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PREDICTING AFFECTIVE PROPERTIES OF TACTILE TEXTURES USING ANFIS MODELLING

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ABSTRACT

A technique commonly used in Kansei Engineering to map affective responses to physical properties of products is to administer a semantic differential questionnaire and analyze the results using multivariate regression. A widely acknowledged problem with this approach is that the statistical analysis techniques are not permissible for the non-linear, ordinal data produced by the scales. To address this limitation, this research assesses the use of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to simulate and analyze the mapping between the physical properties of tactile textures and people's affective responses. Eighteen people were asked to rate the tactile feel of thirty seven textures against six pairs of adjectives on a semantic differential questionnaire. The friction coefficient, average roughness and a thermal parameter of each surface texture were measured. Using collected data, ANFIS models were built to predict the affective responses to tactile surface textures. The resulting ANFIS models always yielded lower errors when compared to regression models and demonstrated a good match between predicted and actual responses. The use of ANFIS models could provide more insightful information than traditional statistical analysis techniques for product designers, in the form of 2D and 3D data plots of affective response, or in the form of fuzzy rules.

Keywords: *Affective Engineering, Touch, Neural Networks*

1. INTRODUCTION

Affective Engineering is concerned with measuring people's subjective responses to products, identifying the properties of the products to which they are responding, and then

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using the information to improve the design. Affective Engineering is a westernized approach to Kansei Engineering which has been pioneered by Nagamachi in Japan since the 1970s (Nagamachi 1995).

The most commonly used approach in affective engineering is to identify adjectives that consumers use to describe the product and embody them into a self-report, semantic differential questionnaire (Osgood et al., 1957). A representative sample of consumers is then asked to rate the degree to which each word describes a range of products. The responses to the questionnaires are turned into a measure of affective response using multivariate regression techniques. This process creates quantitative semantic spaces tailored to the specific context of the products being investigated, against which to regress measures of the physical properties or features of the products (see for example (Henson et al. 2006)).

While this approach is useful for analysis, it does not sufficiently capture the dependencies between product properties to allow the prediction of people's reactions to new products, and the validity of the measurements produced by this process can be disputed for a wide variety of reasons. While not addressing all of the issues, the use of fuzzy or symbolic reasoning available with artificial intelligence techniques is an approach worth exploring to improve the validity of measurements (Nagamachi 2006) and for prediction of people's responses.

In the last five years or so, the use of artificial intelligences techniques to map affective responses to design features in affective engineering has emerged as a substantial research area. There have been examples of the use of artificial intelligence techniques in affective design using fuzzy rule based models (Park and Han, 2004; Hotto and Hagiwara, 2006; Lin et al., 2007), rough sets (Yanagisawa and Fukuda, 2005; Nishino et al., 2006; Zhai et al., 2007) and neural networks (Hsiao and Huang, 2002; Lai et al., 2006; Chen et al., 2006).

In this study, Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed to simulate and analyze the mapping relation between the physical properties of products (in this case tactile surface textures) and people's affective responses. ANFIS was chosen because it combines the advantages of being a fuzzy inference system and an adaptive neural network (Jang et al., 1997).

Section 2 explains the theory of ANFIS in detail. Section 3.1 describes the experimental method of the collection of people's affective responses to tactile surface textures, and Section 3.2 explains how the ANFIS model was trained and the results are presented in Section 4.

2. THEORY

2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

A fuzzy inference system (FIS) implements a nonlinear mapping from an input space to an output space by a number of fuzzy rules constructed from human knowledge. While many expert systems need a rule base, neuron-fuzzy systems use artificial neural networks (ANNs) to identify fuzzy rules and tune the parameters of membership functions in FIS automatically. In this way, the need for the expert knowledge is eliminated. There are several approaches to integrate ANNs and FISs depending on the application type (Nauck et al., 1997). A specific approach in neuro-fuzzy systems is ANFIS which is a Sugeno type FIS implemented in the framework of adaptive neural networks (Jang, 1993).

The ANFIS architecture is depicted in Figure 1. An example with two inputs (x_1 and x_2) each having two fuzzy levels is given. It has five layers where nodes in each layer have different functionality. A circle indicates a fixed node whereas a square indicates an adaptive node whose parameters are changed during the training process. The first order Sugeno type fuzzy rules are then as follows. For a FIS with two inputs (x_1 and x_2) and one output (y) and where each input is assumed to have two fuzzy sets (Wang and Elhag, 2008).

Rule 1: If (x_1 is A_1) and (x_2 is B_1) then $f_{11}=p_{11}x_1+q_{11}x_2+r_{11}$

Rule 2: If (x_1 is A_1) and (x_2 is B_2) then $f_{12}=p_{12}x_1+q_{12}x_2+r_{12}$

Rule 3: If (x_1 is A_2) and (x_2 is B_1) then $f_{21}=p_{21}x_1+q_{21}x_2+r_{21}$

Rule 4: If (x_1 is A_2) and (x_2 is B_2) then $f_{22}=p_{22}x_1+q_{22}x_2+r_{22}$

In Sugeno fuzzy rules, the parameters, p_{ij}, q_{ij}, and r_{ij} are determined during the training phase of ANFIS.

Layers 1 and 4 are adaptive. Adjustable parameters in Layer 1 describe the shape of the membership functions and are referred to as premise parameters. The adjustable parameters in Layer 4 related to the first order polynomials are called consequent parameters. The task of ANFIS in learning is to tune the premise and consequent parameters until the desired input-output mapping from the FIS is achieved. This learning task is accomplished by a hybrid algorithm combining the least squares method and the gradient descent method (Jang, 1993). The hybrid algorithm is composed of a forward pass and a backward pass. In the forward pass of the algorithm, while the premise parameters are held fixed, functional signals go forward to Layer 4 and then the consequent parameters are determined by the least squares method. In the backward pass, while consequent parameters are held fixed, the error measure propagates backwards and the premise parameters are updated by the gradient descent method to adjust the membership functions.

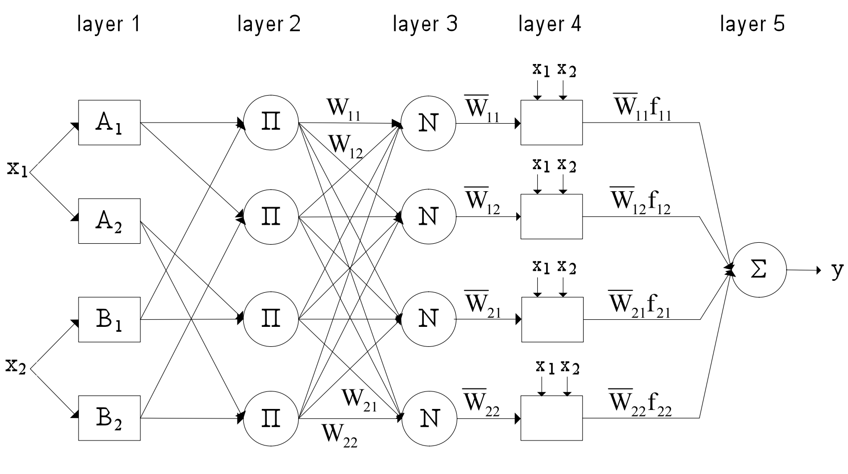


Figure 1: ANFIS architecture

3. APPLICATION OF ANFIS TO THE AFFECTIVE DESIGN OF SURFACE TEXTURES

Eighteen participants (12 males and 6 females), aged from 20 to 60 years, participated in the experiment. Thirty-seven materials with different textures were used as stimuli. Stimuli 1-22 were cardboards; 23-31 were papers and foils; and stimuli 32-37 were laminate boards. The cardboards, papers and foils were packaging materials used for confectionery. The laminate boards were samples of materials typically used for making office furniture and were included to increase the variety of textures. As a result, the 37 stimuli covered a variety of textures with different physical properties, such as roughness, hardness and thermal conductivity. The stimuli were cut into 10cm × 8cm rectangles and were numbered for identification.

The stimuli were presented to the participants in boxes so that they could not be seen. One side of each box was kept open and covered with a small white curtain to prevent sight of the stimuli whilst still allowing participants to touch them. Each participant was asked to place their hands into the box under the white curtain and touch one texture at a time. The stimuli were presented in a random order. No restrictions were given as to which hands or parts of the hand could be used, or for how long the stimuli could be inspected. After touching each stimulus, the participants rated the tactile properties of the stimuli against six pairs of adjectives. The adjectives were "slippery- sticky", "bumpy-flat", "wet-dry", "hard-soft", "smooth-rough" and "warm-cold" on a 20 point semantic differential scale.

The friction coefficient (μ), average roughness, (R_a), a thermal property, rate of cooling on touching (dT/dt) and compliance (c) of the thirty-seven surfaces were measured. Roughness was measured using a commercial stylus surface profilometer (RTH Form Talysurf 120L). Friction coefficients, rate of cooling on touching (dT/dt) and compliance were measured on a piezo-electric force platform (Kistler MiniDyn). For the friction measurement, each stimulus was fixed to the force platform. An experimenter pressed (load F_y) and slid (load F_x) her finger tip against it. F_x and F_y were recorded against time. The friction coefficient was obtained from F_x/F_y. Loads F_y were in the range 0.5 to 3N.

To measure the rate of cooling of the finger when the stimulus is touched, an artificial, polymer fingertip was loaded on to the surface, without sliding (F_y = 1 N). A thermocouple (TC) was embedded just within the tip. Before contacting the surface, the tip was heated by an internal cartridge heater to the temperature of the skin of the human finger, 32 ± 0.2°C. On contact between the loaded finger and the stimulus, the fall of the temperature recorded by the thermocouple against time was recorded. The maximum rate of change (°Cs^{-1}), which occurred at the start of contact, was taken as the measure of the rate of cooling.

Compliance was measured by inserting a soft rubber support between the stimulus and the force platform. The stimulus was pressed with a steel ball of radius 7mm. With 4N loading force, the ball's displacement with increasing load was recorded. The measure of compliance was empirically taken to be the value of the displacement (mm) when F_y= 3N. In all cases, measurements were repeated several times and averages obtained.

3.2. Implementation of the ANFIS models

The aim of the ANFIS was to model and predict the affective response to texture as a function of μ, R_a, dT/dt and c. To do this, six separate ANFIS model were built, one for each of the six adjective words. In each ANFIS model, μ, R_a, dT/dt and c were taken as the input, and the mean average response to a particular adjective word pair was used as the output. Generalized bell membership function was used to define fuzzy levels, because of its smoothness and concise notation. The total number of rules in the structure is 16.

The data for one stimulus were removed during preliminary training runs of ANFIS because it had a negative effect on the performance of the model. The removed sample felt qualitatively different from the other stimuli with an incongruent rough, metallic feel.

The ANFIS models were implemented using MATLAB Version 7.3 with the Fuzzy Logic Toolbox. A hybrid learning algorithm was used. Structure parameters, such as number of epochs and learning rate were determined by trial and error by carrying out preliminary runs. The different ANFIS models were evaluated and the results of the best ANFIS models were presented.

K-fold cross-validation (Stone, 1974) was used to train and validate the ANFIS models. To assess the performance of ANFIS models, Mean Absolute Percent Error (MAPE), and correlation coefficient (R) criteria were used. The smaller the MAPE values, the better the performance. A value of MAPE of less than 10% is regarded as excellent. MAPE is used to determine when to stop training: training is stopped when the MAPE error for test set starts to increase, indicating that a minimum have been achieved.

The Pearson product-moment correlation coefficient (R) was used to measure how well the variation in the predicted outputs is explained by observed values. Threshold statistic (TS) is used to provide information on the distribution of errors.

4. RESULTS AND DISCUSSIONS

The performances of the optimized ANFIS models are presented in Table 1. Satisfactory results were achieved for “wet-dry”, “hard-soft”, “warm-cold”, and “slippery-sticky” adjectives. MAPE values of these four models were lower than 10%, indicating that the relation between physical characteristics of textures and each of these four adjective word pairs is highly significant. On the other hand, no strong relations were observed for “bumpy-flat” or “smooth-rough” adjective pairs.

The MAPE values indicate that the ANFIS models always yielded lower errors when compared to regression models. High error values were observed for “bumpy-flat” and “smooth-rough” adjective pairs in both the linear and exponential regression models. While the performance of the exponential model for “smooth-rough” is very close to that of the ANFIS model, it is too high to be significant.

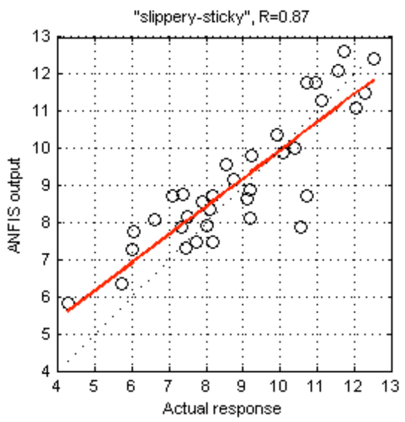
Table 1: Training and test performance of ANFIS models

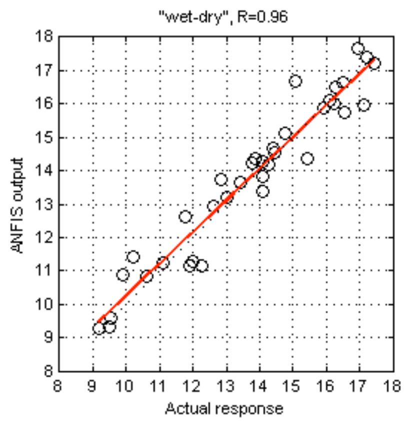
Model for	ANFIS*		Regression* (Linear)	Regression* (Exponential)
	MAPE (training)	MAPE (test)	MAPE (test)	MAPE (test)
Slippery –Sticky	0.09	10.05	15.00	15.51
Bumpy-Flat	0.28	19.83	31.25	33.48
Wet-Dry	0.03	3.61	6.85	6.88
Hard-Soft	0.07	5.80	11.16	12.85
Smooth-Rough	0.39	35.50	46.07	35.76
Warm-Cold	0.09	6.40	11.85	10.50

* 9 fold cross-validation is applied.

Figure 2 shows the predicted outputs of the six ANFIS models against their actual responses. High correlations between actual and predicted values were observed for the models for "slippery-sticky", "wet-dry", "hard-soft" and "warm-cold".

The ANFIS did not achieve satisfactory results for "bumpy-flat" and "smooth-rough" adjective word pairs. The reasons for this can be twofold. First, participants might have had more difficulty evaluating against these words. It is noted that variances of responses to "bumpy-flat" and "smooth-rough" are higher than those





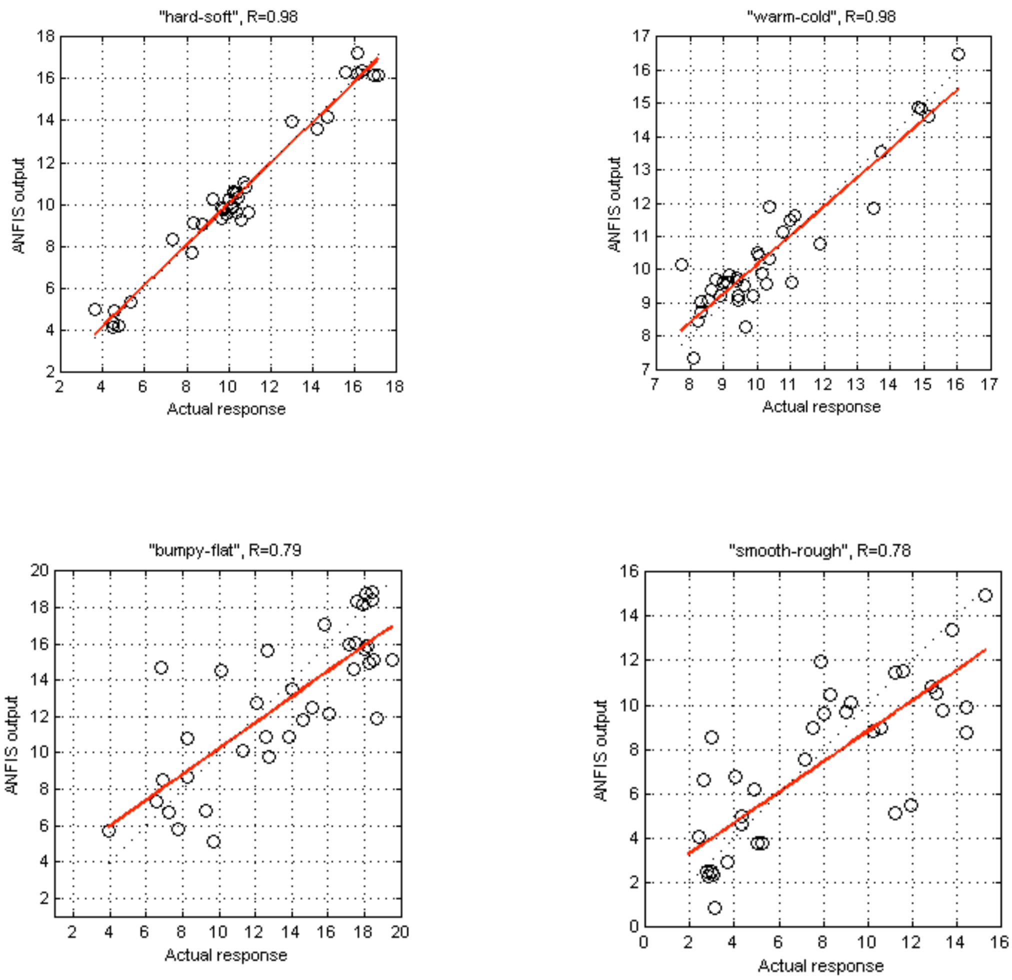


Figure 2: Scatter diagrams showing actual and predicted responses (for test set)

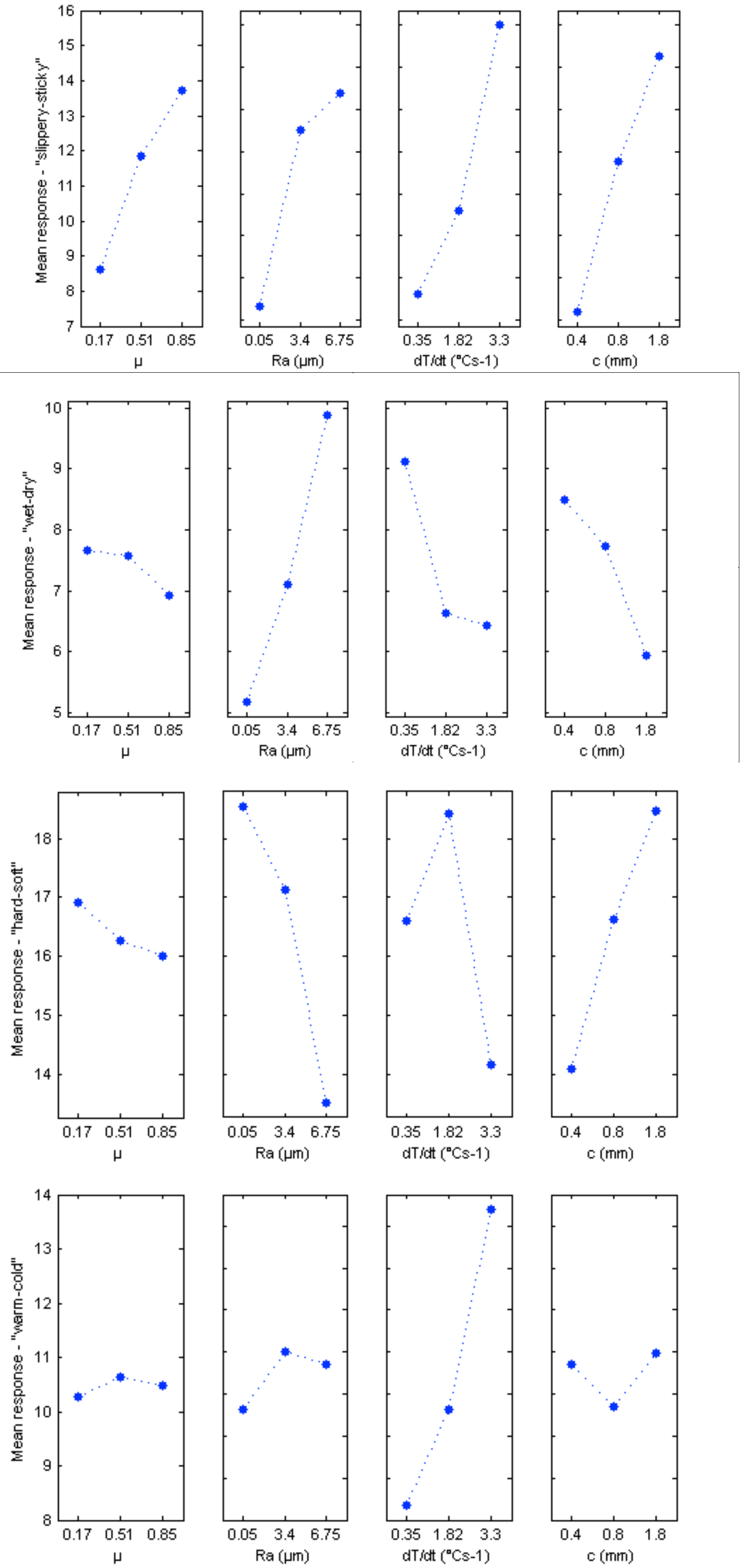


Figure 3: Main effects plots between μ, R_a, rate dT/dt and affective responses.

of other adjective word pairs. Significant differences between participants' evaluation score for the stimuli whose physical parameters are similar might have negative impact on ANFIS's robustness. Second, some of the physical characteristics of the surface texture might be irrelevant for modelling "bumpy-flat" and "smooth-rough" adjective word pairs.

Main effects plots between μ, R_a, rate dT/dt and affective responses are shown in Figure 3. The four physical characteristics are positive and highly significant for the "slippery-sticky" response. The relationship between μ and "wet-dry" response was not significant. R_a, dT/dt and c are highly significant for the "hard-soft" response. μ seems not to have significant effect. dT/dt is the only significant factor on the response "warm-cold.

Most of the stimuli used in this experiment were examples of packaging materials used for confectionery. It is likely therefore that, although the stimuli were not presented to participants in the context of confectionery, the results of this experiment can be generalized and used to predict human responses to confectionery packaging materials. Whether the results can be generalized further, for example to materials with similar ranges of physical properties, cannot yet be determined, because the effect of context on people's perceptions of products is not yet fully understood.

The use of ANFIS is a first step in using soft computing techniques for the analysis of affective responses to tactile surface textures. Through further iterations, it will be possible to choose a more comprehensive range of stimulus materials that is representative of the human experience of touch.

5. CONCLUSIONS

In this study, ANFIS was used to simulate and analyze the relation between the tactile surface textures and people's affective responses. This study has shown that soft computing tools may be more useful than regression analysis for modelling nonlinear affective response to surface textures. It has been demonstrated that ANFIS can be used as a reliable tool to predict affective responses to a particular surface texture.

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