

Interactive genetic algorithms for shape preference assessment in engineering design

by

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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

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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