from pairwise comparisons. AHP is analogous to one dimensional scaling in that it calculates a projection of data points onto a single axis. In AHP specifically, however, the pairwise comparisons are encoded as ratios of importance values between the pairs of attributes. A typical AHP matrix is formed as follows:

$$\text{AHP} = \begin{bmatrix} 1 & 2 & 5 \\ 1/2 & 1 & 4 \\ 1/5 & 1/4 & 1 \end{bmatrix} \tag{1}$$

Here, the off-diagonal values indicate the relative, pairwise scoring of attributes. For instance, the first attribute is set to be twice as important as the second attribute, and thus encoded as $\text{AHP}_{1,2} = 2$. Consequently, the second attribute, compared to the first, attains $\text{AHP}_{2,1} = 1/2$. The eigenvector that corresponds to the largest eigenvalue yields the projection of each attribute in an absolute scale within $[0,1]$. In this particular example, the absolute scores are calculated as $\{0.82, 0.56, 0.15\}$.