6 INVESTIGATING THE RELATIONSHIPS BETWEEN QUANTITATIVE AND QUALITATIVE PROPERTIES OF 3D SHAPES USING FUZZY LOGIC MODELS

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Defining the aesthetic and emotional value of a product is an important consideration for its design. Furthermore, if several designers are faced with the task to create an object that would evoke a certain emotion (aggressive, soft, heavy, etc.) each would most likely interpret the emotion with a different set of geometric features and shapes. In this paper the authors propose an automatic approach to formalize the relationships between geometric information of 3D objects and the intended emotion using fuzzy logic. In addition automatically generated fuzzy rules and sets are developed and compared to the user perceptions and manually constructed ones. The initial findings indicate that the approach is indeed a valid approach to formalize geometric information with emotions.

Keywords: Aesthetics, emotional design, fuzzy logic, design characteristics, genetic algorithms, automatic learning.

1. INTRODUCTION

Designers are easily able to deal with quantifiable objective aspects such as functionality, manufacturability, weight, and other technical properties of the product. However, aesthetics are a contributing but subjective factor in determining the success of a product. Design was mentioned as the most important determinant of new product performance by 60% of respondents in a survey of senior marketing managers.[1] The form of a product is though to contributes to its success through different ways.[2]

Emotional design is increasingly an important approach to differentiate a product within a competitive market. Norman argues that emotional design can lead to users accepting non-optimal functionality or usability.[3] Norman states different ways to define how one responds emotionally to a product: visceral, behavioral and reflective and these interweave both cognitive and emotional responses.[3] Visceral responses appeal to the senses before interaction with the product occurs and they allow users to make quick judgments upon the products and how it is perceived. Only visceral responses are considered in this paper.

It is of interest to understand how the form of a product can be used to evoke the desired emotion in the intended user group. The designer is not always successful in conveying the desired message through the aesthetical form highlighting the difficulty for users/designers to link emotions through words to design characteristics.[4] To achieve that link several studies aiming at identifying the relations between the characteristics of a product's shape and its emotional message have been carried out. A study based upon perceptual psychology (perception of "safety", "friendliness" of a machine) was proposed in Ref. 5. Design and computer science approaches are employed in Ref.6-9. However, in these experiments no systematic and precise specification of a correspondence between product elements and emotional terms was provided. In Ref.10. a study using Kansei engineering and neural networks to cluster objects that have a similar perception among users by focusing color was carried out. Fuzzy Logic was used for validation of aesthetics sensitivity in automatic generation of roof geometries[11] and to evaluate buildings aesthetics based on specific features[12], however they did not link general geometric properties to an emotional context. The research aims and methodology are discussed in detail in the following sections.

2. RESEARCH AIM

The aim of this research is to identify characteristics of a form that can be used to evoke an emotion in users. If this is possible, the research aims to understand if these characteristics can be represented in a fuzzy logic model (rule base and database) which can be used to evaluate forms ability to evoke a particular emotion. The research presented here extends upon a previous study where a manual fuzzy logic model (steps 1–3 of the methodology below) was obtained[13], by adding a genetically generated fuzzy logic model (step 4 of the methodology) for comparison and validation purposes.

The used methodology is based on the analogy of communication presented in Ref.14, combined with a design and computer science approach in order to create a direct link between the space of design variables and the space of aesthetic characteristics. A four step methodology has been employed:

1. Students were asked to create a form which represents a particular set of emotions.
2. Authors created the input premises and the rules representing their attempts to link form to emotion,
3. A fuzzy logic model is constructed and an evaluation was conducted with users,
4. Genetically generated fuzzy rule base and data base are created. The human perception of the forms was used as a learning set to create an equivalent fuzzy logic model automatically without the use of the authors' knowledge (avoiding human bias). The fuzzy rules and sets are compared to those that are manually created (in Steps 2 and 3).

In this paper an evaluation of the models was conducted on the aggressive adjective only. A group of people were shown shapes in the aggressive and edgy category and were asked to rate only the aggressiveness of each of the shapes. As a control test, a number of shapes that were designed to be friendly were included in the evaluation. The work in this paper investigates the perception of images, rather than any associations. Each of the steps of the methodology is discussed together with results in the following sections.

3. CREATING OBJECTS USING TERMS AS CONSTRAINTS

In this research, 3D objects were created to describe given emotions by 60 engineering design students working individually. By selecting 3D forms as opposed to finished products, the fuzzy logic model and subsequent evaluation could focus on visceral responses, and therefore separate behavioral and reflective responses. In addition, the functionality and usability of a product could hinder the perception of user towards a form; hence products were not used for the experiment, by evaluating the form alone the aesthetics are taken out of any functional/behavioral context.[7] Each student was presented with a set of words describing a certain emotion. The terms given were massive and static; light and friendly; dynamic and integrated and; aggressive and edgy.

The students were provided with cubes of foam (200mmX3), and provided with one of the five set of terms. The students were free to use color on their forms, however in this paper only the shapes are considered. Each of the shapes was photographed from a fixed distance and rotated through 45 degrees. Eight of the models created to express aggressive and edgy were selected, together with four expressing light and friendly. The choice of the aggressive adjective (and it's antonym for control) was guided by the geometric properties selected by the authors which can be evaluated using images only. Figure 1, shows the different shapes selected. Shapes 2, 5, 8 and 11 were designed to be friendly and light; the remainders were designed to be aggressive and edgy.

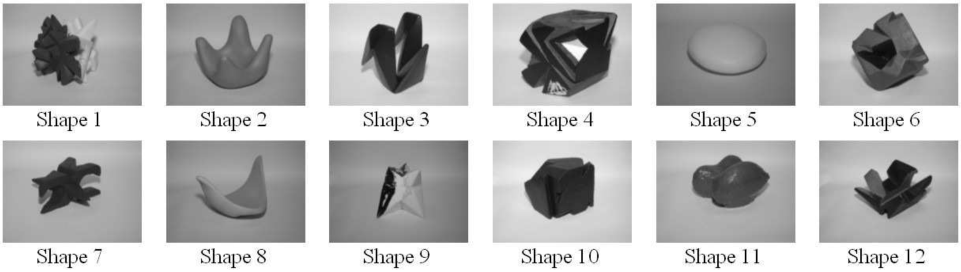


Figure 1. 3D shapes considered for the study.

4. FUZZY DECISION SUPPORT SYSTEM

Fuzzy logic techniques, based on the compositional rule of inference (CRI), are used to handle imprecise knowledge.[16] Such knowledge can be collected and delivered by a human expert. In this paper, the center of gravity (COG) is used for the defuzzification. FDSS Fuzzy-Flou[15] is used as a validation tool for the fuzzy knowledge bases (FKB). Fuzzy logic was selected due to its ability to handle imprecise knowledge as described earlier, and to allow rules be easily refined and tested (as opposed to black boxes approaches). Explicit rules may assist the creation of design guidelines.

5. MAPPING SHAPE PARAMETERS AND AESTHETIC CHARACTERISTICS

In this section, the mapping of the shape parameters to aesthetic/emotion characteristics of the objects is described. Inspired by the Gestalt rules of design, several geometric parameters were singled out depending on the emotion represented. The parameters identified by the authors are as follow: Lines/Curves ratio, Acute/Obtuse angles ratio and Regularity level. These parameters were defined by the authors as a result of the visual analysis made of the 3D objects designed by the students. For each shape considered, the number of curves (NC) lines (NL) acute angles (NAA) and obtuse angles (NOA) were counted using the different views of the photographs. The regularity level (RL) is based on invariance in symmetry; more details can be found in Ref. 13.

5.1. Universe of Discourse of the Input Premises

As stated in the section above the geometric parameters considered are

1. Lines/Curves ratio (LCR):
$$LCR = \frac{NL}{NC + NL} \times 100 \tag{2}$$
2. Acute/Obtuse angles ratio (AOR):
$$AOR = \frac{NAA}{NAA + NOA} \times 100 \tag{3}$$
3. Regularity level (RL): Each object is tested for symmetry and scores one point for each (3 points maximum for three plans of symmetry) while compared to the initial position. RL will be evaluated as follow:
$$RL = \frac{\sum_j^3 R_i}{3} \times 100 \tag{4}$$

6. CONSTRUCTION OF THE FUZZY KNOWLEDGE BASE

FKB is composed of a database and a rule base; the construction of both is detailed.

6.1. Manual Construction of the FKB

The manual construction of the FKB is carried out in the two steps described bellow.

6.1.1. Defining the Database

The database is composed of the inputs/outputs of the FKB. In this paper the inputs, as defined in Section 4. Each of the inputs has two membership functions (Low, High). The choice of a simple database (only two triangular fuzzy sets on each input premise), is motivated by two reasons: (1) the rules are constructed manually, so keeping the rules to a low number helps a tighter design, (2) a more simple FKB tends to have higher generalization properties, which allows it to be used on a broader range of shapes.[16] The output is the level of aggressiveness; ranging from 1 (non aggressive) to 10 (very aggressive), 5 membership functions are used: Not, Slightly, Moderately, Quite and Very.

6.1.2. Defining the Rule Base

At this step the rule base is manually defined by the authors to map the relationships between the different membership functions of the input premises to the membership functions of the output premise. Table 1 presents the sets of fuzzy rules and Figure 2 illustrates the manually constructed FKB (MFKB).

6.2. Automatic Generation of the FKB

The automatic generation of the FKB is performed using a specialized genetic algorithm (GA). GAs are powerful stochastic optimization techniques based on the analogy of the mechanics of biological genetics and imitate the Darwinian survival of the fittest approach.[18] Each individual of a population is a potential FKB, where four basic operations of the Real/Binary Like Coded GA (RBCGA) learning are performed; reproduction, mutation, evaluation and natural selection. The RBCGA developed by

Table 1. Set of if then rules.

LCR	AOR	RL	Conclusion
Low	Low	High	Not
Low	Low	Low	Slightly
Low	High	High	Slightly
Low	High	Low	Moderately
High	Low	High	Moderately
High	Low	Low	Quite
High	High	High	Quite
High	High	Low	Very

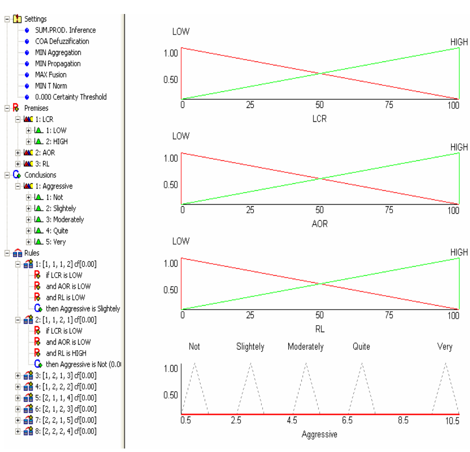


Figure 2. Manually constructed FKB (MFKB).

the authors combines a real coded and a binary coded GA. The reproduction mechanisms are a mutli-crossover proposed by the authors[19] and a uniform mutation.[20]

6.2.1. Performance Criterion of the RBCGA

In this paper, the performance criterion is the accuracy level of a FKB (approximation error) in reproducing the outputs of the learning data (belonging to the design context). The approximation error Δ_{RMS} is measured using the RMS error method:

$$\Delta_{\mathrm{RMS}} = \sqrt{\sum_{i=1}^{N} \frac{(RBCGA_{output} - data_{\ output})^2}{N}} \tag{5}$$

where N represents the size of the learning data. The RMS fitness value ϕ is evaluated as a percentage of the output length of the conclusion L, i.e.

$$\phi = \frac{L - \Delta_{\mathrm{RMS}}}{L} \times 100. \tag{6}$$

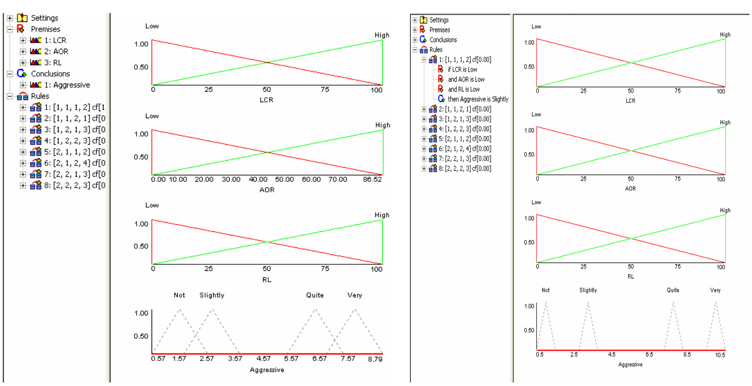
6.2.2. Generation of the Database and the Rule Dase

To generate the FKB using the RBCGA one has to set up the maximal complexity allowed, the multi-crossover probability and the mutation probability.

In this paper the maximal complexity is 5 fuzzy sets per input premise and 10 fuzzy sets on the output. These numbers are set higher than the ones used for the manual construction in order to allow the RBCGA to select from several tradeoffs. The reproduction probabilities are set to: 60% multi-crossover, 40% simplification rate and 5% mutation, more details on these mechanisms are given in. Ref 19 The simplification % was set high, in order to put emphasis on the generalization of the fuzzy model since the learning starts with a possible 5^3 (125) possible rules. The population size is set to 200 and the number of generations to 200. Each run was repeated three times to ensure the robustness of the learning process. At the end of the learning the best individual is selected according to the highest ϕ or lowest Δ_{RMS}.

The selected FKB contains 2 fuzzy sets on each premise which corroborates the choices made for the manual construction. Figure 3 shows the selected genetically generated FKB (GFKB). One can see from Figure 3(a) that premise 2 (AOR) covers the discourse domain from 0 to 86.52% (and not up to 100%), the reason being that none of the shapes had a 100% AOR, the same goes for the output premise where the values range from 1.3 to 7.6.

For a more generalized GFKB the upper limit of the AOR premise is stretched to 100% and the output was changed to cover the range 1 to 10, this will be called the generalized genetically generated FKB



(a) GFKB (b) GGFKB

Figure 3. (a) Genetically generated FKB (b) Generalized Genetically Generated FKB

(GGFKB). These alterations will obviously reduce the accuracy of the FKB regarding the reproduction of the learning set but it increases its usability. It is also important to do such changes to be able to compare the performances of the GFKB to the MFKB. Figure 3(b) illustrates the GGFKB.

7. VALIDATION OF THE FKBS

For validating the FKBs, 12 different shapes were used (8 aggressive + 4 friendly designs). To avoid differences due to different perceptions amongst different user groups, the participants selected for the evaluation all had an engineering or industrial design background, either as undergraduate or graduate students, or working in product development. By adopting this approach the authors acknowledge the subjectivity involved in perception, e.g. due to cultural differences, hence minimize the effect of this through selecting 'homogeneous' groups. A group of 20 students (PhDs and Masters) and professional designers, without knowledge of the purpose of the study, evaluated each shape. The group consisted of 5 females and 15 males. Each object was illustrated by two photographs in the evaluation grid to give a clear idea of the shape to the evaluator.

The evaluators were also shown a PowerPoint presentation with 12 shapes, each of the views lasted 3 seconds. During the evaluation, the participants were shown color photos but asked to focus on the shape; however color was necessary for clarity of the images. The authors are aware of the influence of the colors, textures, etc., on the emotional perception of an object, however in this particular work they were not considered in order to primarily keep the focus on the link between the geometry and the emotion. The participants awarded scores on a scale from 1 to 10. The response average of the 20 evaluators was computed and used as the gold standard. Ideally, low scores for the friendly designs and high ones for the aggressive designs were expected if the MFKB was to correlate successfully to the users' perception. The GFKB reproduces the users' perceptions through a fuzzy model.

The LCR, AOR and RL were calculated for each shape, Table 2 summarizes the obtained results, and these values are submitted as an observation file into MFKB and the GGFKB. The same set is used as a learning/validation set for the GFKB. The outputs of the fuzzy models will assess the predicted level of aggressiveness of the shapes.

The correlation between the human evaluation and the MFKB prediction of the shapes aggressiveness is about 0.879, which can be considered satisfactory. The correlation to the GFKB is 2% higher with 0.896 and to GGFKB is 0.890. Figure 4 illustrates the predicted aggressiveness of the shapes versus the perception of the users. One can see that the GGFKB prediction is for most of the time closer to the real perception values than the MFKB however the general behavior of the curves is similar.

7.1. Comparing the Databases

Form comparing Figures 2 and 3 one can notice that two fuzzy models are similar which confirms the choices of the authors when it comes to the database of the MFKB. The only difference is the absence of the fuzzy set "Moderately" on the output of the GGFKB. However since the COG is used as a deffuzification mechanism, the absence of the latter do not highly effect the output, because middle values can be obtained by firing rules involving the extreme fuzzy sets at the same time.

7.2. Comparing the fuzzy rule bases

Table 3 represents the genetically generated fuzzy rule base, when compared to Table 1, one can see that the first two rules and the last two rules are identical while rules 3, 4, 5 and 6 are different (non-shaded rules).

The difference in the middle rules can partially be explained since the fuzzy set "Moderately" was omitted in the genetically generated FKB, this means that rules 4 and 5 can not be identical. This change also has an influence on the immediate neighboring rules. Furthermore, the common point of rules 3–6 is switching between the high and low memberships for the premises LCR and AOR respectively (Low-High and High-Low).

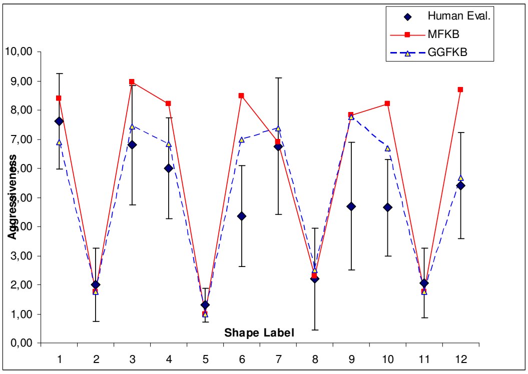


Figure 4. Perception vs. Prediction of Aggressiveness Level.

Table 2. Shapes' Characteristics.

Shape	LCR [%]	AOR [%]	RL [%]
1	100.00	62.24	33.33
2	0.00	0.00	66.67
3	100.00	86.52	33,33
4	96.49	61.11	33,33
5	0.00	0.00	100,00
6	100.00	65.75	33,33
7	83.65	61.02	66,67
8	12.50	0.00	66,67
9	100.00	69.02	66,67
10	100.00	0.00	33.33
11	0.00	69.51	66,66
12	94.23	53.15	0,00

Table 3. Rules Base of the GGFKB.

Shape	LCR	AOR	RL	Conclusion
1	Low	Low	High	Not
2	Low	Low	Low	Slightly
3	Low	High	High	Quite
4	Low	High	Low	Quite
5	High	Low	High	Very
6	High	Low	Low	Slightly
7	High	High	High	Quite
8	High	High	Low	Very

By analyzing Table 2; the closest shapes to having those pairs are number 10 and 11. While the rest of the shapes represent mainly the pairs Low-Low and High-High.

This leads the RBCGA to give lower priority to the pairs High-Low, Low-High since the learning was about reducing the Δ_{RMS}. The middle rules were mainly used as a support to the extreme rules. Furthermore, one can see that when it comes to RL for both shapes 10 and 11 it is neither high nor low which complicates more the rule extraction.

The automatic generation validated the distribution of the fuzzy sets in the database of the FKB. And the extreme rules were reproduced too. Both the automatically and manually constructed FKBs reproduced satisfactorily the human perception of the shapes.

8. CONCLUSION

This paper has shown a manually constructed and a genetically generated fuzzy logic models for evaluating aggressiveness in a form, and has been validated through an empirical study with design students and professionals. The initial results have shown that there are indeed characteristics in a form which characterize how it is perceived. The genetically generated model that doesn't suffer any bias (bias that the authors might have) was very similar to the one manually constructed by the authors which confirms the statement above. The results indicate that design rules for aggression are possible and hence establishing fuzzy logic models for other adjectives is likely to be possible. The implications of the work are that a set of design rules may be established in a fuzzy model and can be easily accessible. This can assist designers in understanding how a form may be perceived by users and how they can change certain geometric ratios to change the emotions induced by their product. The limitation in respect to the automatic extraction of fuzzy models for other adjectives, is the lack of variety of some shapes' characteristics. More shapes would be needed for the learning. Hence, future sets may be supplemented through shapes deliberately created. Since ideally a first sub-set should be used for learning a second subset for cross-validation, while the last should be used for validation.

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