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Making tactile textures with predefined affective properties

Galal Elkharraz, Stefan Thumfart, Diyar Akay, Christian Eitzinger, Brian Henson

Abstract— A process for the design and manufacture of 3D tactile textures with predefined affective properties was developed. Twenty four tactile textures were manufactured. Texture measures from the domain of machine vision were used to characterize the digital representations of the tactile textures. To obtain affective ratings, the textures were touched, unseen, by 107 participants who scored them against natural, warm, elegant, rough, simple, and like, on a semantic differential scale. The texture measures were correlated with the participants' affective ratings using a novel feature subset evaluation method and a partial least squares genetic algorithm. Six measures were identified that are significantly correlated with human responses and are unlikely to have occurred by chance. Regression equations were used to select forty eight new tactile textures that had been synthesized using mixing algorithms and which were likely to score highly against the six adjectives when touched by participants. The new textures were manufactured and rated by participants. It was found that the regression equations gave excellent predictive ability. The principal contribution of the work is the demonstration of a process, using machine vision methods and rapid prototyping, which can be used to make new tactile textures with predefined affective properties.

Index Terms— Feature evaluation and selection, Human Factors, Rapid prototyping, Texture.

1 Introduction

THE study of tactile texture perception is of interest to many disciplines including product design, psychophysics, neuroscience, and computational modeling. While much has been found out about tactile perception [1], application of the knowledge to, say, design a new product with enhanced tactile appeal remains difficult. Studies are perhaps hampered by the inability to create surface topographies in which different variables can be independently controlled. For the most part, researchers of perception have been limited to using tactile stimuli that are either naturally occurring, or either easily purchased or manufactured, such as sandpapers [2], or gratings [3].

This research aims to develop a process for the design and manufacture of three dimensional tactile textures with predefined properties for affective and psychophysical studies of touch. In this research, surface topographies were represented by matrices, with the cell coordinates representing the location of a 'boxel' of the surface, with cell values representing the height of the boxel, This representation makes the topographies amenable to manipulation using image processing techniques and, in this paper, these representations are presented as grey-scale images. However, this research was not concerned with the visual perception of textures. The research reported here only involved humans touching surface topographies, unseen.

Whereas the relationships between visual perception and measurable physical properties have been well-established, the relationships between tactile perception and measurable physical properties of surfaces are less-well characterized. How the dynamic mechanical properties of the finger set up vibrations for the touch receptors in the finger are being studied [4]. The response characteristics of the receptors, the Merkel discs, Ruffini endings, Meissner's and Pacinian corpuscles, responding to strain and rate of change of strain, and thermal receptors, are well-known [5], [6]. Relevant to this work is that when tactile features are greater than about 100µm, pressure cues on a static or moving finger are sufficient for the human to discriminate surface textures, but vibrations generated by a moving finger on a surface are necessary to perceive finer textures [7]. The topographical features on the tactile textures used in this work are of the order of 100µm, and are therefore considered to be coarse textures better perceived via pressure cues.

Unlike in visual perception, the perceptual dimensions of touch are not clear. Hollins et al. [8],[9] identified the perceptions of roughness, hardness and springiness based on studies using multidimensional scaling, whereas Gescheider, Bolanowski, Greenfield and Brunette [10], using similar methods, identified the dimensions of blur, roughness and clarity. Roughness is thought to be important and it remains the most studied of the perceptual dimensions e.g. [11]. However, despite this, perceived roughness does not correspond perfectly with measures of roughness, and a single measure or characterization of roughness has yet to be identified [12]. Others have studied other tactile perceptual dimensions such as soft-

- *G. Elkharraz is with the Faculty of Engineering at the University of Benghazi, Libya.*
- *S. Thumfart and C. Eitzinger are with Profactor GmbH, Im Stadtgut A2, 4407 Steyer-Glenik, Austria. Email: stefan.thumfart@profactor.at.*
- *D. Akay is with the Department of Industrial Engineering, Faculty of Engineering, Gazi University, 06570, Ankara, Turkey. Email: diyar@gazi.edu.tr.*
- *B. Henson is with the School of Mechanical Engineering, University of Leeds, LS2 9JT, United Kingdom. Email: b.henson@leeds.ac.uk.*

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ness [13], but as the stimuli used in this research were all made of the same, hard acrylic material, the perceptual dimension of roughness is the one most relevant to this paper. And these studies have principally been concerned with the perceptual dimensions of touch, whereas the work in this paper is also concerned with humans' affective responses. Studies of affective responses to touch, such as [14], [15], have also been restricted by the inability to control the properties of tactile stimuli.

While there does not seem to be a one-to-one correspondence between perceived roughness and first-order statistical measures of roughness, the rich measures of texture being used in the domain of visual image processing, in which they are referred to as features, have yet to be investigated in the context of touch. Numerous researches have been conducted to build models to correlate human perceptions with visual textures. For example, Kim, Kim, Jeong and Kim [16] proposed a system to classify textile images according to human emotions. This was carried out by extracting features of textile images such as colours and several patterns using different image processing techniques and applying neural networks to the features. Huang, Sobue, Kanda et al. [17] developed a mapping-function using neural networks for mapping features extracted from clothing fabric images to human affective responses. All of these techniques have in common that, based on given textures, they were able to predict with quite good accuracy which visual perceptions or emotions will be triggered when showing them to human beings. Rao and Lohse attempted to identify the higher order perceptual dimensions of human texture perception [18]. They applied dimensionality reduction techniques such as multidimensional scaling, principal components analysis and hierarchical clustering to analyze the results obtained from rating and grouping experiments. The analysis yielded three orthogonal higher order dimensions of texture perception: "repetitive versus non-repetitive", "high-contrast and non-directional versus low contrast and directional", "granular, coarse and low-complexity versus non-granular, fine and high-complexity". Thumfart, Jacobs, Haak, et al. [19] investigated the correlation between human visual emotions and color and texture features. The features were extracted from texture images and were associated with human visual feelings using linear feature selection and neural networks to extract a set of eight texture features which are capable of predicting six human visual feelings.

Section 2 reviews applications of texture analysis in the domain of visual image processing, data acquisition and affect recognition. Section 3 details the texture features considered in this research. Section 4 describes the method, in which twenty four tactile textures were manufactured using a rapid prototyping process. Texture features as used in machine vision research were used to characterize the textures. Human subjects touched the textures, unseen, and rated them against 20 adjectives. The texture features were regressed against a subset of the participants' affective ratings using a novel feature subset evaluation method and a partial least squares genetic algorithm. Because the feature selection method is unusual, it is described in detail in Section 4.3. The resulting regression equations were used to select forty eight new tactile textures that had been synthesized using mixing algorithms and which were likely to score highly against six adjectives, natural, warm, elegant, rough, simple, and like. The results in Section 5 describes how six features, Percentile 90%, GrKurtosis, GLCM mean correlation at distance 2, GrNonzero, GLCM mean sum variance at distance 1, and GLCM range sum of squares at distance 1 were identified that are significantly correlated with the humans' responses, and that the regression equations gave excellent predictive ability of human responses to the new tactile textures.

The principal contribution of the work is that it demonstrates a process, using machine vision methods and rapid prototyping techniques, which can be used to design new tactile textures. The process could be used to create new tactile textures with pre-specified affective and psychophysical properties for experiments leading to a deeper understanding of the perception of touch, and it can be used for improved product design. Members of the machine vision and affective computing communities are perhaps best placed to exploit this process. The significance of the work is considered further in Section 6.

2 Literature Review

Many different techniques to characterize texture features are used in different classification, image retrieval and segmentation problems. Haralick [20] surveyed a number of texture extraction methods: autocorrelation function; optical transforms; textural edginess; structural element; grey level co-occurrence matrix; grey level run length; and the autoregressive model. He divided them into two main categories, structural and statistical. Gool, Dewaele and Oosterlinck [21] reviewed the literature on texture analysis, but also included the use of filter masks such as Laws' features and grey level sum and difference histogram. They found that the structural techniques are better matched to textures that have a regular macro-structure, while the statistical techniques are better matched to micro textures. Other model-based techniques, such as Markov fields and fractals, have been reviewed [22].

One of the first applications of texture features was industrial inspection; for example, to detect flaws on a material's surface. Applications have been reviewed [23],[24],[25],[26]. Xie [24] concluded that statistical and filter based approaches are those most widely applied. Attempts have been made to find correlations between features in images and the surface properties of manufactured components, such as roughness [27],[28],[29]. Others have analyzed tool wear [30] and the rugosity of metal parts [31]. These techniques have also been applied to assess the quality of foods [32], carpet wear [33], ceramic tiles [34], and pipelines [35].

The approach to texture feature recognition used in this research is based on that used by Thumfart et al. [19]. They studied the relationship between textural features and aesthetic judgments of feeling, naturalness, roughness, elegance, complexity, warmth, beauty, colorfulness, and hardness. The features were extracted based on second order statistics, Tamura, Fourier transform, Gabor and color approaches. This resulted in 188 different features which were selected in a two stage process. First, sequential forward selection was used to their number to 31 unique features. Second, a novel selection method called nomination analysis was applied to obtain the correlation between each possible feature group and the aesthetic property that accounts for the inherent noise and subjectivity in the aesthetic judgments of textures. It was concluded that there is a correlation between features and human visual perception. In addition, six of nine aesthetic judgments were predicted with a correlation greater than 0.68. Their work has been continued by including synthesis of new textures using existing texture mixing algorithms and genetic algorithms [36],[37]. The genetic algorithm approach uses mutation and crossover methods on images from a database assessed using a linear regression model. Although the proposed method showed successful improvement by reducing the average distance of nearest neighbor individuals to the target vector over standard texture mixing algorithms, there are some limitations. Both the synthesis of individual textures and the calculation of a large number of texture features in each iteration are computationally expensive.

Of relevance to the research reported in this paper are the attempts to link texture features to people's reactions to the visual textures. This includes both psychophysical and affective responses. The majority of research in this area has been connected to human visual perception. For instance, Julesz [38] conjectured that observers could distinguish pre-attentively between textures with different and similar first order statistics, but not in the third or higher statistics. Tamura, Mopi and Yamawaki [39] calculated new texture features corresponding to visual perception of contrast, coarseness, regularity, roughness, directionality, and line-likeness. Although there are some drawbacks with these features, they are still widely used. In a similar study [40], five previously defined features (coarseness, contrast, busyness, complexity, and texture strength) were modified and expressed in terms of spatial changes in intensity, but the study failed to clarify how visual properties are related to physical ones. Fujii, Sugi and Ando [41] developed a psychological scale for the textural properties of contrast, coarseness, and regularity, related to the autocorrelation function. Later, Jian, Dong, Gao et al. [42] presented three new texture features, directionality, contrast, and coarseness, based on the wavelet transform, that correlate with visual perception of those properties.

Studies have been conducted for image classification derived, not from people's psychophysical perception of textures, but from their ratings against adjectives that reflect affect or emotion (e.g. [16], [17]). In this research, respondents were asked to touch tactile textures, unseen, and then rate them against words on a self-report semantic differential questionnaire [43]. Others have measured affective responses using facial expressions [44]; biosignals, such as electroencephalography [45], audio signals [46]; linguistics [47] and bodily expressions [48]. These techniques have the advantage that they do not rely on potentially unreliable self-report data. Once the affect data have been collected, relevant features need to be extracted before the affect recognition procedure can be implemented [49]. The extraction of affect features is perhaps more challenging when using objective observation of affective response such as facial expressions and biosignals than when using self-report questionnaires, for which the measure of affect is calculated as the mean of the respondents' ratings. In much affective computing research, identification of the affective state involves pattern recognition from signals from different modalities, which then poses challenges concerning synchronization and fusion [49]. Issues of multimodality are assumed not to arise in this work, because all tactile textures were touched unseen by respondents, and the self-report questionnaires are the only source of affective data.

Approaches to affective feature recognition have included sequential forward selection using neural networks [50], support vector machines [51], and fuzzy inference [52]. For a comprehensive review of affect recognition methods, see [53].

3 Texture Features

3.1 First, Second and Higher Order Statistics

First-order statistics measure the likelihood of observing a grey value at a randomly-chosen location in an image [38], [54]. The average intensity in an image, variance and percentile are examples of first-order statistics. For example, the average provides information about the center line average (or average roughness), the standard deviation represents the root mean square height [55], and percentile gives the highest peak under which a given percentage of the pixels are in the image.

Grey level co-occurrence matrices are perhaps the most widely used second order statistics. Haralick, Shanmugam and Dinstein [56] 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 and be positioned along a certain direction, occur in a texture image. In the research reported in this paper, four different directions, 0°, 45°, 90°, and 135°, were used for each distance of one, two, four, and eight boxels, and the four co-occurrence matrices at each distance were averaged into a single matrix.

Higher order statistics include grey run length and absolute gradient. A grey run length is a set of consecutive, collinear pixels that have the same grey level value. Four run length matrices are computed based on four different directions (horizontal, vertical, and two diagonal directions). Five features were proposed by Galloway [57]: short run emphasis; long run emphasis; grey level non-uniformity; run length non-uniformity (RLN); and run percentage. Chu, Sehgal and Greenleaf [58] 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 [59]. In our study, the four run length matrices were averaged into one matrix and then all eleven features were extracted from the averaged matrix.

The absolute gradient of an image is a measure of the spatial variation of gray-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. For this study, five features were calculated from absolute gradient matrix: mean, standard deviation, skewness, kurtosis, and nonzero percentage of the absolute gradient [60]. In this paper, measures based on absolute gradient are prefixed "Gr" to distinguish them from first order statistics.

3.2 Visual Perception Based Feature Methods

These methods include neighborhood grey level difference matrix and Tamura features. The neighborhood grey level difference matrix method (NGLDM) employs textural features corresponding to visual properties of an image [40]. NGLDM is a column matrix formed by summing the absolute value of the pixel being observed minus the average of the pixels in its neighborhood. In this study, the neighborhood was defined as a distance of one and two boxels. Five perceptual features, coarseness, contrast, busyness, complexity, and strength of texture, were calculated from NGLDM at each distance, giving ten features. Tamura, Mopi and Yamawaki [39] developed texture features that have a high correlation with human visual perception. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects.

3.3 Laws' Energy Features

Laws' energy measures were used to characterize textures [61]. Laws' filters of lengths 3×3 and 5×5 were used. The two dimensional convolution kernels were generated from a set of one-dimensional kernels corresponding to level (L), edge (E), spot (S). Nine two-dimensional filters of length three were generated, from which six rotational masks were produced [62]. Those masks that were not directionally invariant were scaled by two to keep the size of features consistent. Similarly, for the 5×5 filters, twenty-five two-dimensional filters of length five were generated and fifteen rotational masks were produced. The masks were convolved with the image, and the mean, standard deviation and entropy of the convolution results were used as texture features.

4 METHOD

4.1 Manufacture of Plaques

The tactile stimuli used in the experiments described in this paper were manipulated on computer as matrices, converted to CAD files, 3D printed and then pressed on to 100mm×100mm pieces of laminate board. This section describes the manufacturing process.

The tactile textures were processed on computer as matrices, with the cell coordinates representing the location of a boxel of the surface, and with cell values representing the height of the boxel. (This contrasts with the use of the term 'voxel' from the field of medical imaging; a voxel represents a fixed-volume element whose position is inferred from its position relative to other voxels.) Arbitrarily, 0 was chosen to represent the topographical peaks and 255 to represent the valleys. When viewed as an image, therefore, the black represent peaks and white the valleys. Using Matlab, the textures were reduced in resolution to 300×150, normalized so that they covered the full height range between 255 and 0, and quantized to 10 levels. The matrices used in manufacture were not square to account for the differences in the resolution of the manufacturing process in the x and y directions. Reducing the resolution was considered necessary, after a pilot study, to account for the loss of resolution of the topographies due to the subsequent manufacturing process. It was also necessary for the tactile textures to be coarse, and the topographical features to be of the order of 100μm, so that the textures could be distinguished based on spatial cues [7]. The matrices were also inverted to take account of a further inversion of the tactile textures during the manufacturing process.

The matrices were exported to a custom-written program that converted them to .stl (stereolithography) format files. The program places the textures on a 100×100×5mm block. The cells of the matrices were thus converted to boxels, approximately 330×660×80μm, and each texture had a relief of 0 to 800μm. Fig. 1 shows some examples of the textures and the .stl shape representations of the tactile plaques they produced.

Each tactile texture was printed using an Objet Eden 330 3D printer, with a nominal resolution of 42μm×84μm×16μm, which uses UV light to cure a photosensitive liquid into a solid, resin component. Because many copies of each texture were required for other experiments not documented in this paper, the 3D printed, resin texture was used as a master for a molding process. The resin master was used to make a die that could withstand the high temperatures of the later reproduction process. Silicone molds were made of each texture and a die was made from each mold using vacuum casting. The dies were used to imprint the textures on laminate board, such as that used on office furniture, kitchen work surfaces, and synthetic hard wood flooring. This manufacturing process was used to allow many copies of each texture to be made. It also allowed visual textures to be incorporated into the boards, under the transparent tactile texture, to be used in further experiments not documented in this paper. The laminate board was made of a core board material, with a transparent acrylic overlay. The boards were made under high temperature and pressure in an industrial process sandwiched between foils, papers, the dies and metal plates. They were pressed at approximately 70 bar at 130°C for 15 minutes. The boards were made as 400×600mm sheets, each containing 24 tactile textures. The boards were then sawn to separate the textures to 24, 100×100mm plaques.

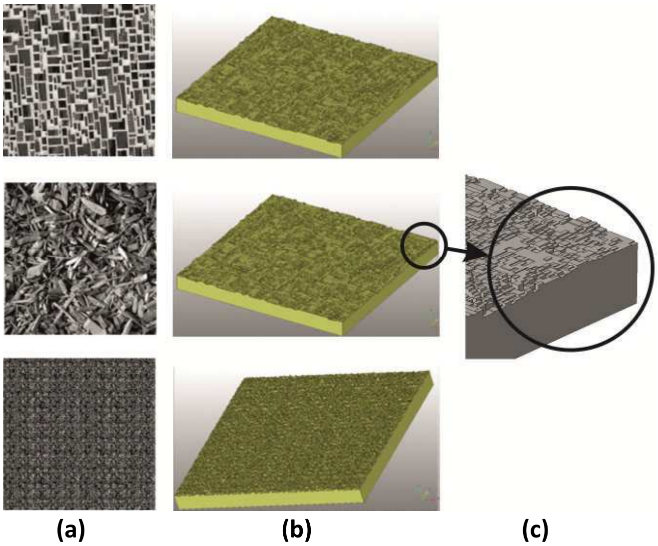


Fig. 1. Examples of the tactile textures used in the first part of the study, (a) displayed as visual images in which the black represents topographical peaks and white the valleys (b) CAD renderings of the (negative of the) resulting tactile textures, and (c) an exploded view of one of the CAD renderings showing detail of boxelated surface.

4.2 Measurement of affective response

Twenty four plaques containing different tactile surfaces (Fig. 2) were manufactured using the process described in Section 4.1. Most of these textures were derived from visual textures and some were copies of already existing tactile textures, read using a 3D scanner. The textures were chosen on the basis of variety of affective response in the visual domain identified in a parallel study [19], and for subjective tactile variety. Each plaque was placed in a large, numbered envelope so that it could be touched, but not seen.

The participants were 18 males and 89 females. The tactile properties of the stimuli were rated by participants against 20 adjectives: natural, cheap, practical, warm, elegant, sticky, harsh, pretentious, depressing, distinguished, inspiring, modern, simulated, rough, simple, hard, wet, playful, exciting, and like. The first thirteen of these adjectives were identified in a previous unpublished study in which 53 female participants touched samples of laminate board in the context of work surfaces. In that study, three focus groups were held in which structured activities were conducted to elicit adjectives that the women used to describe the surfaces, following the procedure in [13]. The words rough, simple, hard and wet were added to increase the number of words used that represented perceptual rather than affective qualities; playful, exciting were added because they had arisen in a similar study in which they had formed a separate construct [63]; and like was added because it is a high-level hedonic evaluation. From these, six adjectives, natural, warm, elegant, rough, simple and like were selected a priori for analysis to reduce the possibility of fatigue bias in the second part of the study, in which it was anticipated more stimuli would be required.

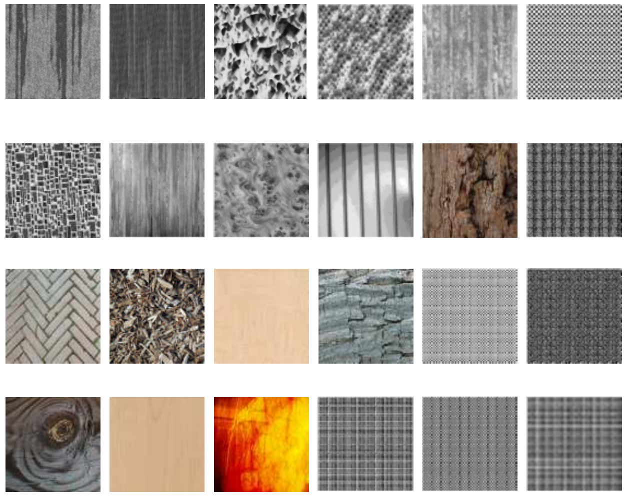


Fig. 2. The 24 visual textures which were converted to tactile textures for the first phase of the study.

These words were chosen because they represent a range that varies from assessment of perceptual qualities of the surface (e.g. rough) to high-level hedonic evaluations of the material (e.g. like), and because in our previous studies they had exhibited relatively low variance of persons' responses on questionnaires. The decision to include natural was informed by the existence of another research project attempting to measure naturalness [64]. The words used in this study are consistent with those used in other affective studies of touch (see for example [65]). Direct comparisons with other studies are difficult, however, because the words used often depend on the context of the investigation.

Semantic differential questionnaires were prepared. 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, denoted by 'not'. 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 feel the plaque. The plaques were presented in a random order for each participant. No restrictions were given such as which hand or parts of hand could be used, or for how long the plaque could be inspected. After touching each plaque, participants were asked to rate the texture against the adjectives on the questionnaire. When rating each texture, participants were asked to not dwell too long analyzing the textures, but to give their instinctive, spontaneous reaction on touching the surface. The textures were presented without specifying any particular hypothetical context of use, other than the context of the experiment itself. Participants' ratings were transcribed to spreadsheets twice, independently by separate researchers.

Participants' responses to the questionnaires were regarded as the 'groundtruth' and were used to test retrieval accuracy during texture selection (see Section 4.3.3). However, the responses were only assumed to be correct for the context of this particular study; no attempt was made to determine the reliability of the scale. Further, it was assumed that the scales produced interval measures that justified the subsequent analysis and modeling techniques used. For a review of the limitations of these assumptions and of other biases for the measurement of affective responses, see [66].

4.3 Prediction of affective properties of textures

A feature based approach was pursued to predict the affective properties of the textures. First a set of features, originally defined for the visual domain, was extracted. The number of features was substantially reduced with two feature selection procedures particularly accounting for the danger of model overfitting.

4.3.1 Extraction of texture features

To predict the affective properties of the textures, a set of characteristic features were extracted from the matrices representing the tactile textures. Most of the software to measure the features of the matrices was implemented in MATLAB. The code that calculated first order statistics and absolute gradient was verified against values obtained from the MaZda software [60]. Code for NGLDM, GLCM and Tamura features was verified against code written independently by other researchers, and the code for the Laws' energy measures was verified manually. The GLRLM features were obtained using the GLRLM Toolbox [67]. Table 1 contains a complete list of the features used. The matrices on which the features were calculated were sized 300×300 pixels.

4.3.2 Selection of features and prediction of affective properties

Given the number of 24 tactile textures, it is not feasible to directly aim for a regression model that incorporates all 196 features. Thus a voting-based feature-selection method was used called nomination analysis to analyze the relationship between participants' responses to the adjectives natural, warm, elegant, rough, simple, and like detailed in Section 4.2.

Owing to the subjective experimental rating task and the low number of samples that caused a high level of noise, 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 [68]. For every single human judgment, SFS starts with the

Table 1. List of the 196 features used in the study.

Class	Feature	Variation
First order statistics	perc1%	
	perc10%	
	perc25%	
	perc50%	
	perc75%	
	perc90%	
	perc99%	
	average	
	variance	
	skewness	
	kurtosis	
	uniformity	
	entropy	
Second order statistics - GLCM	asm	Each at 0°, 45°, 90°, and 135°; and distances of 1, 2, 4, and 8 pixels
	contrast	
	correlation	
	sumOfSquares	
	invDiffMoment	
	sumAvg	
	sumVar	
	sumEntropy	
	entropy	
	diffVar	
	diffEntropy	

Class	Feature	Variation
Higher order statistics - GLRLM	SRE	
	LRE	
	GLN	
	RLN	
	RP	
	LGRE	
	HGRE	
	SRLGE	
	SRHGE	
	LRLGE	
	LRHGE	
Higher order statistics - Absolute gradient	grmean	
	grvariance	
	grskewness	
	grkurtosis	
	nonzero	
Visual perception measures -NGLDM	coarseness	Each at a distance of 1 and 2 pixels
	contrast	
	busyness	
	complexity	
	strength	
Visual perception measures -Tamura	coarseness	
	contrast	
	directionality	
	linelikeness	
	regularity	
	roughness	

Class	Feature	Variation
Law's energy measures	L3E3	*mean, standard deviation,* and *entropy* calculated for each filtered image
	L3S3	
	E3S3	
	L3L3	
	E3E3	
	S3S3	
	L5E5	
	R5L5	
	S5L5	
	W5L5	
	E5S5	
	W5E5	
	R5E5	
	R5S5	
	W5S5	
	R5W5	
	E5E5	
	S5S5	
	L5L5	
	W5W5	
	R5R5	

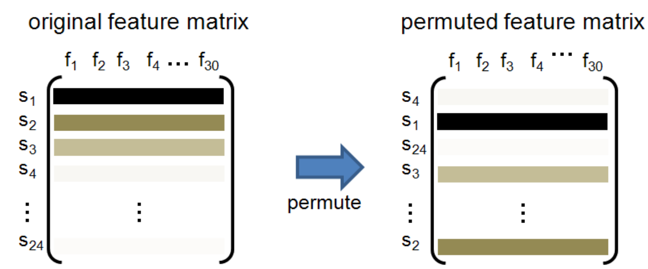


Fig. 3. The rows (representing the samples) of the feature matrix are randomly permuted to destroy the relationships between feature value and tactile response.

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 were added until the prediction error was not significantly (p=0.05, using partial F-test) reduced. A linear regression model was used to predict the target values. Finally, for all responses to the 24 tactile plaques, a set of 40 unique texture features was selected, F_{sfs}.

2. The feature set F_{sfs} was used to build all possible feature subsets of size three. The predictive quality of every single subset for every tactile response was evaluated. Step 2 of the method proposed by Thumfart et al. [19] was modified by replacing the neural network with a linear regression model, due to the relatively low number of plaques. A linear regression model was built using half of the plaques and the tactile responses were predicted for the remaining 12 plaques. The correlations between the predicted and the human responses were measured using the Pearson correlation coefficient.
3. The results of Step 2 were subjected to a parallel analysis 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 identified whether the correlations were 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 (Fig. 3).

It is asserted that the correlations of the randomly permuted dataset are those that can be achieved by chance. Consequently, all of the correlations of the unpermuted dataset larger than the correlation of the randomly permuted dataset are relevant.

This proposed voting method takes into account both the low number of available textures 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. Consequently, the frequency of every feature element of F_{sfs} was counted, being part of a feature subset that reached a correlation > 0.65. The six features with the highest frequency (i.e. the highest number of nominations) were selected for linear regression modeling.

Partial least squares regression (PLSR) [69] was used to verify the results of the use of the wrapper methodology. The performance of PLSR may decrease when there is an excessive number of predictor variables [70] and so a genetic algorithm was used to identify the subset of the texture features which were most useful. The steps taken were as follows:

1. Random predictor variable (texture features) subsets were generated.
2. The fitness value of each individual subset of texture features was calculated using the root mean square error cross-validation of the PLSR model, where the subset was used as the input and the participants' ratings against all 20 adjectives as output.
3. The worse half of the population according to fitness values was eliminated.
4. The remaining individuals were crossed together to get the new generation.
5. A random mutation was made across the new generation.
6. Steps 2 to 6 were repeated until termination criteria were satisfied.

To overcome the risk of over-fitting, the genetic algorithm was run many times, even though a cross validated approach was used. The genetic algorithm's parameters were as follows: population size=64, maximum generation=100, percentage of convergence (percentage of the population of solutions that are identical at convergence) =60, crossover operator=two point crossover, mutation rate=0.005, cross validation=3-fold and number of GA replications= 50.

The texture features that showed highest correlation were identified to develop regression models for human touch feeling for rough, natural, warm, simple, elegant, and like. Because the linear regression analysis assumes all variables are normally distributed, the Ryan-Joiner test was applied to the variables.

4.3.3 Test of retrieval accuracy

Before selecting new textures that satisfy certain human touch affective responses, the robustness of the selected features (used in the regression models), and the predicted human affective responses, to retrieve the closest texture to the query one were evaluated. A database of textures was established using 200, 300×300 pixel, textures [71]. Each texture was divided into nine, non-overlapping 100×100 sub-textures, resulting in 1800 textures. One sub-texture from each texture was used in a testing set and the remaining sub-textures were used as the training set. Grey relational analysis [72], Euclidean and city block distance were used to retrieve the top k (k=1, 2, 3, 4 and 5) textures using both the low-level features, and the six human affective responses. Retrieval was assessed by counting the number of sub-textures retrieved from the same texture as the query sub-texture.

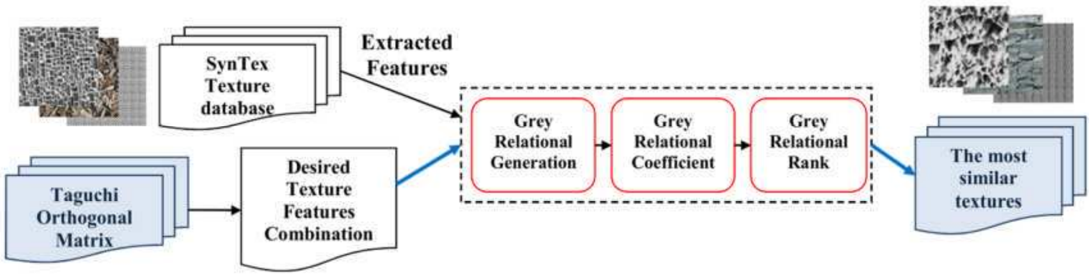


Fig. 4. The framework for texture retrieval.

4.3.4 Manufacture and evaluation of new textures

A database of 900 textures, each sized 300×300 pixels, was established using sources such as Brodatz [73] and VisTex [74]. Many of the textures were synthesized using mixing algorithms applied to our own textures [71]. Firstly, the texture features were computed for all textures in the database. Secondly, Taguchi orthogonal matrices were used to generate different combinations of the top six features that highly correlated to the affective responses. Consequently, six dimensional vectors of these features were obtained and compared to the calculated texture features extracted from textures in the database using similarity measures based on grey relational analysis technique. Textures closest to the desired features vector were selected (Fig. 4). Finally, the regression models were used to predict the affective responses to the new textures.

The 48 new textures were manufactured (Section 4.1). Visual image versions of some of the new tactile textures are shown in Fig. 5. The tactile properties of the new texture plaques were rated by 31 participants against the six adjectives following the procedure outlined in Section 4.2.

To evaluate the accuracy of the prediction models, the Reduction of Error (RE) statistic was calculated for each adjective (1) [75].

$$RE_p = 1 - \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_p\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}_p\right)^2} \qquad (1)$$

Where $\hat{y}_p$ are the predicted values of the affective response for plaque p and $\bar{y}_p$ is the mean value of the measured affective response for plaque p. N is the number of participants and y_i the measured affective response of participant i. Then, the average REs across all plaques were calculated. RE ranges from $-\infty$ to 1. A positive value is an indication of a reasonable level of predictive ability [75].

5 RESULTS

In the wrapper analysis of the first part of the experiment in which the affective responses to touching 24 plaques were measured, 9880 feature subsets were evaluated against participants' responses to all the 20 adjectives used in the first part of the experiment. The histogram of correlations for the un-permuted dataset (Fig. 6) represents the correlations that can be achieved by chance. Only feature subsets which reached a correlation R > 0.65 were used in the final parallel analysis. The top six features, according to the wrapper method, best suited to predict the tactile responses were Percentile 90%, GrKurtosis, GLCM mean correlation at distance 2, GrNonzero, GLCM mean sum variance at distance 1, and GLCM range sum of squares at distance 1. The most important features obtained by PLSR based on genetic algorithm were Percentile 90%, GrKurtosis, GLCM mean correlation at distance 2, and RLN. Features most often included in the model are Percentile 90%, Gr-Kurtosis, run length non-uniformity GLN, and grey level co-occurrence mean correlation at distance 2. These were the only texture features with frequencies of inclusion above 0.60.

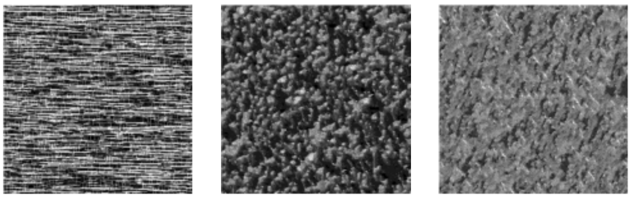


Fig. 5. Some examples of the 48 new tactile textures synthesized for the second part of the experiment.

The correlations between participants' responses to the adjectives are shown in Table 2. The results of the regression analysis are shown in Table 3, and the coefficients of determination (R^2) are shown in Table 4.

The model was checked for different linear regression assumptions. Based on scatter plots, the data fit straight lines, suggesting that linear models are sufficient. The results of the scatter plots were confirmed by ANOVA (Table 5). The values of coefficient of determination,

Table 2 Pearson correlation coefficient between tactile responses to adjectives.

	Natural	Warm	Elegant	Rough	Simple	Like
Natural		.703	.784	-.825	.847	.712
Warm			.940	-.956	.646	.948
Elegant				-.983	.746	.967
Rough					-.793	-.964
Simple						.688
Like						

Significance all at p<.001

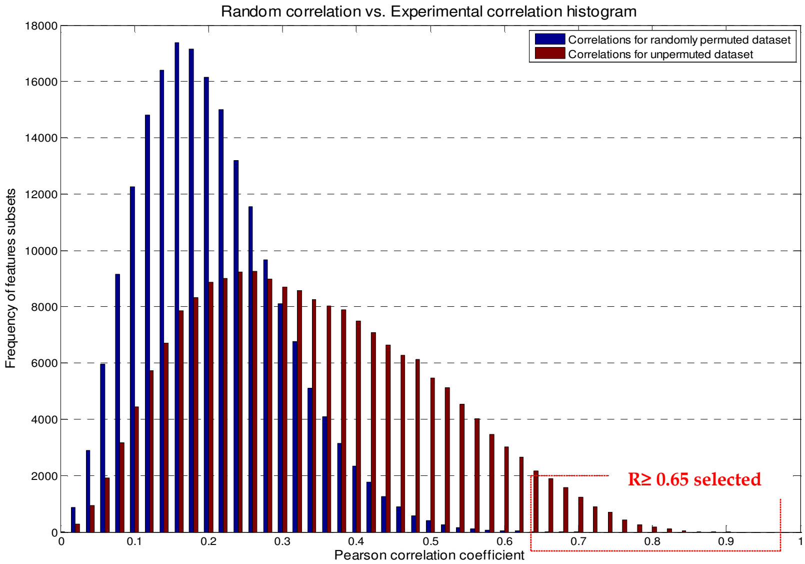


Fig. 6. Correlation histogram for the randomly permuted dataset and the original, un-permuted dataset.

Table 3. Features included in the regression model.

	Natural			Rough			Warm		
Predictor	Coeff.	Beta	p	Coeff.	Beta	p	Coeff.	Beta	p
Intercept	6.5		.00	14.22		.00	1.38		.03
GLCM correlation at distance 2	-1.61	-1.173	.00						
GRNonzero	-2.75	-1.09	.00						
Skewness	0.292	0.48	.018						
Percentile 90%				-0.05	-1.03	.00	0.012	.615	.00
GLCM m-sum variance at distance 1				0.005	.403	.05			
GLCM range sum of square at distance 1				-14.8	-.468	.00			
GrKurtosis							-0.12	-.326	.03
R5E5									

	Simple			Elegant			Like		
Predictor	Coeff.	Beta	p	Coeff.	Beta	p	Coeff.	Beta	p
Intercept	29.3		.00	-2.8		.00	-1.66		.05
GLCM correlation at distance 2	-3.93	-1.33	.00						
GRNonzero									
Skewness									
Percentile 90%				0.029	1.093	.00	0.028	1.035	.00
GLCM m-sum variance at distance 1				-0.004	-.499	.01	-0.003	-.364	.05
GLCM range sum of square at distance 1	4.67	.245	.05	9.11	.528	.00	8.36	.467	.00
GrKurtosis							-0.12	-.326	.03
R5E5	-1.37	-.848	.00						

and the adjusted and predicted coefficients of determination were all statistically significant at $p<.001$. Normal probability plots indicated that it is reasonable to assume that the random errors for these models are drawn from approximately normal distributions. In each case, there was a strong linear relationship between the residuals and the theoretical values from the standard normal distribution.

Table 4. Results of ANOVA to determine whether the regression error and the error variance are independent for each adjective.

	Natural			Rough			Warm			Simple			Elegant			Like		
	Reg	Res	Tot	Reg	Res	Tot	Reg	Res	Tot	Reg	Res	Tot	Reg	Res	Tot	Reg	Res	Tot
Sum of Sq	2.42	1.651	4.07	40.05	14.46	54.51	5.47	3.436	8.906	14.043	5.789	19.83	12.78	3.438	16.22	13.803	3.692	17.49
df	3	20	23	3	20	23	2	21	23	3	20	23	3	20	23	3	20	23
Mean Sq.	.807	.083		13.35	.723		2.735	.164		4.681	.289		4.26	.172		4.601	.185	
F	9.77			18.47			16.714			16.174			24.784			24.92		
Sig.	.000			.000			.000			.000			.000			.000		

Table 5. The coefficient of determination for the 6 adjectives.

	Natural	Warm	Elegant	Rough	Simple	Like
Standard error of estimate (S_e)	0.27	0.40	0.41	0.81	0.51	0.41
Multiple coefficient of determination (R^2)	0.59	0.61	0.79	0.74	0.71	0.79
R^2 Adjusted	0.58	0.60	0.78	0.72	0.70	0.78
R^2 Predicted	0.41	0.52	0.70	0.63	0.63	0.68

Table 6. Nearest neighbour retrieval accuracy for features and for responses to affective adjectives using grey relational analysis.

	k = 1	k = 2	k = 3	k = 4	k =5
Features	98.5%	97.25%	96.67%	95.75%	94.8%

Table 7. Nearest neighbour retrieval accuracy for responses to affective adjectives using grey relational analysis, Euclidean and city block distance

	k = 1	k = 2	k = 3	k = 4	k =5
Grey relational analysis	87.5%	86.5%	83.33%	81.75%	79.1%
Euclidean distance	87.5%	85.0%	82.5%	80.0%	77.3%
City block distance	88.0%	85.75%	82.67%	80.0%	77.5%

The average retrieval accuracies of 200 query textures for the selected features using grey relational analysis are shown in Table 6, and retrieval accuracy against the responses to the affective adjectives are shown in Table 7.

In the second part of the experiments, forty eight new surface textures were predicted based on predefined human touch feeling using the multiple regression model. Table 8 shows that all adjectives have positive reduction

Table 8. The standard deviations of responses, average scores, average differences between actual and predicted responses, and RE values for each adjective.

	Natural	Warm	Elegant	Rough	Simple	Like
σ of average responses	0.48	0.34	0.77	1.13	0.87	0.77
Average score on a seven point scale	3.6	4.2	3.8	4.3	2.8	4.0
Average difference between predicted and actual responses*	5.6%	13.6%	17.8%	18.1%	23.8%	14.2%
Reduction of Error	0.59	0.34	0.26	0.05	0.12	0.33

*expressed as a percentage of the 7 point scale

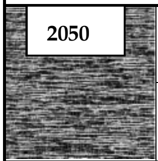
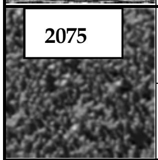
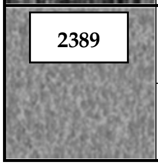
of error ratios. The number of participants was 32, and the estimated effect size for each affective response was between 0.3 to 0.55 at the $p < .05$ level for a statistical power of 0.6 to 0.9. Table 9 shows some examples of the predicted and average responses to some of the textures, normalized to a score between -100 and 100 against each adjective.

6 DISCUSSION

For connections between people's responses to the textures against the pairs of words (Table 2), it was found that the word rough has very strong negative correlations with natural, warm, elegant and simple. Simple and warm were found to have positive correlations. The correlation between rough and warm is consistent with the findings of Hollins et al. [9]. It can be concluded that a surface perceived as rough, not natural, and not simple could be perceived as not elegant.

The parallel analysis 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. On the other hand, the frequency of every feature in the unique feature set was counted, being part of a feature subset that reached a correlation > 0.65 (Fig. 6). Furthermore, the

Table 9. Examples of the predicted and average responses to some of the textures, normalized to a score between -100 and 100 against each adjective.

Texture	Adjective	Natural	Simple	Warm	Rough	Elegant	Like
 2050	Predicted properties	-4	-67	-30	87	-65	-44
	Experimental evaluation	-23	-66	-19	82	-52	-46
 2075	Predicted properties	-18	7	-42	100	-84	-62
	Experimental evaluation	-38	-65	-23	86	-65	-48
 2389	Predicted properties	-12	-15	-5	10	-16	2
	Experimental evaluation	-2	-10	15	6	-14	-12

affective responses to the six adjectives could be predicted with a correlations greater than 0.65. Other research found that there is a relationship between texture features and human aesthetic judgments [19].

From these regression models, it was found that responses to the adjective natural have a negative correlation with GLCM mean correlation, and a positive correlation with Skewness. This means that for a texture with large areas of similar intensities (not natural), the correlation is much higher than for a texture with noisier (random), uncorrelated intensities [75],[76]. In addition, nonzero gradient has a negative correlation with responses to natural. Gr-nonzero is the percentage of non-zero elements in the gradient matrix which implies that the lower the Gr-nonzero value, the higher the variation between the texture's boxels.

Warm has a negative correlation with GrKurtosis and positive correlation with Percentile 90%. Both elegant and like have a strong negative correlation with the GLCM mean sum of variance and a positive correlation with both Percentile 90% and GLCM range sum of squares. Rough has a positive correlation with GLCM mean of sum of variance and a negative correlation with both Percentile 90% and GLCM range sum of squares. A percentile gives the highest height of a boxel under which a given percentage of the boxels in the texture are contained [77]. The mean of sum variance is the variance of the normalized boxel heights, whereas the range of sum of squares is the difference between the largest and smallest sum of square (which indicates how much the height of a boxel differs from the mean) of all four directions. Thus the higher the sum variance and percentile values, the rougher the surface texture. Simple has a negative relationship with the mean correlation of GLCM and R5E5 while it has a positive correlation with the range of sum of square. R5E5 is a measure of the ripples and edges in the texture. The higher the R5E5 value, the more edges and ripples are detected.

It is perhaps surprising that no significant correlations were established between human touch feeling and the features that were extracted from the textures using Tamura and NGLDM, although these features were calculated based on human visual perception such as coarseness, directionality, roughness, and complexity [39], [40]. This contradiction could be evidence that human vision and touch work in very different ways.

The results of the evaluation of the ability of the selected texture features and human affective responses to retrieve the query texture showed that the features had very good retrieval performance (Table 5) compared to the results that were obtained by Kuo and Su [78]. These results help to demonstrate that the selected features are robust enough to represent the texture. The query system was able to assign the predefined affective responses to the closest possible texture available in the database with retrieval accuracies in the range 79.1% to 87.5%. Any misclassification might be caused by the texture feeling different on different parts of the texture. This range of accuracy is acceptable for producing a surface topography for a predefined human affective response.

To verify the ability of the regression model to predict human touch affective responses for textures, 48 new textures were selected, manufactured and touched by humans. Features were extracted from the matrix representations of the new textures and human touch affective responses were predicted using the regression model. The predicted and measured values of the feeling of natural for the majority of plaques were close to each other (Table 7), and have the highest reduction of error (RE) score. But the actual scores were close to the centre of the scale, which might suggest the participants' indifference or a lack of discrimination. Furthermore, the standard deviations between the average scores for natural for each plaque show little variation in the scores between plaques. This could be explained by the plaques being made from the same, hard, plastic material. This argument could be extended to explain the small standard deviation in scores for warm. Although it has been suggested that the assessment of warm depends on the surfaces' roughness, it might be that in this case most plaques were similarly rough, and the surfaces' material was the more pertinent property. For simple, the average difference between measured and predicted scores was quite high, but predictions for simple nevertheless showed a positive RE value.

Table 7 shows that all adjectives have positive reduction error suggesting that the regression models have a reasonable skill of prediction. It is concluded that these regression models are able to predict human affective responses based on touching the surface textures used in this study.

It remains for further research to determine the relative importance of the features identified, and to identify physical interpretations of what they are measures of in terms of touch. Nevertheless, the principal contribution of the work is that it demonstrates a process, using machine vision methods and rapid prototyping techniques, which can be used to design new tactile textures. In research, the process can be used to create new tactile textures with pre-specified psychophysical properties, and with variables independently controlled, for experiments on the perception of touch. Experiments similar to those carried out during the earliest research on vision, in which textures were analyzed in the frequency domain, for example, can now be carried out on touch. In industry, the process can be used for improved product design. Members of the machine vision and affective computing communities are perhaps best placed, in collaboration with psychologist and engineers, to exploit this process.

7 CONCLUSIONS

In this study, an attempt has been made to seek the important textural features corresponding to human touch feeling. To achieve this, twenty four tactile textures were manufactured and characterized using computational features from the domain of computer vision. These textures were touched and rated against the adjectives rough, natural, warm, simple, elegant, and like, by 107 participants. The top six features, according to the wrapper method, best suited to predicting the tactile responses were Percentile 90%, GrKurtosis, GLCM mean correlation at distance 2, GrNonzero, GLCM mean sum variance at distance 1, and GLCM range sum of squares at distance 1. The strongest feature was Percentile 90% because it has correlation with four out of six adjectives. According to these results, a regression model was built to predict the surface texture's topography that satisfies participants' affective responses, and suitable textures were selected from a database using K-nearest neighbors. The estimated human affective responses performed very well for retrieving the closest textures to the specified affective responses. Forty-eight new textures were selected, manufactured, and presented to 31 participants to rate them against the six adjectives rough, natural, warm, simple, elegant, and like. The predicted and the measured adjectives were compared using error reduction and the regression models were found to have a significant skill of prediction. This work has demonstrated a process for developing new tactile textures, which could be used to design surface textures with predefined affective properties for new products, or for affective and psychophysical studies.

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Galal Elkharraz received his BSc in Industrial Engineering in 1998, and his MSc in Manufacturing Engineering in 2004, both from the University of Garyounis, Libya, and his PhD from the University of Leeds in 2011. He is a Lecturer at the University of Benghazi, Libya.

Stefan Thumfart received his Master degree (Computer Science, 2007) and PhD (Genetic Texture Synthesis, 2012) from the Johannes Kepler University Linz. He has been a researcher in machine vision for Profactor since 2006. His research interests include visual inspection of composite materials, texture analysis, feature selection and visual perception.

Diyar Akay received the B.S., M.S. and PhD degrees in Industrial Engineering from Gazi University, Turkey in 2001, 2003 and 2006, respectively. Between 2007 and 2009, he was a researcher at the University of Leeds, UK. He is an Associate Professor with the Department of Industrial Engineering in Gazi University, Turkey. His research interests are affective design, and fuzzy sets and systems.

Christian Eitzinger received his PhD Degree from the Johannes Kepler University of Linz in 2001. He has worked for Profactor since 1997, first as a researcher and since 2001 as head of the machine vision department. He has coordinated major European and national research projects in the field of machine vision and robotics. His main research interests are machine learning methods applied to machine vision and human-machine interaction.

Brian Henson received a BEng in Electronic and Electrical Engineering from Kings College, University of London, in 1990. He achieved his PhD from the University of Leeds in 1999, having first joined Leeds as a research engineer in 1992. He became a Senior Lecturer 2007. His research interests include affective engineering, tactile textures, and the mechanics of touch.