KEER2010, PARIS | MARCH 2-4 2010
INTERNATIONAL CONFERENCE ON KANSEI ENGINEERING AND EMOTION RESEARCH 2010

GENETIC FUZZY GENERATION OF MASS PERCEPTION IN NON-FUNCTIONAL 3D SHAPES

Sofiane ACHICHE

Technical University of Denmark, Engineering Design and Product Development Section, Denmark

ABSTRACT

When designers create new forms they integrate both quantitative objective elements and qualitative subjective elements. However, users will generally react to these forms without knowing the intended Kansei integrated into them by the designer. Human beings are doted with a complex brain structure and it is argued that human attributes originate from three different levels of the brain: the visceral level; the behavioral level and the reflective level. This paper focuses upon the visceral level of reaction by automatically building a link between geometric properties of non-functional 3D shapes and their perception by observers. The link between geometry and human perception is created using a genetic learning algorithm combined with a fuzzy logic decision support system. Human evaluations of the non-functional 3D shapes against two contrary perception adjectives (massive versus lightweight) are used as the learning data set. The non-functional 3D shapes were designed by engineering design students from the Technical University of Denmark who were asked to design non-functional 3D shapes evoking either the adjective massive or light. Eight fuzzy models were developed: three (3) models constructed manually by the author and five (5) genetically generated. The fuzzy models were constructed using different sets of inputs of quantitative geometric properties. Combination of the different inputs resulted in different sets of fuzzy rules that can eventually be used as design guidelines for designers. The results obtained and presented in this paper are very promising. Correlations as high as 99% between fuzzy and human perception were obtained along with errors as low as 0.14 on a scale ranging from -3 to 3.

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

1. INTRODUCTION

Designers can integrate quantitative objective elements such as functionality, manufacturability, weight, and other technical properties into their product more easily than subjective qualitative elements. Furthermore, functionality and usability seem no longer sufficient in a product's success [1] and subjective responses to the product by the customer greatly influence its success [2]. It is now well accepted that aesthetics are a contributing but subjective factor in determining the success of a product, and designers should include characteristics that are visceral or engage the senses [3]. Additionally, according to [4], observers (humans) are doted with a complex brain structure and a variable preference mechanism, some wired at birth and some developed through life experience. Andrew Ortony *et al.* suggest that these human attributes are generated from three different levels of the brain: the visceral level (the automatic, prewired layer), the behavioral level (the part that contains the brain processes that control everyday behavior) and the reflective level (the contemplative part of the brain) [5-6].

It was reported that designers are not always successful in conveying the desired message through aesthetical form. This highlights the difficulty for users/designers to link emotions through words to design characteristics [7]. To achieve this link several studies aimed at identifying relations between the characteristics of a product's shape and its emotional message/perception have been carried out. A study based upon perceptual psychology (perception of "safety", "friendliness" of a machine/car) was proposed in [8-9]. Design and computer science approaches are employed in [10-13]. However, in these experiments no systematic and precise specification of a correspondence between product elements and emotional terms was provided. In [14], a study using Kansei engineering and neural networks to cluster objects that have a similar perception among users by focusing on color was carried out. Fuzzy Logic was used for validation of aesthetics sensitivity in automatic generation of roof geometries [15] and to evaluate building aesthetics based on specific features [16], however they did not link general geometric properties to an emotional context. This paper focuses on the visceral level of reaction by building a link between the geometric properties of non-functional 3D shapes and the perception of these shapes by users/observers on a visceral level. The research objectives and methodology are discussed in detail in the following sections.

2. RESEARCH OBJECTIVES

The aim of the research presented here is to propose computer models that designers can use to assess the perception of their product design from a shape perspective. This will be first done through identification of the characteristics of a form that can be used to evoke a specific perception in users. Another objective of the research also aims to understand the influence of these characteristics and their co-influences in regards to perception. These characteristics are used as inputs variables to fuzzy knowledge bases (FKBs) that can be used to evaluate the ability of the forms to evoke a particular perception. The research presented here can be considered an extension of a previous study where 3 manual multiple input / single output FKBs were developed [17-18]. Both manually and genetically generated FKBs are developed and their efficiency in reproducing human perception is evaluated. The manually constructed models assess one input variable at a time while those genetically generated assess a combination of input variables along with the fuzzy rules that map the relationships between the input variables and the targeted perception.

The methodology used is based on the analogy of communication presented in [11], combined with a design and computer science approach in order to create the link between the space of design variables and the space of aesthetic characteristics. A 6-step methodology has been employed: 1) students created forms (using foam) which represent a particular set of perception, students were allowed to use color, 2) CAD models equivalent to the foam form models were created and colored gray, 3) geometric properties were identified and used as input premises to the FKBs, 4) for each single characteristic the FKB was manually constructed; 5) genetically generated FKBs (rule base and data base) were created using all combinations of the identified geometric characteristics; 6) an evaluation was conducted with users to serve as the comparison to the fuzzy predictions. The human perception of the forms was used as a learning set to automatically generate FKB equivalents. In this paper, evaluation of the models was conducted on a pair of contrary adjectives namely: massive and light. A group of users were shown different shapes designed to appear either massive or light and were asked to rate the massiveness or lightness of each of the shapes. The users did not know which shape was supposed to be massive or light.

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. Each student was presented with a set of adjectives describing a certain perception/emotion. The students' task was to create a shape that best represented the given emotions. The terms given were massive and static; light and friendly; dynamic and integrated and; aggressive and edgy. Only massive and light are considered in this paper. The students were provided with cubes of foam (200mm x 200mm x 200mm), and provided with one of the four sets of adjectives. Hence around 12-15 models representing each set of terms were produced. The students were free to use color on their forms, however in this paper 3D CAD grayscale equivalents of the shapes are used, since FKBs, described in the following sections, consider the form but not the color. Six of the 3D objects created to express massiveness were selected, together with five expressing lightness. Figure 1 shows the different shapes selected. Shapes 3-7 were shapes that were designed to be light with the remainder designed as massive.

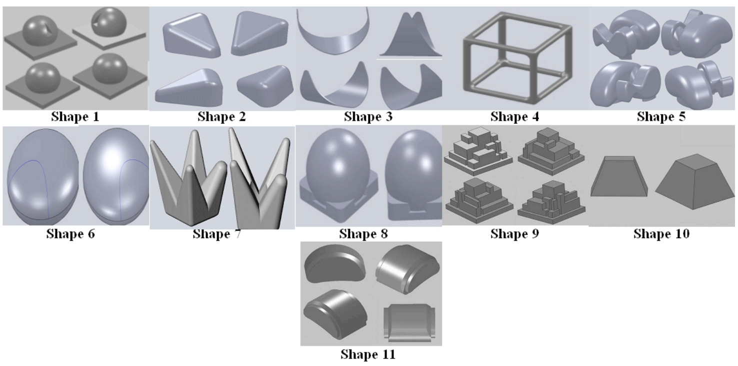

Figure 1: 3D non functional shapes considered for the study

3.1. Mapping shape Parameters and Aesthetic Characteristics

In this section, mapping of shape parameters to the aesthetic characteristics of the objects is described. The parameters linked to Massive/Light are: Volume/Surface ratio (VSR); Centre of gravity ratio (CGR) and Height/Width ratio (HWR). These parameters were defined as a result of a visual analysis of the 3D objects.

3.2. Universe of discourse of the input premises

Geometric parameters form the basis of the inputs of FKBs and are described as follows:

Volume/Surface Ratio (VSR): in order to get a non-dimensional normalised value, the VSR of the shapes was compared to the maximum VSR the design students worked with; i.e. the 200x200x200mm cube. The cube's VSR is given by L/6 (L being the length of one side of the cube); hence the VSR is given by:

$$VSR = \frac{6 \times VSR_{shape}}{L} \times 100 \qquad (2)$$

Centre of Gravity Ratio (CGR): the centre of gravity is given by the z coordinate of the centre of gravity of the shapes, in the direction that it was presented during the evaluation. In order to have a normalised ratio the z coordinate was compared to the maximum possible value (V); hence the CGR is given by:

$$CGR = \frac{z_{cg_{shape}}}{V} \times 100 \qquad (3)$$

Height/Width Ratio (HWR): HWR is obtained by dividing the maximum height of the shape by the maximum width in the direction it was presented to the evaluators, as in Figure 1. However to put this ratio in FKB, one has to normalise the premise (0 to 100%), and in order to achieve this one can use the analogy of scanning a photograph where a height/width ratio of 1.5 is considered tall. This means that each of the shapes' HWR is measured against 1.5, and if higher it is equalled to 1.5; hence, HWR will be evaluated as follows:

$$HWR = \begin{cases} \dfrac{HWR_{shape}}{1.5} \times 100 & if \quad HWR_{shape} \le 1.5 \\ 100\% & otherwise \end{cases} \qquad (4)$$

Table 1 summarizes the obtained results for VSR, CGR and HWR per shapes.

4. HUMAN PERCEPTION

The human perception of the Lightness/Massiveness of the 11 shapes was carried out by a group of 20 people. To minimize 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. 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 3 females and 17 males aged between 24 and 66. Each object was illustrated with the minimum number of views from the CAD models in order to illustrate the shape, i.e. between 2 and 4 views, depending on the level of symmetry. In order to exclude the influence of colors, textures, etc. on the emotional perception of an object and to keep the focus on the link between geometry and perception, the illustrations were all in grayscale. The participants evaluated the eleven shapes using semantic scales ranging from Very Light to Very Massive. A very light shape would be rated as -3, a very massive shape as 3, and a rating of 0 was given for a shape which was perceived as neutral. The order in which the shapes were presented to the participants was randomized to minimize any influence of the ordering of the shapes.

Table 1: Shape Characteristics & Evaluations of the users

Shape	Geometric Characteristics				Human Rating: V. Light to V. Massive	
	VSR [%]	CGR [%]	HWR [%]		HWR [%]	HWR [%]
1	41.12	50.01	45.98		1.65	0,54
2	31.40	17.05	48.00		0.85	1,53
3	02.87	01.08	53.85		-2.25	0,79
4	14.58	50.00	55.55		-1.40	0,94
5	31.42	17.71	44.44		1.20	1,06
6	62.83	02.50	09.88		0.50	1,39
7	50.94	38.95	66.67		0.00	1,17
8	93.66	50.00	78.79		2.68	0,58
9	41.44	50.79	49.38		2.00	0,92
10	59.50	25.00	41.27		1.79	0,79
11	53.61	25.01	38.89		1.10	1,07

The average response from the 20 participants was calculated and used both for learning of the FKBs and as the gold standard to compare to the fuzzy logic model; standard deviations were also calculated for each of the shapes (Table 1 left). It is important to notice that the human evaluators agreed in most cases with the designers' intentions in regards to massive/light perception, apart from shape 7 that was rated neutral instead of light.

5. CONSTRUCTION OF THE FUZZY KNOWLEDGE BASES

FKB is composed of a data base and a rule base. In this paper the constructed FKBs are of the SISO (single inputs/single output) and MISO (multiple inputs/single output) types. SISO FKBs take as inputs the geometric variable VSR, HWR and CGR individually while MISOs are genetically generated and consider all possible combinations of the geometric variables. Eight (8) different FKBs are developed in this paper, with the following sets of input variables:

1. Manually (SISO): a) VSR, b) CGR and c) HWR
2. Automatically using a genetic algorithm (MISO): a) VSR, CGR and HWR (2 different FKBs), b) VSR and CGR, c) VSR and HWR and d) CGR and HWR.

The goal of using these combinations is to find the near-optimal FKB that matches human perception. Furthermore, if more than one FKB is accurate in reproducing the human perception, it will give the designers alternatives concerning which parameters to control in order to alter and/or assess the perception of their models.

5.1. Manual construction of the FKBs

Manual construction of the FKBs was carried out by first defining the databases and then defining the rule bases as described bellow.

5.1.1. Defining the database

The database is composed of the inputs/outputs of the FKB. The manually constructed FKBs use one input and they are similar where each of the inputs has five membership functions distributed evenly; the semantics linked to each input are as follows:

VSR: Very Hollow, Hollow, Average, Dense and Very Dense
HWR: Very Fat, Fat, Average, Slim (Tall) and Very Slim (Very Tall)
CGR: Very Low, Low, Average, High and Very High

The three FKBs share the same output premise with five membership functions ranging from Very Light to Very Massive. Figure 2 illustrates the three manually constructed FKBs.

5.1.2. Defining the rule base

The rule base is manually defined to map the relationships between the membership functions on the input premises and the membership functions on the output premise. The rule base contains 5 'If Then' rules. It is believed by the author that a Very Hollow, Very Slim or Very High shapes will be perceived as Very Light while a Very Dense, Very Fat or Very Low shape will be perceived as Very Massive, the rest of the rules fill-in the middle values.

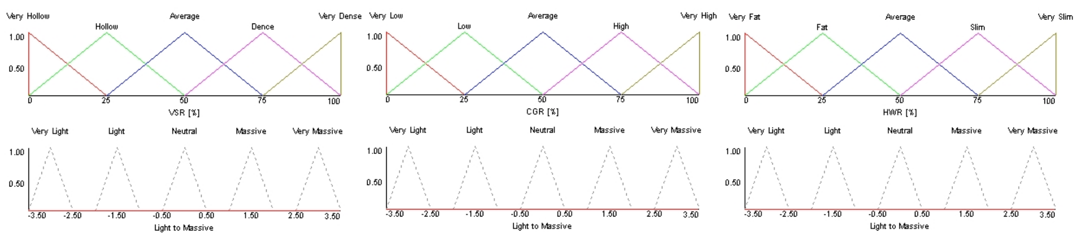

Figure 2: VSR, CGR and HWR SISO FKBs (the data bases)

5.2. Automatic generation of the FKBs

Automatic generation of FKBs was performed using a specialized genetic algorithm (GA) named Real/Binary Like Coded GA (RBCGA). Each individual of a population is a potential FKB, where four basic operations of RBCGA learning are performed; reproduction, mutation, evaluation and natural selection. RBCGA developed by the author combines a real coded and a binary coded GA. The reproduction mechanisms are a multi-crossover defined in [21] and a uniform mutation [22].

5.2.1. 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 is a combination between the Δ_{RMS}, measured using the RMS error method and the absolute error Δ_{ABS}. The next two equations detail these errors.

$$\Delta_{RMS} = \sqrt{\sum_{i=1}^{i=N} \frac{(RBCGA^{i}_{output} - data^{i}_{output})^2}{N}} \tag{5}$$

While the absolute error is measured as follows:

$$\Delta_{ABS} = \sum_{i=1}^{i=N} ABS\left(\frac{RBCGA^{i}_{output} - data^{i}_{output}}{N}\right) \tag{6}$$

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

$$\phi = \left(1 - \frac{\Delta_{RMS} + \Delta_{ABS}}{2l}\right) \times 100 \tag{7}$$

5.2.2. Genetic Generation of the Database and the Rule Base

To generate the FKBs 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 6 fuzzy sets per input premise and 16 fuzzy sets on the output; with these numbers the RBCGA can select from several tradeoffs. The reproduction probabilities are set to: 90% multi-crossover, 10% simplification rate and 5% mutation, more details on these mechanisms are given in [21]. This simplification is used in order to put emphasis on generalization of the fuzzy model since the learning starts with a possible 6^3 (216) or 6^2 (36) possible rules. The population size is set to 200 and the number of generations to 200. Each run was repeated three times to ensure robustness of the learning process. At the end of the learning the best individual was selected according to the highest ϕ. The selected FKBs for the 4 different combinations are as follows:

a) Three Inputs: VSR, CGR and HWR (FKB_VCH)

FKB_VCH is a 3 input / one output FKB. From the last generation of genetic learning two FKBs were selected; the first most accurate one (FKB_VCH1) with 3 fuzzy sets on each premise and 27 fuzzy 'If Then' rules, and the simplest one with 2 fuzzy sets on each premise and 8 fuzzy 'If Then' rules (FKB_VCH2). They respectively have 9 and 5 membership functions on the output. Figure 3 illustrates both FKB_VCHs. One can notice that the membership functions are not evenly distributed on the output premise however they do cover the entire range from very light to very massive. Using the center of gravity as a defuzzification mechanism along with the fuzzy rules enables us to get perception values between these two extremes.

b) Two Inputs: VSR & CGR (FKB_VC)

FKB_VC is a 2 input / one output FKB. Genetic learning produced a near optimal solution with 3 fuzzy sets on each premise and 9 fuzzy If Then rules, 5 fuzzy sets are used on the output. Figure 4 illustrates FKB_VC and one can notice that for CGR the average value is centered close to 1/3. This value corroborates the known principle of stability for triangles; a shape is considered stable with a center of gravity situated at 1/3 of its height; a principle used in the manual approach presented in [18].

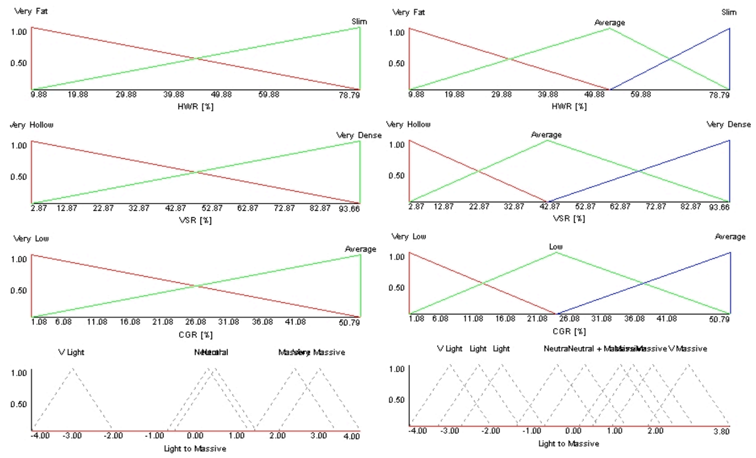

Figure 3: FKB_VCH1 & FKB_VCH2

c) Two Inputs: VSR & HWR (FKB_VH): FKB_VH is a two input / one output FKB. Genetic learning produced a near optimal solution with 3 fuzzy sets on each premise and 9 fuzzy If Then rules, 5 fuzzy sets are used on the output. Figure 5 illustrates FKB_VH, and one can notice the similarity to FKB_VC (slightly different in the distribution of the membership function on the output premise). One could conclude that in the context of this paper the combination VSR/CGR and VSR/HWR influence similarly the perception of mass in non-functional 3D shapes.

d) Two Inputs: HWR & CGR (FKB_HC): FKB_HC is a two input / one output FKB. Genetic learning produced a near optimal solution with 4 fuzzy sets on each premise and 16 fuzzy If Then rules, 8 fuzzy sets are used on the output. Figure 6 illustrates FKB_HC.

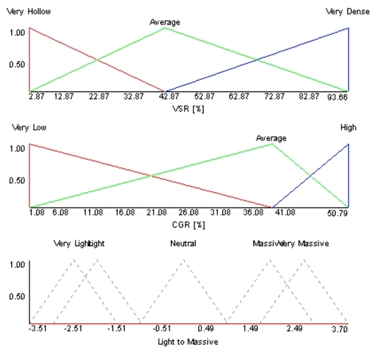

Figure 4: FKB_VC

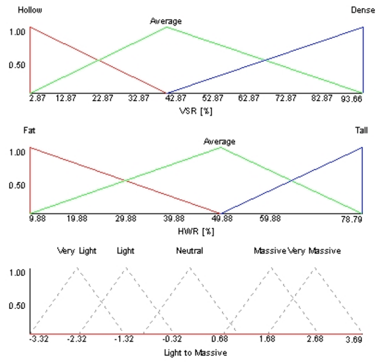

Figure 5: FKB_VH

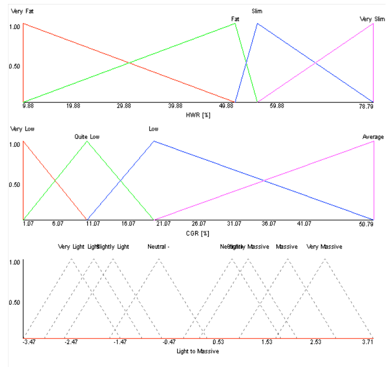

Figure 6: FKB_HC

6. VALIDATION OF THE FKBS

The FKBs were evaluated using the 11 different shapes (6 massive + 5 light designs). Ideally, low scores for the light designs and high ones for the massive designs were expected if the FKBs were to correlate successfully to the users' perception. The VSR, HWR and CGR values summarized in Table 1 are submitted, as an observation file, to the 8 FKBs developed above. The outputs of the fuzzy models will assess the predicted level of massiveness/lightness of the shapes. Table 2 summarizes the fuzzy prediction of the 8 FKBs proposed in this paper versus the (human) perception of the shapes, while Table 3 reports the correlation values along with the error profiles of the fuzzy predictions versus human perception.

Table 2: Evaluation of the users vs. fuzzy predictions

Perception	SISO FKBs (Manual)			MISO FKBs (Automatic Generation)				
	HWR	VSR	CGR	FKB_VCH1	FKB_VCH2	FKB_VC	FKB_VH	FKB_HC
1.65	0.24	-0.53	-0.00	1.70	1.03	1.73	1.75	1.47
0.85	0.12	-1.12	1.98	0.97	-0.11	1.06	0.81	1.12
-2.25	-0.23	-2.83	2.93	-2.25	-1.80	-2.50	-2.32	-2.25
-1.40	-0.33	-2.12	0.00	-1.35	-0.53	-0.97	-1.31	-1.31
1.20	0.33	-1.11	1.94	1.00	0.03	1.05	0.87	1.21
0.50	2.41	0.77	2.85	0.54	0.49	0.81	0.47	0.43
0.00	-	0.0	0.6	0.01	0.37	0.46	-0.05	0.07

	1.00	6	6					
2.68	-1.73	2.62	0.00	2.75	2.42	2.70	2.68	2.66
2.00	0.08	-0.51	-0.05	1.80	0.88	1.89	1.75	1.75
1.79	0.52	0.57	1.50	1.57	1.16	0.98	1.53	1.56
1.10	0.67	0.22	1.50	1.30	1.04	0.98	1.55	1.47

Table 3: Correlation & Error Profiles of the Fuzzy Predictions

	SISO FKBs (Manual)			MISO FKBs (Automatic Generation)				
FKBs	**HWR**	**VSR**	**CGR**	**VCH1**	**VCH2**	**VC**	**VH**	**HC**
Correlation	-0.04	0.77	-0.40	0.99	0.90	0.97	0.99	0.99
Max ABS Error	4.41	2.51	5.18	0.21	1.17	0.81	0.45	0.37
Min ABS Error	0.43	0.06	0.29	0.00	0.01	0.01	0.00	0.00
RMS Error	1.86	1.46	2.15	0.13	0.71	0.35	0.21	0.18
Mean ABS Error	1.55	1.16	1.68	0.10	0.59	0.27	0.15	0.14
Average Error	1.71	1.31	1.92	0.12	0.65	0.31	0.18	0.16

From Table 3 one can see that CGR and HWR are not good indicatives of the perception of massive/light, since the correlation is low and the average error is the highest of the 8 FKBs. VSR as a sole indicator predicted the perception with a 77% correlation, however because of the high error (1.31) one can see in Figure 7 that 5 out of 11 shapes where predicted outside one standard deviation from the human perception. From these results, one can conclude that it is difficult to predict the perception of massiveness using only one of the geometric properties identified in this paper namely: HWR, VSR, CGR, however of these three; VSR has the highest influence on the perception if used individually.

When combining VSR, HWR and CGR to create MIMO FKBs, one can easily see from Table 3 that the error levels went down drastically with the highest value for the average error at 0.65 while the lowest correlation is 90%, both obtained by FKB_VCH2. FKB_VCH1 performed best when considering both the correlation level and error profiles; it takes into account all three identified physical properties as inputs (VSR, CGR and HWR) and uses 27 fuzzy rules. From a practical point of view and in the perspective of using the fuzzy rules as design guidelines by a human designer, 27 fuzzy rules might be too many. The alternative, while still using the three inputs, is FKB_VCH2 that uses only 8 rules. However as one can see in Figure 8, FKB_VCH2 prediction has shape 1 and 9 outside one standard deviation from human perception. This is predictable for two reasons: firstly; the absolute errors are higher and secondly; using simpler FKBs increases generality but decreases precision [23].

The other possibility for reducing the complexity (number of rules) of the FKBs is to use fewer inputs. FKB_VC, FKB_VH and FKB_HC, use two inputs and they reproduced human perception with very high correlation levels ranging from 97% to 99% and low error values. As illustrated in Figure 9, all three FKBs satisfactorily predicted the human perception of massiveness; however FKB_VC and FKB_VH use 9 fuzzy rules in comparison to 16 used by FKB_HC. The low number of rules makes it easier for a human to understand and follow the rules as design guidelines. However, if one uses the FKBs as decision support models then FKB_VC, FKB_VH and FKB_HC are interchangeable and it depends on which parameters the designers prefer to alter.

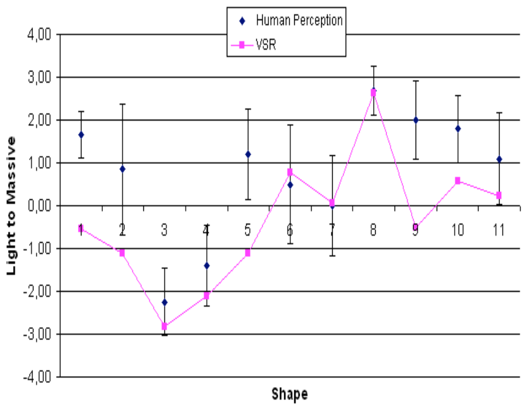

Figure 7: Human Vs FKB_VSR prediction

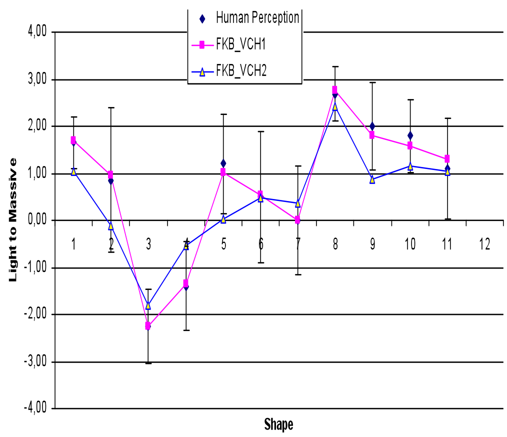

Figure 8: Human Perception vs. FKB_VCH1& FKBC_VCH2 Prediction

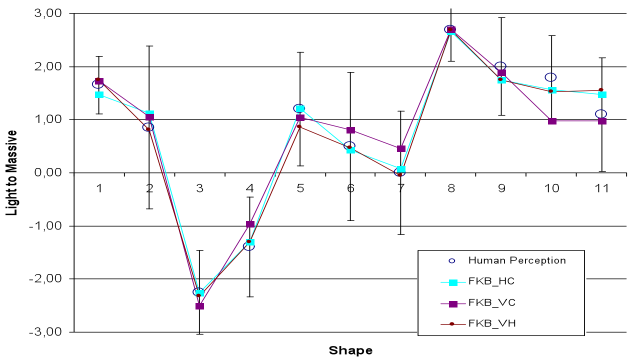

Figure 9: Human Perception vs. FKB_VH, FKBC_VC & FKBC_HC Prediction

7. CONCLUSION

This paper presented genetically generated fuzzy decision support models for the prediction of human mass perception in 3D non-functional shapes. Three physical properties were used as input combinations for the fuzzy logic models to evaluate the lightness/massiveness of the shapes. Three Single Input and Single Output fuzzy models were manually constructed as an attempt to model the link between mass perception and one physical property of the shapes.

From the validation results, it was concluded that it was not feasible to properly predict mass perception using only one of; VSR, CGR or HWR individually. However out of these three parameters, the volume surface ratio (VSR) has the most influence by its own. Combination of the three physical properties as inputs for the fuzzy models provided a very precise prediction of mass perception but with a relatively high number of fuzzy rules. Using only two inputs (3 different combinations) proved effective for predicting mass perception. The results shown in this paper confirm the link between the physical characteristics of a form and how it is perceived by humans/users. The four genetically generated Multiple Inputs Single Output fuzzy models developed in this paper can assist designers in understanding how a form may be perceived by users and how they can change certain geometric ratios to change the perception induced by their product. Additionally, they can alter or evaluate the perception of massiveness of their designed shapes by influencing a combination of several physical properties at the same time. They can choose to either work with: (VSR, HWR and CGR), (VSR and CGR), (VSR and HWR) or finally (HWR and CGR). However in order to make the fuzzy models even more robust, more shapes would be needed for learning. Hence, future sets may be supplemented through shapes deliberately created. Ideally a first sub-set should be used for learning a second subset for cross-validation, while the last should be used for validation which was not done here because only 11 models were available.

8. ACKNOWLEDGMENTS

The author thanks all the participants to the experiment conducted in this paper.

REFERENCES

1. Helander, M. G., and Khalid, H. M., Affective and pleasurable design. In G. Salvendy (Ed.), Handbook of human factors and ergonomics (3rd ed., pp. 543-572). Hoboken, NJ: John Wiley & Sons, 2006.
2. Henson, B., Barnes, C., Livesey, R., Childs, T., and Ewart, K., Affective consumer requirements: A case study of moisture packaging, Concurrent Engineering: Research and Applications, 14(3), pp. 187-196, 2006
3. Norman, D.A., Emotional Design: Why We Love (or Hate) Everyday Things, Basic Books, New York, 2004.
4. Norman, D., Attractive Things Work Better, Emotion and design. Interactions Magazine, ix (4), 36-42, 2002.
5. Norman, D. A., Ortony, A., & Russell, D. M., Affect and machine design: Lessons for the development of autonomous machines. IBM Systems Journal, 42 (1), 38-44, 2003.
6. Ortony, A., Norman, D. A., & Revelle, W. Effective functioning: A three level model of affect, behavior, and cognition. In J.-M. Fellous & M. A. Arbib (Eds.), Who Needs Emotions? The Brain Meets the Machine. New York: Oxford University Press, 2005.

7. Ahmed, S., and Boelskifte, P., "Investigation Of Designers Intentions and a Users' Perception of Product Character." Proceedings of Nordesign, Reykjavik, Iceland, 2006.
8. Lebbon, C. and McDonagh-Philp, D.C., Exploring the Emotional Relationship between Users and Products, Proc. of Designing for the 21st Century II: An International Conference on Universal Design, Rhode Island, USA, 2000.
9. Reid, T., Gonzalez, R. and Papalandros, P., A Methodology for Quantifying the Perceived Environmental Friendliness of Vehicle Silhouettes in Engineering Design, CD-Version, ASME IDETC/CIE, San-Diego, USA, 2009.
10. Wallace D.R., and Jakiela, M.J., Automated Product Concept Design: Unifying Aesthetic and Engineering, IEEE Computer Graphics & Applications, pp. 66-75, July 1993.
11. Van Bremen E.J.J., W.G. Knoop, I. Horvath, J.S.M. and Vergeest, B. Pham, Developing a Methodology for Design for Aesthetics Based on Analogy of Communication, Proceedings of the 1998 ASME Design Engineering Technical Conferences, Atlanta, Georgia, Sept. 13-16, 1998, USA, DET98/DAC-5614.
12. Hsiao S.W. and Wang H.P., Applying the Semantic Transformation Method to Product Design, Design studies, Vol. 19, No. 3, London, Elsevier Science Ltd, 309-330, 1998.
13. Smyth S.N. and Wallace, D.R., Towards the Synthesis of Aesthetic Product Form, Proceedings of DETC'00, ASME 2000 Design Engineering Technical Conferences and Computers and Information in Engineering Conference Baltimore, Maryland, September 10-13, , DETC2000/DTM-14554, 2000
14. Jianning S. and Fenqiang, L., Research of Product Styling Design Method Based On Neural Network; Third International Conference on Natural Computation, Volume 2, pp. 499 – 504, 2007
15. Tsutsumi, K., Sasaki, K., Study on Shape Creation of Building's Roof by Evaluating Aesthetic Sensibility, Mathematics and Computers in Simulation, Vol. 77, pp. 487–498, 2008.
16. Norikazu, I.; Hiroshi, M.; Yukihiro; K., Tomomi, T.; Daisuk, Y., Building exterior design system by hierarchical combination fuzzy model, Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS, VOL. 5, p 2573-2578, 2001.
17. Achiche, S., Ahmed, S., Mapping Shape Geometry and Emotions Using Fuzzy Logic, Proceedings of ASME IDETC/CIE 2008, CD Version, NYC, USA, 2008.
18. Achiche, S. and Ahmed, S., Modeling Perception of 3D Forms Using Fuzzy Knowledge Bases, Proceedings of ASME IDETC/CIE 2009, CD ROM Version, San Diego, USA, 2009.
19. Balazinski, M, Achiche, S. and Baron, L., Influences of Optimization Criteria on Genetically Generated Fuzzy Knowledge Bases, International Conference on Advanced Manufacturing Technology, pp. 159-164, 2000.
20. Achiche, S., Baron, L. and Balazinski, M., Real/Binary Like Coded Genetic Algorithm to Automatically Generate Fuzzy Knowledge Bases, IEEE Fourth International Conference on Control and Automation, Montreal, Canada, pp. 799-803., 2003.
21. Achiche, S., Balazinski. M. and Baron, L., "Multi-combinative Strategy to Avoid Premature Convergence in Genetically-generated Fuzzy Knowledge Bases", Journal of Theoretical and Applied Mechanics, No. 3, Vol. 42, pp.417-444, 2004.
22. O. Cordòn, F. Herrera, P. Villar, "Analysis and Guidelines to Obtain a Good Uniform Fuzzy Partition Granularity for Fuzzy-rule Based Systems using Simulated Annealing", International Journal of Approximate Reasoning, pp. 187-216, 2000.

23. Baron, L., Achiche, S., Balazinski, M., A Genetic-Based Learning Process for Fuzzy Decision Support Systems, International Journal of Approximate Reasoning, Vol: 28, issue: 2-3, pp. 125-148, 2001.