MACHINE VISION APPROACH TO PREDICTING AFFECTIVE PROPERTIES OF TACTILE TEXTURES

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ABSTRACT

Although there has been much research on the perception of roughness, it is not yet fully understood. Further, there is almost certainly more to the perception of tactile textures and patterns than roughness. An experiment is reported that aimed to identify the topographical properties of tactile textures that affect people's affective responses when touching them.

Twenty four tactile plaques were manufactured. The textures for the plaques were copies of visual textures in which the grey scale was converted to height, or were copies of existing tactile textures. The plaques were made using rapid prototyping techniques to manufacture stamps, which were then used to impress the textures onto laminate board. The textures were chosen on the basis of variety of affective response in the visual domain and for subjective tactile variety. In a novel application, texture measures, originally designed for the machine vision domain, were used to characterize digital representations of the tactile textures. These measures are based on concepts such as co-occurrence matrices, grey level run length and absolute gradient. To obtain the affective ratings, the plaques were touched, unseen, by 107 participants who scored them against 20 adjectives on a semantic differential scale. The texture measures computed for the digital representations were regressed against a subset of the participants' affective ratings using a novel feature subset evaluation method and a partial least squares genetic algorithm. Five measures were identified that are significantly correlated and are unlikely to have occurred by chance.

The next step will be to manufacture plaques with systematically controlled features to determine whether the regression model correctly predicts people's affective responses.

Keywords: *tactile perception, texture analysis, wrapper methodology*

1. INTRODUCTION

Due to the dramatic increase in the demand for improving surface topography of everyday products, a considerable interest has been developed over the past few years in studying tactile texture perception. This is of interest to several disciplines including psychophysics, neuroscience, and computational modelling. Texture gives information about surface material and micro-geometry that can be obtained both visually and by touch. Touch extracts much finer and more complex textural information than visual. Different studies have concentrated on the relationship between human visual perception and computational features [1,2]. They measured human discrimination performance and compared these measures with computational results. Research on the relationship between tactile texture perception and textural features has in general been focused on the evaluation of surface roughness using direct contact between the skin and the textured surface [3]. The novelty of this study is to investigate the interaction between computational texture features that are used in the field of machine vision, and human affective responses to touching the textures.

In this paper, the textural properties of the 24 tactile stimuli were computationally assessed using eight broad families of features: lowest level or first order statistics, co-occurrence matrix, run length matrix, absolute gradient, moment invariants, Tamura, and laws' energy measures. These techniques were selected for their reported success at textural pattern in two dimensional grey level images [4].

The rest of the paper is organized as follows. Section 2.1 describes the manufacture of tactile plaques which were rated by participants in a psychological study. Section 2.2 describes how the textural features from 24 stimuli topographies were extracted using aforementioned techniques. Section 3 explains how a wrapper method was applied to identify the most important computational features that affect human touch feeling. Results are presented in Section 5 and conclusions are presented in Section 6.

2. METHOD

The investigation of the tactile textures included three aspects of work: a self-report study to obtain perceptual ratings of materials; measurement of the textural features; and correlation and regression analysis between the two, as shown in Figure 1.

2.1. Psychological measures of texture perception

Participants' feelings on touching a range of tactile textures were measured. This study was concerned with the participants' spontaneous, subjective responses on touching textures.

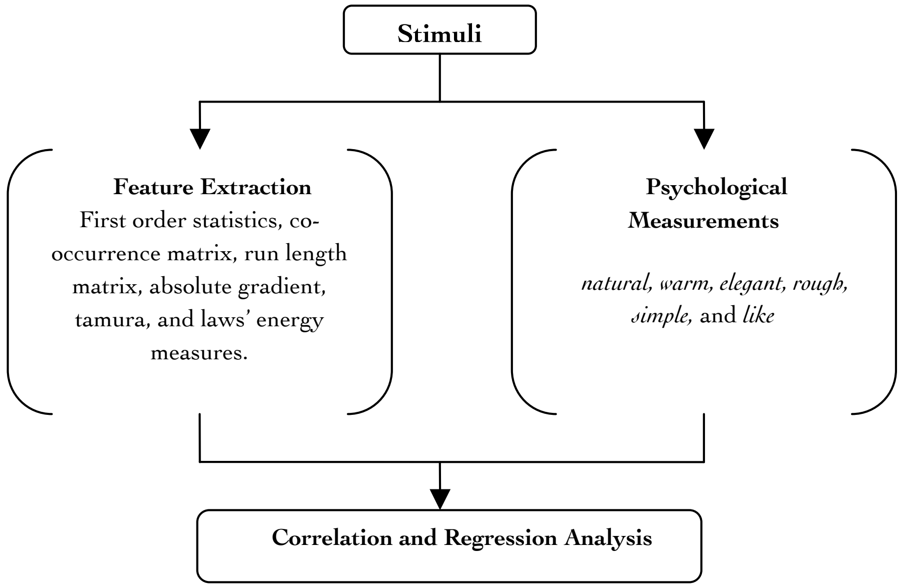

Figure 1: Psychological measurements correlated with computational textural features of the stimuli.

Twenty four stimuli measuring 10cm×10cm, and containing different tactile surfaces, were manufactured with the same type of material (Acrylic). The textures for the stimuli were copies of visual textures in which the grey scale was converted to height (black representing a valley and white a peak), or were copies of existing tactile textures. The textures were chosen on the basis of variety of affective response in the visual domain and for subjective tactile variety. Each stimulus was placed in a large, numbered envelope so that it could be touched, but not seen.

A total of 107 subjects participated in the experiments (18 males and 89 females). All subjects were students and staff of the University of Leeds and ranged in age from 20 to 34 years old.

The tactile properties of the stimuli were rated by participants against 6 adjectives: *natural, warm, elegant, rough, simple,* and *like*. Semantic differential questionnaires were prepared using the 6 words as shown in Figure 2. On each questionnaire, the words were presented on a seven-point bi-polar scale. One end of the scale was anchored with the adjective and the other with the adjective's declarative opposite. The order of the adjectives and the polarity of the scales were presented in a random order.

The purpose and the procedures of the experiment were explained to the participants. Participants were asked to sit at a table where the envelopes were placed and then asked to put their hand inside each envelop and touch the plaque.

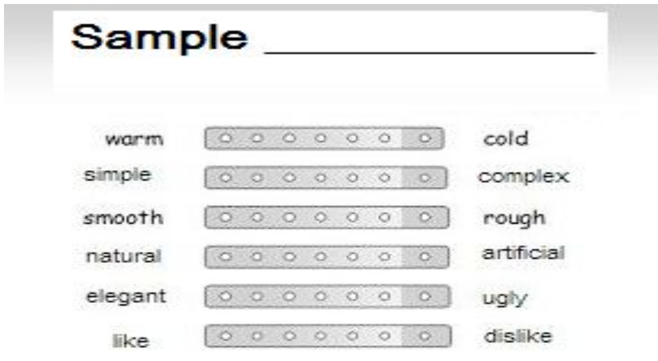

Figure 2: An example questionnaire.

The stimuli were presented in a random order for each participant. No restrictions were given such as which hand or parts of the hand could be used, or for how long the stimulus could be inspected. After touching each plaque, participants were asked to rate the texture against the adjectives on the questionnaire.

2.2. Texture Features

Texture feature extraction is the mathematical procedure of generating descriptions of textured surfaces in terms of measurable parameters. The extracted features represent the relevant surface properties. Eight texture analysis techniques for describing texture features were performed on the 24 texture images with 300×300 pixels that were converted to grey level image (0-255). The visual image versions of the tactile textures are shown in Figure 3.

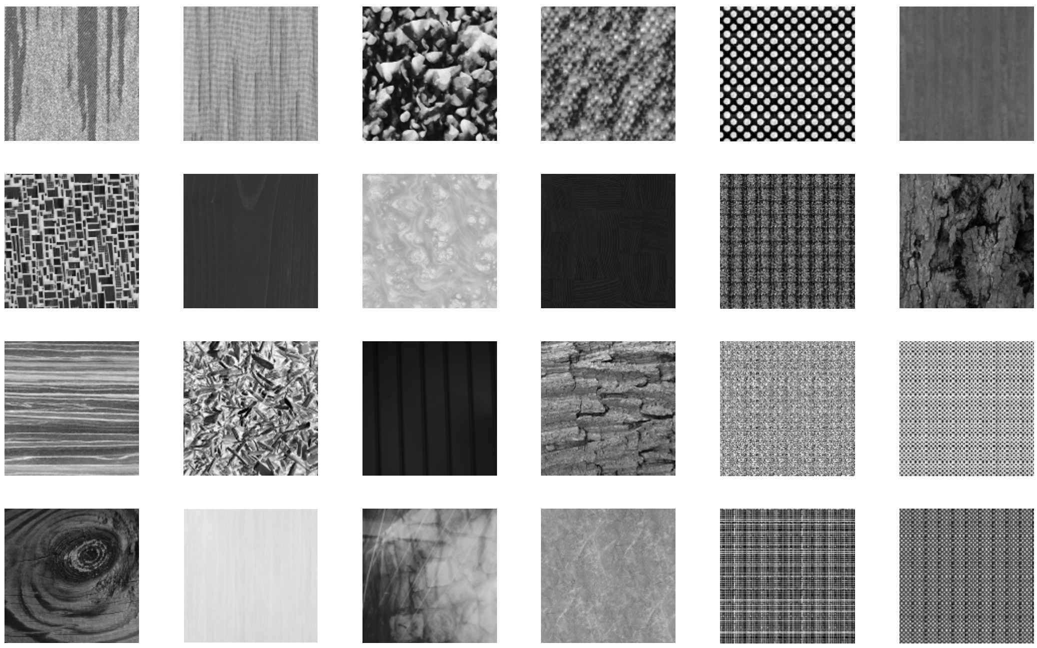

Figure 3: Example of the images used in the experiment.

2.2.1. Lowest level statistics

First-order statistics measure the likelihood of observing a grey value at a randomly-chosen location in the image [5, 6]. The average intensity in an image, variance and percentile are examples of the first-order statistic. For example, the average provides information about the Centre Line Average (or average roughness), the standard deviation represents the root mean square (RMS) height, and percentile gives the highest peak under which a given percentage of the pixels are in the image. Fourteen features were computed: mean, contrast, smoothness, skewness, entropy, energy, and percentiles (1, 10, 25, 50, 75, 90, and 99).

2.2.2. Grey level co-occurrence matrices

Grey level co-occurrence matrices are one of the most widely used second order statistics. Haralick [7] proposed the grey level co-occurrence matrices (GLCM) which give information on how often pairs of grey levels of pixels, which are separated by a certain distance (d) and be positioned along a certain direction (θ), occur in a texture image. Four different directions (0°, 45°, 90°, and 135°) were used for each distance (d=1, 2, 3, 4, 5, 8). Eleven features were calculated from each GLCM: angular moment, contrast, correlation, sum average, inverse difference moment, sum average, sum variance, sum entropy, entropy, diff. variance and diff. entropy. The mean and range of each feature over the four GLCMs were computed, giving in total of 132 features.

2.2.3. Neighbourhood grey level difference matrix

The neighbourhood grey level difference matrix method (NGLDM) employs textural features corresponding to the visual properties of an image [2]. NGLDM is a column matrix formed by summing the absolute value of the pixel being observed minus the average of the pixels in its neighbourhood. The neighbourhood was predefined as a distance of d=1 and 2 pixel. Five perceptual features, coarseness, contrast, busyness, complexity, and strength of texture, were calculated from NGLDM at each distance, giving in total 10 features.

2.2.4. Grey level run length matrix

Grey run length is a set of consecutive, collinear pixels having the same grey level value. Four run length matrices are computed based on four different directions (horizontal, vertical, and two diagonal directions). Five features have been proposed by Galloway [8]: short run emphasis, long run emphasis, grey level non-uniformity, run length non-uniformity (RLN), and run percentage. Chu et al. [9] introduced two additional features, low grey level run emphasis, and high grey level run emphasis. In a more recent study, four new features have been proposed, short run low grey level emphasis, short run high grey level emphasis, long run low grey level emphasis, and long run high grey level emphasis [10]. In this study, four run length matrices were averaged into one matrix and then all eleven features were extracted from the averaged matrix.

2.2.5. Absolute gradient

The absolute gradient of an image measures the spatial variation of grey-level values across the image. Thus, if at a point in the image the grey level varies rapidly from black to white, there is a high-gradient value at that point. The gradient may be positive or negative, depending on whether the grey level varies from dark to light or from light to dark. Five features were calculated from absolute gradient matrix namely; the mean, standard deviation, skewness, kurtosis, and nonzero percentage of the absolute gradient [11].

2.2.6. Tamura

Tamura et al. developed texture features that have a high correlation with human visual perception [1]. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects.

2.2.7. Laws' energy measures

The laws' texture energy measures generate texture features by using local masks to detect various types of textures. In this research, 3×3 lengths of Laws' filters were used. The two dimensional convolution kernels were generated from a set of one-dimensional convolution kernels corresponding to level (L), edge (E), spot (S),: L3=[1 2 1], E3=[-1 0 -1],S3[-1 2 -1]. Nine Laws' masks can be produced: L3TE3, E3TL3, L3TS3, S3TL3, E3TS3, S3TE3, L3TL3, E3TE3, and S3TS3. By combining the symmetrical kernels (such as LTE and ETL), 6 rotational invariant kernels were produced [12]. The Laws features were extracted from digital images that had been filtered by each aforementioned rotational invariant kernel [13]. From each filtered image, three first order statistics (mean, standard deviation, and energy) were computed, giving 18 Laws' texture energy measures in total.

3. FEATURE RELEVANCE EVALUATION

Wrapper methodology was used to find out the most important computational textural features (the features detailed in Section 2.2), that have the highest correlation with the tactile feelings properties (the participants' responses to the adjectives detailed in Section 2.1).

In the last decades, a number of different methods to eliminate features of low importance for the subsequent machine learning method were proposed [14], which can be divided into filter and wrapper methods. Whereas filter approaches evaluate the relevance of a feature based on general characteristics (e.g. correlation between feature and target (variable that should be predicted by the learned model afterwards), wrapper methods apply the learning algorithm (e.g. neural network, support vector machine) directly to assess the relevance of a given feature subset for a target variable.

The relationship between the set of 196 texture features and 6 tactile responses were analyzed. Owing to the subjective experimental rating task and the low number of samples that caused a high noise level, the standard feature selection methods are not applicable for this dataset. To overcome these challenges, an approach following the wrapper methodology was used with three major processing steps:

1. A sequential forward selection (SFS) was applied to reduce the initial 196 texture features using a greedy search method for all perceived responses [15]. For every single human judgment, SFS starts with the feature that is most correlated with the target and adds a new feature which, together with the old one(s), most accurately predicts the target. New features are added until the prediction error is not significantly ($p=0.05$, using partial F-test) reduced. A linear regression model was used to predict the target values. Finally, for all 24 tactile responses, a set of 30 unique texture features was selected.

2. The feature set F_{SFS} was used to build all possible feature subsets of size 3. The predictive quality of every single subset for every tactile response was evaluated. A linear regression model was built using half of the samples and the tactile responses were predicted for the remaining 12 samples. The correlation between the predicted and the human responses was measured using the Pearson correlation coefficient. In total 4060 subsets are evaluated against 6 tactile responses.

3. The results of Step 2 were analyzed using a voting method that allowed both the predictive quality of single features as well as the overall predictability of human tactile responses to be measured. This determines whether the correlations are caused by chance, or represent a significant relationship between texture features and human tactile responses. The subset evaluation was repeated for a random dataset. This random dataset was generated by randomly permuting the ordering of the samples for the feature matrix as shown in Figure 4.

Step 2 of the method proposed in [16] was modified by replacing the neural network with a linear regression model, due to the low number of samples.

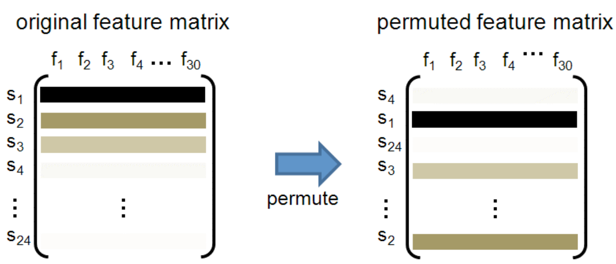

Figure 4: The rows (representing the samples) of the feature matrix are randomly permuted to destroy the relationships between feature value and tactile response.

4. RESULTS AND DISCUSSION

In total 4060 feature subsets are evaluated against the responses to the 6 adjectives. The histogram of these correlations is depicted in Figure 5, (correlations for un-permuted dataset). This result represents the correlations that can be achieved by chance. Consequently it is argued that all correlations of the un-permuted dataset larger than the correlations of the randomly permuted dataset are relevant. Only feature subsets which reached a correlation R > 0.5 were used for the final voting analysis.

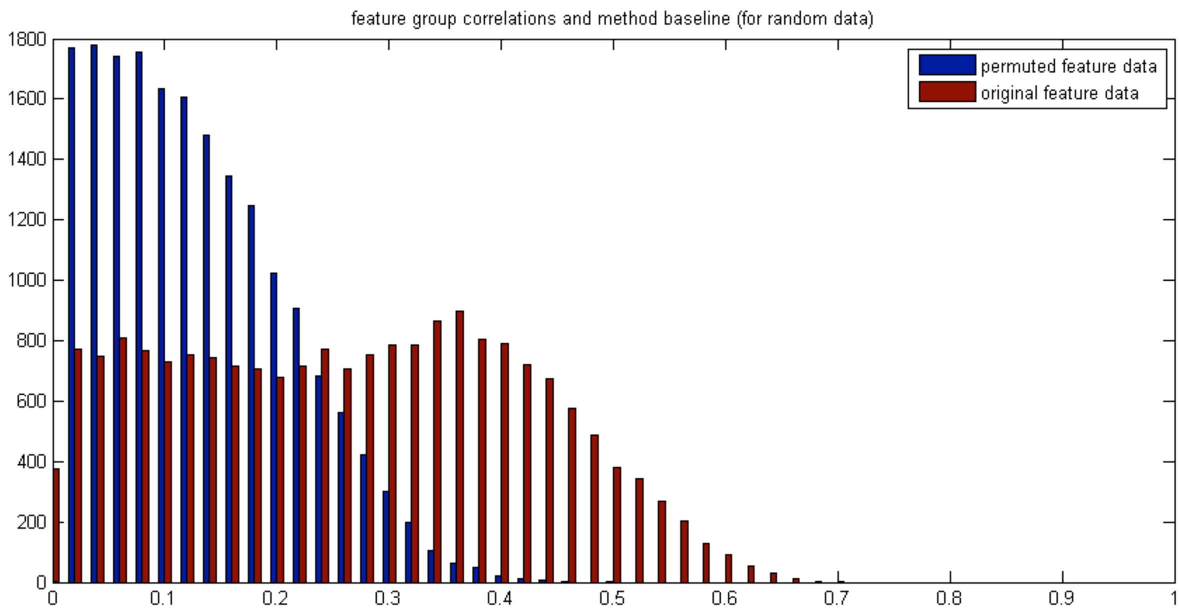

Figure 5: Correlation histogram for the randomly permuted dataset and the original, un-permuted dataset.

This proposed voting method takes into account both the low number of available samples as well as the variations in the experimental data caused by requesting subjective judgments from human subjects. Therefore it would be dangerous to rely on single correlation values. Contrary, we count the frequency of every feature element of F_{SFS}, being part of a feature subset that reached a correlation > 0.5.

The top eight features, according to the wrapper method, best suited to predicting the tactile responses are percentile 90%, range sum of squares, skewness, directionality, mean correlation (d=2), E3S3, mean sum variances, and complexity.

In accordance with the above results, it is possible to synthesize new textures that satisfy consumers' requirements using mixing synthesis algorithms. There are three steps (Figure 6). First, the six adjectives are predicted for each texture on the database using a linear regression approach, which is based on the low level computational features. Secondly, the required adjectives are matched to the most similar textures that have these requirements using a suitable retrieval approach. If the desired adjective does not match a specific texture feature on the database, the mixing synthesis texture approach will be used. For instance, if the query feature was in the middle of two texture features on the database, a new texture, 50% of the two textures, would be produced.

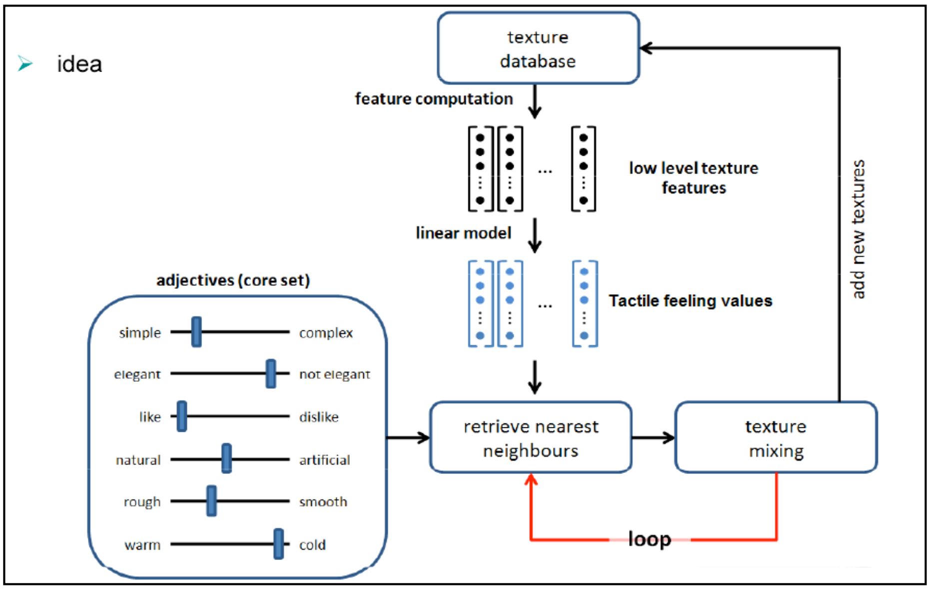

Figure 6: Synthesis algorithm for satisfying certain customer's requirements.

5. CONCLUSION

An attempt has been made to find the most important textural features corresponding to human touch affective responses. 196 computational features were extracted from 24 tactile plaque topographies using first order statistics, co-occurrence matrix, run length matrix, absolute gradient Tamura, and laws' energy measures. 107 participants rated the tactile stimuli against 6 adjective pairs.

The relationship between the computational features and the participants' subjective responses were found using wrapper methods. The results show that the top four features, best suited to predicting the tactile responses are percentile 90%, range sum of squares, skewness, directionality, mean correlation (d=2), E3S3, mean sum variances, and complexity.

ACKNOWLEDGMENTS

This work was partly funded by the UK's EPSRC (EP/D060079/1) and the EC (NEST 043157). The views expressed here are the authors', and not those of the EC.

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