

# **Interactive genetic algorithms for shape preference assessment in engineering design**

by

**Jarod C. Kelly**

A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
(Mechanical Engineering)  
in The University of Michigan  
2008

Doctoral Committee:

Professor Panos Y. Papalambros, Chair  
Professor Richard Gonzalez  
Professor Colleen M. Seifert  
Associate Professor R. Brent Gillespie  
Associate Professor Gregory H. Wakefield

© Jarod C. Kelly

---

All Rights Reserved

2008

When you make a mistake, don't look back at it long. Take the  
reason of the thing into your mind, and then look forward.  
Mistakes are lessons of wisdom. The past cannot be changed.  
The future is yet in your power.

— Phyllis Bottome

to my grandfather, Donald G. Smoke, whose patience and encouragement have resonated  
with me throughout my life



# Acknowledgments

First and foremost, I must thank my parents, Sharon and Dennis Kelly, my sisters, Meghan Mielcarek and Erin Kelly, and my grandparents, Norma and Donald Smoke. Their love, support, advice, and understanding have been a blessing throughout my life; without the strong foundation that they gave me I would never have been able to accomplish what I have. I would also like to thank Jenay Karlson for the love, support and friendship that she has shared with me, it has benefitted my life in more ways than I can express.

I would like to thank my entire committee for their support, challenges, and encouragement. I am forever grateful for the opportunity to work with Panos Papalambros. His passion for people, design and life is a true inspiration. Panos gave me an opportunity to join the Optimal Design Laboratory in May of 2005 after I struggled to find research that fit my interests early in my studies at the University of Michigan. My colleagues in the ODE have also been a pleasure and inspiration to work with, including Erin MacDonald, James Allison, Jeongwoo Han, Kwang Jae Lee, Kuei-Yuan Chan, Subroto Gunawan, Katie Kerfoot, Michael Alexander, Tahira Reid, Diane Peters, Stephen Hoffenson, Andreas Malikopoulos, Bart Frischknecht, Yi Ren and many more.

I would also thank Diann Brei of the Smart Materials and Structures Design Laboratory who allowed me to conduct research with that group for two years before finding the research interests that lead me to the ODE. She gave me a great deal of freedom in searching for a research topic, and I am very grateful for that. I consider it a pleasure to have worked and studied smart material actuators with members of the SMSDL, namely Jonathan Lutz, Brian Barnes, Anupam Pathak, John Redmond, Paul Alexander, and others. There are also a number of people that I have worked with over the years at UM and would like to recognize, Michael Kokolaras, Jean-Francois Petiot, Jan-Henrik Andersen, Pierre Maheut, Charles Covey-Brandt, and others that I will surely regret overlooking.

I have had some fantastic experiences at UM. It was a dream of mine to study at this prestigious university, and while I could not pass up the opportunity to do my undergraduate studies at the University of Oklahoma, I am so glad that I came to UM for my graduate work. I would like thank Ajay Agrawal who encouraged me to pursue graduate school and

gave me my first research experience while at the University of Oklahoma. I have made many friends at UM that I am grateful for, Stephen Walton, Jim Wiswall, Mike Cherry, April Bryan, Smitesh Bakrania, Brad Zigler, Seda Yilmaz, Ross Morrow, John Whitehead, and many more.

I also have an amazing group of friends that has somehow managed to remain strong since high school and I care about them as I would family. Terrence Rindler, Dave Cook, Chris Phillips, Blake Whyte, Peter Meyers, Bethany Stevenson, Melanee Bornemann, Megan Houtman, and Lindsey Rietscha: Portage reunions are a continual must. Jerry Woodfield, Eric Harter, Jason Brown, Simon Brewer, and Forrest Walker are friends that are also very dear to me. I will inevitably leave out people that I care about, and for that I am sorry, but please know that you are in my heart.

I would like to recognize support from the U.S. National Science Foundation, the Rackham Graduate School, the University of Michigan College of Engineering and Department of Mechanical Engineering, and the Antillium Project.

# Table of Contents

<b>Dedication</b> . . . . .	ii
<b>Acknowledgments</b> . . . . .	iii
<b>List of Tables</b> . . . . .	viii
<b>List of Figures</b> . . . . .	ix
<b>Abstract</b> . . . . .	xiii
<b>Chapter 1 Introduction</b> . . . . .	1
1.1 Motivation . . . . .	3
1.2 Shape preference in engineering design . . . . .	5
1.2.1 Aesthetics . . . . .	6
1.2.2 Preference . . . . .	10
1.2.3 Design . . . . .	11
1.2.4 Creativity . . . . .	12
1.3 Research objectives and contributions . . . . .	12
1.4 Dissertation outline . . . . .	13
<b>Chapter 2 Background</b> . . . . .	15
2.1 Engineering design . . . . .	16
2.2 Preference . . . . .	20
2.2.1 Conjoint analysis . . . . .	21
2.2.2 MDS . . . . .	23
2.2.3 MDPREF . . . . .	25
2.2.4 PREFMAP . . . . .	27
2.2.5 Quadratic preference model . . . . .	30
2.2.6 Vector field preference model . . . . .	33
2.2.7 Summary . . . . .	35
2.3 Computer science . . . . .	36
2.3.1 Genetic algorithms . . . . .	37
2.3.2 Interactive genetic algorithms . . . . .	41
2.4 Automated design generation . . . . .	44

<b>Chapter 3</b>	<b>Shape preference in engineering design</b>	47
3.1	Introduction	47
3.1.1	Study goals	48
3.1.2	Course of investigation	48
3.2	Preference tool examination	49
3.2.1	Unimodal examination	51
3.2.2	Bimodal examination	57
3.3	Linking preference to engineering	61
3.3.1	Cola bottle case study	61
3.3.2	Bottled water case study	67
3.3.3	Discussion	74
3.4	Methodology	75
3.4.1	Attribute identification	75
3.4.2	Engineering analysis	76
3.4.3	Optimal design formulation	76
3.4.4	Use in decision making	77
<b>Chapter 4</b>	<b>Interactive evolutionary algorithms in preference assessment</b>	78
4.1	Introduction	78
4.2	Background	79
4.2.1	Interactive evolutionary systems	80
4.2.2	Application of Webber's law to vision	81
4.3	Specification of an interactive genetic algorithm	83
4.3.1	Algorithm mechanics	83
4.3.2	Experimental design	86
4.3.3	Experimental results	86
4.4	IGA Measure of preference with human respondents	88
4.4.1	Training task	89
4.4.2	Experimental design: goal-seeking task	89
4.4.3	Results and discussion: goal-seeking task	89
4.4.4	Experimental design: preference task	93
4.4.5	Results and discussion: preference task	94
4.5	Differences between goal-seeking and preference	99
4.6	Proposed methodology	103
4.7	Conclusions	104
<b>Chapter 5</b>	<b>Interactive evolutionary algorithms in identifying contextual shapes</b>	106
5.1	Introduction	106
5.1.1	Course of investigation	107
5.2	Survey design	108
5.2.1	GUI development	110
5.3	Engineering design	111
5.4	Data collection	113
5.5	Data analysis	114
5.6	Discussion	115

<b>Chapter 6</b>	<b>Interactive evolutionary algorithms and creativity</b>	117
6.1	Introduction	117
6.2	Interactive genetic algorithm design	120
6.2.1	Roulette wheel selection	122
6.2.2	Crossover	123
6.2.3	Mutation	124
6.2.4	Definition of investigated algorithms	125
6.3	Monte Carlo simulation studies	127
6.3.1	Initial study	127
6.3.2	Expanded study	130
6.3.3	Sequential study	132
6.4	Conclusions	135
<b>Chapter 7</b>	<b>Summary, contributions, and future work</b>	138
7.1	Summary	138
7.2	Contributions	140
7.3	Future work	140
<b>Bibliography</b>		143

# List of Tables

## Table

2.1	Distance, in miles, between US cities. . . . .	24
3.1	Values used to answer PREFMAP survey . . . . .	53
3.2	PREFMAP solution b-values . . . . .	53
3.3	MNL model part-worths for data <i>without</i> error distribution term . . . . .	54
3.4	MNL model part-worths for data <i>with</i> error distribution term . . . . .	55
3.5	Values used to answer PREFMAP survey . . . . .	58
3.6	PREFMAP solution b-values for bimodal problem . . . . .	58
3.7	MNL model part-worths for proposed bimodal model, main effects . . . . .	60
3.8	MNL model part-worths for proposed bimodal model, interaction terms . . . . .	60
3.9	Material properties of PET cola bottle . . . . .	65
3.10	MNL model part-worths for preference survey, main effects . . . . .	66
3.11	MNL model part-worths for preference survey, interaction effects . . . . .	66
3.12	MNL model part-worths for bottle water preference survey, main effects . . . . .	70
3.13	MNL model part-worths for bottled water preference survey, interaction effects . . . . .	70
3.14	PREFMAP solution b-values for bottled water study . . . . .	71
6.1	IGA Settings: Initial algorithm . . . . .	125
6.2	IGA Settings: Expanded study . . . . .	126
6.3	IGA Settings: Sequential study . . . . .	127

# List of Figures

## Figure

1.1	The Golden Rectangle incorporates the Golden Section, where $a = 1$ , and $a+b \approx 1.618$ . . . . .	9
2.1	Map showing the distance between US cities, in miles, as developed via MDS. . . . .	24
2.2	Map showing the distance between US cities, in miles, developed by MDS then rotated, mirrored and shown in context. . . . .	25
2.3	This plot of MDPREF data from (11) indicates how people's preferences (vectors) align with products (points). . . . .	27
2.4	The different phases of PREFMAP are suited to different situations. . . . .	29
2.5	This vector model of appeal within the perceptual space, from (67), indicates how well this vector model can predict preference. By looking at the projection of each point onto the vector, we can see that it represents the reported preference order quite well. . . . .	31
2.6	In their study, Petiot and Chablat allowed table glasses to vary in dimension, $d_2$ and $d_3$ as shown. . . . .	32
2.7	This vector model of appeal within the design parameter space, from (67), shows how preference data could be used to improve design. . . . .	33
2.8	A map of relative preference for several vehicles as they relate to vehicle 5 (Clio) reveals the iso-preference lines within a perceptual space. Using this information one could determine that increasing sportiveness and capacity simultaneously would increase the vehicles preference. Figure from (68) . . . . .	35
2.9	Single-point cross over traditionally consists of creating two children from the complimentary genetic material of two parents. The cross over point is randomly determined. . . . .	39
2.10	Binary mutation typically involves the alteration of a single bit within the binary string of an individual. . . . .	40
3.1	Goal model in unimodal comparison of preference tools. . . . .	52
3.2	PREFMAP interpretation of proposed unimodal preference model. . . . .	53
3.3	MNL model interpretation of proposed unimodal preference model <i>without</i> error distribution term. . . . .	55
3.4	MNL model interpretation of proposed unimodal preference model <i>with</i> error distribution term. . . . .	56
3.5	Goal model in bimodal comparison of preference tools. . . . .	57

3.6	PREFMAP interpretation of proposed bimodal preference model. . . . .	59
3.7	MNL model interpretation of proposed bimodal preference model with interaction terms. . . . .	61
3.8	Parameterized bottle shape. . . . .	62
3.9	Screenshot of survey tool. . . . .	64
3.10	MNL model describing preference for cola bottle shape, and most preferred shape. . . . .	67
3.11	Monotonic surface representing bottle weight. . . . .	68
3.12	Pareto frontier of solutions in the cola bottle design MOO problem. . . . .	69
3.13	Pareto optimal solutions of cola bottle design plotted on preference and engineering models. . . . .	69
3.14	MNL model describing preference for bottled water shape, and most preferred shape. . . . .	70
3.15	MNL model describing preference for bottled water shape, and most preferred shape. . . . .	71
3.16	Pareto frontier of solutions in the bottled water design MOO problem using conjoint analysis for preference. . . . .	72
3.17	Pareto optimal solutions of bottle water design, using conjoint analysis, plotted on preference and engineering models. . . . .	72
3.18	Pareto frontier of solutions in the bottled water design MOO problem using PREFMAP for preference. . . . .	73
3.19	Pareto optimal solutions of bottle water design, using PREFMAP, plotted on preference and engineering models. . . . .	73
3.20	Design architecture for a particular pen design. . . . .	75
4.1	Diagram of the human eye with angles to geometrically calculate the length associated with a desired degree of visual acuity. . . . .	82
4.2	IGA process for acquiring user evaluation information . . . . .	84
4.3	Design space mutation operator . . . . .	85
4.4	Generational convergence properties of IGA with differing roulette percentages (left), and mutations rates (right). . . . .	87
4.5	Layout of IGA goal-seeking survey tool. . . . .	90
4.6	Mean and standard deviation of the population of designs for the 34 subjects over 8 generations. . . . .	91
4.7	Mean and standard deviation of the selected designs for the 34 subjects over 7 generations. . . . .	91
4.8	Number of ideal options available to the 34 subjects and the number of times the ideals were selected. . . . .	92
4.9	Number of ideal options available to the 34 subjects, that have the potential to be selected, and the number of times the ideals were selected. . . . .	92
4.10	Parameterized bottle shape. . . . .	94
4.11	Layout of IGA preference survey tool. . . . .	95
4.12	Pairwise-comparison survey tool. . . . .	95
4.13	Ideal bottles selected by subjects, shown in the design space. . . . .	96
4.14	Mean and standard deviation of the population of designs for the 34 subjects over 8 generations. . . . .	97



4.15	Mean and standard deviation of the selected designs for the 34 subjects over 7 generations. . . . .	97
4.16	Number of ideal bottle designs available to the 34 subjects and the number of times the ideals were selected. . . . .	98
4.17	Number of ideal bottle designs available to the 34 subjects, that have the potential to be selected, and the number of times the ideals were selected. . . . .	99
4.18	Generation path of one subject showing available set and selected bottle designs. . . . .	100
4.19	Generational presentation of standard deviation in goal-seeking task. . . . .	101
4.20	Generational presentation of standard deviation in preference task suggesting rapid convergence, or goal-seeking. . . . .	102
4.21	Generational presentation of standard deviation of several subjects in the preference task that demonstrate goal-seeking. . . . .	102
4.22	Generational presentation of standard deviation in preference task suggesting variety-seeking. . . . .	103
4.23	Generational presentation of standard deviation of several subjects in the preference task that demonstrate variety-seeking. . . . .	103
5.1	Vehicle silhouette defined by 12 points with 8 point locations variable in the vertical and the horizontal plane. . . . .	108
5.2	Screen capture of IGA GUI developed in Flash, MySQL and PHP. . . . .	111
5.3	Screen capture of $C_d$ study mesh from Fluent via Gambit. . . . .	112
5.4	Regression plots and R-values for neural network training with $C_d$ data. . . . .	113
5.5	Average $C_d$ values of IGA population and user selected designs over generations. . . . .	114
5.6	Visual overlay of user selected final shapes and mathematical average of the shapes. . . . .	115
6.1	Flow diagram showing IGA process containing both convergent and divergent parental selection. . . . .	126
6.2	Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design. . . . .	128
6.3	Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design. . . . .	129
6.4	Effect of generation and percent of convergent parental population on the mean of the distance of best individual in the IGA population from the goal design. . . . .	129
6.5	Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design at 10% mutation. . . . .	131
6.6	Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design at 40% mutation. . . . .	131
6.7	Effect of generation and percent of convergent parental population on the mean of the best of the IGA population from the goal design at 10% mutation. . . . .	131
6.8	Effect of generation and percent of convergent parental population on the mean of the best of the IGA population from the goal design at 40% mutation. . . . .	131
6.9	Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design at 10% mutation. . . . .	132

6.10 Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design at 40% mutation. . . . . 132

6.11 Effect of sequentially applied divergence and convergence on mean of population . . . . . 133

6.12 Effect of sequentially applied divergence and convergence on best of population . . . . . 134

6.13 Effect of sequentially applied divergence and convergence on range of population . . . . . 136

# Abstract

In the design of artifacts it is important to realize that designs are judged according to functional as well as subjective measures. This is especially true in markets where the technology behind the particular artifact is well established, and the costs of production are uniform across the market. In such cases, users are faced with a decision: the selection of one item from amongst a broad range of similar offerings. The shape of an object, its geometric features, can be one element of the artifact that may elevate it above the competition in user choice. The preference that users have for artifact shape is not a scientifically understood field. Such studies and pursuits are generally the province of artists and industrial designers, who are quite adept at applying their intuition and skills to assess markets and design products to fit them. However, the shape of an object can also have an important impact on its performance. If this is the case, then engineers must be involved in analyzing the design to ensure that it meets performance and safety criteria. This intersection between the form and the function of an artifact lacks tools and applied methods that can allow designers and producers to make scientifically informed decisions to understand the impact of shape preference on performance and vice versa. This dissertation explores how current preference tools can be applied to the understanding of shape preference, as it relates to a specific artifact. It is shown here that a meaningful quantification of both shape preference and performance can be obtained and used in decision making. It is also shown here that interactive genetic algorithms are a tool capable of understanding shape preference. Further, the capacity for interactive genetic algorithms to enhance creativity is also shown.

# Chapter 1

## Introduction

An artifact's shape affects its performance, that shape also impacts the preference that users have for it. An obvious relationship exists between shape and aesthetics. Understanding aesthetics is a goal often associated with art and industrial design. It is difficult to extract an objective metric from aesthetics, but shape preference is a metric that can be quantified. The artifacts that people interact with everyday, the chair, the pen, the light fixture or the cellular phone, are all engineered products whose shapes are important to both their function and preference to users. Thus, there may be a relationship between an artifact's engineered and shape preference qualities. The artifact's shape has an impact on the artifact's perceived functionality, its preference, and its value to people. In the engineering discipline, mathematical models are devised which relate variables to performance. Similarly, in marketing, product attributes are related to user utility or preference. These techniques allow designers, engineers and planners to have a qualitative and quantitative insight into how they ought to design a product to best meet intended goals.

Aesthetics, is defined by Webster's dictionary as "a particular theory or conception of beauty or art: a particular taste for or approach to what is pleasing to the senses and especially sight" (23). Within this work, the aesthetic quality of an artifact is limited to its geometric properties. This neglects aesthetic qualities like color, texture, sheen and the many visual qualities of an artifact that comprise aesthetics. Thus, aesthetics is a broad conceptual field that this dissertation does not address except as a source to understand what

is already known about shape preference.

The field of industrial design has a variety of heuristics that suggest how to design artifacts that will be aesthetically pleasing, or meet a desired aesthetic quality (45; 62; 69). These heuristics point to balance, symmetry, rhythm and proportionality in order to describe the shape of the design. These rules suggest a means of mathematically identifying preferred shapes. We can use these ideas to further postulate that it is possible to identify combinations of shape attributes that yield an optimally preferred design for a particular artifact within a particular context, subject to the physical constraints dictated by an engineering analysis.

Understanding shape preference and relating it to the engineering discipline requires the examination and synthesis of many topics including art, computer science, industrial design, engineering, psychology, and marketing. The following text will provide a motivation for the study of shape preference in engineering design and describe several fields of study that are relevant in its examination.

This dissertation examines the use of preference assessment tools and applies them to the design of artifact shapes, and explores how those preferences relate to technical metrics of that design. This synthesis is believed to be the first of its kind. Further, this dissertation uses Interactive Evolutionary Systems (IES) to examine preference. IES use evolutionary principles to improve a design based upon the interaction between a computer system and a human user. The preference aspect of IES has only been implicitly assumed before, in this dissertation we present evidence to confirm that assumption. Finally, this dissertation explores the use of IES in enhancing creativity. This work spawns directly from the divergent properties of mistuned, and convergent properties of well tuned IES, and the analogy that such divergent and convergent processes are also important to creativity.

## 1.1 Motivation

In a competitive marketplace, products must be developed with great attention to the wants and needs of users. Assessing the subjective tastes of users and utilizing that information within the product design process should ultimately lead to better product designs. Consequently, many investigations have been undertaken to understand how subjective product qualities impact user perception and preference in product design. Kansei engineering, initially developed in the 1970s and often referred to synonymously as Emotional Engineering and Emotional Design, utilizes semantic information to match user wants and expectations in product design (59; 58). Kansei engineering has been successfully applied by Mazda in the development of the world's best selling roadster, the Miata (or Eunos Roadster). The field of engineering has acknowledged the impact that these subjective qualities have on product design, and recent technical conferences (ASME IDETC 2007) have been entirely devoted to its investigation. Further, Liu has suggested the idea of engineering aesthetics in order to seek methods that help designers make better decisions regarding the subjective aesthetic qualities of a product (47; 46). These ideas are well received within the engineering community, and there has been a focused effort to address the subjective qualities of a product in a rigorous manner. A first step in this process is assessing preference and perception of subjective qualities. Assessing and employing preference information is a key element of product design (49; 68; 67). This dissertation examines tools for understanding shape preference and applying that preference information to improve product design. It also explores methods of augmenting creativity to further improve artifact design.

Consumer products within mature markets that garner intense competition are increasingly selected by users based on aesthetic attributes because the technical attributes across product offerings are well met by producers. Thus, given a choice between several products that all meet certain technical expectations, a user may make choices based upon the visual appearance of the products. A scientific understanding of user preference with respect to product shape can provide designers with valuable insights. It can be difficult to understand

the reasons why one design appeals to a user while another does not. But, if all other properties of an artifact (its performance, color, finish, materials, brand, etc.) are held constant while only allowing the shape of that object to change, then we should be able to learn valuable information regarding the appeal of that shape to a user. In this dissertation, we limit the notion of shape preference to say nothing about the inherent ‘beauty’ of a product. In the provided work, shape preference simply means that one product’s shape is more well liked than others in the given context of how the product will be used, and subject to the geometric qualities of the product that are permitted to vary. Portions of this work use preference examinations that are insensitive to the possibility of multiple preferences. However, multiple preferences are highly possible in relation to shape preference. Extending the findings of shape preference from this work to suggest a universal shape preference is inappropriate and unjustified.

Utilizing preference to guide the design of products is highly associated with the field of marketing. One drawback of simply applying marketing demands directly to the design of products is that marketing often fails to recognize the engineering realities of product design. For instance, the market research department of a firm may suggest that users desire chair designs that are infeasibly thin and light based on the physical mechanics of materials. This then requires iteration with the engineering department of the firm and can lead to suboptimal design solutions. It is therefore valuable to integrate the demand-based models developed within marketing to the physics-based models developed within engineering. This has been examined to explicitly show that the optimal designs from engineering and marketing can be, not only, dislocated, but also infeasible (55). In this dissertation, preference information is related to a product’s shape. The goal is to develop designs that integrate this preference information with the physics-based engineering models that are associated with that product’s performance. Thus, a study of shape preference that also examines technical functionality is a study of form vs. function, a classic argument (or trade-off) in design.

Like shape preference, creativity is a critical element of good design. Whether this

creativity is related to the appearance or the performance of the product, it is important in development. Psychologists have employed methods to examine and assess creativity, but methods of enhancing creativity are less structured and considered to be intuitive and immersive. However, consistent and routine creativity is not an anomaly. Many people, firms and companies have attained consistent creativity. Enhancing individual creativity, specifically for the design of artifacts, should lead to designs that are new, exciting, and unique. While enhancing creativity may not equate to preference, it should be noted that preference does not exist in a vacuum. The creative designs of the past are often judged against their counterparts of the present, and what was once highly preferred may currently be blasé. Likewise, what may today be considered unique may someday become the preferred aesthetic standard. Thus, in this dissertation we study creativity and develop a means of enhancing it because doing so can benefit designers and add value to designs.

## **1.2 Shape preference in engineering design**

Engineering design ensures that designed goods meet technical specifications while being safe, efficient, and reliable. For this reason engineering design is not always concerned with the aesthetic appeal of a product. That task is left to industrial designers who are tasked with interpreting the requests of marketers and deploying their own creativity in the creation of a product. There are two typical extremes of design that are often experienced by practitioners: in one, the engineers design a product that meets the requirements posed to them and then the design is handed to industrial designers that attempt to create an appealing enclosure for the engineered product; at the other extreme, industrial designers compose a form that captures the desired aesthetic that is then provided as a bound for engineers to design the product within. These examples represent two ends of a spectrum that assumes no communication or iteration. The true situation has both communication and iteration. However, there are a lack of tools that explain the impacts of either discipline on the other,



this leaves designers, engineers and producers to rely on intuition and heuristics. Further, in many products, the shape of the design has direct implications on engineering performance.

### **1.2.1 Aesthetics**

It is acknowledged that aesthetics can encompass a much greater set of visual and stylistic properties of an artifact than just its exterior shape. But, this narrow definition allows for the specific examination of this one aspect of aesthetics. The work examines how variations in these geometric properties of an artifact can impact preference for and perception of that artifact. Understanding these issues can lead to better product designs. A brief review of aesthetics is appropriate here to understand what has already been learned about shape and preference.

Humans' aesthetic preference is very important in many of their judgments and decisions, well beyond just the selection of an artifact. In the biological sense, humans often assess another person's qualities based upon appearance. For instance, people tend to judge more attractive people as being more intelligent, and it is well documented that people perceived as more physically attractive amass substantial economic gains throughout their lifetime versus those perceived as less attractive (57). The means of judging a person's attractiveness are based on three primary traits: visual, vocal and chemical attributes. While tending to adhere to some general rules, such as symmetry and commonality, aesthetic standards vary between cultures and times (26). Reber et al. suggest, from the perspective of psychology, that aesthetic pleasure is related to processing fluency (71). Processing fluency is defined as the ease with which one recognizes the stimulus that is presented to them, and greater pleasure is associated with greater preference. Thus, aesthetics represent an important aspect that influences many human decisions, but specific rules for pleasing or preferred shapes seem heuristic at best.

The variability of a beauty standard is not unique to the judgment of human beauty. This trait holds for the aesthetic valuation of art as well. The art historian Eco recognized this,

and stated that “...what is considered beautiful depends on the various historical periods and cultures” (17). Eco’s work examined the existence of themes, such as an ‘Adonis’ or the attractive youthful male, which exist as different instantiations within different cultures and times but lack specific visual congruency between them. While rules for assessing beauty may exist in humans, understanding those rules, especially across culture and time, and providing a measure of beauty is difficult. Therefore, it is important to find a means of assessing shape preference in order to effectively design around user wants regardless of geographical or temporal location.

An artifact’s appearance is an important aspect in a person’s overall assessment of that artifact (39). Jordan has determined that usability, which is a discipline within human factors engineering that defines how efficiently a user can accomplish a specified task with a product, was one important component used in determining the amount of pleasure that a user receives from a particular product (39). But, while users rated usability as the *most* important characteristic of a product’s design, aesthetics was the *second most* important aspect. He also discovered that people tended to use pleasurable items more often than those items that were not pleasurable. Thus, since shape is an aspect of aesthetics we can infer that it has a relationship to how pleasurable a product is perceived.

Liu has asserted that while “...designers and decision-makers deal with aesthetic and ethical issues constantly in their practice, they often make aesthetic and ethical decisions on the basis of their gut-feelings and intuitive judgments” (46). He proposed that “engineering aesthetics” should be a new division of ergonomics that applies scientific, engineering and mathematical methods to help make design decisions regarding the aesthetic qualities of a product. He noted that the industrial design community has developed an impressive arsenal of heuristics that aid them in designing the aesthetic qualities of a product (46). But, stated further that, while these heuristics may provide fertile grounds in which to understand the concept of engineering aesthetics, they are not scientific.

Designers have successfully applied design rules, or heuristics, to consumer products

(industrial design) and media layout (graphic design) for years. The application of these heuristics does not inherently dictate a product's appeal; heuristics provide designers with a structure around the creative process of design (79). Liu has noted that, while unscientific, these design heuristics "offer important insights into aesthetic questions and provide useful perspectives from which we can examine aesthetic concepts" (47). The work of Bauerly, in collaboration with Liu, has taken steps toward the scientific investigation of design rules. Their investigations have been specifically focused on the graphical layout of displays and web pages. Bauerly "develop[ed] quantitative methods that match[ed] the perceptual and mental processes of [2D interface] users" (2). His work specifically provided a numerical quantification of the effects of symmetry, balance and compositional blocking, which he identified as three compositional elements of aesthetic judgment. Formulae that he devised to account for each of these compositional elements for 2D interfaces were validated through human experimentation, providing a direct link between human preference and quantifiable design characteristics.

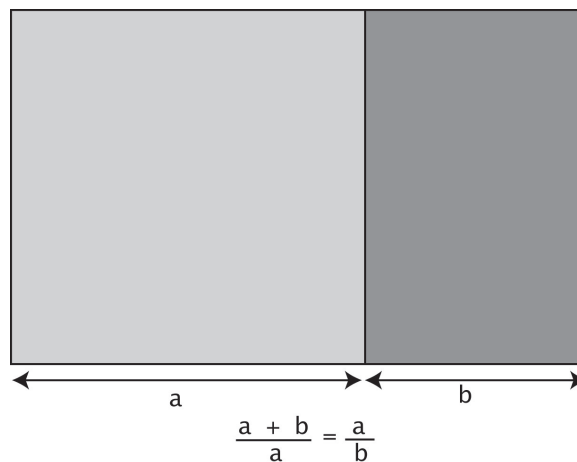
However, preference for compositional characteristics may be context dependent. More specifically, the form of an object may be evaluated by a user based on that object's function. In this case, the applicability of design rules becomes tenuous. In 2D layout design, as investigated by Bauerly, there is less need to consider function. But when designing an object, a vacuum cleaner for instance, form and function are intertwined, and specific components may be dictated by physical laws to have a form that deviates from design rules. The oft cited 'form follows function' axiom may also apply to the perception of the form's beauty.

Some argue that universal rules that govern aesthetics exist, can be quantified, and are capable of being applied to the design (or analysis) of artifacts. Much of this work has focused on the 'golden section'. The golden section is the ratio of two line segments  $a$  and  $b$ , such that the ratio of  $a$  to  $b$  is equal to the ratio of  $a + b$  to  $a$ . This is the famous ratio of 1

to approximately 1.618, when  $a = 1$  (Figure 1.1). Mathematically this is,

$$\frac{a+b}{a} = \frac{a}{b} \approx \frac{1+\sqrt{5}}{2}. \quad (1.1)$$

This ratio has been extensively studied and found to be relevant to many mathematical and biological phenomena, such as the golden rectangle, golden triangle and ratio limit of consecutive numbers in the Fibonacci series (27). It has been extensively studied by psychologists; in fact some of the first psychophysical tests were based on this ratio (19). Green notes that many of the psychological studies of the golden section were methodologically flawed, but asserts, despite this, that there may be a real aesthetic effect associated with the golden ratio, though a fragile one at best (27).



**Figure 1.1** The Golden Rectangle incorporates the Golden Section, where  $a = 1$ , and  $a+b \approx 1.618$ .

The golden section is a specific subset of a larger body of knowledge known as proportionality, which stems from rules of geometric association described by Euclid, and has been used by designers and architects (51). Proportionality is concerned with eleven specific proportions (or relations of two ratios) which some believe to be directly linked to aesthetic significance (33; 66). A necessary step that has not been addressed is whether or not these proportionalities are actually preferred by people regardless of the artifact under question, thus making the link between proportionality and preference.

Aesthetics are important to artifact appreciation, perception, use, and preference. But,

we must stress that aesthetic appreciation is highly subject to user tastes and appreciations that are built upon years of cultural exposure that are influenced by political and moral beliefs. The universality of beauty can be considered in a biological sense, and has been researched as it relates to mate selection, and disgust responses. The beauty of one culture is often at odds with that of another. The judgement of one type of art within the context of another culture will likely lead to critical reviews, but we should not believe that this implies that such art lacks value. Thus, aesthetics is culturally, and temporally relative, and tools to investigate the particular shape preferences of the time must be general, and capable of operating outside of this bias.

### **1.2.2 Preference**

Preference describes the relationship between a person and their affinity for anything, be it art, food, shoes, weather, leisure activities, etc. When one prefers A to B, it means that the person would rather possess or experience A than B. Several methods exist to understand preference. Of interest here are those that focus on a mathematical relationship between variables and preference. The primary concern of this dissertation is the understanding and application of shape preference in engineering design. Thus, we are explicitly interested in the geometric qualities of an artifact. This geometry can be decomposed into a set of variables that define artifact shape. By examining one's affinity for a particular combination of these artifact variables we can understand shape preference.

The principles of preference have been investigated by psychologists and effectively applied by marketers. Preference, and perception, have been exploited for years to influence the visual, auditory, olfactory, gustatory and tactile properties of designed goods. However, the application of these preference tools to the examination of shape preference has been of limited utility. The psychologist, Fechner, for instance, conducted studies to determine the best liked ratio of length to width for rectangles (19). His results suggested a high affinity for the golden section, a specific ratio which will be discussed in the next chapter. Yet, that

work, showing preference for a specific ratio, is difficult to generalize across disciplines.

### **1.2.3 Design**

Design is a general term referring to the creation of essentially anything. Writers, artists, engineers, web-developers, architects, coaches and urban-planners are all concerned with this general concept of design. In this dissertation, we restrict design to specifically examine artifacts. Further, we are concerned with both the technical design of that artifact as well as its shape design. This means that we want to understand how to develop artifacts that meet both the physical demands required by the environments that they are used in as well as the aesthetic expectations of those individuals that interact with them.

When designing an artifact, a set of functional needs must be interpreted and targeted by engineers. Industrial designers must develop a product shape that will appeal to users and tell the proper ‘story’ of the artifact. This story suggests a context for use, and an appropriateness of the particular artifact to meet the expectations of users. If the design fails to meet the technical requirements or to convey the proper message, then the artifact can be considered suboptimal. An optimal design will meet both of these expectations. Therefore, we must be able to evaluate both the technical qualities of an artifact and its shape preference in a predictive manner to assess how well it suits its given task.

Engineering design has a vast set of tools for conducting this type of analysis for many disciplines. Further, optimization techniques have been developed that allow for the development of products that optimally meet technical goals while respecting physical and practical constraints. The fields of industrial design and especially art lack any similar form of evaluation. Their form of evaluation is more intuitive and guttural, thus the assessments lack quantitative analysis of the artifact in question. Again, this work does not presume to say anything about the inherent beauty of any artifact, it attempts to understand how a design’s shape can be interpreted for its preference and perception to users. This then provides a means of valuing one design versus another subject to the constraints of the

design's variables. So, we do not claim that shape preference implies aesthetic value.

### **1.2.4 Creativity**

Creativity is often an assumed role of artists. However, creativity is much broader and expansive. In fact, creativity is merely the development of novel ideas, or the synthesis of disparate ideas in the creation of a new solution or idea. In this dissertation, we are concerned with creativity as it relates to the shape of artifacts. We are specifically interested in the development of tools and techniques that can enhance creativity. Doing so allows creative design to be generally accessible and not simply the province of a select few. In much the same way that tools have been developed to assist in mathematical calculation, a tool for enhancing creativity would not make a virtuoso of everyone, just as mathematical tools do not make mathematical geniuses of their users. The tool would, however, promote improved competency and ability of those that use it. The tool would be intended to help inspire and allow refinement of a design's shape.

This work examines the use of Interactive Evolutionary Systems (IES) as a means of providing individuals with the capacity to increase their creativity. The intent of this tool is to provide users with an easy to use intuitive tool that allows them to both explore potential designs while also allowing design refinement. Many means of enhancing creativity can be postulated, and many software based tools could be developed. This work explores one means of applying IES principles to address creativity enhancement. The theory and application of this tool will be presented.

## **1.3 Research objectives and contributions**

This research attempts to answer several related questions. All of these questions are specifically focused on the concept of shape preference and how it relates to the design of artifacts.

- What methods are available for capturing shape preference?

- What methods can be developed to quickly understand shape preference at the individual level?
- How can shape preference be related to engineering design in a quantitative manner?
- Can an optimization framework be developed that facilitates a greater understanding of product design that accounts for shape preference?
- Can the creativity of designers be systematically enhanced in regards to artifact shape?

Examining the above questions will add a greater level of analytical capability to the aesthetic design of products. Doing so can more appropriately align the design with user wants and expectations. This provides tools for producers to make more informed decisions in the creation of their products and increase the likelihood of market success.

This work has several contributions:

- Application of current preference assessment techniques to understand shape preference.
- Incorporation of shape preference information and technical requirements within an engineering design context.
- Methodology for including shape preference information within engineering design.
- Validation of interactive genetic algorithms for preference assessment capability.
- Identification of vehicle shapes perceived as having good fuel economy along with an associated engineering analysis to understand the related drag coefficient.
- Establishment of interactive genetic algorithms as a tool for enhancing creativity in shape design.

## **1.4 Dissertation outline**

This dissertation first examines important literature from several fields including engineering design, preference, and computer science. This is done to understand each discipline better and provide a justification for many of the techniques and ideas employed in the experimental portion of this work. Second, we will explore the assessment of preference using tools that are currently available within the marketing community, these tools are then combined with engineering analysis to describe methods for improving decision making in product development. This will be explored with a case study. Third, a tool using evolutionary algorithms will be described and validated as a means of understanding individual preference. This will be shown both theoretically and experimentally. A case study will be



used to validate this theory. Fourth, the interactive evolutionary algorithm will be applied to examine users' vehicle shape expectations associated with good fuel economy. Fifth, the evolutionary algorithm developed in the third portion will be examined as a method for enhancing creativity. Finally, conclusions will be drawn regarding the results of this work, and its contributions will be explained along with questions that can be addressed in future work.

# Chapter 2

## Background

When people select an artifact, they are making a multifaceted decision. They are usually unconsciously performing an internal analysis of their options, evaluating each of the options within some framework and then selecting one based upon that analysis. A product's shape may be one dimension upon which a user evaluates an artifact. This aesthetic dimension, defined in this dissertation as an artifact's geometric appearance, often has important engineering ramifications, such as necessitating specific manufacturing processes that may influence the product's technical performance, such as limiting the loads that the artifact can be subjected to, or restricting the size of the components which could be housed within the structure.

Aesthetics is an important aspect of product design widely recognized as a means of adding value to a product (3). Yet, a product's aesthetic is typically left to the best judgment of industrial designers and their interpretation of the current market wants (47). While this approach is often successful, here we seek to understand more deeply the impact that artifact shape has both on user selection and on an artifact's technical performance. Research within the field of Kansei engineering, which attempts to account for human emotions within design, has been directed toward the development of tools that examine these emotional qualities. One factor influencing these emotional qualities is a product's visual appearance (85; 78). According to some, the aesthetic properties (beyond just visual characteristics) are as important as the technical aspects of a product's design in influencing user choice (68).

This issue of aesthetic-based design has even prompted a collective of European universities and businesses to devote their efforts toward the development of tools that aid designers in the creation of aesthetically ‘correct’ designs (21). This chapter will provide an examination of several fields of study that are important in establishing the foundation upon which the proposed research will build; this includes engineering design, preference, computer science, and automated design generation.

## **2.1 Engineering design**

Creating a well-designed product is no guarantee that it will be successful in the marketplace. There are many aspects, such as marketing, brand identification, market trends and intense competition that can all serve to erode a well-designed product’s market share. However, products that do sell well and gain large market shares are typically very well designed. As described already, a product’s aesthetics importantly influence how users will perceive it. Thus, many within academia and industry claim that it is essential to develop and employ techniques for designing appealing products. We have already examined some tools for the assessment of preference, but we will now turn our focus toward the field of engineering design to understand better the tools and techniques used within that field for addressing the wants of the user.

Yannou and Petiot broadly examined the design literature, focusing on suggested and utilized design processes in order to find the commonality among the various methods (84). From this study, they suggested that there are four spaces in which design occurs: stakeholders’ needs space, perceptual space, functional space, and physical space. A product can be developed using these four different spaces by viewing each space as a unique phase of the design process influenced by different agents with different requirements. This design process need not be linear, and it is suggested that good design must exist at some point in all four spaces. They suggest that examining stakeholders’ needs in the perceptual design space

can result in drastically different results from those obtained if those same stakeholders' needs were examined in the functional design space. This suggests that it is important to view the product from many angles, not just the technical side, nor just the aesthetic side. By following this methodology, they suggested that designers could develop products with technical savvy and mass market appeal, both of which are important in successful product development.

Hsiao and Liu stated that product design is a critical activity for firms that wish to succeed in today's competitive marketplace. In fact, they stated that some regard design as the only remaining area of industrial competition (36). They stated that the main difficulties in product design are: 1) translating market information (user preference) into quantitative design goals; 2) identifying those design parameters that meet customer requirements; and 3) generating and evaluating design alternatives. These ideas ring true with the fundamentals that apply to the Quality Function Deployment (QFD) design process, which basically states that designers must ascertain user wants (What's), define concrete product attributes that aide in meeting those wants (How's), and define levels for each of these attributes (How Much's) (24). QFD, used extensively within industry, has been applied to the development of many consumer products that have been successful. Govers stated that within the QFD process (24):

Of all the steps in the total production development process, none deserves more and receives less attention than the definition of the right product for the right customer.

Thus we should note that, according to QFD fundamentals, a well designed product is not just one that performs well, but also one that suits the wants and needs of the user well.

Through the House of Quality in QFD, engineers and designers can use information gathered from consumer focus groups or surveys in order to rank the importance of, and levels for, design characteristics, thus incorporating the voice of the user. While this type of level setting is certainly an improvement over design methodologies that simply rely on designer intuition, it does not typically incorporate metrics for the aesthetics of the product.

QFD relates customer wants through technical design characteristics, thus an ‘aesthetic’ want becomes coded through a design characteristic, the importance, and levels of which are not directly ascertained from the user. Based on its prevalent use within industry, it is apparent that QFD is a useful tool. However, the QFD methodology could be improved by incorporating shape preference as a metric for design.

Hosoy discussed product craftsmanship as a means of determining whether or not a product is well-designed (35). Craftsmanship is the characteristic of a product that makes a user perceive it as being well made during their initial interactions with the product. This differs from what is typically known as product quality, which is the integrity of a product’s ability to function over time. Thus, one measure of a well designed product could be its craftsmanship rating. The tools developed by Hosoy have the ability to map product characteristics to user perceptions, so that engineers can manipulate design characteristics to more appropriately match user wants. Thus, engineers can directly apply these tools to develop well designed products from a craftsmanship perspective. These tools have never been used for the direct investigation of shape preference, and it is unclear whether or not they could be employed for such an assessment since this is not their intent.

One method of learning about user preference is through the use of the Semantic Differential (SD). The SD has been effectively used in the practice of Kansei engineering in an effort to design products that are well suited to user feelings (59). The SD was developed by Osgood to evaluate concepts on a bipolar adjective-based scale (64). In doing so, it was hoped that given a set of bipolar adjectives (‘good’-‘bad’, ‘weak’-‘strong’), a subject could rank a concept, such as classical music, within that framework, typically using a seven point scale. Thus, researchers could obtain some qualitative measure regarding a subjective feature. As mentioned, this SD approach has been crucial to Kansei engineering, which utilizes it to understand how a user feels about a particular attribute of a product. Kansei engineering has been applied to a number of product development activities, including automotive applications (78), robotics (85), home appliance (58) and construction equipment

(60). Most notable among the products developed using the Kansei engineering idea was the Mazda Miata. The Miata was designed from the ground up using this technique, with the targeted audience being young drivers. The resulting automobile (also known as the MX-5, or Eunos Roadster) has become the best selling sports car in the world. This lends credence to the capacity of Kansei engineering, and to the use of the semantic differential as a method of determining user preference for concepts or objects.

However, the author's investigations into the Kansei literature have failed to show that a consistent and reliable methodology exists within the field. While aspects of Kansei remain consistent between studies (the use of the SD, subject queries, translation of subject data to some type of mathematical model), it appears that no methodology exists for the foundation of the mathematical models that ultimately drive design decisions. For example, one study on robotic arms uses purely monotonic models to describe user preference (86). This study conducted optimization based upon these preference models and some models of producer cost to ultimately discover an optimal design point which does not lie at the bounds of the preference models. Yet, we know that the optimal point of a monotonic function lies at one of its bounds (if we simply wish to find that dimension's optimal point), and this result, just like the linear models of preference discussed earlier, is unsatisfactory and nonintuitive. Thus within this work, the only thing preventing the ideal point from being one of the designer-defined bounds is the cost of producing the product. One would hope, instead, that the bounds of the designer simply provide a design space within which an optimal point could be found, and if the optimal point is found to exist on one of those bounds then those bounds should be expanded (unless physical limitations prevent them from moving) until an ideal point is found inside those bounds.

Otto and Wood have written extensively on the design process and focused some attention on current techniques of assessing user wants (65). They stated that "typically, [the] understanding [of what consumer needs are] is conveyed by showing the current product model to a customer and asking for preference information about its features". They also

stated that the major drawback of this technique is that customers typically only discuss the failings of a product, thus a significant amount of effort must be exerted by the questioner to elicit what the user actually expects or wants from a product. They suggest, as does, that the primary tools used for “Needs Gathering” are: one-on-one interviews; questionnaires which ask respondents to rank a list of product criteria; focus groups; and role playing, where the design team acts as though they are the intended customer Baxter (3). While valuable information can certainly be gathered from these techniques, none truly lends itself to the rigorous investigation of user wants in regards to visual characteristics of a designed product, or to the development of a model that describes those wants within the design space.

## **2.2 Preference**

In order to design products well, it is imperative that designers understand the users they intend to design for. This knowledge can take many shapes. Often, we see that outstanding designs come from those that are intimately associated with the field for which they design. For instance, Gary Klein is a passionate cyclist with deep knowledge of engineering. He used his technical and experiential knowledge in the development of many innovations for his Klein bicycles. His deep involvement within the cycling community allowed him to understand the wants of his customers and translate that information into innovative designs desired by users (and ultimately copied by the competition). This method of understanding preference is highly subject to error though, and we know that a person’s self proclaimed ‘great’ idea often falls flat when placed in the market. Thus, marketers use other techniques for preference assessment ranging from focus groups to scientifically developed mathematical models of consumer choice. Due to the nature of this present research, the most interesting type of preference assessment techniques are those scientifically developed methods that yield mathematical models of preference.

There are several techniques within the marketing and psychology communities that

attempt to understand what users want. In the following sections we will examine conjoint analysis, MultiDimensional Scaling (MDS), MultiDimensional analysis of PReference data (MDPREF), the PReference MAPping (PREFMAP) preference mapping algorithm, as well as some new preference modeling techniques.

### 2.2.1 Conjoint analysis

Conjoint analysis is a means of assessing preference that has been used extensively within the social science and marketing communities. The goal of conjoint analysis is to determine the ideal combination of feature attributes based on the preference responses of a test subject or group. It has been frequently used within industry in order to determine information related to product design, concept evaluation, product positioning, and market segmentation (28). This method is based on the principles of utility, and the notion that consumers attempt to maximize their utility when they make choices.

In order to collect data for a conjoint analysis, respondents are shown several potential products, or images of products. Each product is of a similar nature, but the levels of the product attributes are varied. Respondents are then asked to evaluate the products in some fashion; a popular form of evaluation is through selection of one product amongst a set. This type of conjoint analysis is known as discrete choice analysis. Michalek presented a review of the foundations of discrete choice analysis, primarily with reference to the use of the Logit model (54). When using discrete choice analysis for the assessment of utility functions we assume that utility,  $u_{iq}$ , is comprised of a deterministic term,  $v_{iq}$ , and an error term,  $\varepsilon_{iq}$ , where  $i$  and  $q$  are the individual and product respectively

$$u_{iq} = v_{iq} + \varepsilon_{iq}. \quad (2.1)$$

The Logit model assumes that the unobserved error term has a double exponential probability distribution. This assumption, while not being based on theoretical grounds, has been



shown in studies to agree well with the results of a normally distributed probability function, which has more theoretical validity (54). We presume that this deterministic component of utility can be predicted through regression of observed choice data to mathematical models of utility.

A no-choice alternative is included as well. The error term is assumed randomly distributed and of double-exponential form (48; 31),

$$f(\varepsilon) = \exp(-e^{-\varepsilon}) \quad (2.2)$$

to yield the mathematically tractable MultiNomial Logit (MNL) model. Further, the Maximum Likelihood Estimation (MLE) is used to estimate the choice parameters in the utility model:

$$P_{iq} = \frac{e^{V_{iq}}}{\sum_{j=1}^J e^{V_{jq}}} \quad (2.3)$$

$$v_{iq} = \sum_{k=1}^K \beta_{jk} X_{jkq}. \quad (2.4)$$

Here  $P_{iq}$  is the probability that individual  $q$  chooses alternative  $i$ ;  $V_{jq}$  is the utility of the  $j^{th}$  alternative to individual  $q$  composed of attributes  $X_{jkq}$  with an associated part-worth, or alternate-specific constant,  $\beta_{jk}$ , where  $k$  is the level of attribute  $j$ ; see Louviere for a thorough and accessible treatment (48). Care must be taken to avoid violating the MNL model assumptions when using conjoint analysis

It can be difficult to conduct conjoint analysis as the number of attributes and their associated levels increase because the number of responses required of a subject becomes very high. Conjoint analysis can be done at the individual level, or it can be conducted on groups. Some suggest that conjoint analysis on groups does not provide good predictive ability due to the among-person variation in preference (28). Still, conjoint analyses are often conducted on groups in order to obtain generalized information regarding preference

for various attribute levels for use in designing products.

### **2.2.2 MDS**

MultiDimensional scaling (MDS) can be used to understand user perception, and can be extended to user preference through the use of MultiDimensional analysis of PReference data (MDPREF), which is described in the next section. MDS is a method used to analyze the similarity (or dissimilarity) of data regarding a set of ideas or objects (5). It is often employed to understand the relationship between objects which are unlinked by an explicit theory, such as the flavor of foods. In MDS, a subject is asked to compare one object against another by selecting a value for how similar or dissimilar the two objects are. This value is taken as a distance between the objects. When this process is used to determine the distance between all objects within a population then a mapping can be created that shows how each object is related to each other in an  $m$ -dimensional space. Within this  $m$ -dimensional space there are three typical ways of interpreting solution data: first is the manifold way, which maps the data into a meaningful curve or surface in space; second is the dimensional way, which associates data to substantive features of the represented objects; finally, regional interpretation clusters the data into meaningful groups of associated commonality (5).

A good way to explain MDS is with an example of a simple geographical map of the United States. If we create a fully ordered matrix of distances between several cities in the USA and then develop a two-dimensional map such that each city is the appropriate distance from every other city (according to the matrix), then we will have an accurate map of those cities in terms of distance. However, the orientation of this map may not be correct, and may require both reflection and rotation in order to be aligned with our expected version of a map of the USA. We could even consider that the cities could be grouped into states through the use of clustering.

In Table 2.1, we present the distance, in miles, between several major cities within the United States. Given these distances a map can be created that indicates each cities location

relative to the others, Figure 2.1. However, in this map we see that nothing orients the data in a universal way. It is therefore necessary to apply both a rotation and mirroring of this map to obtain a map of these cities that we would typically expect, Figure 2.2.

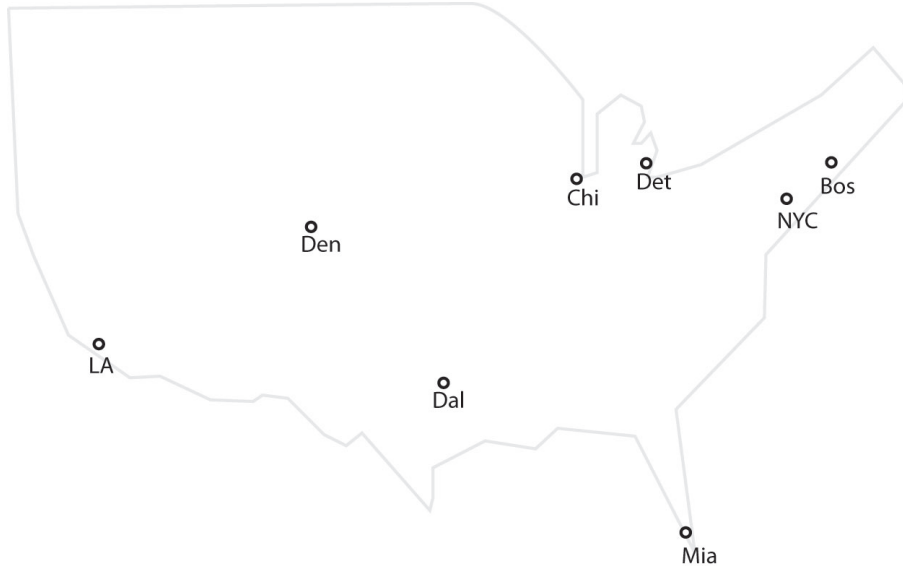
**Table 2.1** Distance, in miles, between US cities.

	Boston	Chicago	Dallas	Denver	Detroit	LA	Miami	NYC
Boston	0	852	1550	1767	614	2595	1261	187
Chicago	-	0	802	917	237	1744	1190	714
Dallas	-	-	0	664	998	1240	1107	1373
Denver	-	-	-	0	1153	832	1725	1630
Detroit	-	-	-	-	0	1981	1159	484
LA	-	-	-	-	-	0	2335	2451
Miami	-	-	-	-	-	-	0	1097
NYC	-	-	-	-	-	-	-	0



**Figure 2.1** Map showing the distance between US cities, in miles, as developed via MDS.

The methods of MDS can be used in an effort to understand a person's or a group's preferences for a particular object's attributes. In fact, preference modeling using MDS as a foundation has been shown as a way to determine the ideal points for subjects in several case studies. An ideal point is the set of values, or characteristics, of a design, or situation, that maximizes that design's preference. One study attempted to determine the most preferred number of children, and gender combinations, that couples would like to have (14). In this type of MDS, subjects were presented with a set of potential solutions and asked to rank how well they liked each solution. These data could then be analyzed with MDS to determine the



**Figure 2.2** Map showing the distance between US cities, in miles, developed by MDS then rotated, mirrored and shown in context.

ideal point for an individual based on the selections and the attributes of the solutions.

### 2.2.3 MDPREF

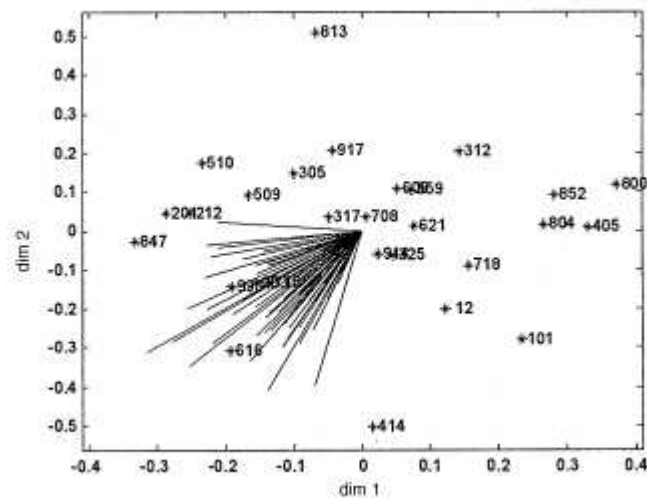
MultiDimensional analysis of PReference data (MDPREF) is an analysis tool that uses data regarding the evaluation of proposed stimuli, obtained through a survey tool, to generate an *internal* mapping of preference. It was developed by Chang and Carroll at the Bell Laboratories in the 1960s and 70s (8). In an *internal* preference analysis only information collected in the MDPREF query is used for interpretation, thus there are no inherent scales on which the data can be explicitly analyzed, but the configuration and segmentation of the data can be useful (13) (87).

The input data for MDPREF consists of an average attribute-by-objects matrix. These average preference evaluations are obtained through the compilation of several surveys regarding the proposed attributes and objects (8). The resulting map of an MDPREF analysis (which is rooted in MDS) contains information for each attribute and each object. Each attribute is represented as a vector, and each object is plotted as a point on a map in an

$m$ -dimensional space. The resulting figure contains descriptive perceptual axes (the attribute vectors) and is populated with points (objects), appropriately positioned within the vector space. By relating each object to each vector we can get a sense of how preferential that object is in regard to each particular attribute. MDPREF is based on a linearized model such that preference increases along each attribute vector towards infinity. Thus, the further away an object's projection onto an attributes vector is from the origin, the better its preference is. MDPREF can be a useful tool in gaining preference information related to product design. In fact, it does provide rank order information for products, and it can be beneficial in gaining qualitative information for design work. However, it does not provide enough information to create a model of the design space that could be used for engineering design because it is based on linearized models, thus indicating that the ideal point of any design always proceeds monotonically to positive or negative infinity, which is an erroneous conclusion because individuals are unlikely to prefer a design attribute at its infinite bound. For instance, an individual may prefer large vehicles, but it is unlikely that they would prefer to operate a vehicle that is as large as it could possibly be made. The MDPREF analysis can only be considered valid within the bounds of the examined design space. The primary benefit of MDPREF is that it is informative; it can show us how one product is perceived to relate to another with respect to a variety of attributes.

Another way that MDPREF is often used is by considering the attributes as subjects and the objects as stimuli. Thus, the preference matrix consists of subject-by-stimuli data, and the representation is such that the subjects are vectors and the stimuli are points. This type of preference mapping is useful for understanding how people respond to different product scenarios (stimuli). Examination of an MDPREF mapping of this type can provide insight into the clustering of people types with how they respond to products. For example, if several vectors are clustered together in one area of a map, while several others are clustered elsewhere on that map, then by examining the products that project preferably onto those vectors a producer may be able to determine a set of products (potentially very different)

that could each garner positive market shares based on their product features. Figure 2.3 indicates how such a plot would look, showing a cluster of an individual's preference (vectors) for specific products (points) (11). These specific clusters of people would provide the motivation toward the production of the preferred products that align with them. While this type of an MDPREF analysis is useful in understanding a market's preferences for certain product offerings, it lacks the desired fidelity for creating a model of shape preference because of its linear assumptions (13).



**Figure 2.3** This plot of MDPREF data from (11) indicates how people's preferences (vectors) align with products (points).

## 2.2.4 PREFMAP

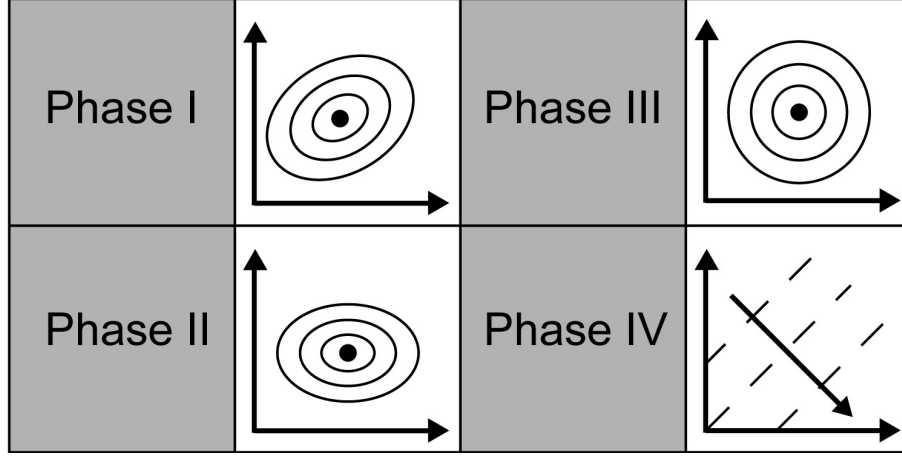
PREFerence MAPping (PREFMAP) is an analysis tool which relates a stimulus space to preference data in order to generate an *external* mapping of preference. It was also developed by Chang and Carroll at the Bell Laboratories in the 1960s and 70s (9). In an *external* mapping of preference, the stimulus space is based on data obtained independently to the preference assessment (9)(13). For instance, if several examples of light were shown to subjects and the subjects rated their preference for each sample, then we could determine brightness preference by mapping the light samples' preference onto a stimulus space of

lumens as the *external* map.

The evaluated data that are input to PREFMAP is a subjective ranking by a subject of his/her preferences for certain stimuli (variations on a particular design, for example). PREFMAP has four different phases of analysis associated with four different types of mapping. Three of these mappings, Phases I through III, are based on an ideal point of preference model, while Phase IV is a vector model of preference. The basic idea behind PREFMAP is that each individual has an ideal point of maximum preference and is capable of ranking different stimuli in such a way that the ideal point is revealed (13). The distances relating an individual's rank to the ideal point are different for each of the phases of PREFMAP. The ideal point assumption appears to be axiomatic. But, it is likely that several 'ideal points' could exist in different regions of a potential design space. For instance, a person may like small sports cars, and large SUVs, but dislike luxury sedans. Thus two distinct ideal points, not one, would exist if vehicles were evaluated in a stimulus space that consisted of size and price as variables.

We can think of each of the first three phases as elliptical paraboloid models of preference with varying levels of complexity where the maximum (or minimum) point is the ideal point. Phase I presents the most general level of preference and describes the preference space as an elliptical paraboloid that can be rotated within the plane (thus the variables are coupled). Phase II is like Phase I, except the paraboloid is not rotated (thus the variables are decoupled). Phase III is simpler yet, as the paraboloid is circular. Phase IV is a vector model where the vector can be thought of as pointing in a direction of ever increasing preference for the given design attributes associated with the stimulus space. Basically, for Phase IV we can imagine that the ideal point predicted in Phase III is very far away from the actual stimuli tested, thus the iso-preference curves of the circular map are nearly parallel and suggest a gradient of ascent toward the ideal point. Figure 2.4 visually shows the difference between the four phases.

Phase IV, being linear and suggesting that the ideal point is infinitely far along some



**Figure 2.4** The different phases of PREFMAP are suited to different situations.

vector, is uninteresting in this current research for the same reasons as discussed with MDPREF. However, Phases I through III of PREFMAP are of interest to this preference investigation because it allows a mathematical model of preference that is nonlinear. In particular, Phase I is the most general form of model development and can serve as the basic equation for both Phases II and III.

Phase I fits user response data (typically averaged over a sample population) to a paraboloid defined by

$$P_{model}(x_1, x_2) = \frac{(x_1 - b_0)^2}{b_1} + \frac{(x_2 - b_2)^2}{b_3} + b_4 x_1 x_2 + b_5 \quad (2.5)$$

where  $P_{model}(x_1, x_2)$  is the model of preference,  $x_1$  and  $x_2$  are design variables, and  $\mathbf{B} = \{b_0, b_1, \dots, b_5\}$  are constants determined by minimizing the distance between observed user response data,  $P_{avg}(x_1, x_2)$ , and  $P_{model}(x_1, x_2)$ , namely:

$$\min F(\mathbf{B}) = \sqrt{\sum_i \sum_j (P_{model}(i, j) - P_{avg}(i, j))^2}. \quad (2.6)$$

From this formulation the maximum preference point of the user is determinable. In this case, the external stimulus space is simply the two design variables weighted on a linear basis.



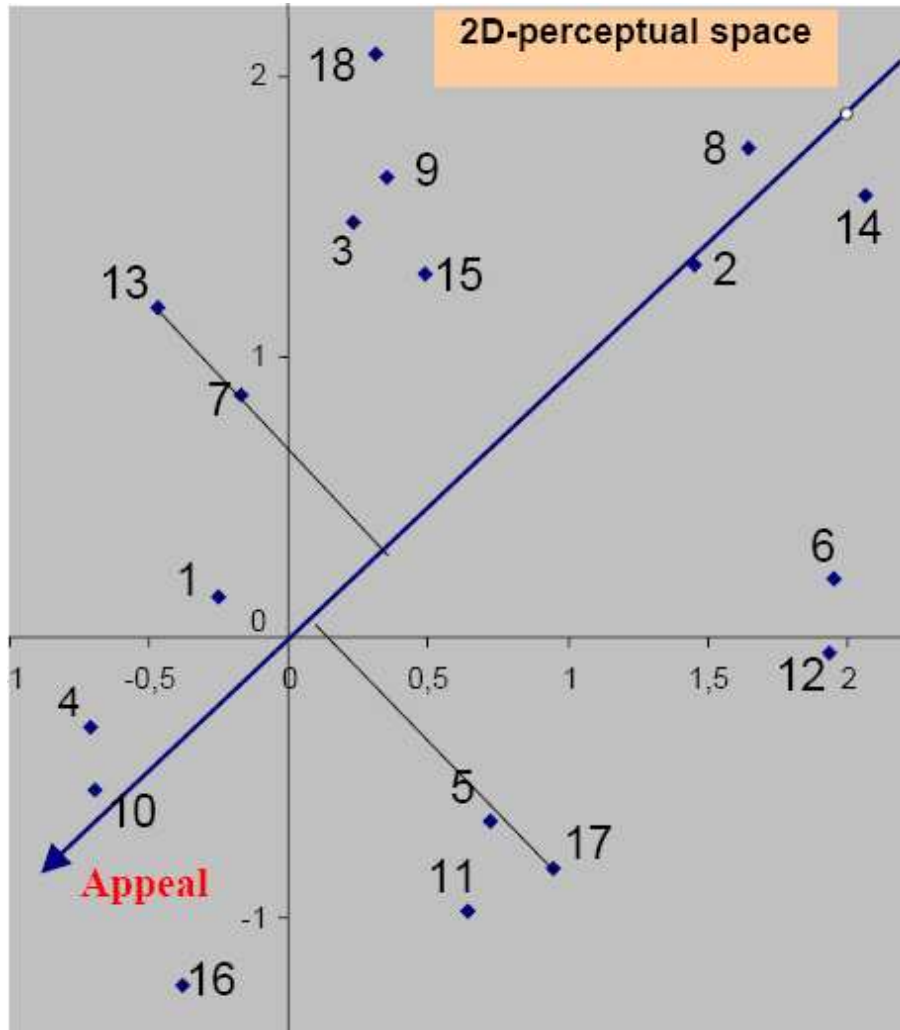
Some recent investigations into a user's aesthetic preference for a table glass shape are founded upon PREFMAP, but vary slightly in implementation (67). This will be discussed next.

### **2.2.5 Quadratic preference model**

As mentioned, work by Petiot and Chablat has investigated how visual preference can be mapped using a technique similar to that of PREFMAP (67). In independent discussions with the author, Petiot has termed his proposed technique the “quadratic preference model” (QPM), so this is the term we adopt here. Much of Petiot's work is related to the investigation of preference and perception, and relating these notions to the domain of product characteristics that engineers can affect. In his study of QPM, which was based on the subjective evaluation of table glasses, he queried a subject in several ways in order to: first, develop a perceptual space; second, assess preference for different table glass shapes; finally, examine how variation of specific design parameters influenced the subject's preference in order to find “appeal derivatives”.

Petiot first used a perceptual space mapping (an external map) to determine how subjects perceive the difference between 18 different glasses. This information was then used, along with an implementation of *metric* MDS, to create the perceptual coordinate system for the table glasses. *Metric* MDS attempts to preserve the stated distances between objects during mapping, while *non-metric* MDS attempts to maintain the rank-order among the objects. With this perceptual coordinate system available, the preference data, which was gathered through a *hedonic* evaluation of 18 table glasses on a scale from 0 to 10, was evaluated using an algorithm similar to PREFMAP. A hedonic evaluation simply means that an object is evaluated based on how well it is liked. The evaluation was a multiple regression of the preference data onto the perceptual axes and it generated a preference vector within the perceptual axes. Thus, it was similar to phase IV of PREFMAP. This plot, shown in Figure 2.5, is interesting because it illustrates how the table glasses project onto the preference

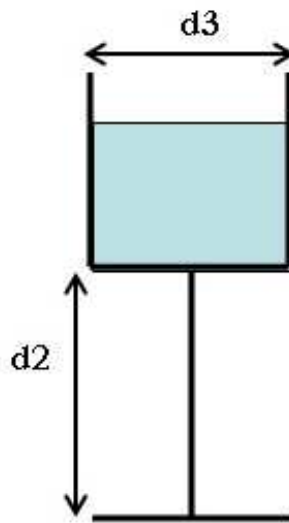
vector from the independently generated perceptual mapping, and it shows how well order is maintained on this preference vector. The preference scores for the 18 glasses (in descending order) were [10, 4, 16, 11, 5, 1, 13, 7, 17, 3, 6, 9, 15, 12, 18, 8, 14, 2]. However, it does not provide insight into the physical characteristics of the table glasses that drive preference.



**Figure 2.5** This vector model of appeal within the perceptual space, from (67), indicates how well this vector model can predict preference. By looking at the projection of each point onto the vector, we can see that it represents the reported preference order quite well.

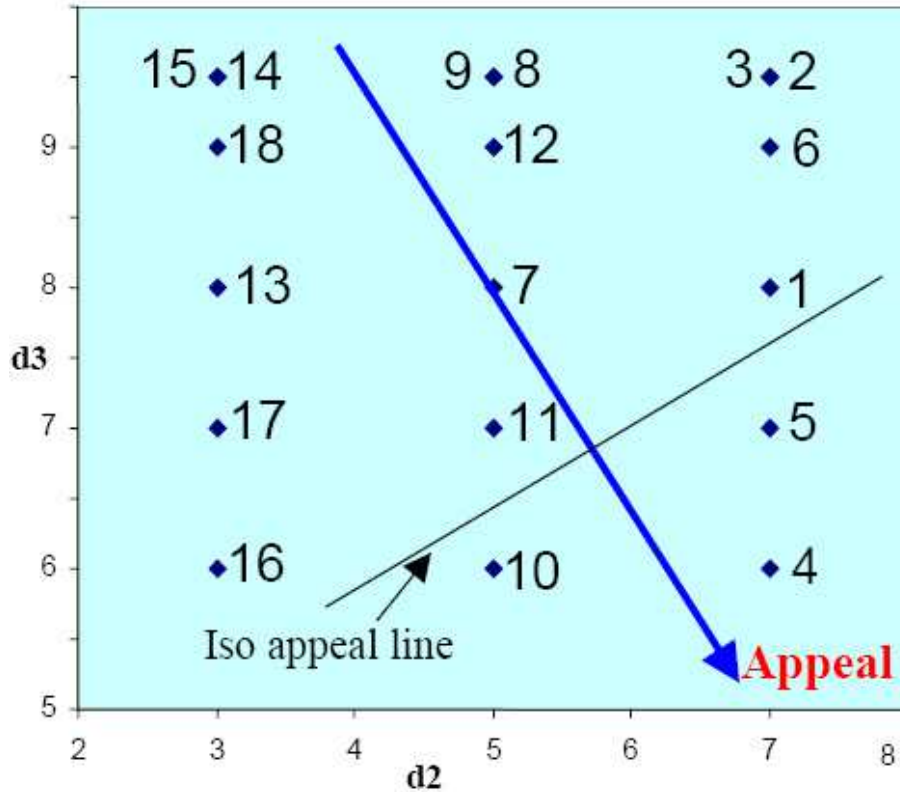
Petiot attempted to understand how the physical characteristics of the table glass influenced preference using a modified formulation of PREFMAP Phase I and mapping the data to the design parameter space of the table glasses, so that the ordinal axis is one design variable of the glass, and the abscissa is the other design variable (again, this is an external

mapping of the data). Figure 2.6 shows the physical meaning of the design variables. The primary difference between this formulation and that of PREFMAP is the introduction of the appeal derivative data. However, independent analysis and discussions with the author have revealed that such information does not actually provide a better data fit. In fact, using a coupled quadratic formulation for the predicted preference and minimizing its variation from the stated preference (in a least squared sense), in order to find the predicted preference coefficients, yields a more accurate predication model than when the appeal derivatives are included.



**Figure 2.6** In their study, Petiot and Chablat allowed table glasses to vary in dimension,  $d2$  and  $d3$  as shown.

The results shown in Petiot’s article (and reproduced here in Figure 2.7) suggest a final mapping of preference within the design space that is once again vectorial. Thus, we are provided with a preference space that is monotonic and suggests that preference will simply increase as we modify the design parameters towards positive or negative infinity as long as they follow the ideal vector. This however, makes little sense in actual design. Perhaps, the primary lesson of this work is that we can only hope to optimize the design towards the bounds imposed in the investigation (or dictated by the designer). This still begs the question: what lies beyond the bounds?



**Figure 2.7** This vector model of appeal within the design parameter space, from (67), shows how preference data could be used to improve design.

### 2.2.6 Vector field preference model

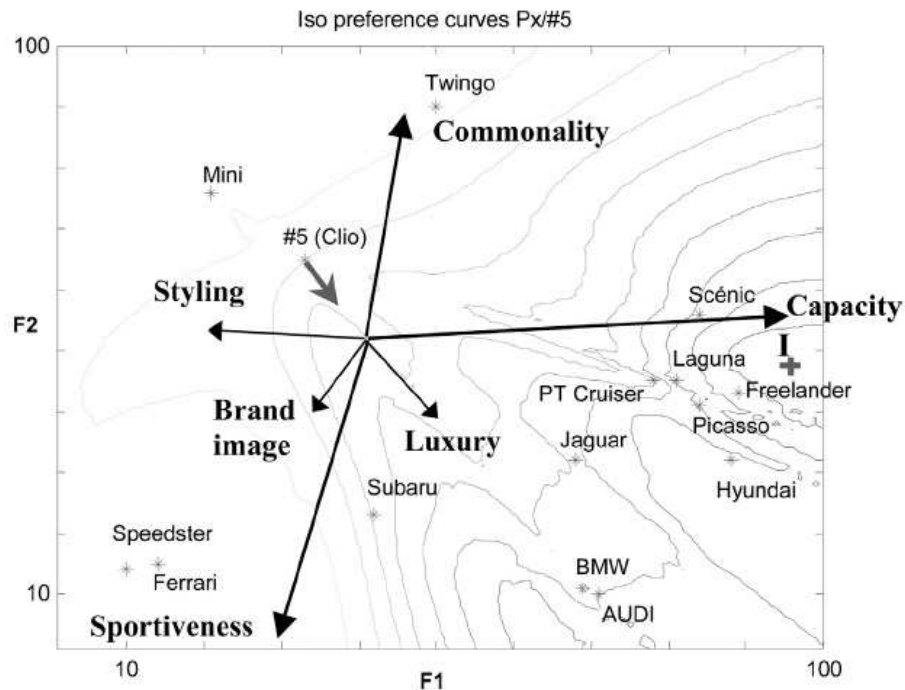
Recently, Petiot and Grognet investigated techniques for modeling customer preference through the use of vector fields (68). This approach uses some of the techniques mentioned previously regarding Petiot’s QPM, and is capable of providing much more detailed information regarding consumer preference between product offerings. This vector field model compares product offerings within an externally developed stimulus space. Examples given within their article show that this stimulus space can be represented as a perceptual space, or as a product characteristic space. This work shows how a perceptual space can be developed using MDS to understand how a user perceives the similarity of products, and then how a semantic axis can be placed within the MDS space based on user rankings of items on those semantic dimensions. In this way, we can understand user perceptions of a product. The researchers also showed that a product’s characteristic space can be used as the stimulus

space, thus we can examine how manipulation of those product characteristics can affect user preference.

The data for the vector field preference model is obtained through the use of pair-wise comparisons to evaluate items. Claiming that hedonic scales used in other preference assessment tools may not be intuitive (thus yielding data of questionable validity), Petiot suggested that pair-wise comparisons are much more intuitive for subjects and yield more accurate data. However, he went on to say that calculation of predictive models from this pair-wise data is problematic, primarily due to intransitivity and inconsistent evaluation. An intransitive evaluation would be one where a subject would prefer item A to B, and item B to C, but then prefer item C to A. Such evaluations could be encountered within decision theory, but in developing many utility theory models decision theorists assume that decision makers are rational and express transitive preference (68). An inconsistent evaluation would be one where, for instance, a subject greatly prefers item A to B, greatly prefers item B to C, but only slightly prefers A to C, when it would be logically expected that they would greatly prefer A to C. The vector field model proposed by Petiot and Grognet can account for both intransitivity and inconsistency.

This model maps the stimulus space with vectors that indicate, from any point on the map, the direction of increasing preference. It can also be used to develop actual surfaces of preference. However, these surfaces will often be relative surfaces because, if a rotational vector field exists for preference then an absolute mapping of preference is impossible for this technique, only irrotational vector fields are capable of yielding absolute preference maps. In one of their examples, they showed how these relative preferences can be used by producers, Figure 2.8. Here they showed that preference, relative to vehicle 5, can be locally increased by increasing that vehicle's capacity, and sportiveness, while decreasing its commonality. While this does not provide explicit design characteristic information it does provide an indication of ways to improve design. It would also be possible to project this information directly onto a more specific design characteristics space to understand how

relative preference changes due to changes in specific vehicle design decisions. This work is very promising and could be employed for the creation of a map of shape preference. It is more interesting than some of the previously noted methods because it does not break preference down into a simple linear model, but allows for ideal points and polarized regions of preference.



**Figure 2.8** A map of relative preference for several vehicles as they relate to vehicle 5 (Clio) reveals the iso-preference lines within a perceptual space. Using this information one could determine that increasing sportiveness and capacity simultaneously would increase the vehicles preference. Figure from (68)

### 2.2.7 Summary

Assessing user preference can be difficult. The methods mentioned here all take a scientific approach to translating user preference into some type of quantifiable information. The difficulties associated with preference assessment are outweighed by the prospect of gaining valuable information which could lead to more informed design choices. These choices could, in turn, provide people with products that are better suited to their wants.

Little work has been published on the application of these tools to the assessment of shape preferences for use in the product design process. This presents the opportunity to apply these techniques to product design in order to understand shape preference and relate it to engineering design.

## **2.3 Computer science**

The field of computer science explores methods and algorithms that can be used to exploit the computational power of computer hardware. The development of computer science has precipitated a movement of analysis and discovery that is of Renaissance proportions. Computational power has allowed scientists and researchers to mathematically explore and simulate scenarios with precision and accuracy beyond the capabilities of former generations of mankind. This has allowed the exploration of hugely important topics, such as meteorological phenomena, which require complex and computationally expensive mathematical models, and the identification of the human genetic makeup. Fast working algorithms have been used by justice systems in order to identify fingerprints of criminals, locate potentially threatening individuals through facial recognition software, and forensically examine a crime scene given a limited amount of a input data.

Computer science has also given rise to artificial intelligence, a promising means of studying and designing intelligent agents. These agents, at their root are capable of ‘simple’ things such as competing against humans in video games, but they are also capable of very complex tasks such as learning languages, synthesizing data and simulating population growth and organization. The field of artificial intelligence (AI) arose in the 1950s under heavy funding from the Department of Defense. Following rapid success, the field met several difficult challenges and has endured several periods of unpopularity. However, the practical capacity of AI methods in deduction, reasoning, problem solving, planning, learning and perception have made them critically important in the fields of logistics, medical

diagnostics and data mining. These learning systems can be a true boon for the examination of complex problem such as creativity, preference assessment and complex systems design.

An important branch of computer science that will be discussed further is the development of evolutionary systems. Built upon the notions of biological evolution, these systems provide a competitive environment in which designs can be tested and modified such that better solutions can be found for problems which can present a number of difficulties such as noisy design spaces, computationally expensive analysis, discrete problems, and unknown underlying mathematical functions.

### **2.3.1 Genetic algorithms**

Genetic Algorithms (GAs) are useful tools for solving both optimization and search problems. They are based upon the principles of biological genetics. In nature, populations grow and change based on the ability of population members to survive. This survival of the fittest leads to a population that is well tuned to its environment. This concept can be used with optimization or search problems in the same way. By describing a potential set of solutions to a problem in terms of a genetic code, an evolutionary process can occur in which subsequent populations of solutions can be propagated based on the 'fitness' of the previous population. This evolution should eventually lead to a population that is well tuned to its environment. GAs have been used successfully for many applications: from optimizing the strength to weight ratio of a bridge, to determining the least wasteful way to fold a box. GAs were first introduced by Holland (34), and there have since been many improvements in their application and implementation. The basic genetic algorithm can be described as follows:

1. A problem is defined.
2. A genetic code describing the solution space of that problem is defined.
3. A fitness function is related to the genetic code.
4. An initial population is created.
5. Each member of the population is evaluated for its fitness.



6. Highly fit individuals are allowed to 'mate' in a process called crossover. This allows a new population of 'children' with potentially fit characteristics from each 'parent' to be created.
7. A new population is generated from the crossover process.
8. A mutation potential is applied to each member of the population. It is important to note that mutation can be highly beneficial to finding new solutions because an unexplored area of the design space may be exposed.
9. The new population is sent back to Step 5, and Steps 5 through 9 are repeated until some convergence criterion (e.g., a specific number of iterations) has been met.
10. The fittest individual in the final population is the solution to the problem.

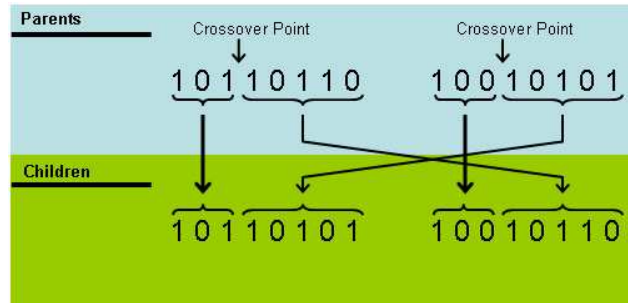
GAs are often successful because they give primacy to those individuals that are fit, and represent good solutions. This primacy allows for the creation of offspring that have a similar degree of fitness, and populations typically converge. However, the breadth of the initial population and the potential for mutations allow for a broad search of the design space, thus enabling the potential for finding the very best solution. It should be noted that GAs do not guarantee the optimal solution. However, they are often effective at finding very good solutions.

To start a GA, it must be assumed that a problem can be parameterized, so that a potential solution can be represented by these parameters. In terms of genetics, each parameter is considered a gene. When several genes are joined together a chromosome is created. Each singular representation of the chromosome within a population is termed a genotype. An individual's fitness is calculated through decoding its genotype, but it will ultimately be limited by the breadth of the chromosome. This means that GAs are very capable of optimization within a prescribed parametric space. However, they cannot create new parameters (genes). In GAs, a gene can be represented in several ways, but the classical form of representation is through binary numbers.

Given the parameterized problem, a fitness evaluation is used to determine the performance of each potential solution. The better an individual's performance, the better its fitness score, and thus the greater its likelihood of being able to reproduce.

In order to generate a new population a reproduction process must be undertaken. This reproduction combines the fit individuals in one population in order to create the new in-

dividuals for the next population. When two fit individuals are selected from an original population they are submitted to crossover. In the simplest form of crossover (single-point crossover), a crossover point is selected within the genotype of the individuals and then one complementary segment from each parent is applied in the creation of a new individual as shown in Figure 2.9.



**Figure 2.9** Single-point cross over traditionally consists of creating two children from the complementary genetic material of two parents. The cross over point is randomly determined.

It is assumed that these crossover functions will be useful in creating a fitter population in the next generation as it is likely that the good portions of each parent will be propagated to the children. For example, if a fitness function can be represented as

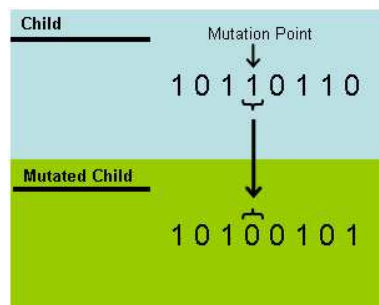
$$f(x) = (x_1 - 2)^2 + (x_2 - 3)^2 \quad (2.7)$$

and we seek to minimize that function while the variables  $x_1$  and  $x_2$  can be described by the set of integer values,  $\mathbf{I}$ , then we are faced with a set of potential solutions of the form  $\{x_1, x_2\}$  where  $\mathbf{x} \in \mathbf{I}$ .

If the crossover function for this problem is simply to take one variable from one parent and the other variable from the other, and the two parents are represented as  $\{2,4\}$  and  $\{3,3\}$ , then the resulting children of the cross over will be  $\{2,3\}$  and  $\{3,4\}$ . The child  $\{2,3\}$  has a fitness value of zero, which is the minimum possible for this problem. This shows how two fit individuals can be combined to create an even better child.

To introduce more diversity, and potentially find drastically new solutions, mutation is utilized. Each individual is subject to a mutation potential (typically this potential is low),

and if a mutation is allowed to occur then one point of the individual's genotype is modified (or mutated) as shown in Figure 2.10. For binary-based GAs, we see that mutation can be randomly applied in order to alter a single point within the genetic code. We also know that a change of one bit in a binary string can have a drastic impact on the representation of a variable within the design space in which it exists. For example, let us assume that a four-bit binary string has an integer representation in the design space, and that the decoding of those integers is that typically associated with binary to integer conversion. Then, if a mutation is applied to a binary string of 0000 the alteration could create the string 1000. Thus a single bit change in the binary space changed the design space variable from 0 to 8. We also know that it is impossible for a single bit mutation to change the binary representation of 7 (0111) to 8 (1000). Thus, in some instances we see that while mutations can help us find new designs there can be 'wells' that exist due to the nature of encoding.



**Figure 2.10** Binary mutation typically involves the alteration of a single bit within the binary string of an individual.

Sometimes *Gray codes* have been employed within GAs due to their *Hamming distance* properties. Gray coding is a means of structuring a binary code such that the Hamming distance between two consecutive numbers in integer space is only one. The Hamming distance between two binary numbers is the number of differences between the bits within those binary numbers. So, the Hamming distance between 000 and 001 is 1, while the Hamming distance between 111 and 000 is 3. Gray coding can be useful in GAs because, while most mutations will allow only incremental changes, some mutations will allow drastic changes. Studies indicate that, while both coding schemes work, in most problems Gray

codes perform better than binary codes, but the programming overhead for Gray codes can be slightly more cumbersome than traditional binary codes (82).

There are many other optimization and search algorithms available. Often, these other algorithms are faster than GAs, because GA calculation can be computationally very expensive. However, GAs are very useful when the proposed design space is not smooth, or when discrete design variables are available. The basis for much of the preceding review comes from (4) and (22), which serve as excellent introductory resources for the topic.

### **2.3.2 Interactive genetic algorithms**

From the perspective of product design it is difficult to query meaningfully a person regarding his or her shape preferences. One potential way of alleviating this difficulty is through the use of an interactive genetic algorithm (IGA). IGAs are based upon the idea of involving a human as an evaluator in an evolutionary process. In IGAs the fitness function of the GA is replaced with a user evaluation of the problem. This idea was first enumerated by Dawkins in the representation of treelike graphical structures which he termed “bimorphs” (15). This led directly to work within the computer art community that basically allowed artists to make aesthetic judgments about a piece of computer generated art, and then alter the art through the aforementioned evolutionary process. This allowed the artwork to be guided by the implicit preferences of the artist. One example of evolutionary art is the “Galapagos” exhibit by Karl Sims, which ran at the NTT InterCommunication Center in Tokyo from 1997 to 2000. It allowed patrons to interact with a population of three-dimensional virtual organisms in order to evolve the population toward the discovery of new and interesting figures (20).

Beyond this, the idea of interactive evolution has been used by several researchers, artists and engineers for a variety of purposes. The commonality between all of this work is centered around the concept that human interaction with potential designs can be useful when the traditional fitness evaluation used within normal GAs is difficult (or impossible) to

describe within a mathematical framework. The human interaction essentially serves as a 'black-box' analysis of the likelihood of success for each individual within a population.

Graf and Banzhaf proposed a system for the evolution of two-dimensional pixel images and three-dimensional voxel images with user interaction (25). Specifically, these researchers applied the IGA methodology to the creation of new design concepts for automobiles in two-dimensions by using bitmap images of current vehicles. They then associated tie-points to specific identifying points of the vehicle. These points were then used, along with user selection, to generate a new population of vehicles. These same ideas were applied to three-dimensional voxel space for the evaluation and alteration of tea pots.

Further, Banzhaf discussed the potential, the limitations and the important issues that surround IGAs (1). One of the potential application areas cited is the field of product design, specifically the assessment of user aesthetic preference for a design through the implicit means of the IGA. He also mentioned the important influence that fatigue could have on a subject during testing, and the potential for a subject to become overwhelmed by the number of available choices that they have to choose from. Finally, Banzhaf alluded to the potential for IGAs to be integrated within the consumer market:

With the advent of interactive media in the consumer market, production-on-demand systems might one day include an interactive evolutionary design device that allows the user not only to customize a product design before it goes into production, but also to generate his or her own original design that has never been realized before and usually will never be produced again. This would open up the possibility of evolutionary product design by companies which track their customers' activities and then distribute the best designs they discover.

Banzhaf highlighted some of the very items being investigated in this dissertation, and his mention of respondent fatigue points to one of the critical barriers that could keep IGA techniques from being effectively utilized. Other issues surrounding the validity of IGAs are: the ability to accurately partition an artifact into important components for variation; providing enough perceptual tiling for each component such that respondents can visually perceive component variance between individuals and generations; coding the genetic structure such

that irregularity is reduced during the mutation process.

More visually advanced systems that employ the IGA techniques have been developed by Cho, et al. Their work has utilized highly refined computer imaging for the development of unique designs. Specific applications have been within fashion design, bottle design and the generation of a realistic green pepper (61; 10). All of these examples use IGA. However, some of the testing methods used may violate human perception constraints. For instance, they suggested that a subject can evolve a green pepper in 30 to 50 generations, requiring 30 to 50 minutes of testing. Yet, other researchers have suggested that subjects tire easily from IGAs and suggest that better information can be gained by reducing the number of evaluations (40). Cho and his colleagues asked subjects to rank each item, within a population of 20, on a scale of 1 to 5. While other researchers used simple ‘survive’ or ‘die’ rules governing whether or not an individual design proceeds on to the next generation (7; 40).

Hsiao and Liu leverage fuzzy theory and back propagating neural networks in conjunction with IGAs as tools to generate and evaluate populations of potential design solutions. This work was utilized in an attempt to design quartz alarm clocks and rolling office chairs (36).

Not all IGA work has been focused on visual stimuli. Work by Wakefield has utilized IGAs in order to address the field of psychoacoustics (16) (75). Here a user’s evaluation of an audio sample is used within the GA process in order to tune a system such that it achieves a preferred auditory response. Their specific applications have included hearing aides and automobile interior design. IGAs have also been used to assess an expert’s opinion regarding the feasibility of complex systems (7). These researchers used experts in the fields of aeroelasticity and manufacturing to assess the ‘fitness’ of a particular design within these two domains and to eliminate those designs that were unlikely to be successful. The use of experts saved on computational resources, and increased the speed of the evaluation.

One important thing to note regarding this branch of research is that, while its preference

assessing capabilities have been assumed, they have never been rigorously tested or verified using another tool. This means that, while we can identify their benefits, we cannot say with anything more than speculation that IGAs can help us identify user preference. All other forms of these algorithms have been used to help tune systems, or toward the development of a design with a defined goal.

## **2.4 Automated design generation**

As opposed to determining aesthetic rules, or even determining the wants of the user, several researchers have examined the idea of enhancing the creativity of the designer through the automatic generation of potential designs. These automated design schemes allow the designer to effectively “encode” a particular design into elements that can be automatically altered. These alterations generate new design ideas, some infeasible, some impractical, but all with the intent of augmenting the abilities of the designer toward the generation of new, exciting, attractive and, ultimately, desirable artifact designs. While demanding more in upfront effort to the designer, from the standpoint of parameterizing the design and defining elements that will be allowed to vary (and often defining some constraints to the variance), this approach of automated design offers an interesting avenue for both design research and application.

One system proposed for automated design, developed by Wallace and Jakiela, operated under the constraints of aesthetic, ergonomic and manufacturing rules (81). The aesthetic rules for this system were based on the design principles of stability, rhythm, organization, and balance, which they based on the “gestalt laws of organization and industrial design guidelines” (81). But, these rules do not have the rigorous scientific validation achieved in the work of Bauerly (2).

Wallace and Jakiela composed a software tool because, in their assessment, the separation of form and function, which they claimed are often at odds due to the differing

design focus of industrial designers and engineers, often leads to unappealing or difficult to manufacture products (81). Their software is general and capable of creating designs for many products, however its database must be informed by catalogs of components that could be part of the design, rules that govern aesthetics, ergonomics and manufacturing, and style elements that affect the appearance of product features, such as corners. They applied the tool to the development of a stereo system. The software was then able to develop several design alternatives that could be used by a designer to enhance their design creativity. The aesthetic rules applied in this work are based primarily on the “weight” of a proposed design’s element placement. This weight is used to provide the software with a context to place components within a defined matrix of three-dimensional space. The manufacturing and ergonomic rules also assist in defining the final form of the product, but as with aesthetics, the specific mathematical formulation and implementation of these rules is not transparent.

Following this idea of providing the designer with tools that allow them to expand their horizon, Smyth and Wallace developed a design tool based on the concept of evolutionary design (74). In their work, a designer initiates the evolution process by defining a “skeleton”, or representative design form, based on existing product geometries. This skeleton is then utilized in the generation of several new design forms which the designer can interact with by selecting the designs that appeal to them. These designs are then combined and mutated (in the traditional sense of genetic algorithms) in order to create new designs. The researchers cite shape grammars, expert systems (design rules), and semantic transformation all as methods for automated design, but note that these ideas are all limited in their ability to generate new and unique ideas. They claim that the coding of a product in a genetic fashion supports this uniqueness and allows the designer the ability to control the evolution of new products, without the need to understand the mathematical structures that provide the backbone of that product generation. The researchers claimed that an interesting aspect of this work is use of the skeletal system to define the initial design, but it seems that this



skeletal structure is nothing more than the definition of the artifact's chromosome (which is a standard practice in all forms of genetic algorithms). Despite this, the work has been interestingly applied to the creation of car door designs. Again, this design tool is intended to aide the designer in realizing new ideas, thus giving the final say in the design to the decisions of the designer, which could be drastically different than the actual wants of the user.

While other methods of automated design exist, most of these systems are focused on techniques for the solution of a problem. For example, given that a specific task must be completed in a specific location, and provided with a variety of constraints, a design is automatically generated from selecting a variety of components from a catalog (72). While this work is interesting, it rarely focuses on the aesthetic aspects of the resulting design, thus it will not be explored in detail here.

# Chapter 3

## Shape preference in engineering design

The question of form versus function has long been pondered by philosophers, artists, designers and art historians. However, this study seeks to examine the form versus function question using mathematical tools. Doing so promotes an understanding of how form impacts both design functionality and shape preference. This facilitates an analytical method in decision making. The purpose of this study is to first highlight the capacity of different tools in understanding shape preference and then show that combining them with engineering design allows meaningful objective decisions to be made regarding shape preference.

### 3.1 Introduction

To investigate the interplay between shape preference and engineering objectives, we formulated two case studies that focus on the design of plastic bottles. We used conjoint analysis and PREFMAP to obtain the shape preference information of a sample population. From the engineering standpoint, the bottle was analyzed using finite element analysis (FEA) to reduce the mass of material used while respecting its stress constraints. We then used the resulting models to examine the tradeoffs that existed between maximizing shape preference and minimizing material volume in the bottle design, two possibly competing objectives. In doing this we hoped to show that, despite the difficult nature of understanding shape preference, tools exist that allow us to understand shape preference and inform an overall

design process that accounts for functional engineering realities.

### **3.1.1 Study goals**

This study has several goals.

- Explore modeling differences between conjoint analysis and PREFMAP.
- Examine shape preference for two design case studies: cola bottle, and bottled water designs.
- Relate engineering analyses to preference information to observe design tradeoffs.
- Devise a generalized methodology for applying shape preference information in product design.

### **3.1.2 Course of investigation**

To examine the alignment of shape preference and engineering, a broadly focused study of preference was conducted. In this study, the differences between conjoint analysis and PREFMAP were examined to both identify the differences between these methods and to show how these differences can affect what is known about a preference space, especially when compared to an analytical representation of that space mathematically. To do this both PREFMAP and discrete choice analysis were used to develop a mathematical representation of both a predefined unimodal and bimodal mathematical function.

Following that, two studies will be described that attempt to understand preference as it relates to bottle design. In the first study, conjoint analysis was used to examine the design tradeoffs between aesthetic preference and engineering functionality in the design of cola bottles. In the second study, both conjoint analysis and PREFMAP were used to determine the same design tradeoffs in the case of bottled water designs. This second study was done to reduce the impact that currently dominant shapes in the cola bottle sector have on the results. Subjects for both studies were university aged students from the Ecole Centrale de Nantes, in France. A software program was used to collect data from the subjects, and the data was analyzed using both commercial and newly developed software. The chapter will conclude

with a proposed methodology for collecting and using shape preference information in product design.

## 3.2 Preference tool examination

To illuminate potential differences between the PREFMAP and conjoint analysis modeling techniques, we used a test function representing the ‘real’ preference. The two analysis models were then tested in their ability to reproduce this function using only information requested by the querying tool of each technique and subject to that model’s own constraints. The goal was not necessarily to ascertain which method was better, but to show that these two techniques yield different results and must be applied judiciously to design problems.

We know that PREFMAP is only capable of yielding a single best solution, so its usefulness in spaces that are multimodal is of questionable value. In fact, to get proper results one would have to either assume the regions of modal interest and then test these locations separately. On the other hand, the data collected in a single course of investigation could be analyzed to identify the disparity between a unimodal solution and the data, and if a threshold of accuracy was unacceptable then a method of identifying an appropriate model could be formulated. However, this method would require a significant amount of data to obtain a model of valuable fidelity. Recall that the equation describing the most general PREFMAP model, phase I, is:

$$P_{model}(x_1, x_2) = \frac{(x_1 - b_0)^2}{b_1} + \frac{(x_2 - b_2)^2}{b_3} + b_4 x_1 x_2 + b_5. \quad (3.1)$$

An important assumption must be placed upon this development of PREFMAP. We require that the mathematical model be an elliptical paraboloid. This then requires that the curvatures of  $P_{model}$  with respect to  $x_1$  and  $x_2$  be of the same sign. In our studies, we will require that they are both negative; implying that the model has a single maxima point. Further, we must ensure that a saddle point does not exist. Therefore, the following conditions

must be met:

$$\left(\frac{\partial^2 f}{\partial x_1^2}\right) \left(\frac{\partial^2 f}{\partial x_2^2}\right) - \left(\frac{\partial^2 f}{\partial x_1 \partial x_2}\right) > 0, \quad (3.2)$$

$$\left(\frac{\partial^2 f}{\partial x_1^2}\right) < 0, \quad (3.3)$$

$$\left(\frac{\partial^2 f}{\partial x_2^2}\right) < 0. \quad (3.4)$$

If we expand and simplify Equation 3.1, we arrive at:

$$b_1 b_3 P_{model}(x_1, x_2) = b_3 x_1^2 + b_1 x_2^2 + b_1 b_3 b_4 x_1 x_2 - 2b_0 b_3 x_1 - 2b_1 b_2 x_2 + b_1 b_3 b_5. \quad (3.5)$$

Taking the partials derivatives and simplifying yields:

$$\left(\frac{\partial^2 f}{\partial x_1 \partial x_2}\right) = b_4, \quad (3.6)$$

$$\left(\frac{\partial^2 f}{\partial x_1^2}\right) = \frac{2}{b_1}, \quad (3.7)$$

$$\left(\frac{\partial^2 f}{\partial x_2^2}\right) = \frac{2}{b_3}. \quad (3.8)$$

If we use these within Equation 3.3 we obtain:

$$\left(\frac{2}{b_1}\right) \left(\frac{2}{b_3}\right) - b_4^2 > 0. \quad (3.9)$$

$$\begin{aligned}
\mathbf{min} \quad & F(\mathbf{B}) = \sqrt{\sum_i \sum_j (P_{model}(i, j) - P_{avg}(i, j))^2} \\
\mathbf{s.t.} \quad & -\left(\frac{2}{b_1}\right) \left(\frac{2}{b_3}\right) + (b_4)^2 \leq 0 \\
& b_1 < 0 \\
& b_3 < 0
\end{aligned} \tag{3.10}$$

By devising the above form of the PREFMAP model we can guarantee that the *b-value* solutions will be appropriate for the type of output required to model the example functions proposed next.

Discrete choice analysis can be used to collect data that can be used in a MultiNomial Logit (MNL) model. This modeling technique can identify important relationships between design attributes. This type of model can account for both main effects and interaction effects under the right circumstances (63). This increased flexibility comes at a significant cost. The amount of information that must be gathered in a discrete choice study is significantly greater than that associated with PREFMAP. Further, it is common practice that this information only be assessed at the aggregate level, while PREFMAP can be used at both the aggregate and individual levels. Other techniques of examining conjoint analysis, such as hierarchical Bayesian conjoint, can be useful in reducing the required amount of data collected, but this method is not addressed within this work.

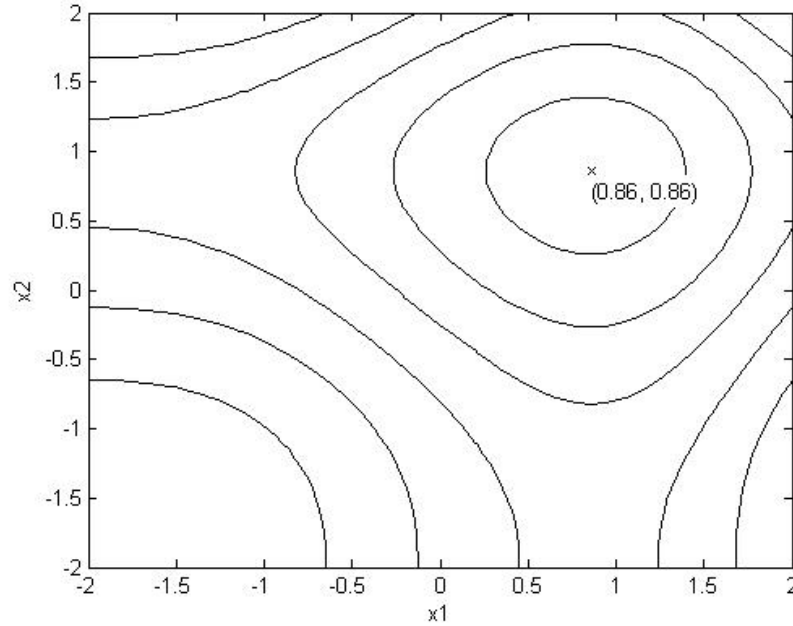
A more detailed development of the discrete choice models developed within this work will follow.

### 3.2.1 Unimodal examination

We defined an example unimodal ‘goal’ preference function as:

$$f(x_1, x_2) = [(x_1 - 2.5)(x_1 + 3)(x_1 + 2)]^2 + [(x_2 - 2.5)(x_2 + 3)(x_2 + 2)]^2. \tag{3.11}$$

This polynomial surface (see also Figure 3.1) has ridges and a single maximum  $(x_1, x_2) = (0.86, 0.86)$  within the intervals  $[-2, 2]$  for  $x_1$  and  $[-2, 2]$  for  $x_2$ . To provide preference information the design space was discretized into a 5-by-5 grid of equally spaced points. We used this model and the discretized decision space as a way to inform both the PREFMAP and discrete choice query tools.



**Figure 3.1** Goal model in unimodal comparison of preference tools.

### **PREFMAP**

For the PREFMAP query we ranked the 25 design points by scaling the function values at the discrete points to be integers between one and nine, as shown in Table 3.5. This scale is typical of actual PREFMAP surveys, where *one* corresponds to least liked and *nine* to most liked. This information was then used in Equation 3.10 to create a predicted model of preference. Table 3.5 shows the values that were provided to the PREFMAP query for each design point. This information was then regressed to the characteristic PREFMAP equation.

PREFMAP yielded an elliptical paraboloid centered at  $(x_1, x_2) = (1.03, 1.03)$ , Figure 3.2. The b-values associated with Equation 3.1 are shown in Table 3.2. Clearly, it would

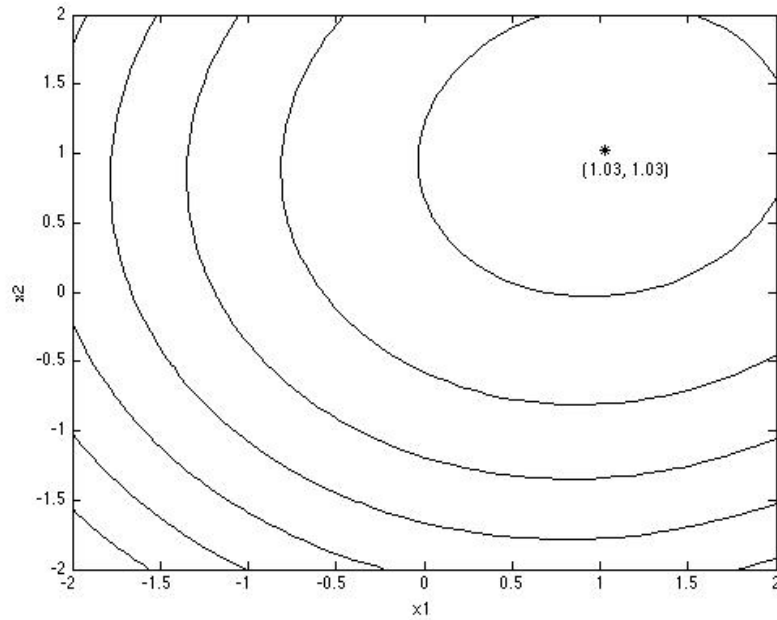
**Table 3.1** Values used to answer PREFMAP survey

x1 \ x2	-2	-1	0	1	2
-2	1	2	4	5	2
-1	2	2	4	6	3
0	4	4	7	8	5
1	5	6	8	9	6
2	2	3	5	6	3

be impossible for a paraboloid model to identify the ridges associated with Equation 3.11. However, we do notice that these results provide a solution that identifies the appropriate quadrant of the design map for further investigation and it identifies the general trends well.

**Table 3.2** PREFMAP solution b-values

$b_0$	$b_1$	$b_2$	$b_3$	$b_4$	$b_5$
0.9439	-1.7470	0.9439	-1.7471	0.0940	5.3882



**Figure 3.2** PREFMAP interpretation of proposed unimodal preference model.

Using the results of this PREFMAP study could allow a producer to properly identify an area of interest in the design space. Its optimal point indicates that it would provide the producer with a design point that closely matches the actual optimal design point. This



shows us that the generality of this model to certain unimodal design situations may yield results that are desirable by the market of interest. Thus, it can be used to determine some valuable information about the market data.

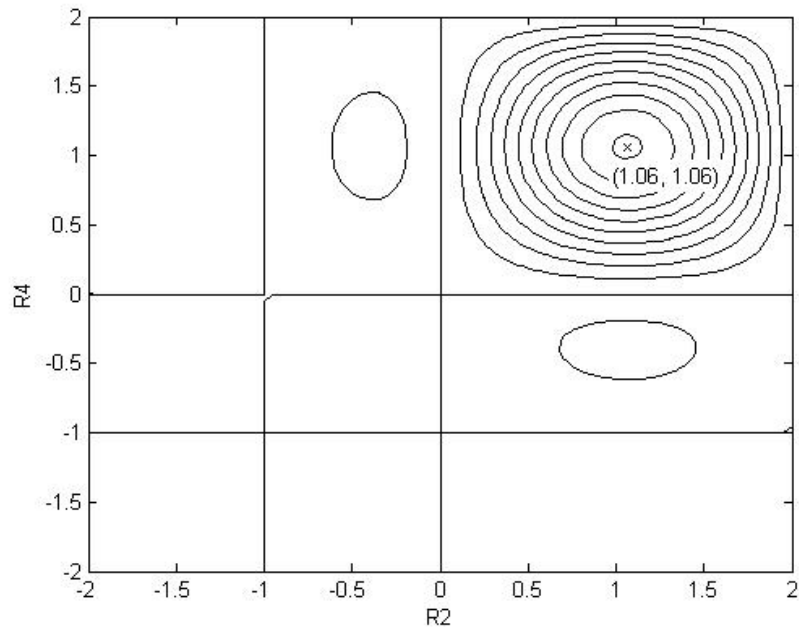
### Conjoint analysis

The discrete choice analysis query was formed using Sawtooth Software’s Choice Based Conjoint module (63). Forty ‘subjects’, modeled by computer agents, were used to answer the survey with their preferences defined by the function in Equation 3.11. Each unique survey consisted of sixteen questions; each question had five options: four were designs selected from the discrete set, and one was a no-choice option. To highlight one assumption of the MNL model, we used Equation 3.11 to answer these questions in two different ways. First, the agents answered each question using Equation 3.11, such that the option presented in the set with the greatest functional value was chosen from the set. Second, each question was answered using Equation 3.11 along with an error term having a double exponential distribution. These data were then analyzed with Sawtooth’s SMRT module, and the resulting part-worths for each attribute level were analyzed in a MNL model, thus creating an interpretation of the full-factorial marketplace (50). This describes how each design option is preferred relative to every other option. We then fit natural cubic splines to this data to obtain a continuous and differentiable model of preference.

The MNL model derived from the first set of answers mentioned above is shown in Figure 3.3 with part-worth values in Table 3.3. The model is polarized at an optimal value of  $(x_1, x_2) = (1.06, 1.06)$  and appears relatively insensitive to the ridges of Equation 3.11. The optimal point is located near the discrete choice  $(x_1, x_2) = (1, 1)$  available in the survey.

**Table 3.3** MNL model part-worths for data *without* error distribution term

$\beta_0$	$\beta_{11}$	$\beta_{12}$	$\beta_{13}$	$\beta_{14}$	$\beta_{15}$
-36.05	-45.75	-28.31	25.52	60.04	-11.50
	$\beta_{21}$	$\beta_{22}$	$\beta_{23}$	$\beta_{24}$	$\beta_{25}$
	-45.50	-28.50	25.63	59.90	-11.53



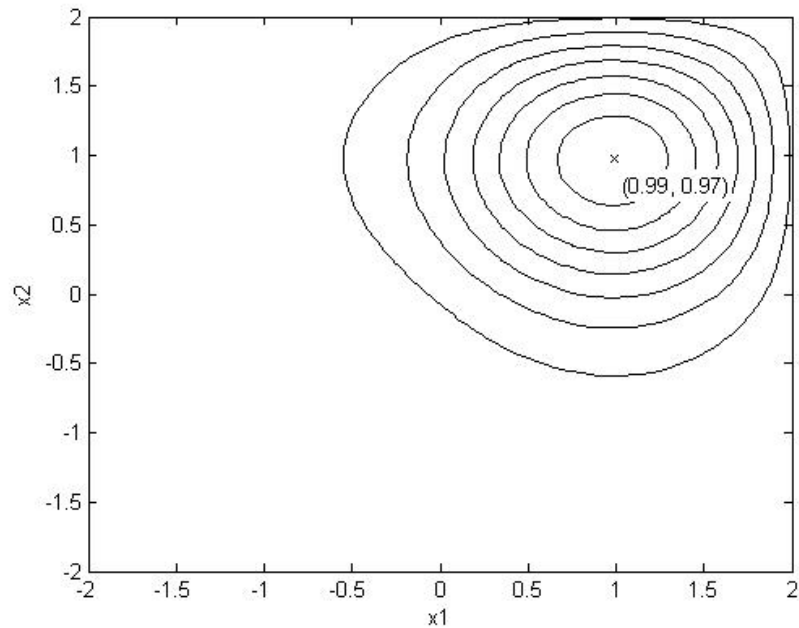
**Figure 3.3** MNL model interpretation of proposed unimodal preference model *without* error distribution term.

**Table 3.4** MNL model part-worths for data *with* error distribution term

$\beta_0$	$\beta_{11}$	$\beta_{12}$	$\beta_{13}$	$\beta_{14}$	$\beta_{15}$
-17.14	-1.59	-0.82	0.85	1.86	-0.31
	$\beta_{21}$	$\beta_{22}$	$\beta_{23}$	$\beta_{24}$	$\beta_{25}$
	-1.32	-1.037	0.90	1.82	-0.36

Figure 3.4 presents the MNL model results using the second set of answers that included the random error term, with part-worth values in Table 3.4. This model, while not fully able to recreate the original model, is much more successful than that shown without the error distribution accounted for. The ideal point coincides with the ideal design option available in the discrete set. However, the contours are less polarized toward that point and more gradient information is available to understand the preference space.

Indeed, the error term is an important assumption of discrete choice analysis. Using ‘perfect’ preference data without an error term, the MNL model quickly identifies the most preferred option and defines the design space so that the most preferred option takes outstanding preference over all other options. At the extreme, using survey information from a



**Figure 3.4** MNL model interpretation of proposed unimodal preference model *with* error distribution term.

large number of respondents answering perfectly according to a specified preference model, the MNL model would specify precisely the most preferred option, but would obscure the slopes and curvatures of the surrounding design space. Thus, if the most preferred design was technically infeasible, which might occur in a marketing survey, then identifying acceptable alternative designs would be very difficult.

A marketing survey will never have perfect data, it will always contain human error, and this is accounted for in the mathematical model with the inclusion of simulated error. Thus, in the exercise of exploring a predefined preference model and comparing it to another preference model we must account for this modeling assumption.

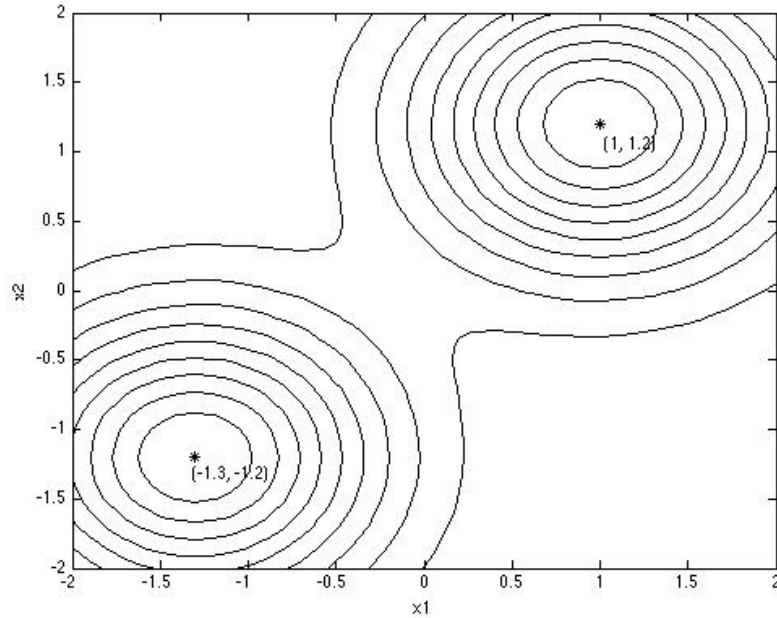
### 3.2.2 Bimodal examination

To further explore the differences between PREFMAP and conjoint analysis we defined an example bimodal ‘goal’ preference function as:

$$f(x_1, x_2) = \frac{1}{e^{((x_1-1)^2+(x_2-1.2)^2)}} + \frac{1}{e^{((x_1+1.3)^2+(x_2+1.2)^2)}}. \quad (3.12)$$

This mathematical model has two points that represent locations of highest preference, one at  $(x_1, x_2) = (1, 1.2)$  and the other at  $(x_1, x_2) = (-1.3, -1.2)$ . These two points have the same value, thus neither dominates the other. We would therefore hope that a model of preference would be capable of understanding such a bimodal response of users to such an incident, and further, be able to accurately identify those two optimal locations.

This model, shown in Figure 3.5, was examined within the intervals  $[-2, 2]$  for  $x_1$  and  $[-2, 2]$  for  $x_2$ . Therefore, the design space was again discretized into a 5-by-5 grid of equally spaced points, as was done in the unimodal case. We used this model and the discretized decision space as a way to inform both the PREFMAP and discrete choice query tools.



**Figure 3.5** Goal model in bimodal comparison of preference tools.

## PREFMAP

For the PREFMAP query we ranked the 25 design points by scaling the function values at the discrete points to be integers between one and nine, as shown in Table 3.5. This scale is typical of actual PREFMAP surveys, where *one* corresponds to least liked and *nine* to most liked. This information was then used in Equation 3.10 to create a ‘predicted’ model of preference. Table 3.5 shows the values that were provided to the PREFMAP query for each design point. This information was then regressed to the characteristic PREFMAP equation.

**Table 3.5** Values used to answer PREFMAP survey

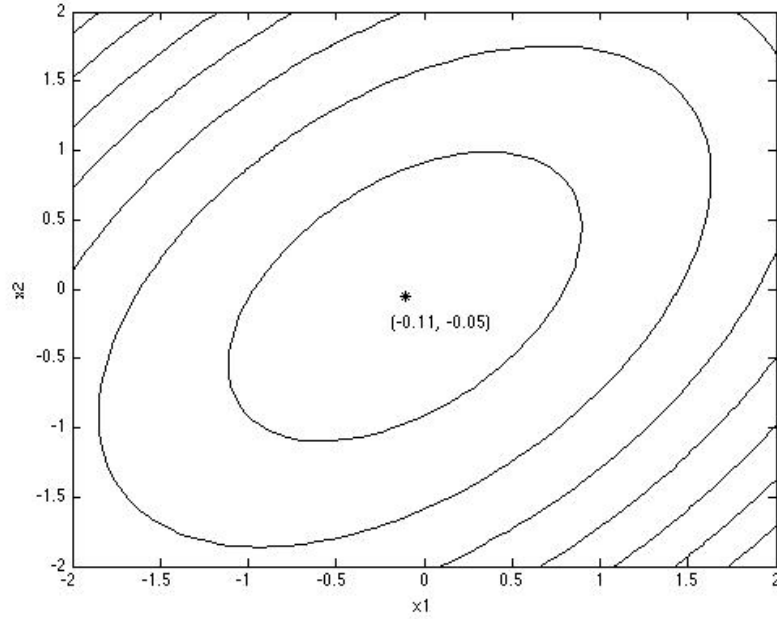
x1 \ x2	-2	-1	0	1	2
-2	4	5	2	1	1
-1	6	8	3	1	1
0	2	3	2	3	2
1	1	1	4	9	4
2	1	1	3	5	3

PREFMAP yielded an elliptical paraboloid centered at  $(x_1, x_2) = (-0.11, -.05)$ , Figure 3.2. The b-values associated with Equation 3.1 are shown in Table 3.6. Clearly, it would be impossible for a paraboloid model to appropriately model the proposed bimodal function.

**Table 3.6** PREFMAP solution b-values for bimodal problem

<b>b<sub>0</sub></b>	<b>b<sub>1</sub></b>	<b>b<sub>2</sub></b>	<b>b<sub>3</sub></b>	<b>b<sub>4</sub></b>	<b>b<sub>5</sub></b>
-0.0848	-1.6953	0.0000	-1.8264	0.5403	5.3191

This bimodal function examination shows an important limitation of PREFMAP that should not be discounted: it will, by nature, be insensitive to the identification of multiple preference locations, both local and global. Further, as seen in the example it has the effect of distorting a bimodal model into a unimodal model that may predict optimality in regions having poor functional values.



**Figure 3.6** PREFMAP interpretation of proposed bimodal preference model.

### Conjoint analysis

The previous formulation of the MNL model could only account for main effects and not interaction effects. The main effects are influenced by each attribute independent of each other attribute. Equation 3.13 accounts for interaction terms, which link one attribute to another. Due to the nature of the bimodal design space in our example it is appropriate to use this formulation of the MNL model, because interaction effects should be significant.

$$v_i = \sum_j \sum_k (\beta_{jk} \delta_{ijk} + \sum_l \sum_m \beta_{jklm} \delta_{ijklm}). \quad (3.13)$$

This discrete model of preference was then made continuous by fitting a cubic spline through the design points (55). Doing this allows us to model the example design space. Note that in this analysis we again include an error term having a double exponential distribution to meet the requirements of MNL models.

The main effects coefficients are presented in Table 3.7 and the interaction effects are shown in Table 3.8. Using cubic splines to fit this data, the resulting model was developed,

**Table 3.7** MNL model part-worths for proposed bimodal model, main effects

$\beta_{11}$	$\beta_{12}$	$\beta_{13}$	$\beta_{14}$	$\beta_{15}$
-0.10	0.09	-0.07	0.20	-0.12
$\beta_{21}$	$\beta_{22}$	$\beta_{23}$	$\beta_{24}$	$\beta_{25}$
-0.10	0.20	-0.16	0.19	-0.12

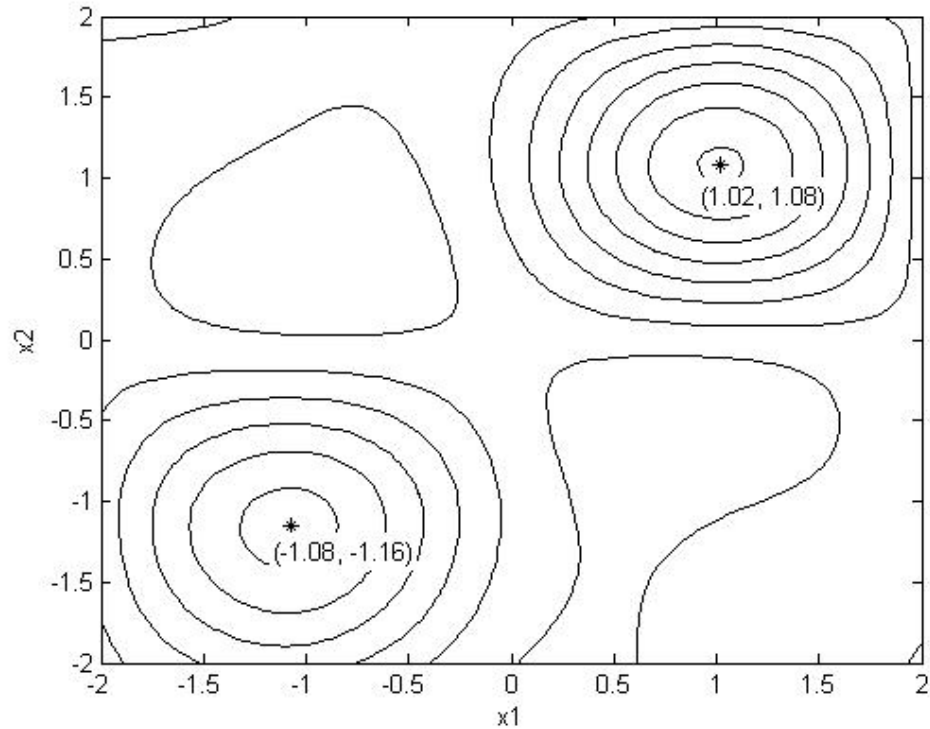
**Table 3.8** MNL model part-worths for proposed bimodal model, interaction terms

	$\beta_{jk11}$	$\beta_{jk12}$	$\beta_{jk13}$	$\beta_{jk14}$	$\beta_{jk15}$
$\beta_{11lm}$	0.21	0.29	0.18	-0.32	-0.36
$\beta_{12lm}$	0.74	1.03	-0.33	-1.03	-0.41
$\beta_{13lm}$	-0.29	-0.06	-0.07	0.28	0.13
$\beta_{14lm}$	-0.34	-1.02	-0.14	1.20	0.29
$\beta_{15lm}$	-0.33	-0.24	0.36	-0.14	0.34

see Figure 3.7. In this figure we see that the model predicts two points of local optimality, as we would hope based upon the example function. The location of these two locally optimal points are  $(x_1, x_2) = (-1.08, -1.16)$  and  $(x_1, x_2) = (1.02, 1.08)$ . These points are in good agreement with the actual optimal points on the real bimodal surface. This model also provides a great deal of gradient data that can be used in instances where the optimal points are infeasible in a larger design problem.

In general it is tempting to conclude that using discrete choice analysis to develop a MNL model will provide us with a better model of the design space. On the surface, such a statement is true. However, this statement neglects an important issue: data collection. Given unlimited resources in time, money and available respondents from a particular market segment, we would employ discrete choice analysis to obtain data. However, given practical realities, it may be beneficial to employ PREFMAP as a means of identifying a coarse understanding of the design space.

Yet, if we really want to understand the design space, both the points of optimality and the related effects of perturbations within that design space, then it would be beneficial to use discrete choice analysis with a MNL model. This does provide a practical constraint on data collection as the number of responses needed increases dramatically as both the attributes and levels of design space increase.



**Figure 3.7** MNL model interpretation of proposed bimodal preference model with interaction terms.

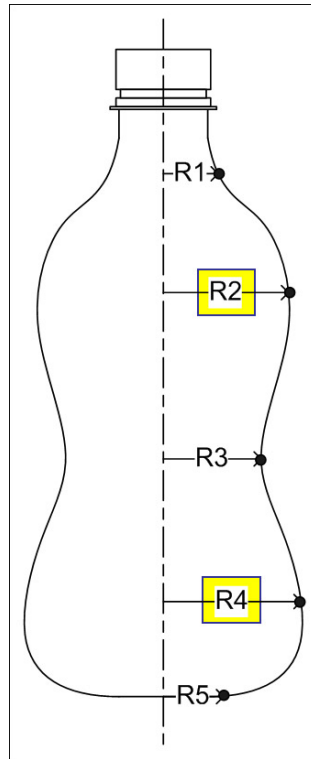
### 3.3 Linking preference to engineering

Now that we have described some techniques to collect preference data, we will attempt to use them to explore shape preference for bottle designs. In the first study, we look at cola bottle design using only conjoint analysis. In the second study, we look at the design of bottled water bottles using both PREFMAP and conjoint analysis

#### 3.3.1 Cola bottle case study

Branding through shape is important to the beverage industry. Much effort is put forth in creating unique and appealing bottle designs (43; 80; 29). The bottle shape used for this study was defined by a spline fit through five points, and subjected to prescribed end conditions. Two of the five points were considered variable, points *R2* and *R4* in Figure 3.8, and





**Figure 3.8** Parameterized bottle shape.

provided sufficient shape differentiation. Values for  $R2$  and  $R4$  were constrained between 25 mm and 50 mm. The other three points were fixed parameters during optimization. Point  $R1$  was set for a perfectly vertical end condition, while  $R5$  was set with an end condition to create an angle of 20 with the horizontal. In the engineering analysis the variables were continuous. In the conjoint analysis we discretized the design space with five possible values for  $R2$  and  $R4$ , spaced at an increment of 6.25 mm, thus creating a design space with 25 different designs.

### **Preference assessment**

The conjoint analysis survey was administered to 39 college-age individuals from the Ecole Centrale de Nantes, France. Each respondent answered a survey consisting of sixteen questions, and each question offered the respondent four shapes and the no-choice option to choose from, as shown in Figure 3.9. Each individual received a unique survey, thus creating

an efficient survey design. The data were analyzed using Sawtooth Software to obtain part-worths for each variable and level of the two design variables. Equations 3.14 and 3.15 below are simplifications of Equations 2.3 and 2.4. Equation 3.14 states that each individual bottle design,  $i$ , has a particular probability of being selected based upon the summation of its variable (or attribute) part-worths compared against all other design offerings:

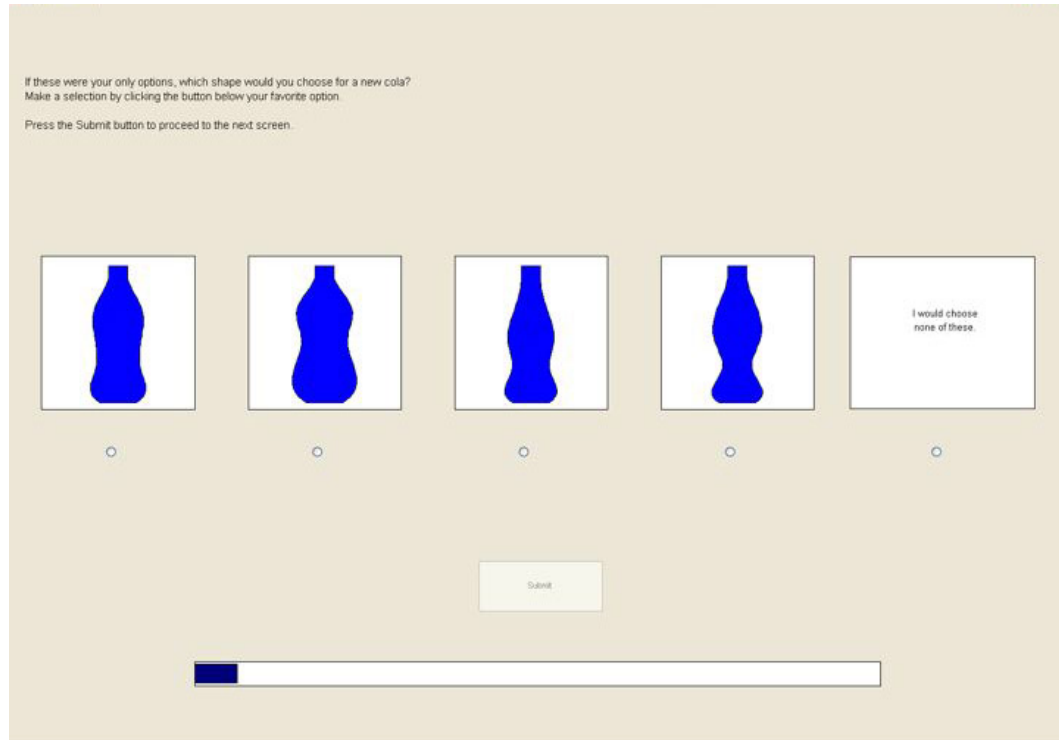
$$P_i = \frac{e^{V_i}}{\sum_{j=1}^J e^{V_j}}, \quad (3.14)$$

$$v_i = \sum_j \sum_k \beta_{jk} \delta_{ijk}. \quad (3.15)$$

Note that  $V_i$  is a linear combination of part-worth coefficients,  $\beta_{jk}$ , and a binary dummy variable,  $\delta_{ijk}$ , such that  $\delta_{ijk} = 1$  when alternative  $i$  possesses attribute  $j$  at level  $k$ . This formulation can only account for main effects and not interaction effects. The main effects are influenced by each attribute independent of each other attribute. Equation 3.16 accounts for interaction terms, which link one attribute to another:

$$v_i = \sum_j \sum_k (\beta_{jk} \delta_{ijk} + \sum_l \sum_m \beta_{jklm} \delta_{ijklm}). \quad (3.16)$$

Now,  $\delta_{ijklm} = 1$  when alternative  $i$  possesses attributes  $j$  and  $l$  at levels  $k$  and  $m$ , respectively. Their inclusion in an analysis is warranted in situations, such as shape preference, where it is likely that one attribute is not independent of the other. We therefore used the MNL model that accounted for interaction. This discrete model of preference was then made continuous by fitting a cubic spline through the design points (55). Doing this allowed us to use the design space to locate an optimally shaped bottle design.



**Figure 3.9** Screenshot of survey tool.

### **Engineering model**

From an engineering viewpoint, we desired the bottle shape that used the least amount of material to hold the desired amount of fluid and resisted the internal pressure without plastic deformation. The internal gauge pressure for this experiment was chosen to be 300 kPa (60 psi). The analysis model was built using the finite element package ANSYS (56). An axisymmetric solid model was created with a spline shape as previously described. This spline shape was given a uniform wall thickness treated as a design variable. The cap section was given a double wall thickness to prevent a high level of stress in that area (52). The bottle's bottom section was designed according to an available patent since this is typically the critically stressed location of bottle designs (70); the wall thickness here was also increased slightly to accommodate increased stress. While this bottom section of the bottle is not flat, it is axisymmetric, so it appears flat to the user in a side view and is therefore consistent with the figures shown to respondents in the conjoint survey. The maximum von

**Table 3.9** Material properties of PET cola bottle

Youngs Modulus	Tensile Strength	Poisons Ratio
1.25 GPa	25 MPa	.3

Mises stress within the bottle was calculated to ensure that the bottle would avoid exceeding the materials tensile strength. Cola bottles are typically blow molded from polyethylene (PET), therefore, PET was selected in this design problem. Its material properties are shown in Table 3.9. A simple, linear multi-objective formulation was used.

$$\begin{aligned}
 \mathbf{min} \quad & f(R2, R4) = w_1 f_1(R2, R4) + (1 - w_1) f_2(R2, R4) \\
 \mathbf{subject\ to} \quad & g_1(R2, R4) - \sigma_{max} \leq 0
 \end{aligned}$$

Here  $w_1$  is an objective weighting,  $f_1$  is the shape preference function (scaled by 500),  $f_2$  is the material volume calculation (scaled by 106),  $g_1$  is the maximum von Mises stress in the bottle, and  $R2$  and  $R4$  are the shape variables. In this problem, wall thickness was fixed at 1 mm to simplify the calculation and to make the trade-offs between the two objective functions clearer. The convex hull of the Pareto frontier set was calculated by varying  $w_1$  between zero and one.

### Combining the data

The preference model, obtained through survey data, is presented in Figure 3.10 along with the optimal shape. A MNL model that included interaction effects was used, along with splines fit to a discrete set of potential bottle designs, to generate this contour plot. The values of the main effect and interaction effect part-worths are in Tables 3.10 and 3.11. Interaction terms were considered significant according to the ‘2 log likelihood test’ and included in the model (63). The optimal design was  $(R2, R4) = (32.16, 31.61)$ .

The shape is similar to that of cola and other soda bottles in the market. The results of

**Table 3.10** MNL model part-worths for preference survey, main effects

$\beta_0$	$\beta_{11}$	$\beta_{12}$	$\beta_{13}$	$\beta_{14}$	$\beta_{15}$
-0.82	-0.15	0.47	0.44	-0.04	-0.73
	$\beta_{21}$	$\beta_{22}$	$\beta_{23}$	$\beta_{24}$	$\beta_{25}$
	0.11	0.51	0.28	-0.14	-0.76

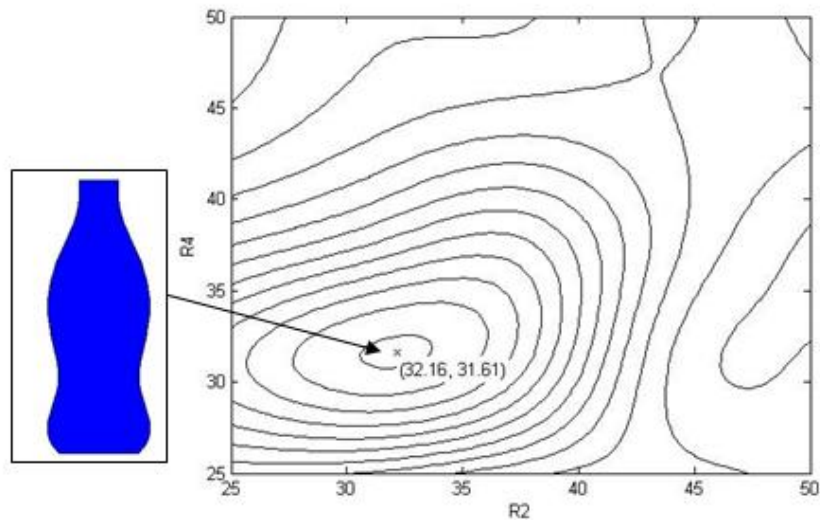
**Table 3.11** MNL model part-worths for preference survey, interaction effects

	$\beta_{jk11}$	$\beta_{jk12}$	$\beta_{jk13}$	$\beta_{jk14}$	$\beta_{jk15}$
$\beta_{11lm}$	0.66	0.84	0.41	-0.43	-1.48
$\beta_{12lm}$	-0.07	0.44	0.15	-0.34	-0.19
$\beta_{13lm}$	-0.43	0.23	0.32	-0.02	-0.11
$\beta_{14lm}$	-0.27	-0.78	-0.06	0.24	0.86
$\beta_{15lm}$	0.11	-0.74	-0.82	0.54	0.91

the conjoint study suggest that individuals gravitate toward a shape that they are familiar with. In fact, from the stand point of semantics (i.e., the message conveyed by the shape), the result suggests that subjects may prefer this particular shape for a cola bottle specifically because they have encountered it as a cola bottle shape so often previously: This shape means cola bottle to these respondents. This supports the notion that we tend to prefer what we are familiar with.

Of course, the empirical evidence here is quite flimsy. Given a greater level of context for this particular bottle it is possible that a different shape would be preferred. For instance, if we tasked users with selecting the shape that would pour a fluid most easily or if we could find users unfamiliar with cola bottles (arguably difficult), then we may have gotten different results. The goal here was to examine a notion of raw preference, but shape preference was possibly based on familiarity: A cola bottle ‘should’ look like that.

From the engineering perspective the wall thickness should be as small as possible to reduce material volume, subject to the stress constraint. Further, the values of  $R2$  and  $R4$  will be minimized to further reduce the amount of material used to make the bottle. This is shown in Figure 3.11, which shows monotonic decrease toward  $(R2, R4) = (25, 25)$ . Note that this figure is presented with a wall thickness of 1 mm to show the general trend. The optimal bottle design has  $(R2, R4) = (25, 25)$ , and a wall thickness of 0.98 mm. The maximum von



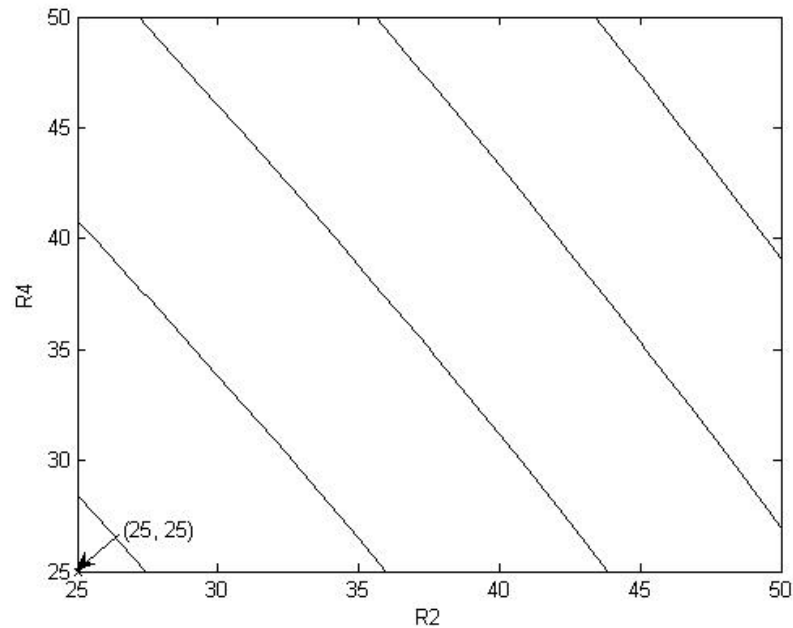
**Figure 3.10** MNL model describing preference for cola bottle shape, and most preferred shape.

Mises stress for the bottles occurred in roughly the same place on the bottles bottom. More importantly, no bottle design will fail with a wall thickness of 1 mm. Therefore, the constant wall thickness assumption is reasonable.

The Pareto solutions are shown in Figure 3.12 and are also plotted on the individual objective surfaces in Figure 3.13 to visualize the trade-off between maximizing preference and minimizing material volume. These two objectives are shown to compete. One may argue that constraints restricting the interior volume of acceptable bottle designs may change the optimal design. This is true; however, the simplified model exposes the asserted quantification of design trade-offs between shape preference and engineering functionality. More refined engineering models are certainly possible.

### 3.3.2 Bottled water case study

In the examination of cola bottles we encountered issues that confounded our study. Namely, users appeared to have a distinct notion of what cola bottles should look like based upon market saturation with cola bottles whose shapes are similar to that of Coca Cola™ bottles. This result helped us identify that the MNL model can be useful in determining shape



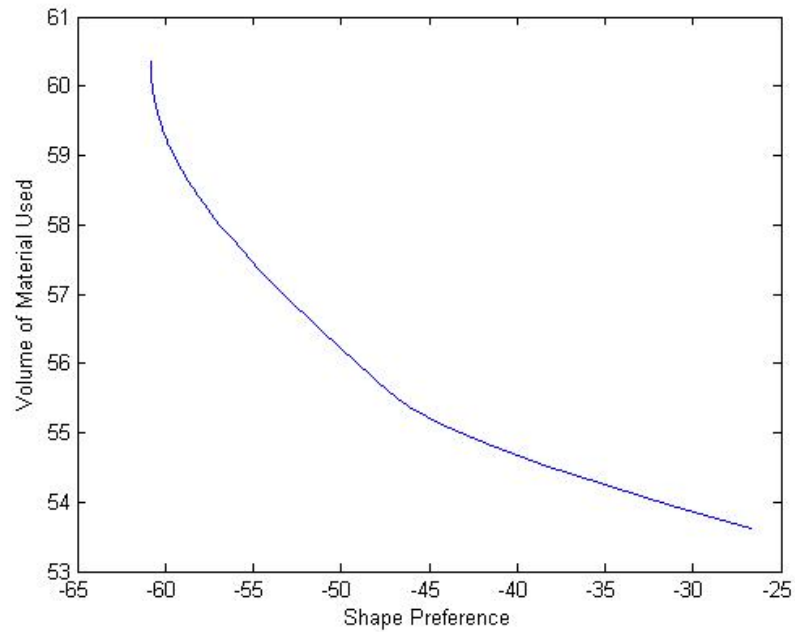
**Figure 3.11** Monotonic surface representing bottle weight.

expectations of consumers. That is to say, given a specific context, users were quite adept at identifying a preference for a known shape. This was captured by the MNL model and gives us some confidence that such a model is valuable for understanding shape preference in other contextual instances.

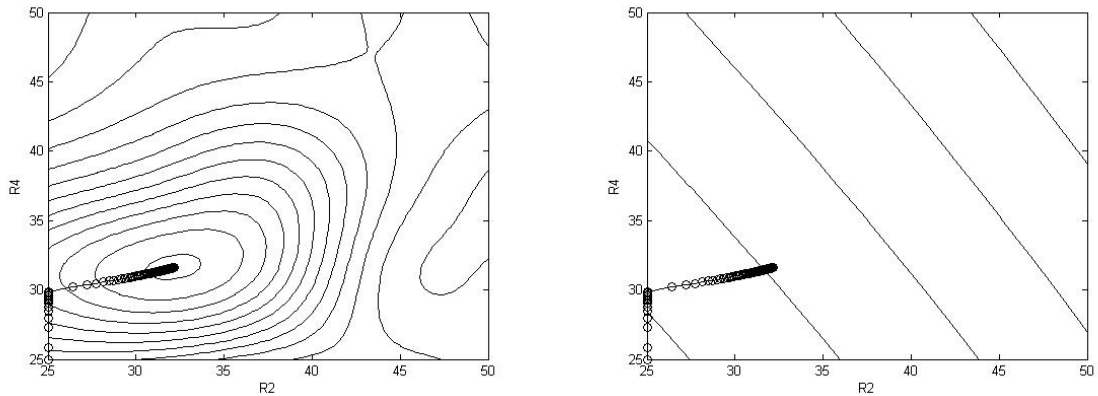
In an attempt to limit a preconceived notion of an appropriate shape we again conducted a bottle study. However, in this instance we provided users with a different context for their evaluations. We asked them to express their preference for the shapes of bottled water designs. We believed that such an alteration of the experiment would help identify a different preference space that would not be so predictable.

### **Preference assessment**

For the water bottle study 40 college age students for Ecole Centrale de Nantes were queried about their preferred shape for a water bottle using both a discrete choice survey and PREFMAP survey.



**Figure 3.12** Pareto frontier of solutions in the cola bottle design MOO problem.



**Figure 3.13** Pareto optimal solutions of cola bottle design plotted on preference and engineering models.

The discrete choice data was analyzed, as before, using a multinomial logit model with interaction effects. The results of this study indicate that, once again, subjects had an affinity for the bottle shape often associated with Coca Cola™. This may indicate that, beyond a particular visual attraction, this shape may connote a level of functionality. For instance, the ‘waist’ of the bottle may be taken to indicate the proper location to place ones hand. The ‘weight’ of the top versus the bottom of the bottle may assure users that the bottle will not



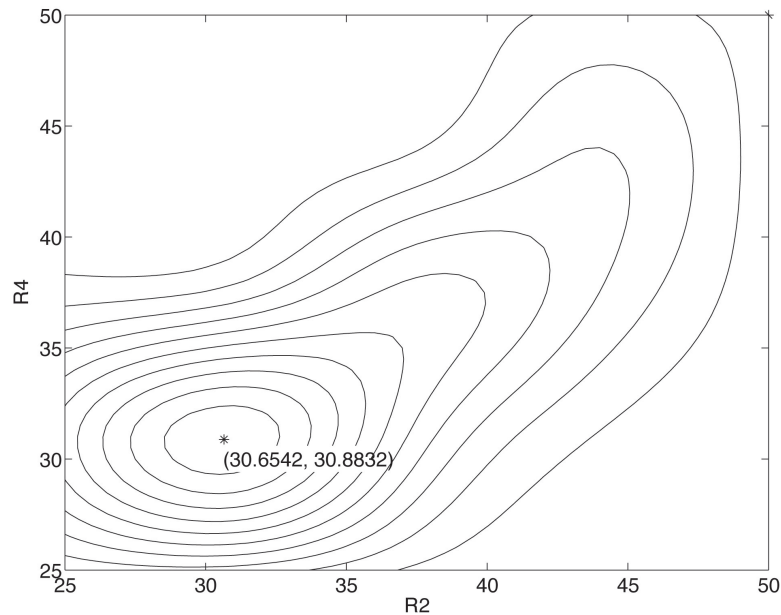
**Table 3.12** MNL model part-worths for bottle water preference survey, main effects

$\beta_0$	$\beta_{11}$	$\beta_{12}$	$\beta_{13}$	$\beta_{14}$	$\beta_{15}$
-0.28	-0.20	0.47	0.54	0.35	-1.16
	$\beta_{21}$	$\beta_{22}$	$\beta_{23}$	$\beta_{24}$	$\beta_{25}$
	-0.17	0.90	0.74	-0.61	-0.85

**Table 3.13** MNL model part-worths for bottled water preference survey, interaction effects

	$\beta_{jk11}$	$\beta_{jk12}$	$\beta_{jk13}$	$\beta_{jk14}$	$\beta_{jk15}$
$\beta_{11lm}$	1.36	1.31	0.02	-2.07	-0.62
$\beta_{12lm}$	0.81	1.15	-0.14	-0.65	-1.15
$\beta_{13lm}$	-0.42	0.26	0.55	0.28	-0.67
$\beta_{14lm}$	-1.56	-1.04	0.20	1.53	0.87
$\beta_{15lm}$	-0.19	-1.68	-0.63	0.90	1.59

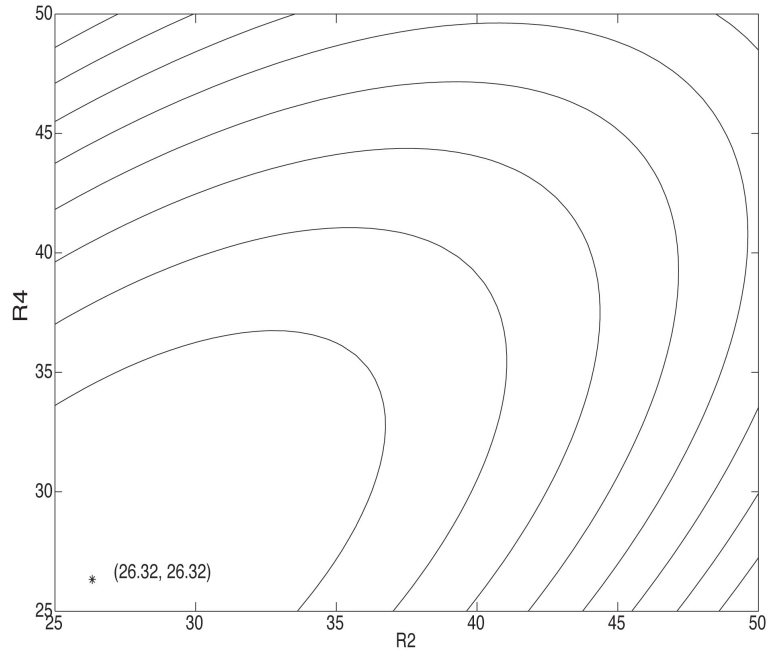
tip over easily, i.e. its center of gravity is low. Tables 3.12-3.13 show the associated beta values and Figure 3.14 shows how the preference model varies with R2 and R4.



**Figure 3.14** MNL model describing preference for bottled water shape, and most preferred shape.

We also queried users with the PREFMAP evaluation tool. Using this data we can see how the two models, PREFMAP and MNL, relate to each other in regards to this bottle design. The PREFMAP space of shape preference is shown in Figure 3.15 and the b-values

are shown in Table 3.14. It is interesting to note that both the MNL and PREFMAP models suggest a rotated preference space, thus an inherent interaction between the R2 and R4 variables is found. Whats more, this trend indicates, in both cases that there is a nearly 1:1 ratio of preference between R2 and R4. Thus, people appear to prefer R2 and R4 that are of equal proportions.



**Figure 3.15** MNL model describing preference for bottled water shape, and most preferred shape.

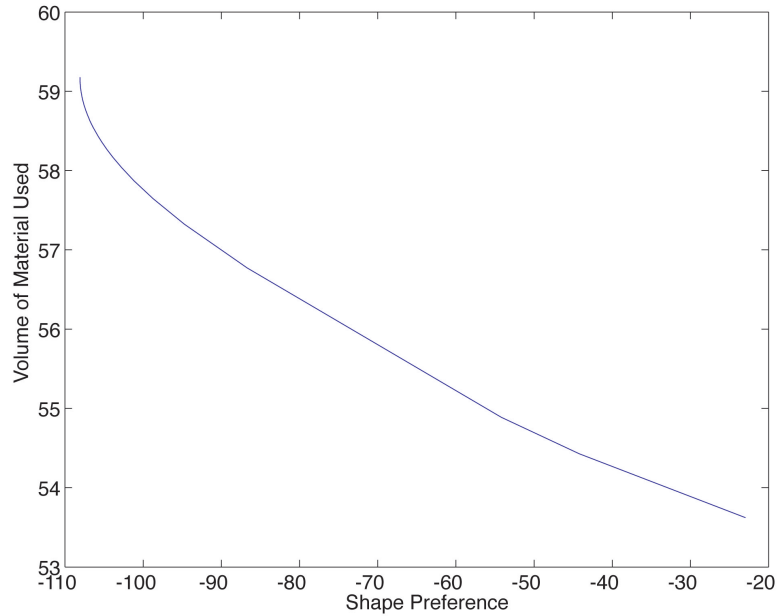
**Table 3.14** PREFMAP solution b-values for bottled water study

$b_0$	$b_1$	$b_2$	$b_3$	$b_4$	$b_5$
10.00	-1.57	10.00	-1.57	0.79	-20.00

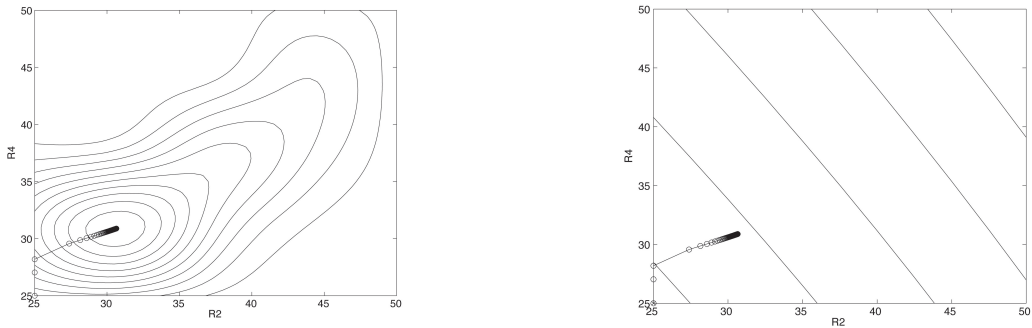
### Combining the data

The engineering analysis for this bottle is exactly the same as the cola bottle design. Thus, we are not surprised to notice that the Pareto curve associated with the design provides information that is quite similar to that of the cola bottle, Figure 3.16. We notice that there is not a colocation of the optimally preferred and engineering optimal design and we can tell

by looking at the preference space, and engineering space figures that distinctly different shapes will be produced by the two differing objectives. In Figure 3.17 we present the preference space, and engineering space with Pareto optimal design points shown on them to understand how varying R2 and R4 will affect the design.



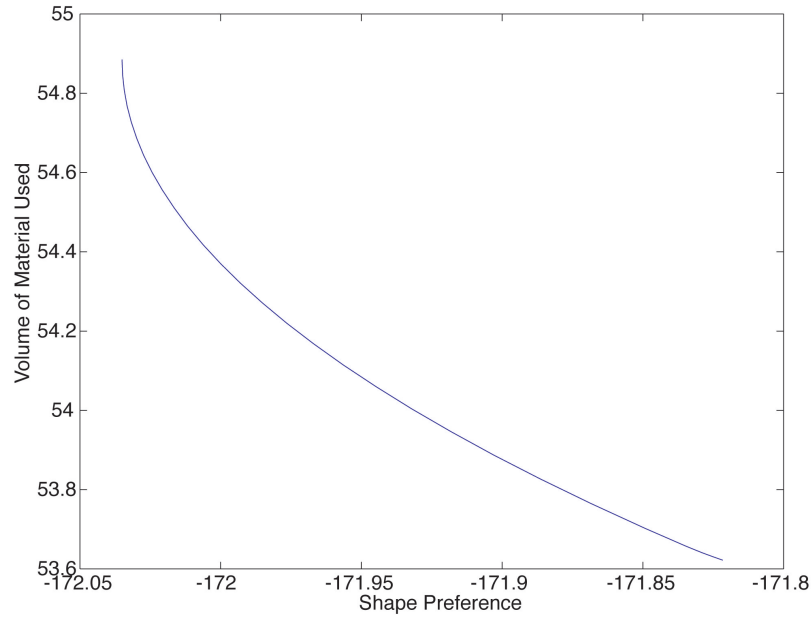
**Figure 3.16** Pareto frontier of solutions in the bottled water design MOO problem using conjoint analysis for preference.



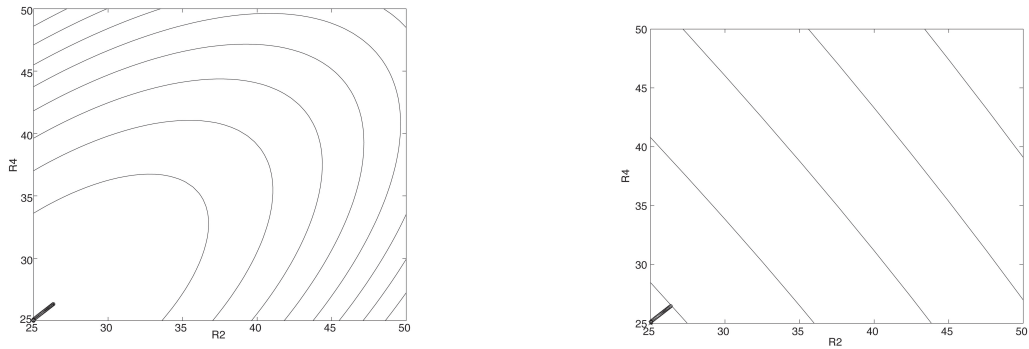
**Figure 3.17** Pareto optimal solutions of bottle water design, using conjoint analysis, plotted on preference and engineering models.

We again present the Pareto curve (Figure 3.18) and the associated Pareto points (Figure 3.19) on the models of preference and engineering to understand the tradeoffs between the

design choices. These figures show how the PREFMAP interpretation of shape preference impacts design decisions. In this case, we notice a linear path between the engineering and preference optimality points. This indicates the preference gradients impact on the Pareto figure.



**Figure 3.18** Pareto frontier of solutions in the bottled water design MOO problem using PREFMAP for preference.



**Figure 3.19** Pareto optimal solutions of bottle water design, using PREFMAP, plotted on preference and engineering models.

### 3.3.3 Discussion

This study indicates that users may have a particular preference for the shape of water bottles based on an association with historically well-marketed bottle shapes. Further, the shape may actually provide an affordance for the user, or a suggestion of how to use the object. We also note that this study limited users to a selection between two variables, R2 and R4. If the bottle were parameterized in a different manner then it is likely that different results would be found. This study can only speak to the impact of these two variables on shape preference, subject to the constraints imposed by the bottle's architecture as explained previously in the chapter. However, this study does indicate that we can discover distinct relationships between the variables R2 and R4 and how they are related to shape preference by using both PREFMAP and discrete choice analysis. Further, we can use that information along with an engineering model to learn about the tradeoffs between the goals of minimizing material used, and maximizing shape preference.

Meaningful quantification of a product's shape preference is possible using standard methods from psychology and marketing. The methods have limitations and experiments to elicit preference must be conducted carefully. In the presented study we used two variables (or attributes) to define the variations in a particular product offering. Doing so allowed easy generation and interpretation of results. A more complex design model may describe the product with more variables. In this case, the amount of data needed for statistical validity of the MNL model would increase significantly.

A quantification of shape preference allows it to be included along with engineering attributes to explore products that are optimal in a multidisciplinary design sense, specifically exploring trade-offs between form and function. In the study presented, form and function have distinct trade-offs that meaningfully affect each other. Balancing these trade-offs is still a decision that the designer must ultimately make, presumably of quality higher than without the trade-offs quantification.

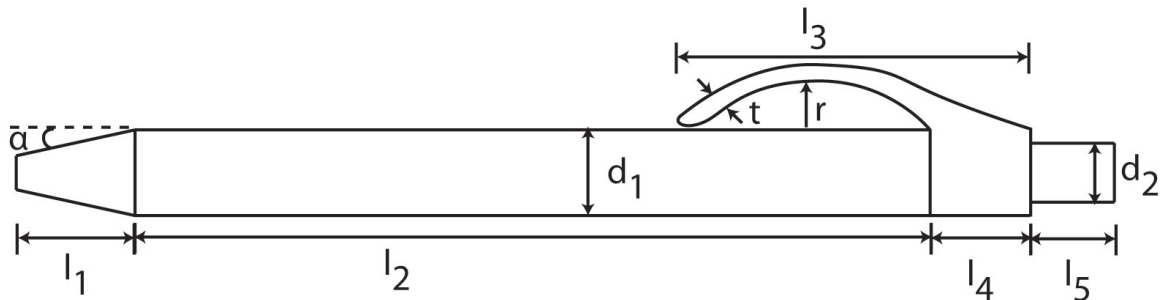
## 3.4 Methodology

Here we describe a general methodology that can be applied to understanding shape preference of any product. We further describe how the combination of an engineering model can be used in an effort to obtain information regarding the decision space associated with the product in a holistic fashion that accounts for shape preference and engineering design.

### 3.4.1 Attribute identification

Identifying the characteristic attributes of a product that affect a user's shape preference for that product is very important. Doing this requires some pre-processing of a particular design architecture. One could use Principle Component Analysis (PCA) to help identify which aspects of the design's architecture have the greatest impact on the shape preference of the artifact (38).

For instance, consider a potential design architecture for a pen, as shown in Figure 3.20. Here we have identified nine variables for the design architecture. This is only one way of parameterizing the space. In fact, we could examine ratios, spline points or other basic geometric dimensions. But, via PCA, we can obtain a good understanding of which variables have the greatest impact on the users' perception of the design. We can then use those high-impact variables as the design variables in shape preference assessment, while leaving the other parameters of the architecture fixed.



**Figure 3.20** Design architecture for a particular pen design.

Let us assume that we conducted a PCA study to identify the three most important

variables related to pen preference. Further, assume that we found that  $r$ ,  $t$  and  $l_2$  were the variables of most importance. We could then use these variables over a defined range to obtain shape preference information within the design space. We could obtain this information by using PREFMAP or discrete choice analysis as described earlier in this chapter. Such information could yield a mathematical model of preference and help us in decision making. The goals of this type of analysis are to define an artifact in a parameterized way and develop an understanding of how parameter variation affects the shape preference that users have for that artifact.

### **3.4.2 Engineering analysis**

Based upon the parameterized design space we could use engineering principles to identify the impact of design decisions on the performance or cost of the the design options. Identifying which metrics of the design are most important (i.e. identifying the design objective) is a decision that must be made by the design engineers and management. But, given an objective function and set of design constraints, the design could then be examined for an objective analysis of the engineering and shape preference goals. Thus, we now have an engineering model and a shape preference model which we could use cooperatively in decision making.

### **3.4.3 Optimal design formulation**

As we have shown in the two case studies, this form versus function question is a multi-objective optimization problem. Multi-objective optimization problems can be formulated in a number of a ways. One way is to minimize a weighted sum of several objectives. For a given functional weight,  $\alpha_i$ , associated with function,  $f_i(x)$ , this means,

$$\mathbf{min} \quad \sum_{i=1}^n \alpha_i f_i(x), \quad \alpha > 0, i = 1, 2, \dots, n. \quad (3.17)$$

Selection of  $\alpha_i$  for the different functions is not a trivial task. In this dissertation, we chose to represent the Pareto frontier of the multi-objective optimizations considered. To do this, we chose  $\alpha_1 = \omega$ , and  $\alpha_2 = 1 - \omega$ , where  $0 \leq \omega \leq 1$ . This developed the convex hull of the Pareto frontier. The convex hull only represents those Pareto points that are on the convex boundary, therefore, when sampling data for this type of optimization it is possible to neglect Pareto points that are not on that convex hull, hence the representation of the frontier may not be completely accurate.

Multi-objective optimization is a well established field and sources of information pertaining to it can be easily located, but it is beyond the scope of this dissertation to provide a detailed overview or commentary on which methods are appropriate for which cases. We chose the weighted sum method for its relative simplicity, but other techniques could certainly have been considered.

### 3.4.4 Use in decision making

The primary benefit of conducting this sort of an investigation is its ability to transform ideas regarding shape preference beyond the level of intuition and into the field of mathematical modeling. Doing this allows shape preference to be a quantifiably meaningful consideration in the design process. This extends from the impact that the artifact's shape would have on preference on to the physical implications of such a shape.



# Chapter 4

## Interactive evolutionary algorithms in preference assessment

### 4.1 Introduction

Incorporating subjective preference in design has become increasingly important in product development (24; 9; 48; 58; 67; 41; 68; 55). Efforts to understand such preferences include use of interactive evolutionary systems (IES) (77; 7; 16; 10; 30). IES have proven effective in locating goal-based stimuli, such as the clearest sound, or the color red. However, their ability to locate a user's most preferred design within a set has only been implicitly assumed. This investigation provides evidence that supports this assumption for shape preferences.

In the following, we motivate the IES investigation for preference, describe their potential, their known problems, and suggest means of solving some of these problems. We then focus on IES as a method for understanding a user's most preferred design. We introduce an interactive genetic algorithm (IGA) implemented in our experimental studies, and explain how the IGA parameters were tuned using Monte Carlo simulation. We apply our experimental design to explore two questions. First, to what extent can users find a predefined shape using the IGA? This shows how effective the IGA is at allowing subjects to seek out a specific goal, and is a question examined by other researchers. Secondly, we ask to what extent can users find their most preferred design among a set? This is the critical

aspect of this work and we employ an independent means of assessing user preference via pairwise-comparison to validate the results. Doing this allows us to make statements regarding the IGA's abilities as a preference assessment tool, something that previous studies cannot claim. We conclude with observations about the value of this approach.

## 4.2 Background

Research in engineering, marketing and psychology has resulted in methods that help designers understand user preferences for both objective and subjective product attributes (24; 9; 48; 58; 67), including shape preference (67; 41). Objective attributes, such as technical performance metrics, are typically measurable and easier to explore in terms of user preferences. Subjective attributes, such as the appeal of a product's shape, have generally not been measured and have thus been more difficult to incorporate into a quantitative design process. Researchers have recognized this problem and have increasingly tried to incorporate preference information in quantitative engineering design methods (41; 68; 55). Michalek shows that improved designs result when marketing, engineering, economic and user viewpoints can be expressed and analyzed in a comprehensive optimization framework (55).

Users have difficulty expressing explicit shape preferences because they often need context and visual examples to discern what appeals to them. Therefore, researchers have proposed and implemented interactive tools that attempt to elicit individual preferences from users (77; 7; 16; 10; 30; 83). However, recent research has examined shape preference information alongside engineering analysis in a form vs. function study and showed that, for some designs, form and function optimality are not collocated (41). It also raised questions about how well current preference assessment tools could function in deciphering shape preference. That work motivates examination of other techniques for obtaining preference information. There is implicit acceptance that IES can be used for eliciting preference

information (10; 30; 83), but there has not been substantive evidence that this is indeed the case. In this chapter we present evidence to suggest that IES are truly capable of helping us understand user preference, at least for shapes.

### **4.2.1 Interactive evolutionary systems**

Several researchers have employed IES in a wide range of applications, all using human interaction to affect the evolution of a design. Takagi offers a detailed survey of this literature (77). With IES, researchers involve a human to speed up the design process or improve the design. In some cases, it is simply more efficient to consult experts in a field and show them potential designs than to use a computationally expensive computer simulation (for example, aeroelastic analysis) to determine good designs (7; 40). Many researchers have attempted to understand user wants using IES. There have been numerous IES developed that use similar methods, but they all serve the same purpose: based on a current set of design options and user decisions the IES attempts to improve future designs.

One type of IES is the IGA, a subset of genetic algorithms (GAs). GAs are used to solve optimization and search problems by emulating principles of biological evolution (34). By genetically encoding potential design options a solution can be found through survival of the fittest. IGAs are similar to GAs, except the fitness function of the GA is replaced by a user evaluation of solution options. In some cases, the user entirely replaces the fitness function, and in other cases the user is consulted to augment some analytical function. Dawkins proposed this idea first in the representation of treelike graphical structures (15). The concept has been applied to several fields where fitness functions are not apparent, such as visual design systems (10), psychoacoustics (16), and complex systems (7; 40). Interactive genetic algorithms have also been used to understand preference at the individual level (30; 83).

Much of the IGA work implies that the evolutionary process will yield a user's preferred design. In the present study we look for evidence that supports this assumption for product

shape preferences. Some researchers have investigated IGAs' preference capability by giving subjects a 'goal-seeking' task, such as finding a specific shape or color (10; 30). The use of experts to find viable solutions is a goal-seeking task where the goal is a perceived functionality. Understanding preference is uniquely different from finding a shape, color, or design solution that meets a specific criterion. Preference may have little to do with performance criteria, or even oppose them. So, while IES have been shown to work for goal-seeking tasks, the assertion that they also work for assessing preference, while compelling, has not been substantiated.

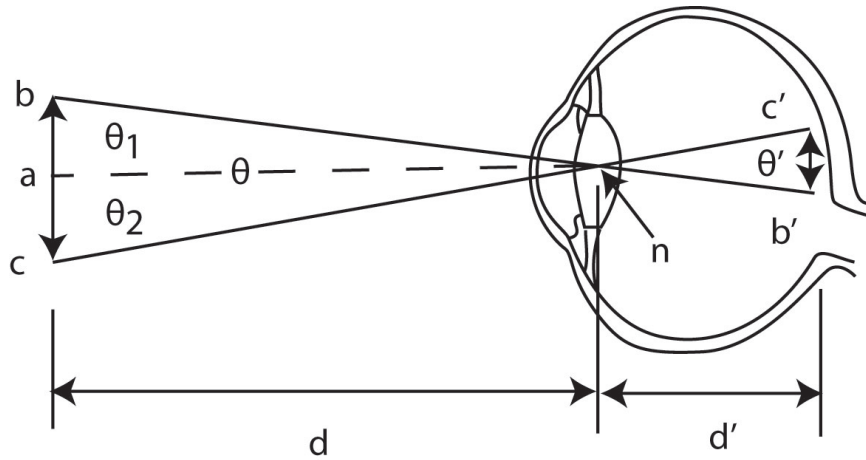
#### 4.2.2 Application of Webber's law to vision

Research in the field of vision has yielded a wealth of understanding related to the mechanisms that control the eye, and methods to correct a number of visual deficiencies and diseases. Some of the earliest research in psychophysics was conducted by Fechner in 1860 in the work *Elemente der Psychophysik* (18). The most important aspect of vision for the present study is the ability of subjects to discern differences between design options. Thus, a knowledge of visual sensitivity and acuity are of great importance. In general, Weber's Law, first described in 1834 and later quantitatively formulated by Fechner, stated that a 'just noticeable difference' (JND),  $\delta u$ , of sound and light is universally influenced by the background stimulus of comparison,  $u$  (73). The law claims that the fraction relating the difference in perception and the background stimuli is equal to some constant,  $k$ . More information regarding psychophysics can be found in (76).

$$\frac{\delta u}{u} = k \quad (4.1)$$

There are also relevant physics related to the human eye as a sensor. The JND is a by-product of the performance of the eye's sensory capacity. There are several components of vision that can be explored. Visual acuity is one way to describe the eye as a sensor.

Normal visual acuity is characterized by the ability to resolve a spatial pattern separated by a visual angle of one minute of arc. One minute of arc is  $\frac{1}{60}$  of a degree. Thus, the visual angle subtended by a spatial pattern can be determined through geometry. Figure 4.1 shows an illustration of the eye and will be referenced in defining the variance required to ensure that the increments of visual stimuli respect this definition of visual acuity.



**Figure 4.1** Diagram of the human eye with angles to geometrically calculate the length associated with a desired degree of visual acuity.

If we extend rays from  $\overline{bc}$  through the point  $n$  and extend them onto the retina, then we form two similar triangles,  $\Delta b'c'n$  and  $\Delta bcn$ .  $\theta = \theta'$  because of these similar triangles, so we can determine the angle perceived by the retina. Thus, using geometry we find that:

$$\tan(\theta_1) = \frac{|\overline{ba}|}{d}, \quad (4.2)$$

$$\theta_1 = \arctan\left(\frac{|\overline{ba}|}{d}\right), \quad (4.3)$$

$$\theta = 2 \times \arctan\left(\frac{|\overline{ba}|}{d}\right). \quad (4.4)$$

Consequently, we can determine the distance  $|\overline{bc}|$  that should be of perceptible change to the human eye based on the definition of visual acuity:

$$|\overline{ba}| = \tan(\theta_1) \times d, \quad (4.5)$$

$$|\overline{ba}| = \tan\left(\frac{\theta}{2}\right) \times d, \quad (4.6)$$

$$|\overline{bc}| = 2 \times |\overline{ba}|, \quad (4.7)$$

$$|\overline{bc}| = 2 \times \left( \tan\left(\frac{\theta}{2}\right) \times d \right). \quad (4.8)$$

Since normal visual acuity is one minute, or  $\frac{1}{3600}$  radians, this means that over a distance of one meter the human eye can discern two objects that are distanced by 0.28 mm. We have used this distance as a our JND limit in all of our visual experiments in an effort to allow subjects to notice differences between visual stimuli. This is certainly not taken as an exhaustive study of the human eye's perceptual ability. Each person has their own distinct visual acuity, but we can confidently apply this rule as a means of justifying JND choices for human subjects.

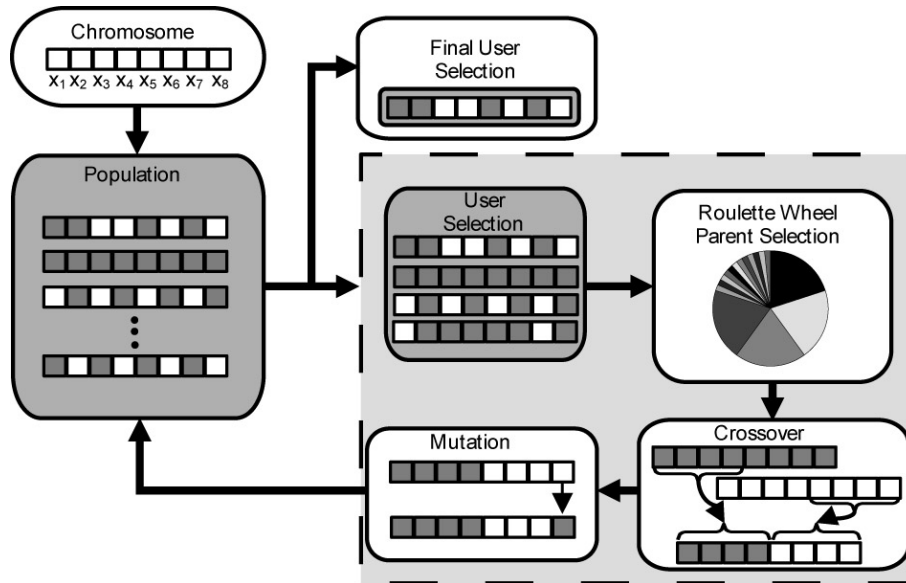
### 4.3 Specification of an interactive genetic algorithm

In this study we use a generational IGA to query users about their preference for specific shapes. We present the mechanics of this IGA and describe parameter tuning.

#### 4.3.1 Algorithm mechanics

The IGA creates an initial population of designs from a defined chromosome and presents them to a user, who then selects a subset of these individuals based on preference, see Figure 4.2. The IGA uses this information to select individuals for genetic mating, thus creating new individuals with genotypes determined by the parents. The new individuals mutate based on a random process. The IGA presents this new set of individuals to users again, and the process is repeated for several generations. In the final generation, the user selects the

preferred design from the available set and this is taken as the user's ideal shape.



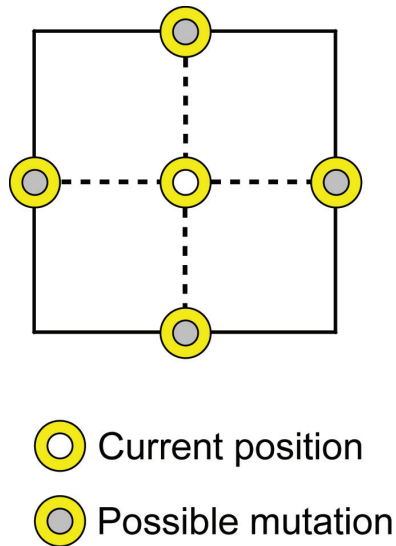
**Figure 4.2** IGA process for acquiring user evaluation information

For this study, we used a two-variable, 8-bit (4 per variable) binary coded chromosome yielding 256 design options. This is a small design space by most standards in both the design and GA communities. This chromosome dictates the shape of visual designs presented to users by defining the location of points through which splines are fit. Some researchers have proposed IGA systems in which users must rank each design within each set of a generation, while others have argued that such ranking causes user fatigue (7; 10; 40). Instead, they propose that users should identify their most and least preferred among a set because these are easier to identify than a whole ranking. This consequently reduces fatigue and provides a wealth of information. In our experiment, users evaluated shapes within a generational population of 16 and selected their four favorite choices for each generation, except for the final generation, when the user selected his/her single favorite design from that population. We believe this process is manageable cognitively because visual processing is fast and the images are static.

Roulette wheel selection facilitated the mating process. The four dominant individuals were given large, but equal, percentages of the roulette wheel, while the other individuals

were given small, but also equal, wheel percentages. Roulette percentage was a design parameter examined through Monte Carlo simulation. Mating was based on single-point crossover. The crossover point was randomly determined. Under crossover with roulette selection, it was likely that user-selected designs were chosen as parents for the next generation. Allowing the other designs to be parents permitted design diversity. In the proposed crossover scheme, each set of parents produced one offspring. No parents were ever removed from the mating pool. Thus, a single parent was allowed to spawn many children and could even mate with itself.

Mutation increased diversity in the population and potentially exposed a more preferred design. Initial studies showed that simple binary mutation methods were insufficient for this IGA. Thus, a design-space mutation operator was developed that allowed design variables to be incremented by one discrete unit in the design space. The proposed mutation operator allows local search within a preferred area. Figure 4.3 shows how mutation affects the design. We see that the design only changes in one dimension of the design space, and at only a single increment. This mutation operator functions gradually on the design options, but it also serves to change the binary structure of the individuals in a larger way than bit-space mutation operators.



**Figure 4.3** Design space mutation operator



### **4.3.2 Experimental design**

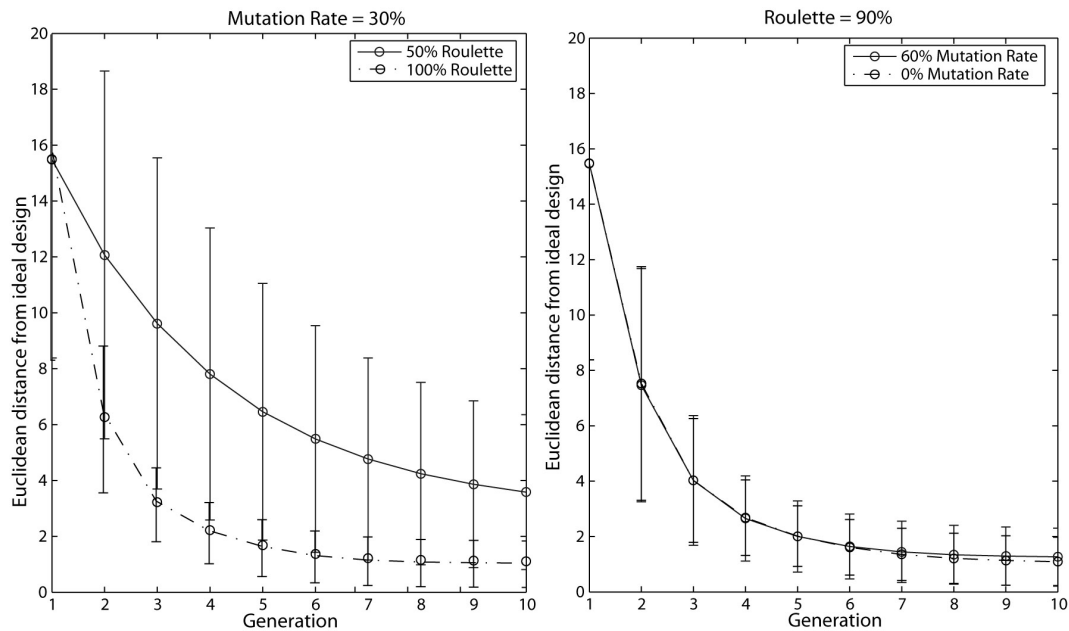
Tuning parameters for the IGA were determined using Monte Carlo simulation with a computer agent. Four selections were made in each generation, except the final generation when the agent selected only one. The computer agent made selections similar to a human user, except the agent evaluated each individual to find those with the shortest Euclidean distance between themselves and a ‘goal’ design. This goal design was a random string of eight bits, thus no preference was given to any particular schema. The tuning parameters were the percentage of the roulette wheel allocated to selected individuals and the mutation rate.

We examined the percentage of ideal solutions achieved and population convergence. The average and standard deviation of the Euclidean distance of the population at each generation were calculated. We averaged these results over 10,000 trials for each parameter combination. The initial design population spanned the design space with 16 equally-spaced designs. However, the encoding associated with this population raised fixed schema issues in the binary variable domain. Fixed schema refers to the tendency of repeated groups of bits to propagate through a population, if too many of them exist initially then they can cause premature convergence based on their specific bit sequence, and this sequence may not actually be the best option. In our case, the initial set of designs has a very limited number of schema due to the manner in which the designs are incremented in the design space. The effect of the design-space mutation operator on bit-space genes reduced this problem, because instead of changing a single bit, it changes multiple bits for an incremental design space change.

### **4.3.3 Experimental results**

Figure 4.4(left) and Figure 4.4(right) show the effect of roulette percentage and mutation rate, respectively, on the mean and standard deviation of the distance from the ideal design

for the agent-based search. Mean information is shown as a line, and standard deviation is shown as an error bar. Mutation rate had little effect on the mean and standard deviations of the IGA populations. The mean in Figure 4.4(right) shows that the IGA improved as generations increased. The standard deviation describes the amount of coherency between individuals within the population. These values converged toward a small number showing that the IGA could find an optimal design. Increasing the roulette percentage decreased the mean and standard deviation, see Figure 4.4(left), thus increasing the agent’s likelihood of finding the goal design.



**Figure 4.4** Generational convergence properties of IGA with differing roulette percentages (left), and mutations rates (right).

We examined the IGA parameters’ effects on the agent’s ability to achieve the actual goal design. The impact of increasing mutation rate from 0% to 50% caused the percentage of goal solutions achieved to rise from 20% to 93%. The impact of the roulette percentage was negligible between the range of 60% and 100%, while below 60% the unselected individuals greatly impacted the following populations and caused lower likelihood of goal design achievement within the generational constraint. This shows that increasing mutation rate increased the likelihood of achieving the precise goal design in the final generation. The

difference between this result and that shown in Figure 4.4(right) is that a high mutation rate improved the agent's ability to locate precisely a specified goal design instead of simply being near it.

We used this information to make decisions regarding IGA parameters. We chose to set mutation rate at 50%, which is high in comparison with the published standards, but proved to yield the best performance in our setting. The roulette wheel percentage was set at 90% to allow population diversity through crossover with non-user-selected designs.

## **4.4 IGA Measure of preference with human respondents**

Validation with human subjects is important since we cannot assume that users will find their preferred design simply because the GA is effective. To validate the IGA as an effective tool in assessing shape preference two aspects of the IGA were experimentally investigated: first, was the user's ability to find a predefined shape, termed 'goal-seeking' ability; second, was a user's ability to find a preferred (and unknown to the testers) shape for a bottle design. The first study was validated by comparing the dimensions of a user's final shape with those of the predefined shape. The second study was validated with a paired-comparison study where several foils were placed against the user's preferred shape as described later.

Thirty-four subjects participated in the validation study. No demographic information was collected on the subjects, but they were mainly college students. They were presented with a survey containing four separate parts.

1. First, they completed an example task to familiarize themselves with the IGA.
2. Second, they selected their favorite shape for a cola bottle design using the IGA.
3. Third, they used the IGA to 'evolve' a circle; *this task was a distraction between the previous task and the next one.*
4. Finally, subjects completed a pairwise-comparison study indicating their preference for different bottle shapes; this task was used to validate the subjects' preference for their favorite bottle design in the second task.

#### **4.4.1 Training task**

In a training task, subjects were informed about the adaptive nature of the survey, and given instructions on completing it. They used the IGA to ‘find’ (evolve) a rectangle from an initial set of shapes that did not contain a rectangle. This task allowed users to interact with the interface, become familiar with the process, and ask questions before proceeding to the main tasks. Figures were presented in a four-by-four grid. In the first four generations, subjects selected four figures they thought looked most like rectangles. In the final generation, they selected only one.

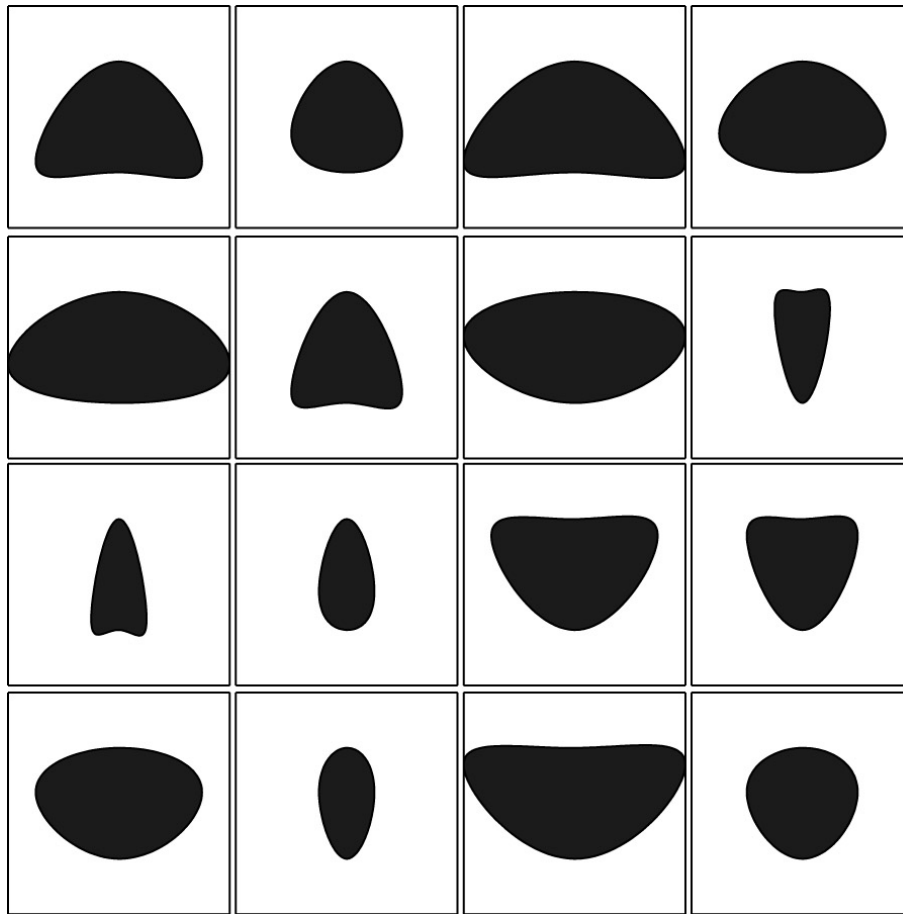
#### **4.4.2 Experimental design: goal-seeking task**

The goal-seeking task was presented as the third task for users. In this task, respondents used the population to evolve a circle. Figure 4.5 shows the initial survey population presented to subjects. The x- and y-position of one point defined the variance in shape. Only a single design option created a circle. We assumed that subjects could discern a circle from the other shapes.

The goal-seeking task served two purposes: First, to validate the IGA’s ability to allow user evolution of a predefined shape; second, to distract the user from the preferred shape task. It required subjects to focus cognitively on something other than bottle shapes. Doing so reduced their capacity to remember the ‘ideal’ shape they chose in the preference task, which was important for the pairwise-comparison task (12).

#### **4.4.3 Results and discussion: goal-seeking task**

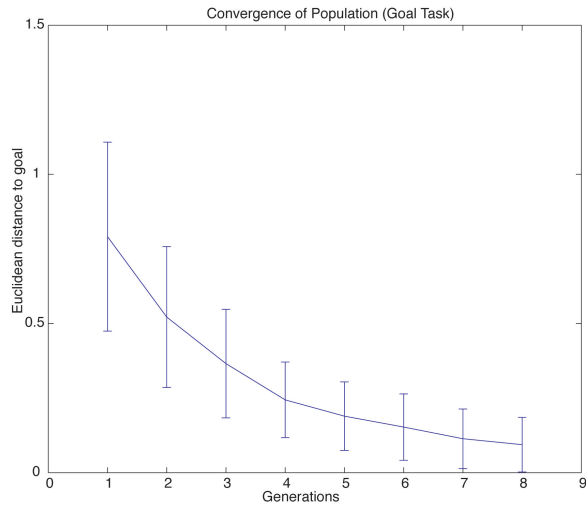
In the goal-seeking task, users attempted to evolve a circle shape. Of the 34 subjects, 91% stated that they had found the objective in a self-report question. In actuality, 68% of subjects found the circle, while the other 32% were less than 1.5 discrete design points (or roughly 6%) away from the circle shape, on average. This is an encouraging result and is similar



**Figure 4.5** Layout of IGA goal-seeking survey tool.

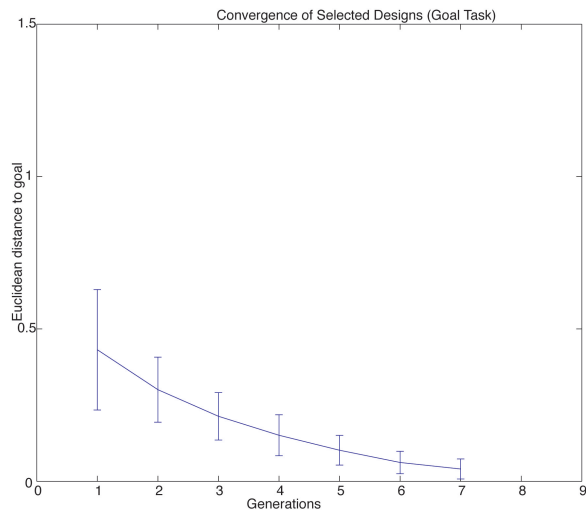
to the agent-based search in its ability to find the random goal design. The disagreement between the stated and actual ability of subjects to find the goal shape leads us to believe that self report is not a reliable measure of the IGA's ability to achieve the goal design. This may be due to the subject's inability to perceive differences between the goal shape and their final shape, especially given the small difference between the goal shape and average error distance of 1.5 discrete units. We used Webers Law, as described in the Background chapter, to design the shape variable increments, but it still may have been a problem (44).

We also examined how the population of available designs converged during the course of the IGA goal task trials. Figure 4.6 presents the mean and standard deviation of the population of designs that were available for selection. The trend shows a distinct convergence of the population toward the intended goal design. This supports the hypothesis that users



**Figure 4.6** Mean and standard deviation of the population of designs for the 34 subjects over 8 generations.

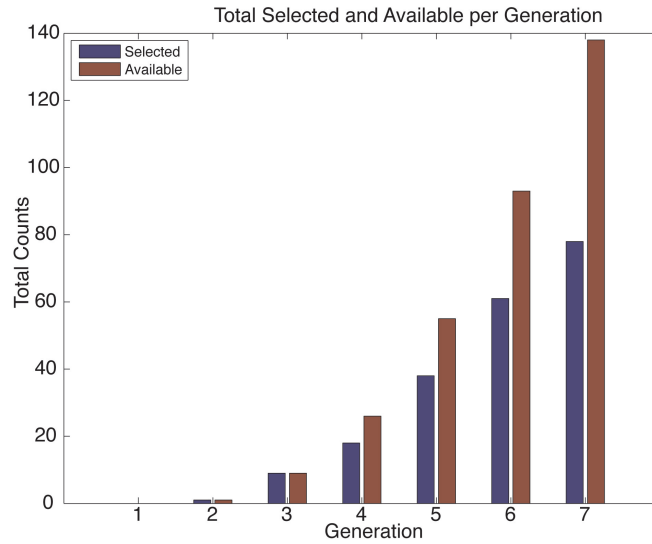
can employ the IGA to seek out predefined shapes. Figure 4.7 shows the mean and standard deviation of the four selected individuals during the course of the trials, obviously the final selection is only a single data point, so it is not included.



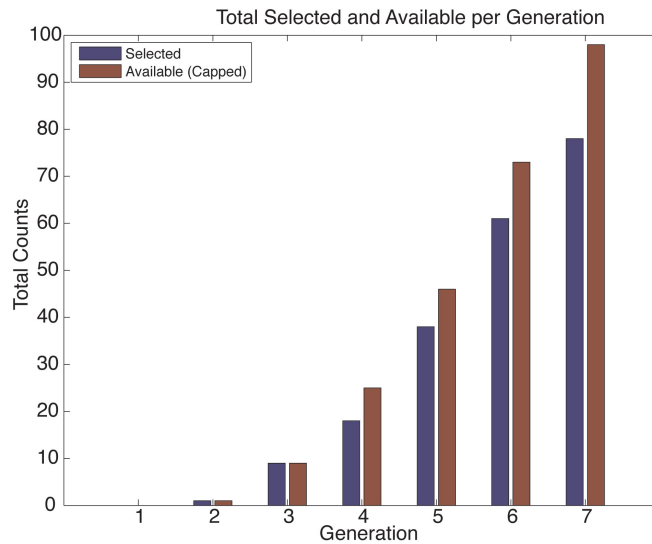
**Figure 4.7** Mean and standard deviation of the selected designs for the 34 subjects over 7 generations.

Figures 4.8 and 4.9 show the raw data regarding the number of times the ideal shape, the circle, was presented to the users along with the number of times that shape was selected. Figure 4.8 shows the entire number of the times the ideal was shown per generation, however, Figure 4.9 presents only the ideal shapes that could potentially be selected; a maximum of

four per generation. Thus, if eight of the ideal solutions were presented, then, at best, half of those would go unselected. The trend shows that as generations increase the likelihood of having an ideal solution to select from increases. It also shows that the total number of ideal selections chosen increases.



**Figure 4.8** Number of ideal options available to the 34 subjects and the number of times the ideals were selected.



**Figure 4.9** Number of ideal options available to the 34 subjects, that have the potential to be selected, and the number of times the ideals were selected.

One interesting thing to notice is that not 100% of the available ideal designs are selected

in Figure 4.9. This likely indicates a few problems: first, subjects may not have been able to discern the differences between shapes well enough; second, the fatigue effect may have caused subjects to rush their decisions and make erroneous choices; third, users may have become tired of the task and actually were trying to seek some variety. The first and second problems likely account for the bulk of the error, but this highlights the fact that, unlike a decision model, human users may make incorrect choices. However, this data strongly suggests that the IGA is sensitive to the requests of the user and can be used to locate a predefined goal.

#### **4.4.4 Experimental design: preference task**

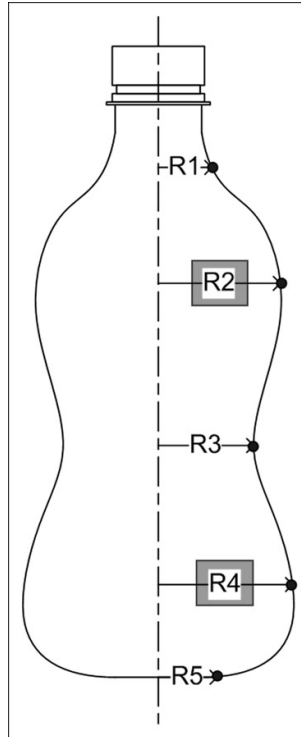
In IGA-based preference experiment, subjects used a population of bottle shapes to identify their most preferred cola bottle shape. Two experiments were performed to evaluate this question. First, we employed the IGA to obtain the user's most preferred design. Second, we compared this most preferred design against a group of foils in a pairwise-comparison task.

Before beginning the task, users were provided the following context. *Consider that a soda company wants to sell a cola. What bottle shape would you like for that cola?* The bottle shape was defined by a spline fit through five points, and subjected to prescribed end conditions, see Figure 4.10 (repeated from Figure 3.8). Two of the five points were considered radially variable, points  $R2$  and  $R4$ . The other three points,  $R1$ ,  $R3$ , and  $R5$ , were radially fixed. All points were vertically fixed. Point  $R1$  had a vertical end condition, while  $R5$ 's end condition forced an angle of  $20^\circ$  with the horizontal.

For the preference experiment, users were asked to select the four shapes they liked most for a cola bottle. Shapes were presented in a four-by-four grid (Figure 4.11). Users selected four shapes in the first seven generations and one shape in the final; this was their IGA-ideal design.

Following identification of the IGA-ideal design, a pairwise-comparison study was



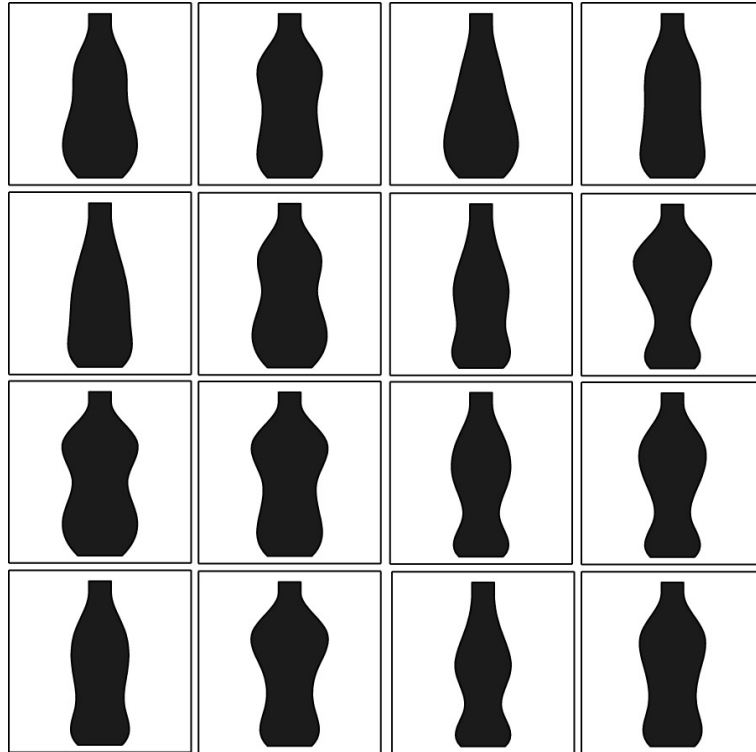


**Figure 4.10** Parameterized bottle shape.

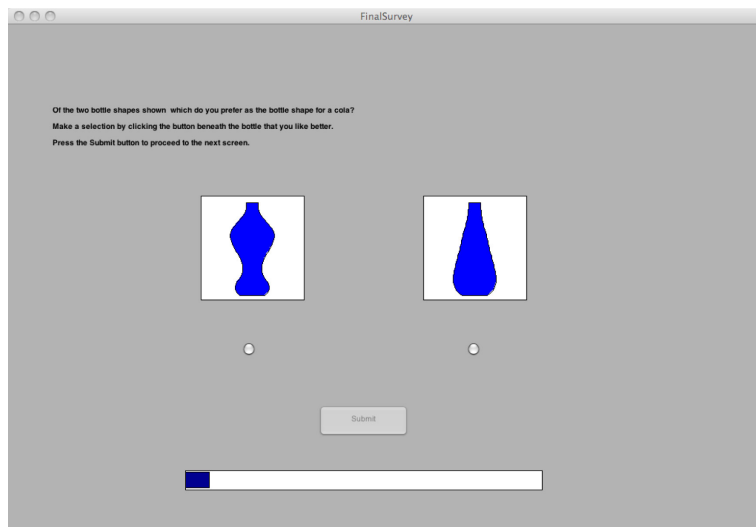
conducted in which subjects were shown 15 pairs of bottle shapes. They selected their most preferred shape among the two, Figure 4.12. Seven of the 15 sets contained the subject's IGA-ideal design. These seven instances of the IGA-ideal were randomly placed in the set of 15. The IGA-ideal was also randomly placed on either the left or right. This experimental setup was designed to control for several effects: right/left preference, early versus late exposure preference and the ability of the user to recognize the reappearance of their IGA-ideal design.

#### **4.4.5 Results and discussion: preference task**

We quantified user satisfaction with their IGA-ideal design through choice proportion. The choice proportion measure indicates the number of times the IGA-ideal design was chosen in the pairwise-comparison task. Respondents selected their IGA-ideal design versus other design options in 91% of the pairwise-comparisons. This suggests that the respondents



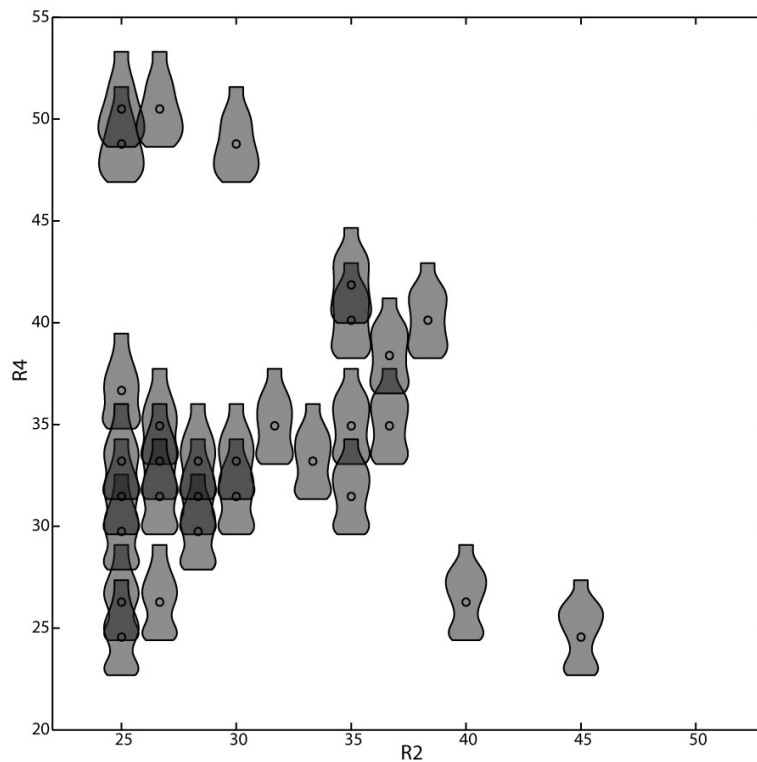
**Figure 4.11** Layout of IGA preference survey tool.



**Figure 4.12** Pairwise-comparison survey tool.

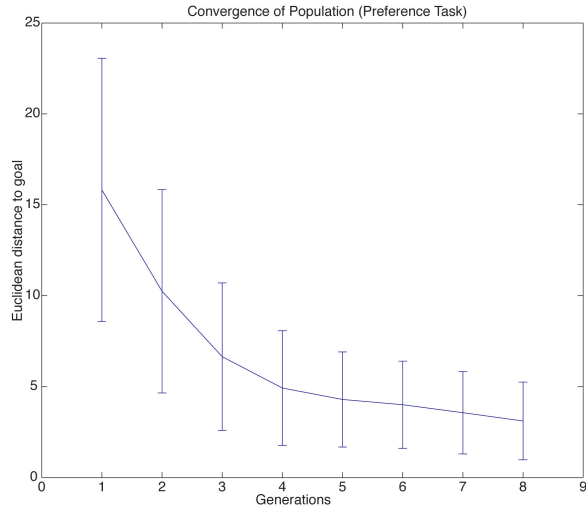
did prefer their IGA-ideal over foil options, thus providing evidence to support the IGA's ability to assess preference. Figure 4.13 shows the IGA-ideal designs of the 34 subjects plotted within the  $R^2 \times R^4$  design space. We notice that there are some clusters in an area that suggests a preference for the highly recognizable Coca Cola<sup>TM</sup> bottle shape. However,

examining this figure more closely shows that there exists numerous outliers from the typical cola bottle shape. So, while some users were highly influenced by the marketing associated with the cola industry, and chose their preferred designs accordingly, we can postulate that other users were truly more interested in finding a shape that they uniquely liked. This can be seen by observing the upper left corner of Figure 4.13. Those bottles have a ‘tear drop’ shape that varies a great deal from most cola bottle shapes currently on the market. Thus, this suggests that a subset of cola drinkers might be quite attracted to this tear drop shape and choose it over the classic Coca Cola™ shape.



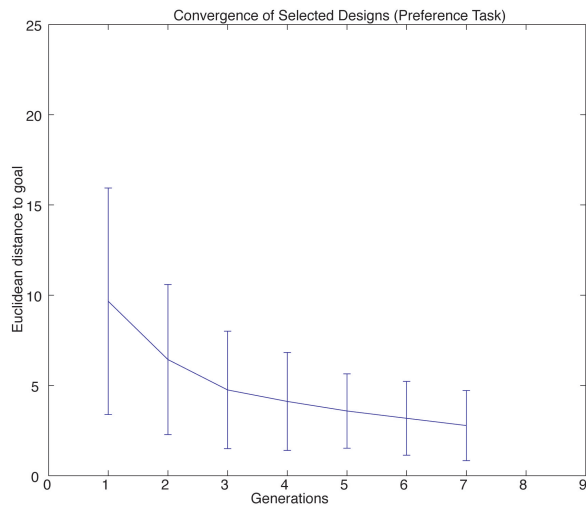
**Figure 4.13** Ideal bottles selected by subjects, shown in the design space.

We examined how the population of available bottle designs converged during the course of the IGA. Figure 4.14 presents the mean and standard deviation of the population of designs that were available for selection. The ordinate shows the Euclidean distance of the population from the goal design. In this case, the goal design was the final selection of each user. So, all of the measurements are relative to some individual favorite design. But, the trends show that there is a definite convergence over the generations towards the preferred



**Figure 4.14** Mean and standard deviation of the population of designs for the 34 subjects over 8 generations.

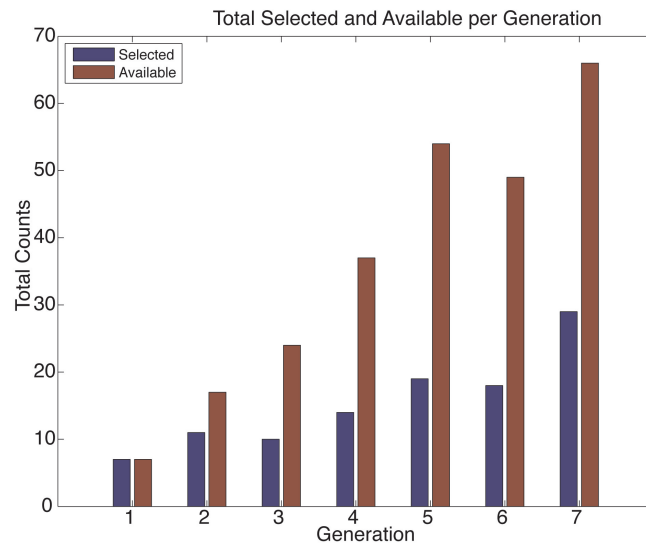
design. Figure 4.15 shows the mean and standard deviation of the four selected individuals during the course of the trials. Again, the final selection is only a single data point, so it is not included.



**Figure 4.15** Mean and standard deviation of the selected designs for the 34 subjects over 7 generations.

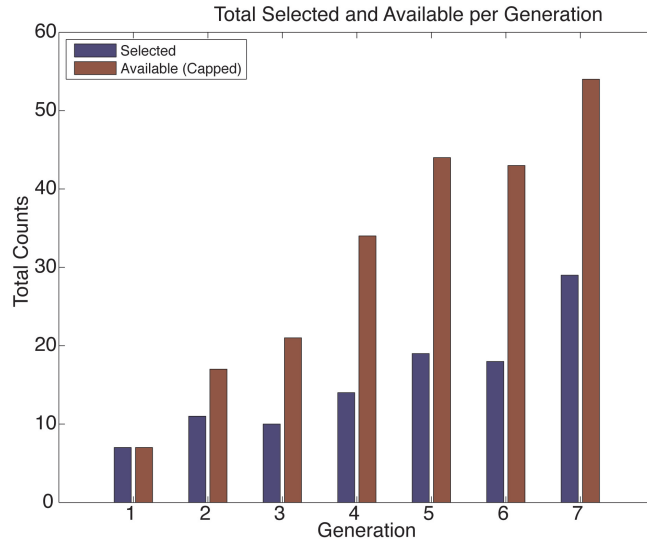
Figures 4.16 and 4.17 show the raw data regarding the number of times the IGA-ideal bottle shape was presented to the users during the course of the IGA, along with the number of times it was selected over the generations. Figure 4.16 shows the entire number of times the ideal was shown per generation, however, Figure 4.17 presents only the ideal shapes that

could potentially be selected; a maximum of four per generation. We notice an increase in the user’s ability to identify and select their preferred design over the number of generations, but it also points out that the user does not make perfect choices and is likely seeking variety in the selected choices. This does not mean that the user does not necessarily like the preferred design, but that they are curious about what else is available, and because they gained an understanding of how the tool worked, they attempted to find potentially new and interesting designs.



**Figure 4.16** Number of ideal bottle designs available to the 34 subjects and the number of times the ideals were selected.

Figure 4.18 illustrates the selection process by presenting the bottles shown to a single user on the  $R2 \times R4$  design space for 8 generations. Filled shapes represent bottle designs selected by the user, while unfilled ones went unselected. The population converges to a specific area as generations increase (generations are noted in the bottom right corner of each plot). Not every generation shows 16 design options, or 4 selections. This is due to repeated bottle shapes, both shown and selected. The figure shows how user selections, prompted by the IGA, refine the population toward the most preferred design.

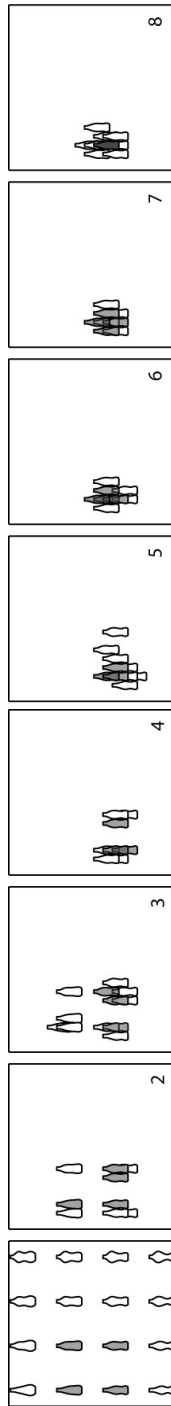


**Figure 4.17** Number of ideal bottle designs available to the 34 subjects, that have the potential to be selected, and the number of times the ideals were selected.

## 4.5 Differences between goal-seeking and preference

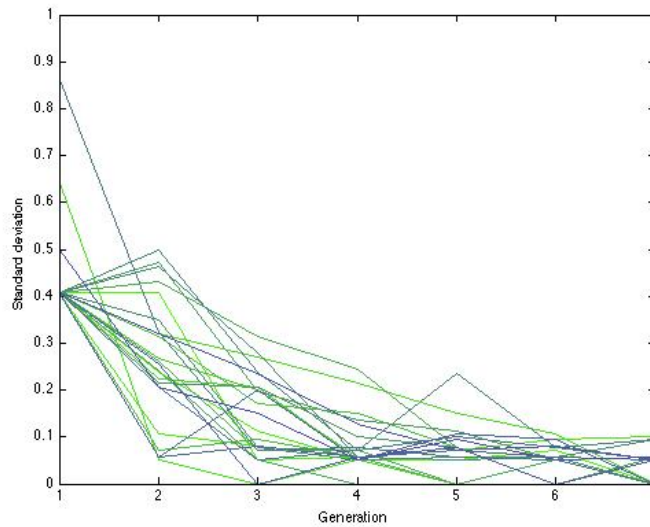
We have mentioned here that there is some distinction between goal-seeking and preference elicitation. This differentiation stems from the idea that when one expresses preference they may not have an inherent understanding of what they like prior to observation of their options. Thus, the options that they observe can impact their preferences and may cause those preferences to change. But, we would like to see if there is any truth to this notion.

We believe that, in goal-seeking tasks, users will know the precise design that is their intended goal. Hence, they ought to have a predictable generational convergence. This convergence can be observed by examining the standard deviation of the data collected in the IGA-based goal-seeking task. Because this data consists of two variables, we calculate the Euclidean norm of that data to see the combined effect on standard deviation. Figure 4.19 shows that as generations proceed each individual has a systematic and consistent decrease in standard deviation of the population. This indicates that users are aware of a design which they are seeking and they are making choices that lead them toward a single solution.



**Figure 4.18** Generation path of one subject showing available set and selected bottle designs.

In the situation of preference elicitation we expect that users may not know exactly what they prefer until they are presented with several options. Thus, we expect to observe a different pattern of standard deviation compared to that of the goal-seeking task. We



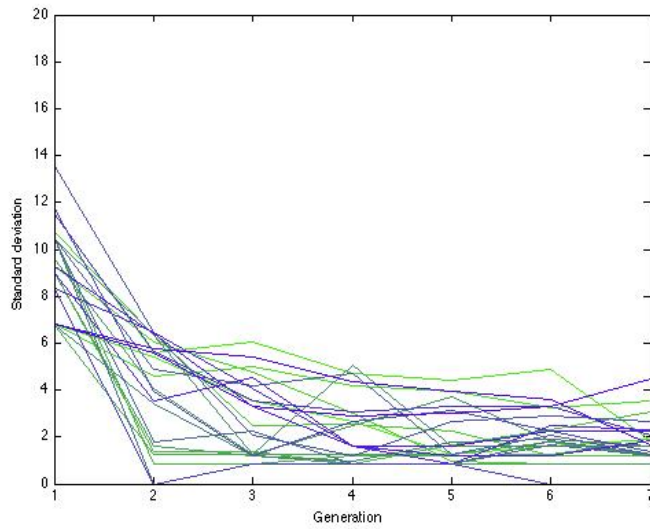
**Figure 4.19** Generational presentation of standard deviation in goal-seeking task.

observed two distinct trends in examining the data. We found that a portion of the population had a good idea of what they preferred, this is represented by their standard deviation's generational pattern, shown in Figure 4.20. We also show four of these plots individually, so that the trends can be seen more clearly, Figure 4.21. We see that these plots are very similar to those seen in the goal-seeking task, indicating that users quickly identify a goal design and make selections in an attempt to produce that preferred goal.

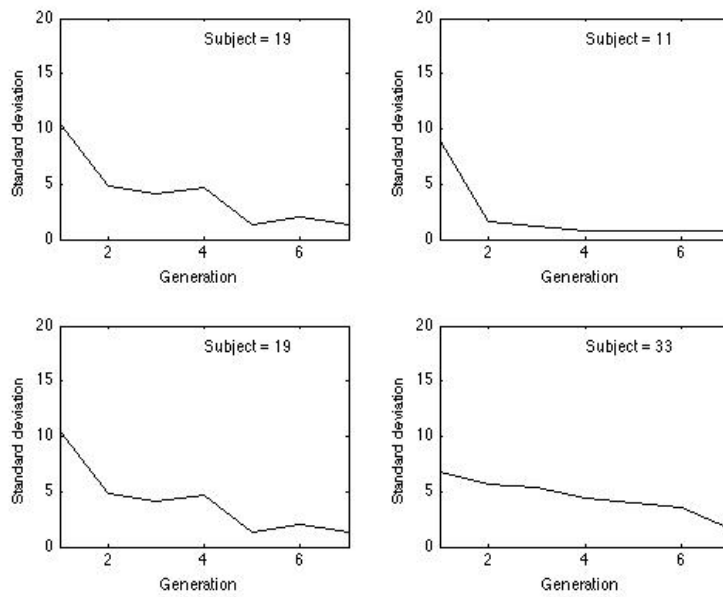
Another portion of the population seemed to take a longer period of time to converge toward a single design, this likely indicates that they were seeking variety, or that they had a multi-modal preference space, Figure 4.22. Again, we present four of the individuals' plots for greater clarity, Figure 4.23. In this case, we see that subjects take longer to converge toward a single design, but we note that convergence is generally observed.

What we see from these figures is that the idea of preference seems to differ in an important way from goal-seeking for some people. Given the context of the posed question, it is possible that users were seeking out the cola bottle shape often associated with Coca Cola™. But, we cannot know exactly what users were thinking as they responded. It is apparent, though, that some users maintained a great deal of variety in their populations



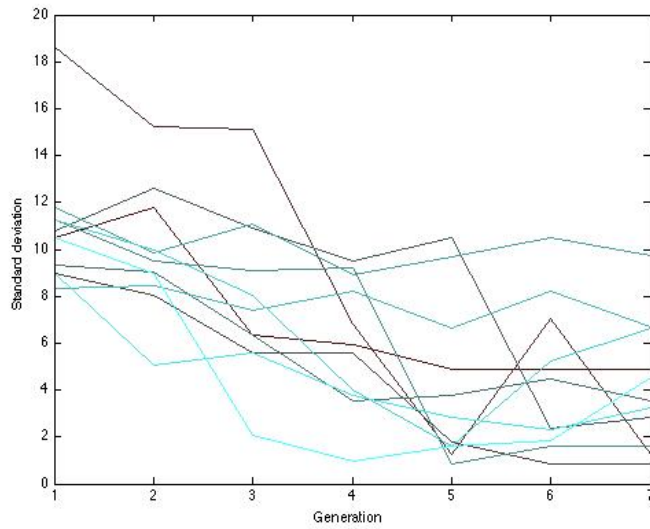


**Figure 4.20** Generational presentation of standard deviation in preference task suggesting rapid convergence, or goal-seeking.

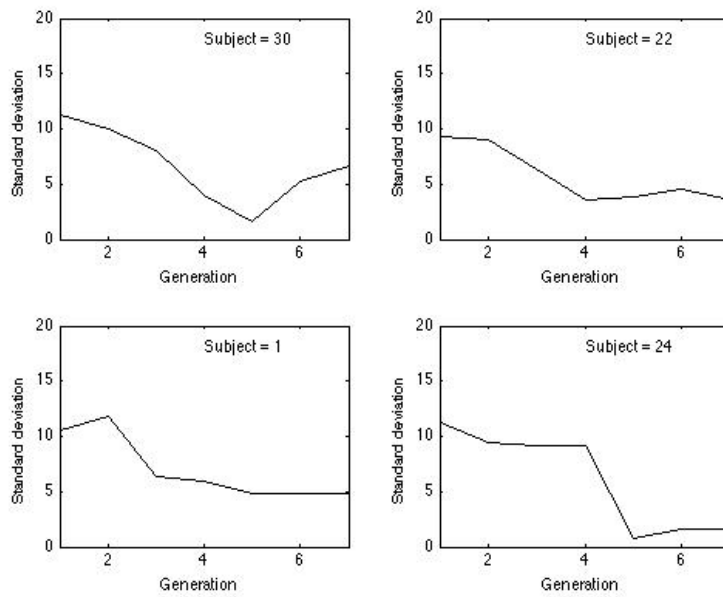


**Figure 4.21** Generational presentation of standard deviation of several subjects in the preference task that demonstrate goal-seeking.

before converging on a single preferred design. This supports the idea that users may be influenced in their choices by the options that are presented to them.



**Figure 4.22** Generational presentation of standard deviation in preference task suggesting variety-seeking.



**Figure 4.23** Generational presentation of standard deviation of several subjects in the preference task that demonstrate variety-seeking.

## 4.6 Proposed methodology

Here we outline the methodology we followed in this study and propose it as a validated approach that others can use when employing IES for assessing preference, both visual and

otherwise. If the results of the pairwise-comparison task and the preference task do not align well then it may suggest that the IGA was mistuned, or the just noticeable difference of the stimuli were not taken into account.

1. Conduct a Monte Carlo simulation or similar tuning method to obtain efficient parameters for an IES type of algorithm.
2. Present questions to users in a contextualized manner.
3. Allow a group of users to employ the IES to determine a preferred design.
4. Employ a distraction task to reduce the users ability to recall their most preferred design.
5. Conduct a pairwise-comparison study between the most preferred design and other design options to validate results from Step 3.

## 4.7 Conclusions

The shape preference capacity of the IGA is an often made but not substantiated assumption. We provided confirmatory evidence in support of the IGA's ability to allow users to evolve a population first towards obtaining a predefined shape, and second towards expressing shape preference. We tested the expression of preference using pairwise-comparisons. Both the goal seeking and preference assessment abilities of the IGA were positively confirmed. This confirmation is necessary for further research with this IGA, particularly in exploring the differences between it and other preference elicitation techniques. In the specific study, a possible bias may exist due to user familiarity with a cola bottle shape from a leading brand. A bias may also exist to the specific user population. Allowances for these possible biases would be useful in future studies. However, it does not diminish the result that the IGA can be used to identify that preference.

The proposed IGA elicits user shape preference. These preferences may be based on aesthetics, perceived usability, functionality, or a combination. No effort to distinguish among them was made in this study. An early Monte Carlo study allowed effective and efficient IGA tuning for convergence to a preferred design, thereby reducing user fatigue. Further, the IGA used a cognitively inexpensive selection process for user evaluation of

design options.

This IGA implementation yielded an ideal design point, but it does not relate a mathematical model of preference to the entire design space. This limits the use of the current IGA within a broader product optimization scheme because it lacks gradient information. Future studies may examine the sensitivity of the ideal design, thus allowing us to gain more information about the acceptable design space.

The results of this research suggest that IES can fulfill two different needs within design. First, an IES can be used to understand a population's aggregate preference for a design. This provides designers and engineers with more information as they conduct detailed design. Second, for highly customizable designs, an IES could quickly and effectively identify a preferred design for a singular user. These practical benefits should improve a producer's ability to understand their users and develop products that suit their wants.

# Chapter 5

## Interactive evolutionary algorithms in identifying contextual shapes

We have found that IGAs can be used to understand user preference and they can also be used to identify predefined shapes. We further suggest that, given these capabilities, IGAs are capable of allowing people to identify suggested shapes that match a particular contextual notion. Because of this, we are interested in using the IGA to determine if there is a vehicle shape that users identify as having good fuel economy.

### 5.1 Introduction

People understand luxury. There is a visual characteristic of luxury that extends beyond brand and price tag. Without those brand and price prompts, what is it that suggests luxury to people? It is likely some quality of an artifact's aesthetic that is enticing and communicates the messages of luxury, perhaps its shape. We wondered then, if there might also be some aspect of vehicle shape that people may associate with a design that achieves good fuel economy. We sought to find if there was a particular vehicle shape that communicated this idea in a consistent way. We used the IGA ideas developed in Chapter 4 as a means to understand the answer to this question.

If we could identify a vehicle shape that is associated with good fuel economy, then we could use that shape as a way to communicate such a message to users. In doing this, we

could provide them with a proper understanding of the vehicle's message without having to rely on explicit marketing or a user's knowledge. The vehicle would convey this message itself through its shape.

Further, we wanted to understand if users could consistently identify a vehicle shape that truly had a minimizing impact on fuel economy. To support this we used data regarding the coefficient of drag associated with various vehicle shapes in order to identify whether or not the findings of this study were in agreement with the associated physics. It is assumed that, all other factors held equal, a vehicle with a better coefficient of drag will obtain better fuel economy.

### **5.1.1 Course of investigation**

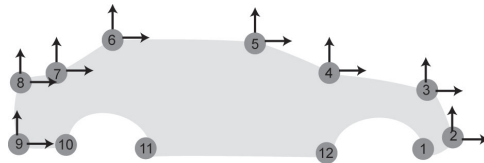
For this study, we used the previously developed IGA in a web-deployable format to rapidly collect data from users regarding the shapes of vehicle silhouettes that they associated with good fuel economy. We analyzed the results in an individual and aggregate manner to identify how well both individuals and populations understood the impact of a vehicle's shape on fuel use. We also conducted studies regarding the drag coefficient of vehicle designs. In this way we had a scientific basis that could support or contrast the findings from the shape study.

We expected that users would generally have an understanding of what vehicle shapes provide the best fuel economy. We expected vehicles with lower drag coefficients to have better fuel economy. We expected users to select shapes that were very streamlined with very few surfaces that would increase drag, such as a vertical or frontward sloping surface. We parameterized the vehicle silhouette and provided users with a known direction for its forward movement, in an effort to provide them with a proper orientation. We assumed that doing so would provide them with enough information to make decisions regarding the vehicles fuel economy. The parameterized vehicle shape was also analyzed using Computational Fluid Dynamics (CFD) to understand its drag characteristics. At no

point did we inform users that drag was of interest in this study. We hoped to find that users would intuitively minimize drag to improve fuel economy.

## 5.2 Survey design

We conducted a vehicle shape study to determine the number of points needed to describe typical vehicle shapes. Numerous vehicle silhouettes were examined and transparently overlaid. This allowed experimentation with points and splines to determine the minimum number of points needed to capture a wide range of vehicle shapes. Twelve points were selected and shapes were generated by allowing the vertical and horizontal location of eight control points to vary, see Figure 5.1. Thus, there were a total of sixteen variables. To examine the impact of vehicle shape on the user's perception of fuel economy we allowed these design points to vary and used an IGA to query them regarding their perceptions. We further posed a question for users to consider while they were taking the survey. We primed users with this text. *Today you will be presented with several vehicle designs. We would like to know which ones you think look like they would go farthest on a single tank of fuel.*



**Figure 5.1** Vehicle silhouette defined by 12 points with 8 point locations variable in the vertical and the horizontal plane.

To understand the effect of different shapes on users' perception of fuel economy, we allowed them to evolve a population of shapes. During the evolution, we asked users to select 4 from amongst a set of 16 potential design options based upon how far they felt the shape would travel on a single tank of fuel. Because the number of design points was large in comparison to our previous studies we expected that it would take users more generations to evolve a vehicle shape that they believed was green, than to evolve an aesthetically

preferred bottle shape, as was done in the previous chapter. Having subjects conduct more generational selections raised concerns regarding user fatigue. Going beyond 15 generations was generally deemed fatiguing by members in a pilot study. Thus, we capped the required number of generations at 15 to prevent users from becoming bored and distracted during their tests.

This IGA was composed of real-valued variables, as opposed to discrete-valued variables. This meant that a different means of crossover and mutation were required compared to those examined in the previously examined discrete case. For crossover, an interpolating mating procedure was used. If we consider that the real-valued genetic variables of each parent represent points on a line within the variable space, then we describe the interpolating mating procedure as selecting a random point along that line, between the two parental points, and assigning that point to the child. This form of mating is required, as opposed to simple replacement because it allows blending and averaging to occur within the population, something that cannot be achieved with real-valued replacement. To explain further, consider that parent,  $p_1$ , and parent,  $p_2$ , mate. Then all of their variables will be a linear combination of their parents, such that:

$$c_i = p_{1i} + \alpha(p_{2i} - p_{1i}) \quad (5.1)$$

Where  $c_i$  is the  $i^{th}$  variable in the child,  $c$ , composed of a linear combination of the parents',  $p_1$  and  $p_2$ ,  $i^{th}$  variable. This was done for each variable,  $i$ , within the genome where  $\alpha$  is a random value between null and unity. The mutation was a random application of mutation pressure to each variable value. Thus, this mutation acted at each variable within a set, not simply each individual, this provided more variety than mutation of each individual alone. Mutation rate was set to 10%, and was applied to each variable. Thus, this mutation operator applied a 10% likelihood of mutation to each variable of each individual. This led to a great deal of design variety. Increased design variety was hoped to help reduce user fatigue. The roulette percentage for this IGA was specified at 80%, to be consistent with previous



findings.

### 5.2.1 GUI development

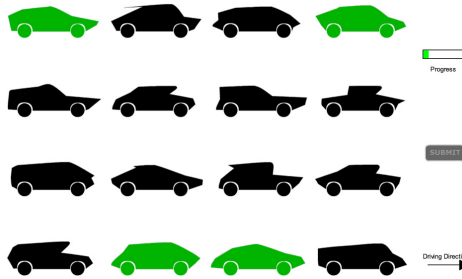
For user studies we developed a web-based survey that interfaced Adobe Flash with a MySQL database through PHP scripting. The IGA functions of this survey were developed in PHP. We used Adobe Flash as a GUI front-end to provide smooth and visually appealing figures to users that could be generated quickly and parametrically. One idea for developing figures was to generate a detailed solid model, parametrically vary that model at discrete units within the design space, and then save those images in a database for quick access by the GUI. This approach would require a large picture database to account for the 12 variables at many levels. Instead, we developed a spline function within Flash based upon the built-in *curveTo()* function. The *curveTo()* function is based on a quadratic Bezier spline, but cubic Bezier splines allow greater control. Thus, we developed an approximate cubic Bezier spline using two quadratic Bezier splines via midpoint interpolation.

The database was created in MySQL and all calculations were conducted in PHP. Using MySQL we tracked variable values and user selections, a capability not native to Flash. Therefore, we communicated to the MySQL database through PHP and back to Flash via PHP and XML code. While this code has been specifically defined for vehicle silhouettes it can be applied more generally to investigate any shape.

Figure 5.2 shows a typical screen that users saw. Figures were randomly placed throughout the 4-by-4 matrix grid, and a black screen was briefly shown between generations in order to reduce the user's ability to clearly identify shape changes from one generation to the next.

Following the user's interaction with the IGA survey, they were asked a few follow up questions to understand more about their selections. Users were given the three following open ended questions:

- Do you believe that the final car you selected is environmentally friendly? Why or



**Figure 5.2** Screen capture of IGA GUI developed in Flash, MySQL and PHP.

Why not?

- In what situations would you want to drive the car that you chose? When would you not want to drive the car that you chose?
- Do you like the way your final car design looked? Why did it, or why did it not appeal to you?

After these questions we also asked for the user's age, gender, level of education, and make and model of their current car, if they had one.

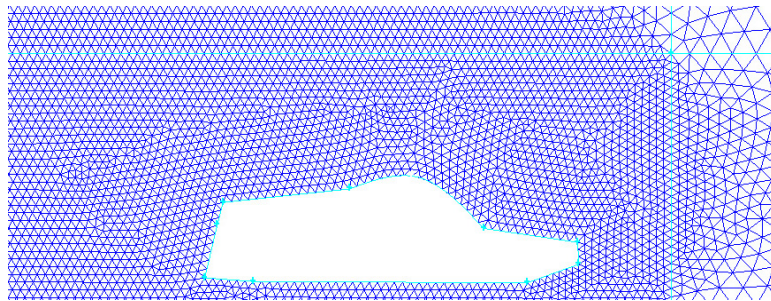
### 5.3 Engineering design

For the engineering design of this vehicle, we focused on developing an aerodynamic model that could inform us about the coefficient of drag,  $C_d$ , associated with the design variables. To do this, we employed CFD software to analyze air flow around the shape of the vehicle, defined by Non-Uniform Bezier Splines (NURBS) curves and straight lines. NURBS are a generalization of Bezier splines. These shapes differ slightly from the shapes that were viewed by the subjects, because the viewed shapes were based on a modified cubic Bezier spline. While the NURBS shapes were slightly different, the intent of this study was not for absolute accuracy of the CFD model, but for trend identification.

A Latin-Hypercube design of experiments method was used to develop a surrogate model of the coefficient of drag space in relation to the design variables. To do this, the NURBS curves, associated with differing variable combinations were submitted to the CFD package Fluent, which used Gambit as a preprocessor for mesh generation and then calculated the  $C_d$ .

The design space for this simulation was quite large, 16 variables, and the computational runtime of any CFD program was quite high. The surrogate model allowed us to understand how the coefficient of drag changed with respect to the design variables, but we caution that the results of this computation should be viewed as trends and not absolutes. Therefore, while we cannot say with confidence that a particular design has a  $C_d = .3$ , we can say that design A with a  $C_d = .3$ , is likely better than design B with a  $C_d = .5$ , with a high level of confidence. We only use this to examine trends.

In the engineering analysis of vehicle body shapes a simple 2D model was used. This model did not account for issues associated with more complex models, such as vortex shedding. But, it does offer a valuable insight into the impact of shape on  $C_d$ . In fact, such a model, in neglecting some of the more complex fluid flow phenomena, may actually represent a model of drag that is consistent with a layman understanding of the association between shape and drag. Figure 5.3 shows how the CFD software, Fluent, and its visualization tool, Gambit, were used to examine airflow around the vehicle. In reference to Figure 5.3, air would impinge upon the vehicle from the right, i.e. the vehicle is driving to the right. The mesh indicates the discretization of the fluid space, and provides an understanding of how detailed the results can be. This figure does not show fluid flow vectors passing around the shape, just the discrete mesh.



**Figure 5.3** Screen capture of  $C_d$  study mesh from Fluent via Gambit.

Using the data from 900 CFD simulations, conducted using a Latin-Hypercube sampling, a neural network was trained using a 60%, 20%, 20% partitioning of the data for training,

validation and testing, respectively. The neural network consisted of a single layer of 50 neurons. The developed model had acceptable accuracy for the purposes of this experiment. A greater number of simulations would lead to even better predictions, however, the simulations were computationally time consuming and some integration problems between the CFD and DOE sampling program, LMS Optimus, caused a great deal of manual iterations. The results of the neural network models training are presented in Figure 5.4. We can see that the R-values associated with training, validation and testing are all within an acceptable range. They were 0.98, 0.85 and 0.91, for the training, validation and testing, respectively. This gives us reasonable confidence that we can use this surrogate model to obtain  $C_d$  values for a given set of input variables. Remember, that there are 16 design variables associated with the vehicle's shape.

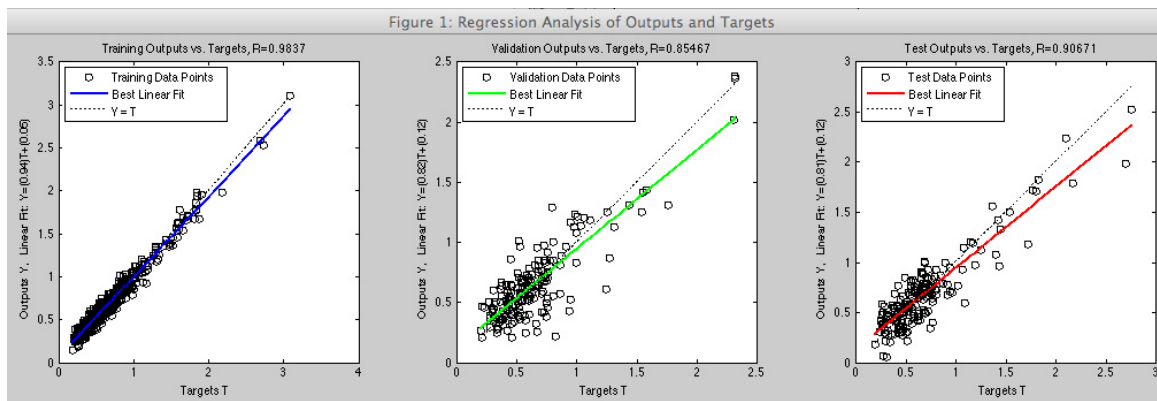


Figure 5.4 Regression plots and R-values for neural network training with  $C_d$  data.

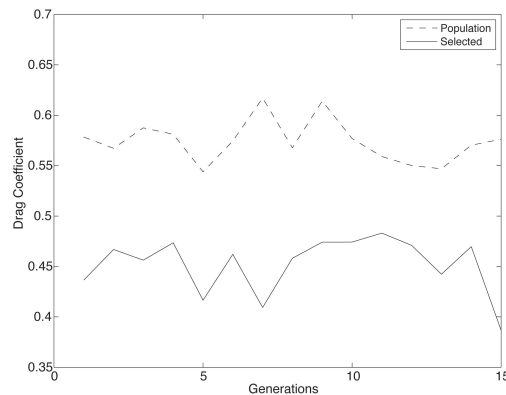
## 5.4 Data collection

Using the IGA to query subjects regarding their associations between fuel economy and vehicle shape led to some interesting observations. First, it should be noted that many of the 16 subjects in this study were engineering students, so their understanding of drag may be greater than most people. However, using this IGA subjects were able to consistently select vehicle shapes that had better  $C_d$  values than the other options offered within the population

presented to them. Subjects were presented with 15 generations of evolutionary designs.

## 5.5 Data analysis

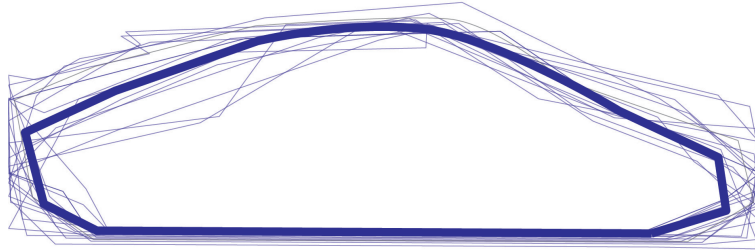
Figure 5.5, shows that the mean  $C_d$  of the selected vehicles was consistently lower than the population of offered vehicles. It also shows that, in the final generation, users selected shapes that were much better than the average of their previously selected shapes. This observation was noted by some subjects in the follow up questioning. Some indicated that they didnt always think that four vehicles were well suited candidates in each generation, but the nature of the algorithm required them to make four selections. Thus, if they could have self-selected the number of individuals which they selected there may have been a decrease in the  $C_d$  over generations. As shown, we do not notice a consistent decrease in either the population or selected  $C_d$  with respect to generation, excepting the final selection generation.



**Figure 5.5** Average  $C_d$  values of IGA population and user selected designs over generations.

One very intriguing aspect of this study was an examination of the final shapes that were selected by users. These shapes are presented in Figure 5.6 . All of the final selections of the users are presented in an overlay, represented as the thin lines. The thick black line indicates an averaged fit based on a mathematical averaging of these points. We note that

user selected shapes are shown here with straight lines but not Bezier curves, as was the condition on a few points shown to users. This caveat does not lessen the value that these final shapes have on understanding user choice. The averaged shape included the Bezier curve by including a manual manipulation of the lines.



**Figure 5.6** Visual overlay of user selected final shapes and mathematical average of the shapes.

## 5.6 Discussion

From this study, we find that individuals have some association between vehicle shape and fuel economy. Further, they can use the IGA to select shapes that consistently perform better than the average of their offered shapes. We do not propose that the shapes selected by users indicate preference, only an indication that they recognize some relationship between vehicle shape and fuel economy. Whats more, we can make no claims that they associate shape with drag, they may simply have sought shapes that were associated with vehicles that they already knew achieve good fuel economy. However, from user comments we know that several users expressed that they sought shapes based on perceived drag coefficient, therefore we know that, for some individuals, this IGA facilitated a rudimentary expression of aerodynamic understanding. And, that understanding was consistent with the findings of the engineering study, indicating that given this contextual basis, users can make selections that lead them toward good solutions.

One confounding aspect of this study lies in the phrasing of the task posed to users. By stating “...on a single tank of fuel”, several users believed that boxier vehicles, similar to

SUVs, would be larger and thus have larger tanks of fuel that could serve to weigh them down. Thus, by not stating that all vehicles had the same fuel capacity, we allowed users to make improper inferences. However, we note that the final shapes selected, and especially the average, resemble those of compact sedans, which generally do have good fuel economy. So, with that particular context in mind, users were able to evolve shapes that fit their idea of good fuel economy.

# Chapter 6

## Interactive evolutionary algorithms and creativity

This study proposes that creativity can be enhanced through the use of Interactive Genetic Algorithms (IGAs). Divergent and convergent thinking are important processes in creativity. We recognize that an analogy exists between the divergent and convergent processes of the mind and the divergent and convergent capacity of genetic algorithms (GAs). We use GAs as a way to try to understand how IGAs could be employed as creativity tools. In the context of design processes, a convergent process hones in on specific designs, while a divergent process explores design possibilities through brainstorming. This study uses Monte Carlo simulation to explore the effect of merging two GA populations, developed by the divergent and convergent methods, within a single population to allow selection. The results suggest that population diversity benefits from these population combinations while not adversely affecting the ability of the IGA to find a goal design.

### 6.1 Introduction

IGAs are powerful tools that have been used in several ways in the design community, e.g., for the identification of preference, and for the generation of new ideas (16; 10). The generation of new ideas is particularly important to the notion of creativity. By using IGAs we hope to allow designers to enhance their creativity through design space exploration.



Similarly, by engaging product users in the creative design process, we believe that the desires of the user can be more effectively met. Thus, moving the user to the ground level of the creative process may be a means of improving design. We believe that by exploiting the evolutionary nature of IGAs, we can explore a vast design space in an intelligent manner that allows designers and users to identify new and creative designs that appeal to them.

In Guilford's summary of creative abilities in the arts he stated that, "creative artistic talent is not a unitary or uniform commodity but is to be accounted for in terms of a large number of factors or primary mental abilities" (32). He went on to state that fluency, flexibility and originality are known factors that are of obvious relation to creative ability. "All of them come under a general class of factors known as productive-thinking abilities and in a subclass of divergent thinking abilities." Mednick offered this definition of creativity: "The forming of associative elements into new combinations which either meet specified requirements or are in some way useful. The more mutually remote the elements of the new combination, the more creative the process or solution" (53). He identified serendipity, similarity and mediation as three ways of achieving a creative solution. Serendipity is essentially the accidental discovery of a creative solution from an unintended source. Similarity is the recognition of patterns between the elements of different ideas. Mediation is the ability to notice the commonality between two associative elements and bring them into contiguity.

One way to consider the process of creativity is through the notion of convergent and divergent thinking (6). Convergent thinking is characterized by analyzing and refining one's ideas toward a single, best solution, while divergent thinking is characterized by developing new ideas that build towards new solutions that differ from each other. Thus, to be creative one must use divergent thinking to develop a number of potential ideas, but they must also use convergent thinking in order to narrow down their ideas into a few viable solutions.

Tests of creativity draw on these divergent and convergent process notions. The "Unusual Uses Test" (UUT) asks people to think of as many different functions for an object as possible (32). This can be taken as a metric for divergent thinking. Tests of creativity like

the “Remote Associates Test” (RAT) require people to generate a single ‘creative’ answer for each presented problem (53). Thus, it is linked to convergent thinking.

We can also see this divergent and convergent process in the field of product design. Many product design processes suggest that the creative process has a period of broad idea generation followed by a period of selecting concepts (65). Generally, this process is represented sequentially and often referred to as brainstorming, and down-selection, for divergence and convergence, respectively. However, simply suggesting that convergence must follow divergence ignores the reality of the way that people think. Humans do not simply turn on and off their creativity. People are creative at different times for different reasons.

We recognize a similarity between these concepts of creativity and the processes that are associated with GAs from Chapter 2. A well tuned GA, one that is good at finding the desired solution in a reasonable amount of time, has the property of convergence. Over time, this GA will refine and improve its designs such that it explores regions of local and global optimality. However, tuning GAs is actually an important aspect which must be considered when using them for problem solution. This is because a mistuned GA is capable of large degrees of divergence. This divergence, while not necessarily prohibiting location of optimality, slows the process down and often develops populations that are highly diverse. While divergence should be avoided when using GAs for search and optimization problems, we believe that it might be a very effective means of assisting people in the creative process if used interactively.

It is important to state that the creative potential involved in a study that has predefined bounds and a parameterized space is a point of legitimate argument. We do not suggest that an IGA will be capable of defining any brand new idea that lies outside the predefined architecture of the design space it is provided with. However, the claim that such a framework cannot represent creativity seems false. Consider, for example, three chefs given the exact same ingredients to create a dish. Certainly, these chefs would have different ideas about

how much of each ingredient to use in their recipe. In fact, by varying the quantities enough it is likely that their recipes would in no way resemble each others. It is contended here that such a task requires creativity, and by extension the work using the proposed IGA also requires that same concept of creativity.

This study provides a framework for how IGAs can be synthesized to enhance creativity. It also describes the design of an IGA that is tailored for use in creativity enhancement. Next, we test that IGA using Monte Carlo simulation to examine the effectiveness of it in aiding creativity. We will finish with a discussion of the findings and conclusions.

## **6.2 Interactive genetic algorithm design**

IGAs can help enhance creativity because they can operate in both divergent and convergent ways. In IGAs the evaluation function is based on input from a user. Their input regarding a previous population of design options influences the makeup of a new population. To enhance creativity, we wanted to expose users to new and interesting design concepts while retaining some of the characteristics that the user already identified as well-liked. The only metric that was used to understand what a user liked was the selection of a design concept. If the user selected a concept, then that indicated the user believed that concept was creative. A concept that was not selected was presumed to be less creative. We recognize that favoring these selected individuals too highly can quickly limit the range of the design space. So, we wished to retain design characteristics that are well-liked, while allowing other aspects of the design to change, thereby exposing the user to new design concepts that may be unexpected, and interesting.

Real-valued variables were used for this IGA. This was done, in opposition to binary numbers, for several reasons. First, real-valued versions of genetic algorithms can be just as reliable in problem solution as binary-formed GAs. Second, real-valued variables can avoid difficulties associated with hamming distances that can often be an issue in binary GAs (37).

Finally, using real-valued variables reduced the size and complexity of the database needed to collect information during Monte Carlo simulation while still allowing the IGA to be investigated for metrics of creativity enhancement.

This IGA was designed to explore the effect that divergent and convergent operations could have on the creative capacity of human users. To model convergence, we employed typical practices from the GA community. We applied high rates of probability that ‘fit’ designs would become ‘parents’ to the designs of the following generation. We then submitted the newly created designs to a relatively low mutation pressure. This aspect of the IGA represents design refinement; it is the part of the process where the user can focus attention on specific characteristics of appealing designs and cause positive change towards a goal design. While the users’ goal design is not known a priori, this process allows them to converge upon designs that appeal to them.

Mistuned GAs have a unique property wherein they may drastically diverge from their intended goal. Further, they also develop populations that diverge, thus the standard deviation of the population tends to increase, rather than decrease. Modeling divergence using IGAs can be thought of in several ways. One possible thought would be to apply very high mutation rates that could function on one individual at several variables. This type of divergence can be thought of as extreme random mutation. Such divergence is not systematic; it relies on very little information from the previous design set and its primary mode of exploration is the proverbial ‘shot in the dark’. While mutation is critical for the algorithm it is not systematic. Therefore, in an effort to broadly explore the design space using information about the previous population, we provide high rates of parental probability to those individuals from the population that go unselected by the user. In doing so we retain portions of the design space that were deemed unfavorable by the user. Through combinations with other portions of the design space, and through typical mutation we hope to expose portions of the design space that are unexpected, inspiring, and unique.

### **6.2.1 Roulette wheel selection**

In order to combine these two forms of parental selection, convergent and divergent, we partitioned the new population into two sets: one set developed by convergence and one set developed by divergence. User selection of four creative individuals from a population of sixteen individuals gave those designs a high probability of parental selection in the convergent process. On the other hand, in the divergent process the twelve unselected individuals had higher probabilities of selection. In both the convergent and divergent processes we used roulette wheel selection to determine parents. The difference in the process was the allocation of the roulette wheel to the individuals (22). Earlier, in Chapter 4, we determined that supplying 80% of the roulette wheel to the selected individuals, such that each selected individual garnered 20% of the wheel while the remaining twelve individuals had 1.66% of the roulette wheel, showed good results in preference identification (42). Therefore, we used that scheme in our convergent process. For the divergent process, we used a similar wheel allocation, only we provided 80% of the wheel to the unselected twelve individuals and 20% to the four selected individuals, resulting in roulette percentages of 6.66% and 5% for the unselected and selected individuals, respectively.

Thus, we broke the parental process into two pieces: convergent population creation and divergent population creation. For convergent population creation, well-liked individuals had a high likelihood of becoming parents of the next generation. For divergent population creation, there was an increased likelihood that the unselected individuals would be parents for the following generation. We believed that this allowed synthesis of the two types of thinking used in creativity. It should be noted that this process allows convergence and divergence to occur simultaneously. This differs from design processes that advocate a period of pure divergent thought sequentially proceeded by a period of convergent thought.

We examined this sequential method as well. In this process, the first four generations of selection were considered divergent, and then a final set of 21 generations were considered convergent. The 5th generation of individuals was composed of the 16 selected individuals

from the previous 4 generations. We hoped that this would seed the convergent process with a good set of initial designs. In the divergent process 100% of the population was developed using the divergent crossover method, and in the convergent process 100% of the population was created using the convergent process. We varied the roulette percentages associated with both the divergent and convergent parental populations. Further, we restricted the mutation in divergence to be 5% applied at each variable, and in convergence to be 1% at each variable.

During parental selection no parents were ever eliminated from the parental pool during their generation. This allowed a parent to mate several times in populating the new generation. Further, parents were allowed to mate with themselves. Also, each set of parents produced only one offspring.

### **6.2.2 Crossover**

In this study we explored two types of mating procedures. The first mating technique used in this IGA was a simple single-point crossover. In this scenario the genetic material, design variables, from one parent was shared with those from another parent. Specifically, a random value assigned which string of variables would be shared from each parent, with one parent providing all data up to and including the index number provided by the random value, and the other parent provided all complementary information to complete the new design's chromosome. Thus, whole values were shared between the two parents. Therefore, unlike in binary crossover, it is impossible for a new design variable value to be generated in this type of crossover.

This initial crossover procedure was quickly identified as inadequate because it limited the introduction of new variable values. This meant that only mutation would change the actual value of a variable. This, essentially, provided fixed schema that dominated the population. Therefore, we addressed this issue by using a second mating procedure that utilized interpolation. If we consider that the genetic variables of each parent represent points on

a line within the variable space, then we describe the interpolating mating procedure as selecting a random point along that line, between the two parental points, and assign that point to the child. This form of mating is suggested, as opposed to simple replacement, because it allows blending and averaging to occur within the population, something that cannot be achieved with real-valued replacement. To explain further, consider that parent,  $p_1$ , and parent,  $p_2$ , mate. Then all of their variables will be a linear combination of their parents, such that:

$$c_i = p_{1i} + \alpha(p_{2i} - p_{1i}) \quad (6.1)$$

Where,  $c_i$ , is the  $i^{th}$  variable in the child,  $c$ , composed of a linear combination of the parents',  $p_1$  and  $p_2$ ,  $i^{th}$  variable. This is done for each variable,  $i$ , within the genome and  $\alpha$  is a random value between null and unity.

### 6.2.3 Mutation

Mutation enhances the search of genetic algorithms by providing new and unique designs that may be well suited to a particular problem. In this IGA, we needed mutation as a way of introducing new variable values into the population, as well as exposing potentially exciting design spaces. We explored two forms of mutation: First, mutation of a single variable within a given individual; second, mutation of each variable within each individual. Applying mutation pressure to each individual and then causing mutation of a single variable causes less variety than applying a consistent mutation pressure to each variable. The key is to find the balance between too little and too much mutation. Too little would cause a high degree of similarity amongst design options, while too much would cause random mutation to dominate population development. Mutation was simply a random generation of a new real-valued number within the feasible design domain for that variable.

## 6.2.4 Definition of investigated algorithms

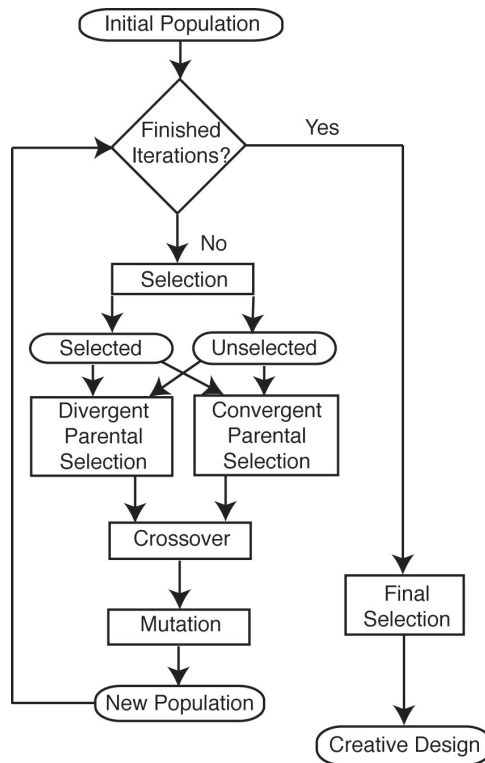
The first algorithm that was used in this study had the aspects mentioned above: real-valued chromosomes, divergent and convergent roulette selection, single point crossover, single child generation from a set of parents, and single variable mutation. The roulette wheel percentages for the selected individuals were 20% and 5% for the convergent and divergent roulette scenarios, respectively. Likewise, the roulette wheel percentages for the unselected individuals were 1.66% and 6.66%, respectively. Finally, a mutation rate of 5% was investigated. The flow diagram shown in Figure 6.1 outlines the general procedure followed in this IGA and Table 6.1 provides a review of the IGAs specifications.

**Table 6.1** IGA Settings: Initial algorithm

Chromosome type	Real valued
Number of variables	8
Mating scheme	Single point crossover
Convergent parental population	
—Selected individual roulette %	20%
—Unselected individual roulette %	1.66%
Divergent parental population	
—Selected individual roulette %	5%
—Unselected individual roulette %	6.66%
Mutation type	Single variable
Mutation rate	5%

Due to results of this first study, shown in the next section, we developed the modified mating procedure that used an interpolating crossover method, and multipoint mutation potential. In a second study we examined the effect of these new crossover and mutation operators. The settings for that study are shown in Table 6.2. We again assigned roulette wheel percentages for the selected individuals at 20% and 5% for the convergent and divergent roulette scenarios, respectively. Likewise, the roulette wheel percentages for the unselected individuals were 1.66% and 6.66%, respectively. But, in these studies we allowed the mutation rate to vary between 0% and 50% to examine the effect on the population convergence and diversity.





**Figure 6.1** Flow diagram showing IGA process containing both convergent and divergent parental selection.

**Table 6.2** IGA Settings: Expanded study

Chromosome type	Real valued
Number of variables	8
Mating scheme	Variable interpolation
Convergent parental population	
—Selected individual roulette %	20%
—Unselected individual roulette %	1.66%
Divergent parental population	
—Selected individual roulette %	5%
—Unselected individual roulette %	6.66%
Mutation type	Multivariable variable
Mutation rate	0 to 50%

Finally, in a third study, we explored the possibility of using a sequential divergent-to-convergent process. The mechanisms for that study were interpolating crossover and variable mutation rates, depending upon whether the algorithm was in its divergent or convergent state. The settings for this study, summarized in Table 6.3, were as follows: real

valued chromosomes with eight variables; divergent crossover and mutation in the first 4 generations; presentation of the 16 selected individuals from generations 1 through 4 in generation 5; 21 generations of convergent crossover and mutation. It is a different process than in the first and second studies, but the intent is the same: find the goal design while facilitating overall population convergence and range maintenance.

**Table 6.3** IGA Settings: Sequential study

Chromosome type	Real valued
Number of variables	8
Mating scheme	Variable interpolation
Convergent parental population	
—Selected individual roulette %	variable%
—Unselected individual roulette %	variable%
Divergent parental population	
—Selected individual roulette %	variable%
—Unselected individual roulette %	variable%
Mutation type	Multivariable variable
—Divergent process %	5%
—Convergent process %	1%

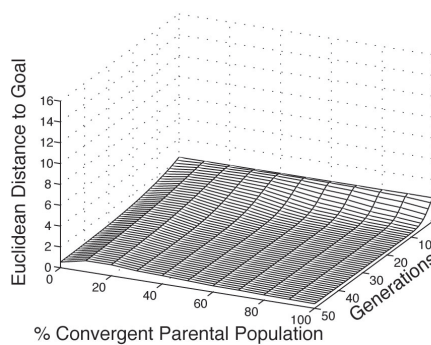
## 6.3 Monte Carlo simulation studies

### 6.3.1 Initial study

To understand the effect of splitting the parental populations between convergent and divergent processes in the first two studies we employed a Monte Carlo simulation of a guided search using Matlab. For these studies the settings of the IGA were as described above. The variables of interest were the amount of the new population that was developed from the two different parental populations, and the mutation rate. We allowed the population mixing to vary from a population that was fully comprised of the divergent parental population to one that was fully comprised of the convergent population. We allowed mixing of the different populations at ten percent intervals, and in each case we conducted 10,000 trials. Similarly, we varied mutation rate at 10% intervals and again ran 10,000 trials.

The test chromosome was eight variables long consisting of real-valued numbers, and each variable had a range from 0 to 10. Mutated variables were random numbers restricted within these bounds. To test the IGA, we used a randomly-defined goal design as the desired ‘creative’ design. While this may seem restrictive and counterintuitive to the intent of creativity this was done to test the ability of the IGA to find a goal design while still preserving a large range of available options to the user. Identifying this predefined goal design provides an understanding of the best case scenario for the IGA. We also defined the initial population as a randomly-generated set from the eight variable design space. The goal of this study was to show that the IGA allowed convergent thinking to occur while still maintaining the varied design space associated with divergent thinking.

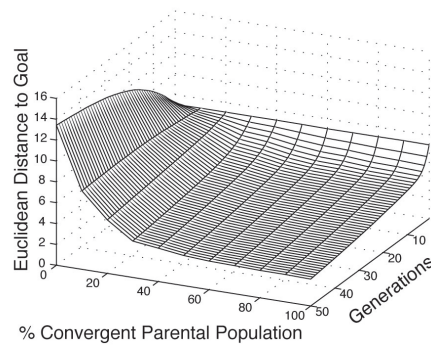
The fitness of each individual was its Euclidean distance from the goal design. The four individuals closest to the goal design were the selected individuals and garnered their appropriate share of the roulette percentage as described in the section on roulette wheel selection. The twelve remaining individuals were unselected and treated likewise. Each of the 10,000 trials ran for 50 generations before conclusion. While this is a small number for a GA, it is a large one for an IGA. Reducing the number of generations helps avoid user fatigue.



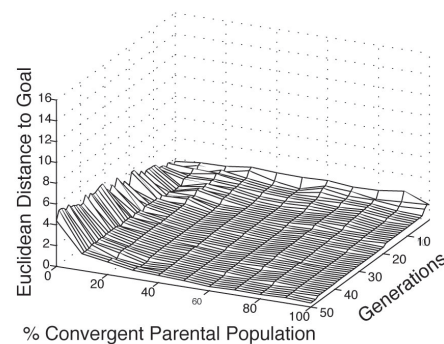
**Figure 6.2** Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design.

Figure 6.2 presents the effect that varying parental population has on the IGA population’s mean distance from the desired goal design over the course of 50 generations.

This uses the IGA settings for the initial study, so replacement is used in crossover. We see that as percent convergent parental population varies from 0% (entirely divergent) to 100% (entirely convergent) the average value of the population's Euclidean distance to the goal design generally improves over the generational process. However, we see that a fully divergent process actually increases the average of the population's distance from the goal. A similar pattern exists in the standard deviation of the population (figure not shown), both generationally and in relation to the parental process. This suggested that this form of IGA may be useful in identifying predefined goals, and hence facilitate convergent thinking. This dissertation has already shown that this correlates well to an individual's ability to identify their preferences using the IGA.



**Figure 6.3** Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design.



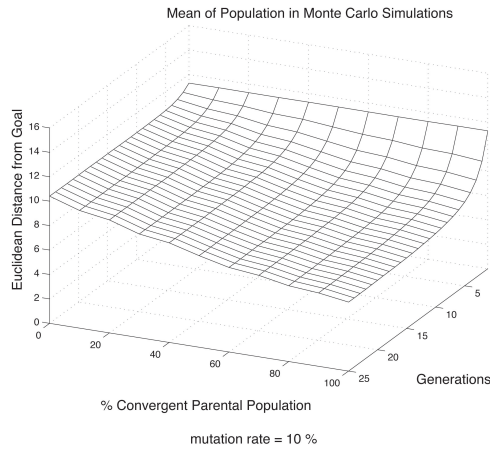
**Figure 6.4** Effect of generation and percent of convergent parental population on the mean of the distance of best individual in the IGA population from the goal design.

Figure 6.3 shows how the range of the population's distance to the goal design was affected by the two types of parental populations for this initial study. As generations increased, there was a reduction in the range of the population. But, with a more divergent parental process, this effect is lessened. Thus, while the diversity of the population is decreasing over generations, this effect can be reduced by using a more divergent process. Maintaining diversity is tantamount to the notion of creativity in this work, but converging toward a specified goal indicates the ability to appropriately refine a design, which is another aspect of creativity. Therefore, we must balance these two goals. Figure 6.4 shows the parental and generational impact on the average of the best individual in the population over the 10,000 trials. We see that a fully divergent parental population has a detrimental effect on the ability to find the goal design. But, as a portion of the population becomes convergent, we notice a marked and systematic improvement of the IGAs ability to get near the goal design.

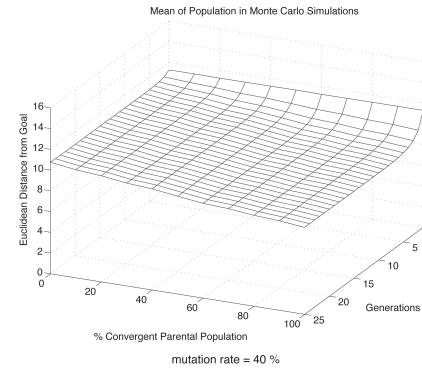
### **6.3.2 Expanded study**

Synthesizing the data from the Monte Carlo studies allows us to make an informed decision about these initial settings for the IGA. We wished to maintain diversity amongst the population to promote the discovery of interesting designs while still allowing users to refine those designs so that they are appropriate for the intended application. Thus, we can see from Figures 6.2 - 6.4 that diversity is not well maintained using this form of the algorithm. We therefore investigated another proposed algorithmic form, but we simulated only 25 generations as opposed to 50. The results of those simulations can be seen in Figures 6.5 - 6.10. The figures suggest that convergent populations are more likely to reach goal designs, and the best available design in the population is improved by convergent populations. We also see that increasing mutation rate has a detrimental effect on the ability of the goal design to be obtained. We also notice a somewhat discouraging result that opposes the theory posed here. In the figures indicating range, Figures 6.9 and 6.10, we can see that the

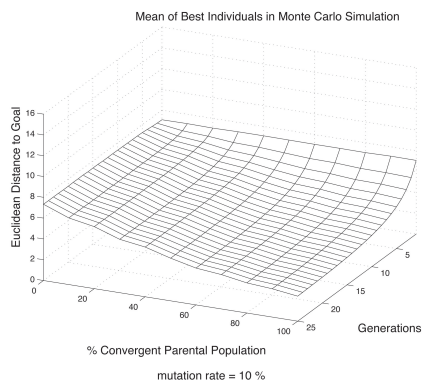
inclusion of the divergent population does very little to impact diversity. The primary intent of incorporating the divergent population was precisely so that it could do this.



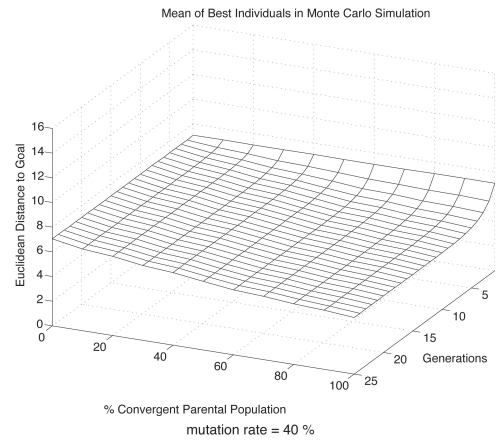
**Figure 6.5** Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design at 10% mutation.



**Figure 6.6** Effect of generation and percent of convergent parental population on the mean of the IGA population from the goal design at 40% mutation.

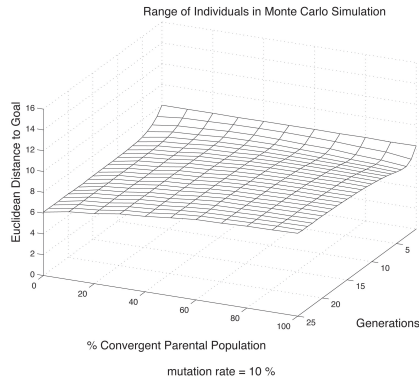


**Figure 6.7** Effect of generation and percent of convergent parental population on the mean of the best of the IGA population from the goal design at 10% mutation.

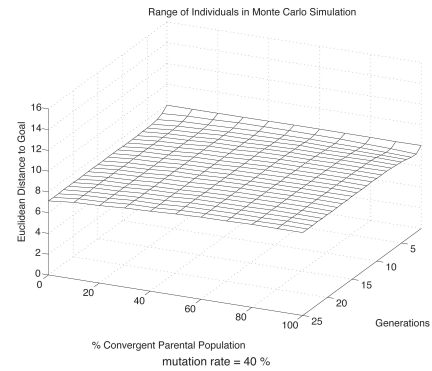


**Figure 6.8** Effect of generation and percent of convergent parental population on the mean of the best of the IGA population from the goal design at 40% mutation.

We believed that a population that maintained a diverse range of individuals would improve the IGA’s capacity to enhance creativity. The Monte Carlo studies in the second study suggested that the proposed method allowed this to happen. However, it did not suggest that incorporating a divergent process alongside a convergent process provided any benefit. It should be noted that there are still numerous combinations of divergent and



**Figure 6.9** Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design at 10% mutation.



**Figure 6.10** Effect of generation and percent of convergent parental population on the range of the IGA population from the goal design at 40% mutation.

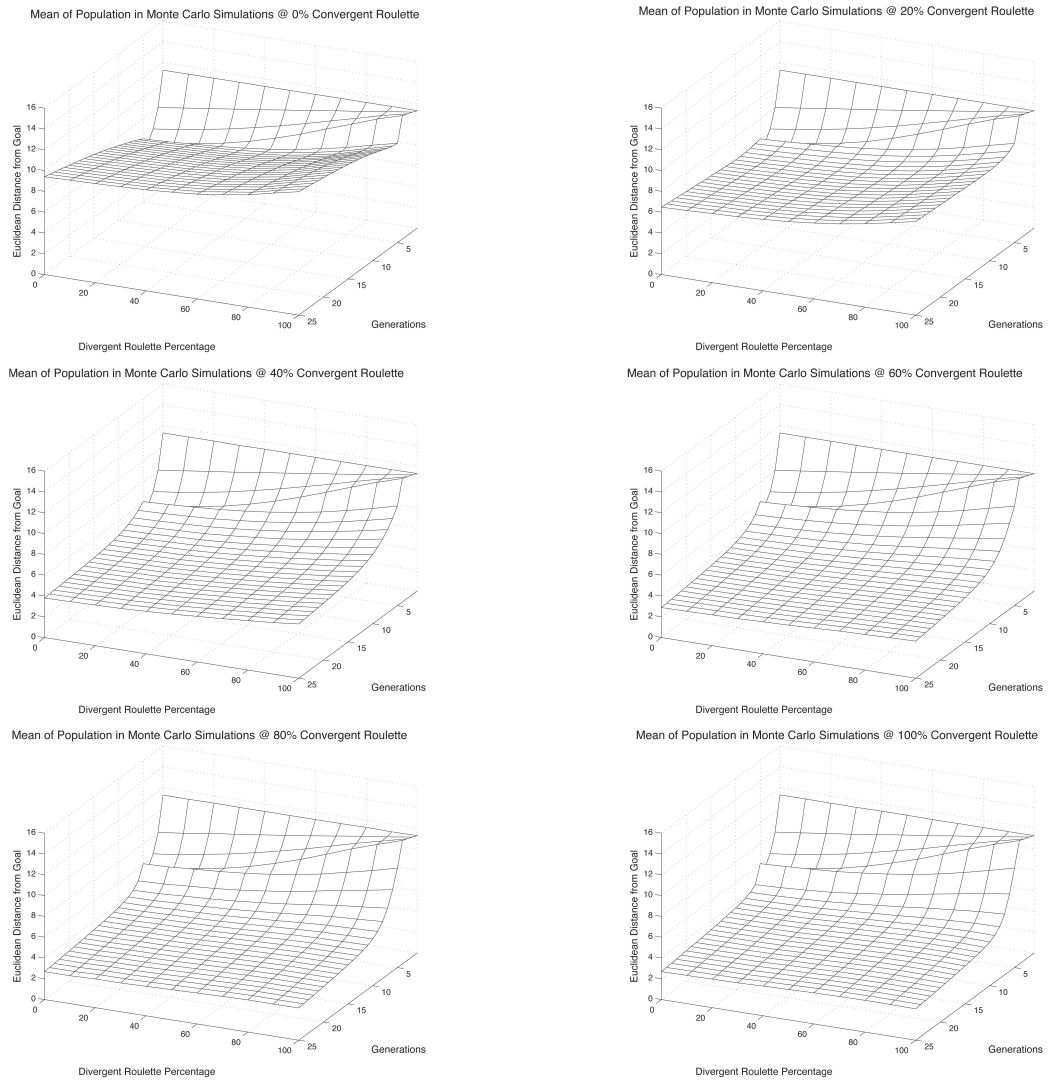
convergent populations that could be explored. The percent of the parental population that is favored has not been adjusted in this study, so, an investigation of that may yield better results.

Despite the finding, that the divergent and convergent populations did not seem to blend in a beneficial fashion based on these current studies, the primary goal of this study was to facilitate convergence and goal attainment while maintaining diversity. The results do suggest that this is possible with a fully convergent population that has a mutation rate of 10% applied to each variable.

### 6.3.3 Sequential study

In this final examination of the synthesis of divergent and convergent parental processes we used a sequential approach wherein the first four generations of the GA were generated using divergent procedures and the final 21 generations were developed using convergent procedures. In Figures 6.11 through 6.13 we present sets of 6 plots that illustrate the impact that roulette wheel percentage allocated to selected individuals has on the population's mean, best and range of values. The sets are composed of figures that have axes relating the number of generations and divergent roulette wheel percentage to the Euclidean distance

of the population from the goal design. Each separate figure in the set indicates a different allocation of the convergent roulette wheel percentage between 0 % and 100 %.

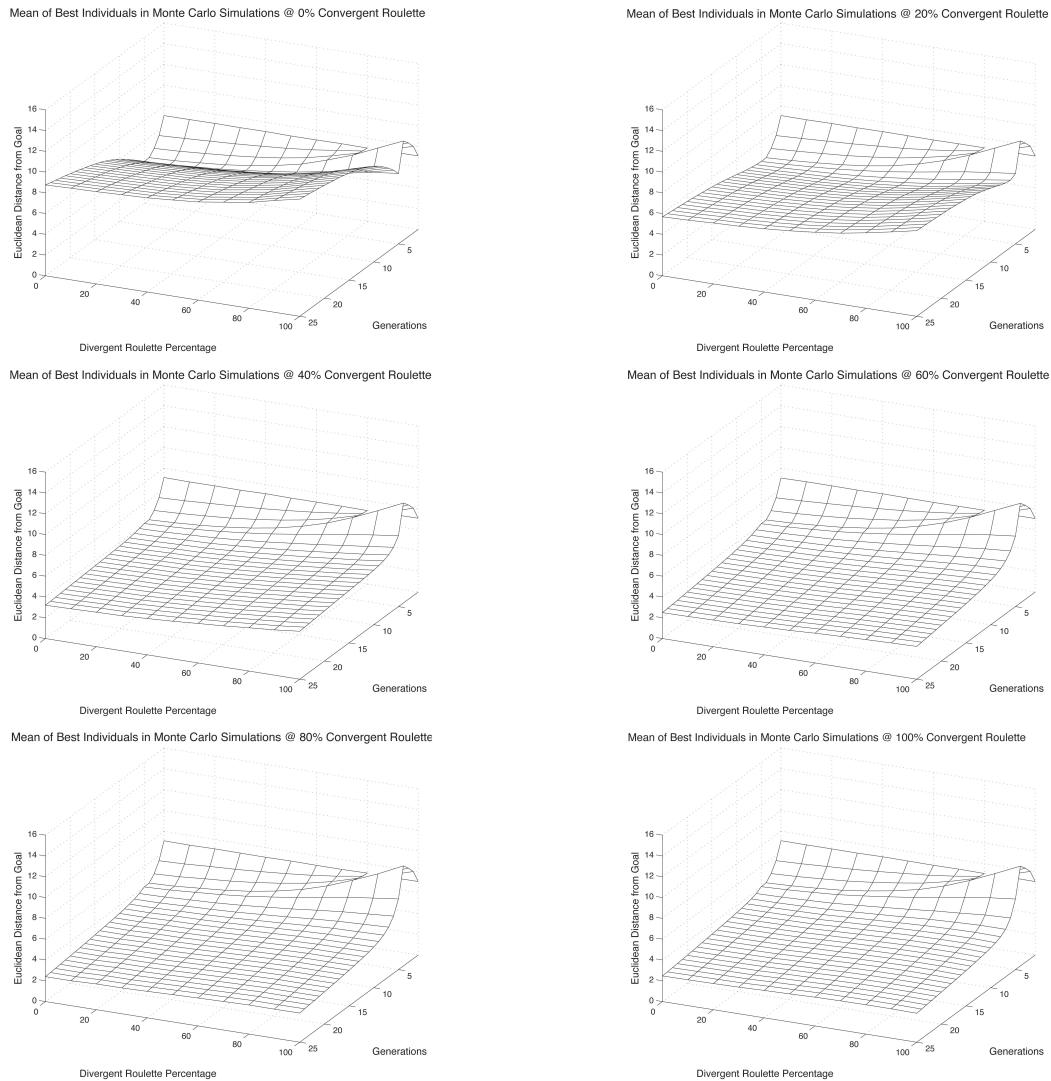


**Figure 6.11** Effect of sequentially applied divergence and convergence on mean of population

Figure 6.11 shows how the Euclidean distance of the population mean is affected by the previously mentioned variables. We see that as more of the roulette wheel is allocated to the selected individuals in the convergent process we observe an improvement in convergence, indicating an ability to get near the desired goal design. Figure 6.12 shows how the Euclidean distance of the best individual in the populations is affected. As more of the roulette wheel is allocated to the selected individuals in the convergent process we also observe an



improvement in convergence. This indicates an ability to get to the exact desired solution, and not just near it. We notice in both the population mean and the best of the population that increasing the convergent roulette percentage beyond 60% yields diminishing returns. Further, we also notice that the divergent roulette percentage has very little impact on the population beyond 10 generations.



**Figure 6.12** Effect of sequentially applied divergence and convergence on best of population

Finally, in Figure 6.13 we observe the range of the Euclidean distance from the goal design. We notice that the range of the population is not well maintained over the course of 25 generations for any of the differing convergent roulette percentages. However, the more

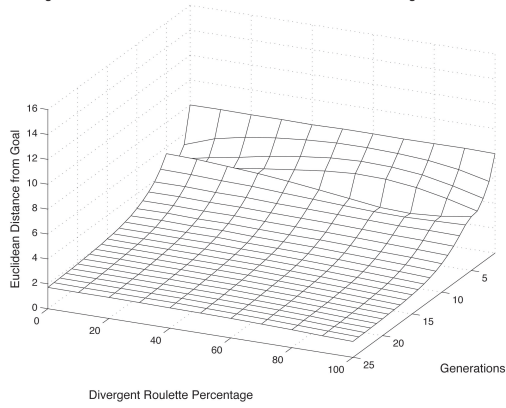
important characteristic in this case is how the divergent roulette percentage impacts the first 5 generations. In this case, we observe that a peak exists in the 5th generation, this is due to the reintroduction of previously selected designs. This peak is strongest when divergence is at 0%, and it tends to have less prominence as divergence increases. These trends indicate that the divergent roulette percentage facilitates variety, and improves selection. In this scenario, the goal is a known design. In a creative situation this goal design may not be known a priori, so a high rate of divergence improves the possibility that a creative design might be found.

These sequentially applied form of the IGA may be a significant improvement over the simultaneous concepts of the other two studies. This sequential process allows systematic development of new ideas and refinement of those ideas toward a favorite. It does not maintain a large range throughout the process, but it does keep a large range during its first several generations. This early range increases the likelihood that a unique concept will be found early and the convergent process seems to facilitate design refinement, as indicated by an improvement in the mean of the population and best individual in the population.

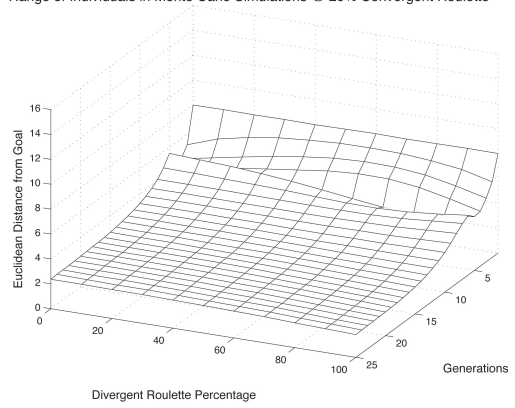
## **6.4 Conclusions**

In this study we have described the development of an IGA-based tool that is proposed to enhance creativity. The basis for this creativity enhancement is founded upon the principles of divergent and convergent thinking. We discovered through this study that including the notion of divergence through a separate population developed from unselected individuals did not improve diversity while it adversely affected convergence towards a goal design. The results of this simultaneous approach lead to the investigation of a sequential approach. The sequential approach to creativity appears to have merit in the notion of creativity. It facilitates the idea of brainstorming at an early stage of the design process, and it then contains the refinement stage that improves the likelihood of achieving some desired goal.

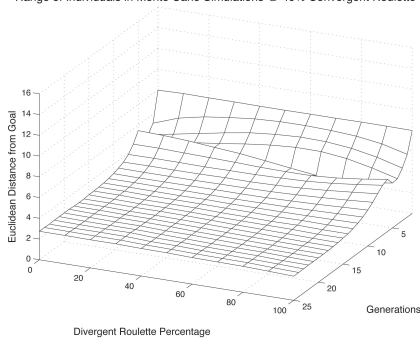
Range of Individuals in Monte Carlo Simulations @ 0% Convergent Roulette



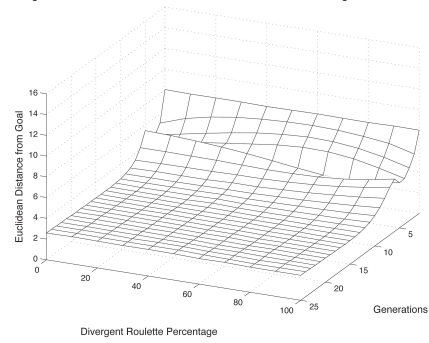
Range of Individuals in Monte Carlo Simulations @ 20% Convergent Roulette



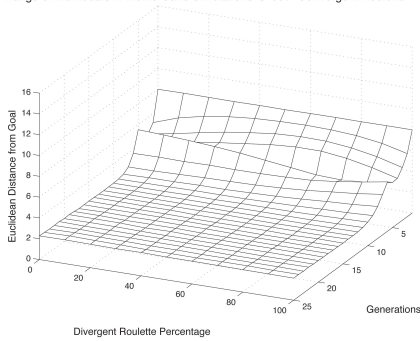
Range of Individuals in Monte Carlo Simulations @ 40% Convergent Roulette



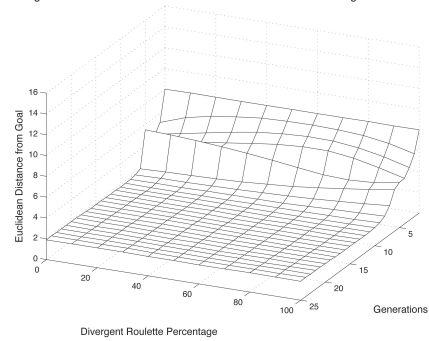
Range of Individuals in Monte Carlo Simulations @ 60% Convergent Roulette



Range of Individuals in Monte Carlo Simulations @ 80% Convergent Roulette



Range of Individuals in Monte Carlo Simulations @ 100% Convergent Roulette



**Figure 6.13** Effect of sequentially applied divergence and convergence on range of population

The notion of creativity lends itself to several types of investigation. The one chosen here sought to improve a users ability to develop many different ideas while also permitting them to refine those ideas toward a well liked design. The methods presented here represent only a few ways that researchers could explore methods of systematically improving creativity with an enhancement tool. This field seems very well suited to further investigation, because the shear volume of computation, ideation and generation that is allowed by the computer,

but it requires human inspiration and insight to yield truly creative ideas.

# Chapter 7

## Summary, contributions, and future work

### 7.1 Summary

This dissertation has examined the use of shape preference information within engineering design. It has shown that currently available tools for determining preference can be used to gain an understanding of shape preference. Further, this knowledge of preference information has been shown to make a valuable contribution to the product design process. Interactive Genetic Algorithms (IGAs) were explored for their ability to ascertain preference information as well. These IGAs offer fertile ground for understanding preference and adaptively offering users with new options that will likely appeal to them. The IGA was used to determine preference for bottle shapes, and it was used to identify whether or not a green vehicle silhouette can be readily identified by users. Finally, the IGA was examined as a tool that could systematically induce creativity.

Aesthetics play an important role in product design. It distinguishes one product from another and account for stylistic differences that can be functionally relevant to the product's performance. In Chapter 3 we proposed and implemented a procedure to not only collect information regarding shape preference, but also incorporate that data within a physics based modeling optimization of functionality. Our findings showed that, in the case of bottle

design, there is a dislocation between what is most appealing to users and what is most technically sound. We then proposed the use of weighted sum multi-objective optimization to develop a Pareto frontier that could be used by designers and managers to understand the tradeoffs that exist when attempting to design a product toward a technical goal, and toward a preferred shape. This study showed that the intuition of industrial designers need not be the only informative evidence to support a particular stylistic desire, further, we have shown that strictly meeting a particular shape preference can have a detrimental effect on product performance.

IGAs offered an interesting avenue of pursuit into the field of shape preference. While IGAs had previously been used as a means to assist computationally expensive problem solving, and they had been used in some forms of goal based audio and visual design, they had not been shown to be capable of interpreting shape preference from a user. The study in Chapter 4 used a case study of bottle shapes to show that user preference could be captured using the IGA, and this was independently validated using pairwise comparison. We further confirmed previous results that the IGA could be quite effective in goal-seeking tasks. Then, in Chapter 5 we used the IGA to identify vehicle silhouettes that were associated with good fuel economy. This subjective data was correlated against a model of the coefficient of drag for the same set of vehicle shapes. We were thus able to see how perception agreed with reality on one metric of greenness. We found that users generally had a good understanding of how vehicle shape impacts aerodynamic drag, and how drag effects fuel economy.

Finally, in Chapter 6 we explored how the IGA could be used as a tool to assist creativity. Using the analogy between design, creativity and genetic algorithms regarding convergence and divergence, we developed an IGA that could assist in the creative design process. We used Monte Carlo simulations to provide evidence for using both convergent and divergent processes at the same time to facilitate the identification of the best design while still maintaining a great deal of design diversity. We also conducted user studies that examined how the tool impacted the creativity of individuals.

## 7.2 Contributions

This dissertation embodies several contributions to the field of engineering design. These contributions provide a foundation that future researchers and practitioners may use to improve both product designs, and the product design process. The contributions of this work are as follows:

- This dissertation developed a procedure for examining shape preference information within the design process. We proposed methods using conjoint analysis and PREFMAP to understand preference, and combined that with fundamental engineering analyses. We showed that doing so could have an important impact on the decisions that designers must make when conducting design. We found that there were distinct tradeoffs between developing designs that met preference criteria and those that met engineering criteria.
- This dissertation validated the IGA as a preference assessment tool. The IGA had been previously assumed as a tool that could understand preference, but no research existed that confirmed this evidence. This dissertation confirmed it, and in doing so, has opened the door for others to use the IGA as a method for rapidly understanding the preference characteristics of design artifacts. We can also say, based on our results, that users are quite capable of using the IGA to answer a question that is posed to them. We cannot state with certainty the required number of generations, the specific settings for mutation, or the settings for crossover that will be well suited for all situations. We believe that increasing variables will require an increased number of required generations, but we do not have any rules for this associated, yet.
- Finally, this dissertation has shown that IGAs offer fertile ground for further investigation as creativity enhancement tools. The studies here do not support the claim that divergence and convergence, when synthesized, can facilitate creativity. However, the study did show that convergence, goal attainment and diversity could all be attained using the IGA developed, and user studies suggest that this does improve creativity.

## 7.3 Future work

This dissertation has laid the groundwork for future endeavors into the quantification and implementation of shape preference information within the design process. Numerous case studies could be conducted to further confirm the usefulness of the methodology that was proposed and implemented in Chapter 3. One important idea that should be examined further is whether or not there is a best way to decompose a particular design architecture. In this

dissertation, only points along splines were considered as design variables. However, the ratios of design elements, and their absolute dimensions have not been rigorously explored. Nor has the aspect of absolute size. Further, due to the tactile nature many artifacts, we propose that the creation of numerous prototypes, through rapid prototyping technologies, could further improve a user's understanding and appreciation for an artifact. Thus, they could make a more accurate judgement regarding their preference.

A major limiting factor in the development in the IGA used in this dissertation is that it provides no systematic method for understanding the true preference space for a design. It is currently limited to the simple understanding of an ideal point. This ideal point, while useful and intuitive in its method of identification, cannot provide enough information for designers to make strong claims about aesthetic design decisions when the technically optimal design does not align well with the most preferred aesthetic point. Therefore, the data that is collected during the IGA should serve as a basis upon which a more fundamentally mathematical model of preference can be built.

One benefit of the IGA is its ability to quickly obtain information related to preference. To further enhance this we developed a web-based application to present, manipulate and database the decisions of users. One drawback of this software is its drawing function. Initially, Adobe Flash was used due to its perceived ease of use. However, in retrospect, this program, while user friendly on many levels, lacks some of the detailed functionality that we had hoped for in its graphical presentation of shapes. Therefore, we believe that a Java based interface may actually provide better functionality and drawing capabilities. While this is not a fundamental question of research, it does highlight an area of this work that could use improvement.

Finally, as a means of improving the IGA's capacity to interpret user preference, and as a way of enhancing creativity several methods from the Artificial Intelligence (AI) should be investigated for their application to the GA process. Several learning algorithms show promise, but a method like reinforcement learning suffers from the need for repeated failures



to guarantee future success. The field of creativity within AI may represent a place of fertile ground, where the ideas posed in this dissertation could be improved by the insights and practices of the AI community.

The fundamental role that shape plays in the preferences that people have for artifacts indicates that this field of study will be of growing importance over the coming years. This is because the costs and technology associated with product design are becoming very even across the marketplace. This is not to say that technical advances cannot give firms a significant advantage over their competition, it simply recognizes that an ad hoc methodology relying purely on intuition and heuristics can be augmented by a scientific methodology to increase the likelihood of developing aesthetically preferred artifacts that will likely benefit both the user and the producer.

# Bibliography

- [1] W. Banzhaf. *Interactive evolution*, chapter C2.10. Handbook of Evolutionary Computation. IOP Publishing Ltd and Oxford University Press, 1997.
- [2] M. Bauerly and Y. Liu. Computational modeling and experimental investigation of effects of compositional elements on interface and design aesthetics. *International Journal of Human-Computer Studies*, 64(8):670–82, 08/ 2006.
- [3] M. Baxter. *Product Design: A Practical Guide to Systematic Methods of New Product Development*. CRC Press, 1995.
- [4] D. Beasley, D. R. Bull, and R. R. Marting. An overview of genetic algorithms: Part 1, fundamentals. *University Computing*, 15(2):58–69, 1993.
- [5] Ingwer Borg and Patrick Groenen. *Modern Multidimensional Scaling: Theory and applications*. Springer, 1997.
- [6] D. R. Brophy. Comparing the Attributes, Activities, and Performance of Divergent, Convergent, and Combination Thinkers. *Creativity research journal*, 13(3 & 4):439–455, 2001.
- [7] M. A. Buonanno and D. N. Mavris. Small supersonic transport concept evaluation using interactive evolutionary algorithms. In *Collection of Technical Papers - AIAA 4th Aviation Technology, Integration, and Operations Forum, ATIO, Sep 20-23 2004*, volume 1, pages 411–426, 2004.
- [8] J. J. Chang and J. D. Carroll. How to use mdpref, a computer program for multidimensional analysis of preference data. *Bell Telephone Laboratories, Murray Hill, MJ*, 1969.
- [9] J. J. Chang and J. D. Carroll. How to use pefmap and pefmap-2: Programs which relate preference data to multidimensional scaling solutions. *Unpublished manuscript, Bell Telephone Labs, Murray Hill, NJ*, 1972.
- [10] S. B. Cho. Towards creative evolutionary systems with interactive genetic algorithm. *Applied Intelligence: The International Journal of Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies*, 16(2):129–38, 03/ 2002.

- [11] P. Courcoux and P. C. Chavanne. Preference mapping using a latent class vector model. *Food Quality and Preference*, 12(5):369–372, 2001.
- [12] N. Cowan. Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information processing system. *Psychological Bulletin*, 104(2):163–191, 1988.
- [13] A. P. M. Coxon, J. E. Jackson, P. M. Davies, H. V. Smith, L. Sachs, and J. Schmee. The users guide to multidimensional scaling. *TECHNOMETRICS*, 27(1), 1985.
- [14] M. L. Davison. *Multidimensional Scaling*. Krieger Publishing Co., Malabar, Florida, USA, 1983.
- [15] R. Dawkins. *The Blind Watchmaker*. Harlow : Longman Scientific and Technical, 1986.
- [16] E. A. Durant, G. H. Wakefield, D. J. Van Tasell, and M. E. Rickert. Efficient perceptual tuning of hearing aids with genetic algorithms. *IEEE Transactions on Speech and Audio Processing*, 12(2):144–155, 2004.
- [17] U. Eco. *History of Beauty*. Rizzoli, New York, 2004.
- [18] G. T. Fechner. *Elemente der Psychophysik*. Breitkopf & Härtel, 1860.
- [19] G. T. Fechner. *Vorschule der Aesthetik*. Breitkopf & Härtel, 1897.
- [20] M. Frauenfelder. Do-it-yourself darwin. *Wired*, 6(10):164, Oct 1998.
- [21] F. Giannini and M. Monti. Cad tools based on aesthetic properties. *Eurographics Italian Chapter*, July 11, 2002 2002.
- [22] D. E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing Co., Inc. Boston, MA, USA, 1989.
- [23] P. B. Gove et al. *Webster's third new international dictionary of the English language*. Merriam-Webster, 2002.
- [24] C. P. M. Govers. What and how about quality function deployment (qfd). *International Journal of Production Economics*, 46-47:575–585, 1996.
- [25] J. Graf and W. Banzhaf. Interactive evolution of images. In *Proceedings of Fourth Annual Conference on Evolutionary Programming, 1-3 March 1995*, pages 53–65, / 1995.
- [26] K. Grammer, B. Fink, A. P. Møller, and R. Thornhill. Darwinian aesthetics: sexual selection and the biology of beauty. *Biological Reviews*, 78(3):385–407, 2003.
- [27] C. D. Green. All that glitters: A review of psychological research on the aesthetics of the golden section. *Perception*, 24(8):937–968, 1995.

- [28] P. E. Green and V. Srinivasan. Conjoint analysis in marketing: New developments with implications for research and practice. *Journal of Marketing*, 54(4):3–19, 1990.
- [29] M. Grimm. Drink me. coca cola. *American Demographics*, 22(2):62–63, Feb 2000.
- [30] Z. Gu, M. Xi Tang, and J. H. Frazer. Capturing aesthetic intention during interactive evolution. *Computer-Aided Design*, 38(3):224–237, 2006.
- [31] P. M. Guadagni and J. D. C. Little. A Logit Model of Brand Choice Calibrated on Scanner Data. *Marketing science*, 2(3):203–238, 1983.
- [32] J. P. Guilford. Creative abilities in the arts. *Psychology review*, 64(2):110–8, 1957.
- [33] T. Heath. *History of Greek Mathematics*. Dover Publications, 1981.
- [34] J. H. Holland. *Adaptation in Natural and Artificial System*. The University of Michigan Press, Ann Arbor, Michigan, USA, 1975.
- [35] I. Hossoy. Modeling of craftsmanship perceptions in vehicle interior design using tools from engineering and psychology, 2003.
- [36] S. W. Hsiao and E. Liu. A neurofuzzy-evolutionary approach for product design. *Integrated Computer-Aided Engineering*, 11(4):323–338, 2004.
- [37] L. Ingber and B. Rosen. Genetic algorithms and very fast simulated reannealing: A comparison. *Mathematical and Computer Modelling*, 16(11):87–100, 1992.
- [38] I. T. Jolliffe. *Principal Component Analysis*. Springer, 2002.
- [39] P. W. Jordan. Human factors for pleasure in product use. *Applied Ergonomics*, 29(1):25–33, 1998.
- [40] R. Kamalian, Y. Zhang, H. Takagi, and A. M. Agogino. Reduced human fatigue interactive evolutionary computation for micromachine design. *Machine Learning and Cybernetics, 2005.Proceedings of 2005 International Conference on*, 9, 2005.
- [41] J. Kelly and P. Y. Papalambros. Use of visual preference information in design. In *Proceedings of the International Conference on Engineering Design*, August 2007.
- [42] J. Kelly, P. Y. Papalambros, and G. H. Wakefield. Evidence for Using Interactive Genetic Algorithms in Shape Preference Assessment. *Computer-Aided Design, in review*, 2008.
- [43] B. Lamons. Absolut fortune: One liquor’s success story. *Marketing News*, 35(4):8, Feb 12 2001.
- [44] R. G. Lanzara. Weber’s Law Modeled by the Mathematical Description of a Beam Balance. *Mathematical biosciences*, 122:89–94, 1994.
- [45] W. Lidwell, K. Holden, and J. Butler. *Universal Principles of Design*. Rockport Publishers, 2003.

- [46] Y. Liu. The aesthetic and the ethic dimensions of human factors and design. *Ergonomics*, 46(13-14):1293–1305, 2003.
- [47] Y. Liu. Engineering aesthetics and aesthetic ergonomics: Theoretical foundations and a dual-process research methodology. *Ergonomics*, 46(13-14):1273–1292, 2003.
- [48] J. J. Louviere, D. A. Hensher, and J. D. Swait. *Stated Choice Methods: Analysis and Applications*. Cambridge University Press, 2000.
- [49] A. S. MacDonald. Aesthetic intelligence: optimizing user-centred design. *Journal of engineering design*, 12(1):37–45, 2001.
- [50] E. F. MacDonald, R. Gonzalez, and P. Y. Papalambros. The Construction of Preferences for Crux and Sentinel Product Attributes. In *Proceedings of the International Conference on Engineering Design*, August 2007.
- [51] L. March. *Architectonics of Humanism: Essays on Number in Architecture*. Academy Editions, 1998.
- [52] J. P. McEvoy, C. G. Armstrong, and R. J. Crawford. Simulation of the stretch blow molding process of PET bottles. *Advances in Polymer Technology*, 17(4):339–352, 1998.
- [53] S. Mednick. The associative basis of the creative process. *Psychological Review*, 69(3):220–232, 1962.
- [54] J. Michalek. Demand modeling using discrete choice analysis-part 1 and part 2, 2004.
- [55] J. J. Michalek, F. M. Feinberg, and P. Y. Papalambros. Linking Marketing and Engineering Product Design Decisions via Analytical Target Cascading\*. *Journal of product innovation management*, 22(1):42–62, 2005.
- [56] S. Moaveni. *Finite element analysis: theory and application with ANSYS*. Upper Saddle River, NJ, 2003.
- [57] M. Mulford, J. Orbell, C. Shatto, and J. Stockard. Physical attractiveness, opportunity, and success in everyday exchange. *American Journal of Sociology*, 103(6):1565–1592, May 1998.
- [58] M. Nagamachi. Kansei engineering: A new ergonomic consumer-oriented technology for product development. *International Journal of Industrial Ergonomics*, 15(1):3–11, 1995.
- [59] M. Nagamachi. Kansei engineering and comfort. *International Journal of Industrial Ergonomics*, 19:79–80, 1997.
- [60] K. Nakada. Kansei engineering research on the design of construction machinery. *International Journal of Industrial Ergonomics*, 19(2):129–146, 1997.

- [61] H. Nishino, H. Takagi, S. B. Cho, and K. Utsumiya. A 3d modeling system for creative design. In *Proceedings of ICOIN-15, 15th International Conference on Information Networking, 31 Jan.-2 Feb. 2001*, pages 479–86, / 2001.
- [62] D. A. Norman. *The Design of Everyday Things*. Basic Books New York, 2002.
- [63] B. Orme. CBC user manual, version 2. 0. *Sawtooth Software, Inc., Sequim, Wash.*(<http://www.sawtoothsoftware.com>), 1999.
- [64] C. E. Osgood. Semantic differential technique in the comparative study of cultures. *American Anthropologist*, 66(3, Part 2: Transcultural Studies in Cognition):171–200, Jun. 1964.
- [65] K. N. Otto and K. L. Wood. *Product Design: Techniques in Reverse Engineering and New Product Development*. Prentice Hall, 2001.
- [66] H. J. Park. *A Quantification of Proportionality Aesthetics in Morphological Design*. University of Michigan, 2005.
- [67] J. F. Petiot and D. Chablat. Subjective evaluation of forms in an immersive environment. In *Proceedings of Virtual Concept - 2003*, November 5-7, 2003 2003.
- [68] J. F. Petiot and S. Grognet. Product design: a vectors field-based approach for preference modelling. *Journal of engineering design*, 17(3):217–33, 06 2006.
- [69] D. Pye. *The Nature and Aesthetics of Design*. Herbert, 1978.
- [70] A.B.M.B. Rashid. Plastic container having base with annular wall and method of making the same, January 23 2001. US Patent 6,176,382.
- [71] R. Reber, N. Schwarz, and P. Winkielman. Processing fluency and aesthetic pleasure: Is beauty in the perceiver’s processing experience? *Personality and Social Psychology Review*, 8(4):364–382, 2004.
- [72] Y. Rong and Y. Bai. Automated generation of fixture configuration design. *Journal of Manufacturing Science and Engineering*, 119(2):208–219, 1997.
- [73] J. Shen. On the foundations of vision modeling I. Webers law and Weberized TV restoration. *Physica D: Nonlinear Phenomena*, 175(3-4):241–251, 2003.
- [74] S. N. Smyth and D. R. Wallace. Towards the synthesis of aesthetic product form. *Proceedings of Design Engineering Technical Conference 2000/Design Theory Methodology-14554*, ASME, New York, 2000.
- [75] A. Sterian, P. Runkle, and G. H. Wakefield. Active sensory tuning of windnoise using a genetic algorithm. In *1995 International Conference on Acoustics, Speech, and Signal Processing, 9-12 May 1995*, volume vol.5, pages 2967–70, 1995.
- [76] S. S. Stevens. *Psychophysics*. Wiley New York, 1975.

- [77] H. Takagi et al. Interactive evolutionary computation: Fusion of the capabilities of EC optimization and human evaluation. *Proceedings of the IEEE*, 89(9):1275–1296, 2001.
- [78] C. Tanoue, K. Ishizaka, and M. Nagamachi. Kansei engineering: a study on perception of vehicle interior image. *International Journal of Industrial Ergonomics*, 19(2):115–128, 1997.
- [79] E. Tjalve. *A Short Course in Industrial Design*. Newnes-Butterworths Boston, 1979.
- [80] T. Vanderbilt. Bottled up. *International Design*, 48(3):44, May 2001.
- [81] D. R. Wallace and M. J. Jakiela. Automated product concept design: unifying aesthetics and engineering. *Computer Graphics and Applications, IEEE*, 13(4):66–75, 1993.
- [82] L. D. Whitley. An overview of evolutionary algorithms: practical issues and common pitfalls. *Information & Software Technology*, 43(14):817–831, 2001.
- [83] H. Yanagisawa and S. Fukuda. Interactive Reduct Evolutional Computation for Aesthetic Design. *Journal of Computing and Information Science in Engineering (Transactions of the ASME)*, 5(1):1–7, 2005.
- [84] B. Yannou and J. F. Petiot. Needs, perceptions, functions and products: Highlight on promising design methods linking them. In *Integrated Design and Manufacture in Mechanical Engineering*, pages 1–10, 2002.
- [85] M. Yoshimura. Strategies for implementing aesthetic factors in product designs. *International Journal of Production Research*, 39(5):1031–1049, 2001.
- [86] M. Yoshimura and S. Horie. Aesthetic design of machine systems using evaluation maps. In *2001 ASME Design Engineering Technical Conference and Computers and Information in Engineering Conference, Sep 9-12 2001*, volume 2 of *Proceedings of the ASME Design Engineering Technical Conference*, pages 1309–1317, September 2001.
- [87] N. D. Young, M. Drake, K. Lopetcharat, and M. R. McDaniel. Preference mapping of cheddar cheese with varying maturity levels. *Journal of Dairy Science*, 87(1):11–19, Jan 2004.