DETC2007-35409

MEASUREMENT OF HEADLIGHT FORM PREFERENCE USING CHOICE BASED CONJOINT ANALYSIS

Surya Swamy
Graduate Student

Seth Orsborn
Graduate Student

Jeremy Michalek
Assistant Professor

Jonathan Cagan
Professor

Department of Mechanical Engineering
Carnegie Mellon University
Pittsburgh, PA 15213

ABSTRACT

The measurement and understanding of user aesthetic preference for form is a critical element to the product development process and has been a design challenge for many years. In this article preference is represented in a utility function directly related to the engineering representation for the automobile headlight. A method is proposed to solicit and measure customer preferences for shape of the automobile headlight using a choice task on a main-effects conjoint survey design to discover and design the most preferred shape.

1. INTRODUCTION

It has been said that the eyes are the window into a person's soul. In the same way, the headlights of a vehicle give a glimpse into its underlying character. While the form of most vehicles is captured through many components working in concert, the headlights are unique attributes that stand out. Many vehicles are identifiable solely by their headlights, which communicate the brand, vehicle class, and overall aesthetic.

Engineers need to account for the headlight placement within the vehicle, ensuring that a proper spread of light will contact the road. There needs to be enough room to accommodate the grill and provide a joint between the hood and front bumper. The overall area of the headlight is an indication of the potential brightness of the headlight.

Designers want a headlight that supports the gestalt of the vehicle, especially the front and ¾ views. The shape of the headlight is important due to its position. It is the foremost feature in the ¾ view leading into the beltline and the front quarter panel.

In this work, we consider a headlight from the front view of a vehicle. In particular, we have chosen the Honda Accord from the 2003 model year, since testing of different headlight forms is most effective when compared on the same platform. A 2-D Bezier curve representation of a headlight is used in conjunction with discrete choice analysis and conjoint analysis to capture form preference of a consumer for a set of headlight design alternatives.

Understanding user aesthetic preference for form has been a design challenge for many years. In many instances, the aesthetic properties of products hold equal importance to their functionality. Research has explored how to address the representation of design space and the design elements to facilitate design exploration. Agarwal & Cagan (1998), and Chau *et al*. (2000) used shape grammars to understand the design space used for product development. Further, Giannini *et al*. (2006) sought to maximize the impact of aesthetics (form included) in the CAD environment by investigating relationships between shape geometry and aesthetic character. Van Breemen *et al*. (1999) have studied the relationship between aesthetic form and its perception by the user. Most relevant to this work, McCormack *et al*. (2004) modeled vehicle brand and Orsborn *et al*. (2006) modeled vehicle classes using shape grammars.

In product development, the measurement of user preference is essential to the understanding and application of this preference to future designs. Preference has been successfully represented using vector models (Petiot & Grognet, 2006), which provide the designer with a description of perceptible attributes. Semantics have been used to understand qualitative attributes related to product form and its implications (MacDonald *et al*., 2006). Semantic differential, combined with robust design, has been used to ascertain form preference related to vehicles (Lai *et al*. 2005). Thurston *et al*. (1994) used utility functions to optimize the mechanical design process based upon modeling the engineering constraints. Utility functions have also been used in a variety of decision-

based design applications to model preferences of the designer, the producer, or the consumer (Lewis *et al.*, 2006). In particular, several authors have made use of established quantitative techniques common to market research: Li and Azarm (2000, 2002) developed a product selection approach using conjoint analysis survey-derived utility functions to explicitly measure consumer preferences and account for them in design optimization; Wassenaar and Chen (2003, 2005) used discrete choice analysis with revealed preference data to predict expected profit as a function of product attributes and demographic information; and Michalek *et al.* (2005, 2006) applied the analytical target cascading (ATC) decomposition methodology to coordinate models of engineering and market performance, including Bayesian estimation of a mixed logit specification to model heterogeneity of preferences in the market and design a line of products. In the proposed work, preference is represented in a utility function, directly related to the engineering representation for the automobile headlight, and choice-based conjoint survey data is used to measure shape preferences and optimize for the most desirable design.

2. ENGINEERING MODEL

It has been shown (Orsborn *et al.*, 2006) that most headlight shapes can be represented in 3D using four (top, bottom, inner, outer) 4-control point Bezier curves. Since the endpoints of each curve are connected, the result is 12 control points each with three degrees of freedom. To simplify our representation, we have considered the headlight only from the front view of the vehicle i.e. a 2-D representation. This results in a total of 24 variables: 12 independent control points, each with a horizontal and vertical coordinate. The parametric form of a cubic Bezier curve is $B(x) = P_0t^3 + P_1t^2(1-t) + P_2t(1-t)^2 + P_3(1-t)^3$, where P_0, P_1, P_2, P_3 are the control points and $t \in [0,1]$. Rather than use these control points as variables, we pose an alternative reparameterization in Table 1. A geometric representation of these variables is provided in Figure 1. In the new parameterization, L_i is the tangent length, which, for a given end point of the interior polygon, is the distance between the tangent intersection (with neighboring tangency) and the given end point. The distance between an interior control point and its closest end point is calculated as a percentage s_i of L_i. Another variable to be considered is alpha (α_i), which is the angle between *w* of the interior polygon and the tangent line. Finally, **r** is the position vector of the interior polygon and is measured in terms of its coordinates $\mathbf{r_x}$ and $\mathbf{r_y}$ shown in reference to the entire vehicle in Figure 2.

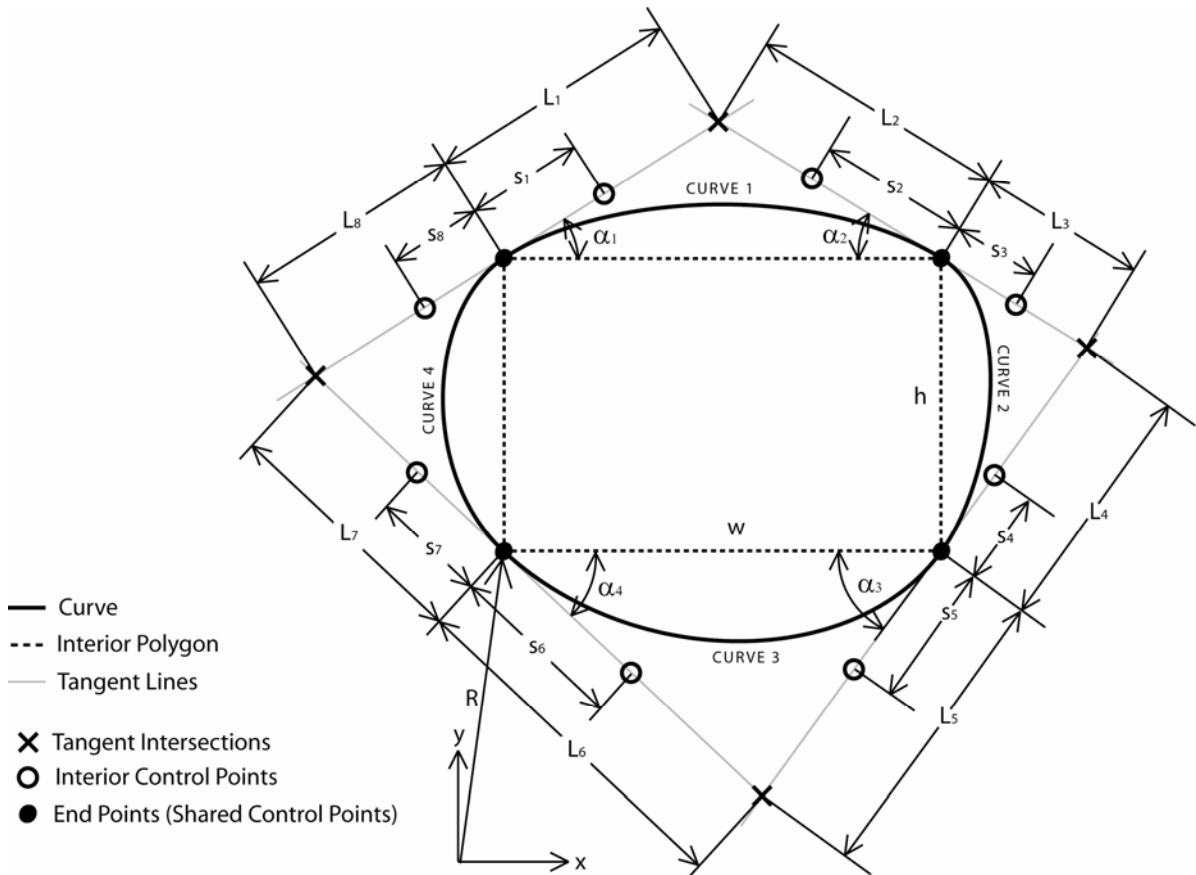This parametric representation allows each variable to

Figure 1: Pictorial Explanation of Variables

have a shape "meaning" that is as "independent" as possible from the others. To the extent that consumer's preferences for each of these parameters are independent of the other parameters, a main-effects conjoint design, discussed in the next section, will be sufficient to estimate preference. While parameterization in terms of the coordinates of the curve control points will clearly not be independent (people do not have preferences for "control point positions" directly), the parameterization shown in Figure 1 allows each parameter to roughly represent a particular aspect of the shape. Specifically, h and w represent size, alpha represents skewness, and s represents sharpness. It is important to note, however, that the proposed representation restricts the set of possible headlights that can be drawn, although it is possible to generalize the parameterization to relax this constraint.
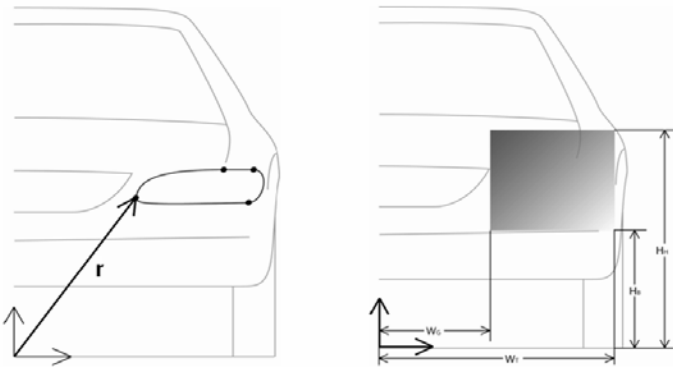

Figure 2: r-vector and feasible design space

Table 1: Variable List for Headlight Representation

Variable	Description	Unit	Upper Bound	Lower Bound
Height (h)	Height of Interior Polygon	Inches (in)	N/A	N/A
Width (w)	Width of Interior Polygon	Inches (in)	N/A	N/A
Percentage (s)	% of L	N/A	100	0
Alpha (α)	Angle between interior polygon and tangent line		$\pi/2$ radian (90 degrees)	0 radian (0 degrees)
Position Vector $r = rx, ry$	Position Vector of Interior Polygon	Inches (in)	$rx + w + C2max \leq WT$	$rx \geq WG + C4max$
			$ry + h + C1max \leq HH$	$ry \geq HB + C3max$

Also, to ensure that all possible designs lay within the feasible design space, the Grill Width (W_G), Track Width (W_T), Height of Bumper (H_B) and Height of the Hood (H_H) of the vehicle were used as parameters to constrain the feasible design space, as shown in Figure 2. These values are listed in Table 2. Furthermore, the horizontal and vertical coordinates of the position vector **r** have upper and lower bounds to ensure the headlight stays within the above bounded area.

The horizontal width and vertical height of the headlight, which must also be within the bounded area, are a combination of w, h, and C_i^{max}. To calculate C_i^{max}, each curve was discretized into ten points as shown in Figure 3. C_i^{max} is the maximum B_i value (y for the upper and lower headlight curves, x for outer and inner headlight curves) for a given curve.
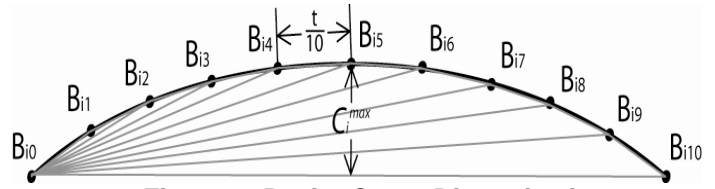

Figure 3: Bezier Curve Discretization

Table 2: Parameter List for Engineering Model

Parameter	Description	Unit
Grill Width (WG)	Width of Grill	16.23 Inches (in)
Track Width(WT)	Track Width of Car	34.40 Inches (in)
Bumper Height(HB)	Height of Bumper	19.25 Inches (in)
Hood Height(HH)	Height of Hood	35.80 Inches (in)

The control points P_{ij} for each curve j are found from the geometry shown in Figure 1. These are detailed as follows, where $\mathbf{r} = [\mathbf{r_x}, \mathbf{r_y}]$, $\mathbf{h} = [0, h]$, and $\mathbf{w} = [w, 0]$:

$$(1)$$

$$P_{01} = P_{34} = \mathbf{r} + \mathbf{h}$$
$$P_{11} = \mathbf{r} + \mathbf{h} + [s_1 L_1 \cos(\alpha_1), s_1 L_1 \sin(\alpha_1)]$$
$$P_{21} = \mathbf{r} + \mathbf{h} + \mathbf{w} + [-s_2 L_2 \cos(\alpha_2), s_2 \sin(\alpha_2)]$$
$$P_{31} = P_{02} = \mathbf{r} + \mathbf{h} + \mathbf{w}$$
$$P_{12} = \mathbf{r} + \mathbf{h} + \mathbf{w} + [s_3 L_3 \sin(90 - \alpha_2), - s_3 L_3 \cos(90 - \alpha_2)]$$
$$P_{22} = \mathbf{r} + \mathbf{w} + [s_4 L_4 \sin(90 - \alpha_3), s_4 L_4 \cos(90 - \alpha_3)]$$

$$P_{32} = P_{03} = \mathbf{r} + \mathbf{w}$$
$$P_{13} = \mathbf{r} + \mathbf{w} - [s_5 L_5 \cos(\alpha_3), s_5 L_5 \sin(\alpha_3)]$$

$$P_{23} = \mathbf{r} + [s_6 L_6 \cos(\alpha_4), -s_6 L_6 \sin(\alpha_4)]$$
$$P_{33} = P_{04} = \mathbf{r}$$
$$P_{14} = \mathbf{r} + [-s_7 L_7 \sin(90 - \alpha_4), s_7 L_7 \cos(90 - \alpha_4)]$$
$$P_{24} = \mathbf{r} + \mathbf{h} + [-s_8 L_8 \sin(90 - \alpha_1), -s_8 L_8 \cos(90 - \alpha_1)]$$

s_i is expressed as a percentage of L_i. In order to find L_i (Figure 1), the Law of Sines was applied, as shown in Eq.(2). Given a set of input variables, the calculation of these tangent lengths was an intermediate step in the calculation of the s_i

values. Together, these were used to calculate the distance between an interior control point and its closest end point given by $s_i L_i$.

$$\frac{L_1}{\sin(\alpha_2)} = \frac{L_2}{\sin(\alpha_1)} = \frac{w}{\sin(180-(\alpha_1+\alpha_2))},$$

$$\frac{L_3}{\sin(90-\alpha_3)} = \frac{L_4}{\sin(90-\alpha_2)} = \frac{h}{\sin(-\alpha_2-\alpha_3)},$$

$$\frac{L_5}{\sin(\alpha_4)} = \frac{L_6}{\sin(\alpha_3)} = \frac{w}{\sin(180-(\alpha_4+\alpha_3))},$$

$$\frac{L_7}{\sin(90-\alpha_1)} = \frac{L_8}{\sin(90-\alpha_4)} = \frac{h}{\sin(-\alpha_1-\alpha_4)},$$

(2)

With this, a 2-D Bezier curve representation of a number of possible headlight design alternatives can be generated within the feasible design space. The next step was to conduct a design of experiments to determine user preference for specific product attributes with the purpose of determining the design alternative with maximum utility.

A conjoint study along with a discrete choice analysis was employed to do this, as described in the subsequent section.

design was constructed for this conjoint analysis (Wu and Hamada, 2000).

Because conjoint relies on "stated choice" survey data, rather than observed "revealed preference" data from the marketplace, there is always a concern that what consumers say on a survey may not match what they do in practice. The alternative, to use econometric analysis of past purchase data in the marketplace, involves a number of difficulties and significant assumptions on the structure of the market (such as endogeneity), since the experimenter is unable to do a controlled experiment. Additionally, such studies make it difficult to test consumer reaction to new product concepts that have not yet been produced. While it is possible to combine both types of data to reduce potential biases (Louviere *et al*, 2000), for purposes of the current study, the conjoint survey was determined to be most appropriate.

In a conjoint study, respondents are presented with a set of products or product descriptions which they have to evaluate. One way for respondents to indicate their preference is by either ranking or rating their preferred options from the given set. Here, a choice-based conjoint study is employed where respondents are asked to choose one alternative when presented with a set of alternatives so as to indicate form preference.

The product attributes in this preference model were taken

Table 3: Variable Discretization for Conjoint Analysis

	Variable	Unit	1	2	3	4	5	6	7	8
x1	Rxw	in	Rx1w1	Rx1w2	Rx1w3	Rx2w1	Rx2w2	Rx2w3	Rx3w1	Rx3w2
x2	Ryh	in	Ry1h1	Ry1h2	Ry1h3	Ry2h1	Ry2h2	Ry2h3	Ry3h1	Ry3h2
x3	s1	%	0	33	66	100				
x4	s2	%	0	33	66	100				
x5	s3	%	0	33	66	100				
x6	s4	%	0	33	66	100				
x7	s5	%	0	33	66	100				
x8	s6	%	0	33	66	100				
x9	s7	%	0	33	66	100				
x10	s8	%	0	33	66	100				
x11	α1	radian	0.314	0.63	0.94	1.256				
x12	α2	radian	0.314	0.63	0.94	1.256				
x13	α3	radian	0.314	0.63	0.94	1.256				
x14	α4	radian	0.314	0.63	0.94	1.256				

3. PREFERENCE MODEL

Conjoint Analysis. To determine which specific product attributes were important to users, a conjoint analysis was performed. Conjoint Analysis has been used to develop efficient survey designs by applying design of experiments (DOE) techniques to the design of surveys. Notable literature on conjoint analysis and experimental design include Louviere's (1988) seminal paper and Green and Srinivasan's review (1990). A main-effects, fractional factorial survey

directly from the variables described earlier in the mathematical model: $\mathbf{r}$, w, h, s, and α. This re-parameterization was chosen with the assumption that interactions between variables could be ignored and main effects would be enough. There was concern that unless the relationships between $\mathbf{r_x}$ & w, and $\mathbf{r_y}$ & h were further constrained that some potential designs would fall outside the allowable design space. Each of these four variables were broken into 3 distinct levels (covering the parametric space) and then combined into 8 levels, leaving out the combination of the largest values. The eight s-values were each broken into four levels: 0%, 33%, 66%, and 100%.

Rx1 = 16.23 in	Ry1 = 19.25	w1 = 3.03	w1 = 3.03 in.
Rx2 = 22.29	Ry2 = 24.77	w2 = 6.06	h2 = 5.52 in.
Rx3 = 28.34	Ry3 = 30.28	w3 = 9.09	h3 = 8.28 in.

The four α-values were likewise broken into six equal levels between zero and π/2 radians. To prevent calculation errors and colinearities between α and **s**, the outside values of zero and π/2 were dropped to leave four increments: 0.31, 0.63, 0.94, & 1.26. It was determined that the crisp corners on some headlight designs would then be possible by having an s-value of zero, regardless of the tangent angle.

This produces a total of 14 product attributes from which the rest of the variables can be calculated. These variable discretizations used in the conjoint analysis are summarized in Table 3. A full factorial of these attributes would produce over 1 billion possible designs.

Utilizing the statistical software SAS (Kuhfeld, 2003), it was found that 72 questions (each with 3 alternatives) involving 64 designs would be sufficient to estimate main-effects. While this might seem like a large number of questions, it was determined that the amount of time to answer each question is actually short due to the fact that the task is simply a comparison of pictures. The resulting survey is such that all designs are easily distinguishable from one another. While respondent fatigue is often a concern when designing surveys (Rea & Parker, 1997), based on feedback obtained from respondents, it was determined that respondent fatigue is not of major concern here.
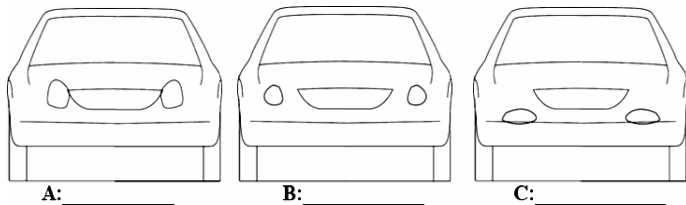

Figure 6: Example Survey Question

It is interesting to note that each survey option (3 per question) consists of just a single drawing, as shown in Figure 6. Respondents were asked to select one preferred design amongst the three alternatives presented in each question. The 14 attributes are essentially hidden from the respondents, who only see a line drawing of a headlight being modified on a front view of a static vehicle. This survey was presented to 18 graduate level mechanical engineers at Carnegie Mellon University. The results of the conjoint survey were subsequently used in determining the design with the maximum utility by performing a discrete choice analysis, as described in the next sub-section. It is important to note that the preferences of the surveyed population are not representative of the U.S. market: The sample size is too small, and the respondent group is not representative; thus, the survey can be seen as a pilot study. Additionally, we do not account directly for preference heterogeneity in the population.

Discrete Choice Model. Discrete choice analysis has enabled the modeling of consumer choices with uncertainty, where it is assumed that consumers exhibit utility maximizing behavior (Train, 2003). In our study, random utility models (RUMs) are used to relate aesthetic headlight attributes to observed individual choices. The derivation of this model assumes the existence of a set of J product alternatives numbered $j = 1, 2,....., J$, where each consumer (respondent) obtains a certain utility level from each alternative. The probability that the choice of alternative j is observed implies that alternative j possesses the highest utility:

$$P_j = \Pr[v_j + \xi_j \geq v_{j'} + \xi_{j'}, \forall_{j'} \in J]. \qquad (4)$$

Here, utility is composed of an observable, deterministic component v_j for a product j, and an unobservable, error component ξ_j. The assumed distribution of this random error component determines the nature of the discrete choice model. For instance, choice probabilities take on a well-known closed form expression if they are derived under the assumption that the unobservable utility component is independently and identically distributed following the extreme-value distribution, as is the case for the popular logit model used here.

In order to map product characteristics onto utility, a linear mapping of product characteristic levels (conjoint part-worths) is employed. Part-worths of discrete values provide no information about intermediate values, which are necessary to optimize over continuously valued product characteristics. In this work, cubic splines were used to interpolate between intermediate values. In the discrete case, the observable component of utility v_j for a product j is:

$$v_j = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{kl} \delta_{jkl,} \qquad (5)$$

where δ_{jkl} is a binary dummy variable. Here, $\delta_{jkl} = 1$ indicates that alternative j possesses characteristic k at level l, and β_{kl} is the part-worth coefficient of characteristic k at level l. Given a set of observed choice data, the preference coefficients β can be estimated such that the likelihood of the model predicting the observed data is maximized. A standard maximum likelihood formulation is used for estimation of the coefficients conditional on the data (Loviere *et al.*, 2000).

Once the coefficients were found, the values of the attributes that maximize utility can be found conditional on the β's. This was accomplished in two ways. For the α and s attributes, the β-values were plotted against the discretized attribute values and a cubic spline was matched to the points. An example is provided in Figure 7. Additional plots of β part-worth coefficients versus α and s attribute values generated have been included in the Appendix. The peak of the cubic spline was found and thereby, the maximum β-value and its associated attribute value were estimated.
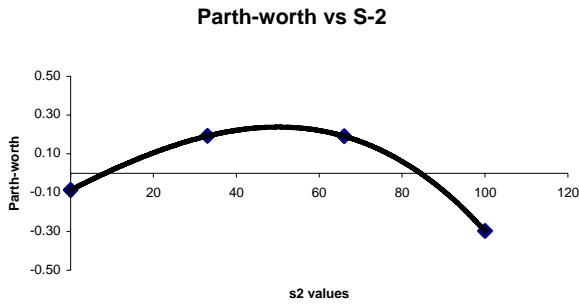
Parth-worth vs S-2

Figure 7: β vs. s₂

The $R_x w$ and $R_y h$ combinations are two-dimensional attributes, which were plotted against the β-values as the third dimension (Figure 8). There was a single point missing in the grid which had to be estimated before the optimal part-worth coefficients could be calculated. The β-value for this point was found using a truncated finite element method. Since the values surrounding this point are clearly below the maximum, it was determined that this was sufficient. The maximum β-value was then found using the coordinate descent method, which involves solving a multivariate problem by iteratively performing univariate search along each direction.
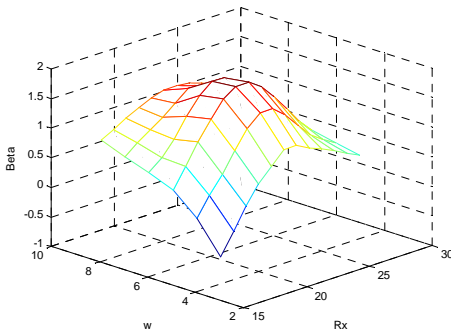
Figure 8: R_x & w vs β

Preference Model Results. The maximum β-values and their related attribute values for the 14 attributes are summarized in the following table. It should be noted that while R_x & w and R_y & h share a maximum β-value, they have distinct attribute values.

Table 3: Maximum β and Related Attribute Values

	s1	s2	s3	s4	s5	s6	s7	s8
βmax	0.7	0.7	0.5	0.8	0.9	0.7	0.6	0.9
value	100	50	80	21	18	24.4	71.3	30

	Rx	w	Ry	h	α1	α 2	α 3	α 4
βmax	1.8		1.6		0.6	0.8	0.7	0.8
value	22	6.8	24	5.9	1.3	0.3	0.3	0.3

These β-values give a utility value, U_{max} = 9.18. When inserted into the formulation described earlier, this corresponds to the most preferred headlight design. For a comparison, the maximum utility of any of the sample designs used in the survey was 6.17.
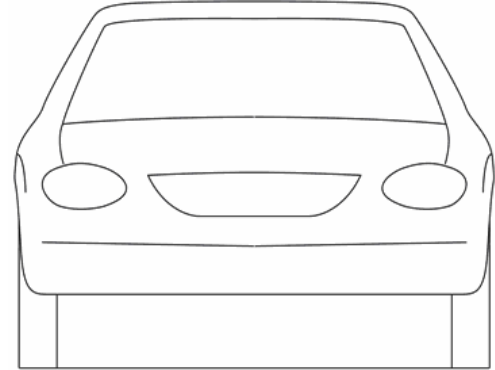

Figure 9: Headlight with Maximum Utility

It is difficult to compare the final result directly to the existing headlight on the 2003 Honda Accord because the chosen Bezier curve representation is more restrictive than that needed to recreate the existing design. Still, the results are encouraging in that the headlights appear reasonable, the shape is relatively conventional (as would be expected when "averaging" preferences over a population with the aggregate logit model), and the solution is more conventional than most, if not all, of the alternatives in the survey. Future work could include generalization of the parametric shape class and a follow up survey to verify that the solution is indeed preferred by the respondents.

4. CONCLUSIONS

The measurement and understanding of consumer preference is a critical element to the product development process. Previous attempts at understanding qualitative attributes of product form and its implications have included the use of vector models, semantics and utility functions. In this paper preference is represented using utility functions directly related to the parametric form representation for a broad class of automobile headlight shapes and based on consumer survey choice data. Discrete choice conjoint models are used to measure consumer choices among a set of alternatives and determine which specific product attributes are important to the consumer. The study allows quantitative measurement of consumer preferences for a broad class of organic shapes and optimization of the design to maximize desirability.

There are a number of possible areas for future improvements to the proposed approach. First, survey respondents for this study included a small group (18) of graduate engineering students who do not represent the ideal, diversified target market. Capturing the preferences of a diversified and statistically significant group of individuals

who characterize the target consumer demographic would make study results more practical for supporting vehicle design in practice. Furthermore, heterogeneity of preferences in the consumer population is not captured in the present model because the basic logit model aggregates preferences across the population. Mixture models could be used in the future to account for heterogeneity in order to determine which segment of the population is attracted to a particular design and to design product lines with variants that attract different segments (Michalek *et al*., 2006; Shiau *et al*., 2007). Inclusion of cost and profitability models in the future could also extend scope.

The main-effects model used to design our survey is based on the assumption that interaction effects between headlight attributes can be assumed negligible. In the future, it would be insightful to determine if any of the interaction effects should be included and account for interaction effects between the attributes of the headlight as well as interaction effects between headlight attributes and other vehicle attributes. In good vehicle design there is a gestalt between the different individual features – the headlight and the grill, fender, hood line (see Lewin, 2003). In our study the headlight was varied independently of the body design, which remained fixed. Also, the current model is a 2-D representation of the headlight system. It would be useful and interesting to extend this to include a 3-D representation to add realism and include side views of the vehicle. However, as the complexity of the form increases, more variables will be required to describe the attribute space. This, in turn, will create computational difficulty. Orsborn *et al.* (2007) have shown that multi-dimensional scaling techniques can be effective in reducing the design space while maintaining fundamental shape relationships.

The parameterization used in the proposed model resulted in seventy-two questions (fractional factorial); so increasing the number of parameters to generalize the design space or attempting to account for interaction effects would make the conjoint survey very large. This could be addressed by giving respondents different sub-surveys or using adaptive conjoint techniques. However, exploring all curves on a vehicle body using the proposed method is not possible without a significant change in the approach.

In conclusion, this paper presents a 2-D Bezier curve representation of a Honda Accord (2003 model year) headlight, which is used in conjunction with discrete choice analysis and conjoint analysis to capture form preference for a set of headlight design alternatives. The resultant headlight design with maximum utility (Figure 9) appears to be a reasonable and conventional design most preferred by survey respondents.

ACKNOWLEDGMENTS

REFERENCES

Agarwal. M. and Cagan. J., 1998, "A Blend of Different Tastes: The Language of Coffee Makers", Environment and Planning B: Planning and Design, 25(2), pp. 205-226.

Chau, H.H., de Pennington, A., and McKay, A., 2000, "Shape Grammars: Capturing the Quintessential Aspects of Industrial Design for Consumer Products," Greenwich 2000 International Symposium, Greenwich, UK.

Giannini, F., Monti, M. and Podehl, G.., 2006, "Aesthetic-driven tools for industrial design," Journal of Engineering Design, 17(3), pp. 193-215.

Green, P.E. and Srinivasan, V., 1990, "Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice," Journal of Marketing, 54(4), pp. 3-19.

Green, P., Wind, J. and Rao, V., 1999, "Conjoint analysis: methods and applications," taken from The Technology Management Handbook, R. C. Dorf (editor), CRC Press: Boca Raton, FL.

Kuhfeld, Warren F., 2003, "Conjoint Analysis," SAS Institute Publications. http://support.sas.com/techsup/tnote/tnote_stat.html

Lai, H.H., Chang, Y.M. and Chang H.C., 2005, "A robust design approach for enhancing feeling quality of a product: a car profile case study," International Journal of Industrial Ergonomics, Vol. 35, pp. 445-460.

Lewin, T., 2003, How to Design Cars Like a Pro, Motorbooks, Osceola, WI.

Lewis, K, Chen, W. and Schmidt, L., 2006, Decisions Making in Engineering Design, ASME Press, New York, NY.

Li, H. and Azarm, S., 2000, "Product Design Selection Under Uncertainty and With Competition Advantage," ASME Journal of Mechanical Design, 122(4), pp. 411-418.

Li, H. and Azarm, S., 2002, "An Approach for Product Line Design Selection Under Uncertainty and Competition," ASME Journal of Mechanical Design, 124(3), pp. 385-392.

Louviere, J.J., 1988, Analyzing Decision Making: Metric Conjoint Analysis, Sage Publications, Newbury Park, CA.

Louviere, J., Hensher, D. and Swait, J., 2000, Stated Choice Methods Analysis and Application, Cambridge University Press, Cambridge, UK.

MacDonald, E., Lubensky, A., Sohns, B. and Papalambros, P., 2007, "Product Semantics in Wine Portfolio Optimization", International Journal of Product Development, accepted.

McCormack, J.P., Cagan. J. and Vogel C.M., 2004, "Speaking the Buick Language: Capturing, Understanding, and Exploring Brand Identity with Shape Grammars", Design Studies, Vol. 25, pp. 1-29.

Michalek, J.J., Feinberg, F.M. and Papalambros, P.Y., 2005 "Linking marketing and engineering product design decisions via analytical target cascading," Journal of Product Innovation Management, Vol. 22, pp. 42-62.

Michalek, J.J., Ceryan, O., Papalambros, P.Y. and Koren Y., 2006, "Balancing Marketing and Manufacturing Objectives in Product Line Design," Journal of Mechanical Design, 128(6), pp. 1196-1204.

Orsborn, S., Boatwright, P. and Cagan, J., 2007, "Identifying Product Shape Relationships Using Principal Component Analysis", Research in Engineering Design, in review.

Petiot, J. and Grognet, S., 2006, "Product design: a vectors field-based approach for preference modeling," Journal of Engineering Design, 17(3), pp. 217-233.

Rea, L.M. and Parker, R.A., 1997, Designing and Conducting Survey Research: A Comprehensive Guide, Jossey-Bass, San Francisco, CA.

Shiau, C.S., Tseng, I.H., Heutchy, A.W. and Michalek, J.J., 2007, "Design optimization of a laptop computer using aggregate and mixed logit demand models with consumer survey data," in review, ASME International Design Engineering Technical Conferences, Sept. 4-7, Las Vegas, Nevada, USA, DAC-34883.

Thurston, D., Carnahan, J. and Liu, T., 1994, "Optimization of Design Utility," Journal of Mechanical Design, 116(3), pp. 801-808.

Train, Kenneth E., 2003, Discrete Choice Methods with Simulation, Cambridge University Press, Cambridge, UK.

Van Bremen, E.J.J., Sudjone, S. and Horvath, I., 1999, "A contribution to finding the relationship between shape characteristics and aesthetic appreciation of selected products," Proceedings of ICED99, Munich, pp. 1765-1768.

Wassenaar, H. J. and Chen, W., 2003, "An Approach to Decision Based Design with Discrete Choice Analysis for Demand Modeling," ASME Journal of Mechanical Design, 125(3), pp. 490-497.

Wassenaar, H. J., Chen, W., Cheng, J. and Sudjianto, A., 2005, "Enhancing Discrete Choice Demand Modeling for Decision-Based Design," ASME Journal of Mechanical Design, 127(4), pp. 514-523.

Wu, C.F. and Hamada, M., 2000, Experiments: Planning, Analysis, and Parameter Design Optimization, John Wiley & Sons, New York, NY.
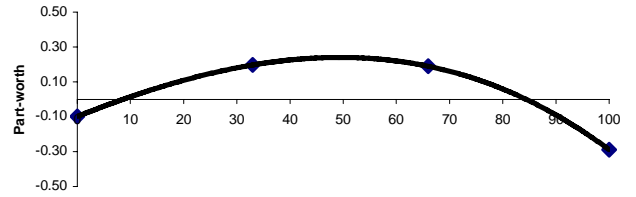
APPENDIX - SPLINE INTERPOLATED PART-WORTHS
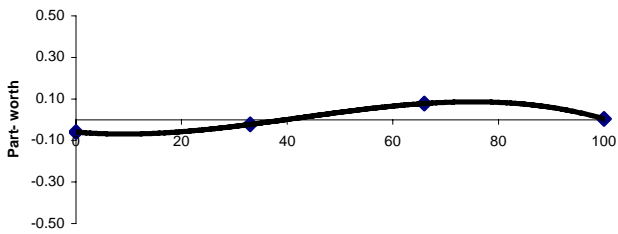
Part-worth vs s1
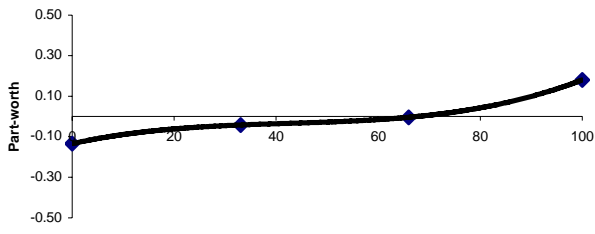
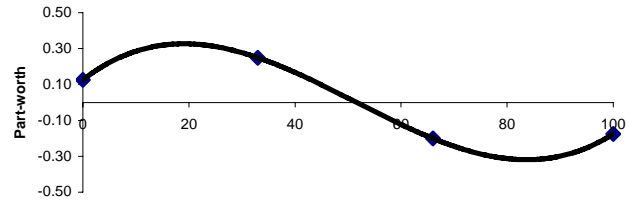**s1 (0-1)**

Part-worth vs s2
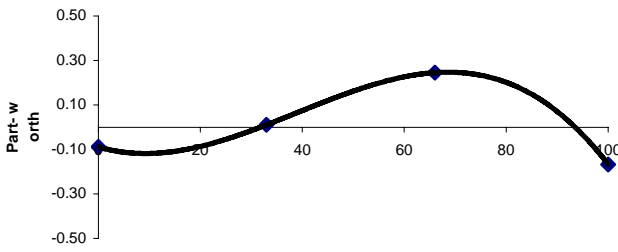

s2 (0-1)

Part-worth vs s3

s3(0-1)

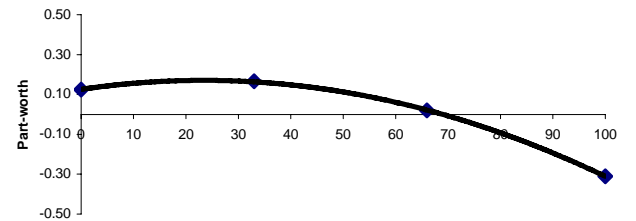### Part-worth vs s4

s4(0-1)
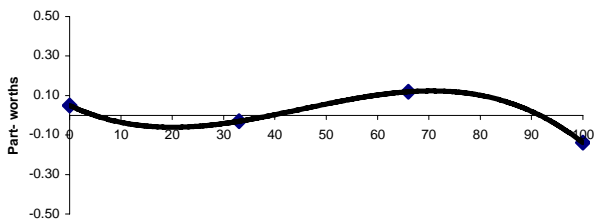
Part-worth vs s5

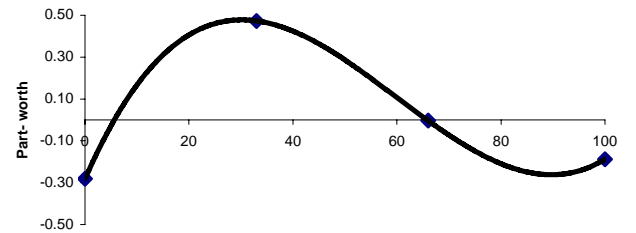**s5(0-1)**

Part-worth vs s6

s6(0-1)

Part-worth vs s7

s7(0-1)

Part- worth vs s8

s8(0-1)

Part-worth vs alpha 1
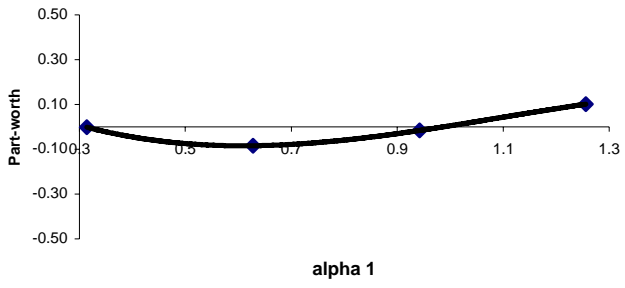
alpha 1

Part-worth vs alpha4
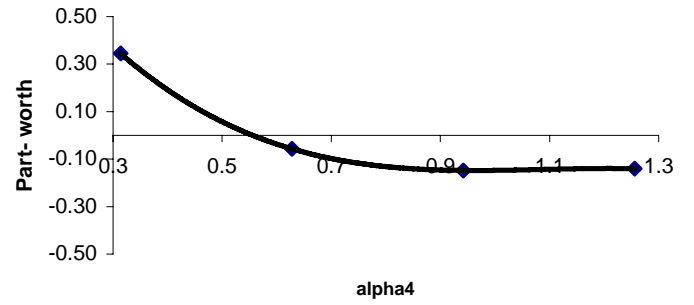
alpha4

Part-worth vs alpha 2

alpha 2

Part-worth vs alpha3

alpha3