이미지 텍스쳐 기반 햅틱 텍스쳐 저작: 초기 연구

Towards Automatic Haptic Texture Authoring Based on Image Texture Feature: An Initial Study

Noman Akbar, Waseem Hassan, Arsen Abdulali, and Seokhee Jeon
Department of Computer Engineering, Kyung Hee University, 446-701, Republic of Korea
Email: {noman.akbar, waseem.h, abdulali, jeon}@khu.ac.kr

Abstract

This paper presents an initial effort towards establishing the relationship that haptic perception of texture can be represented by image feature values. Using this relationship, a haptic texture model can be efficiently and even automatically assigned to a mesh that has an image texture mapped onto it. This paper shows the initial evidence that the relationship exists, and can be used for this purpose. An image feature space and a perceptual haptic texture space are defined, and the correlation between the two spaces was found through a psychophysical experiment with limited real samples of sandpaper. The testing result shows that a considerable relationship exists. Additionally, a relationship between the image features and relevant adjectives was found, which can be used for perceptual adjective-based haptic texture authoring. This work can be a basis for reducing the efforts and time required for haptic contents creation.

I. Introduction

Surface texture has two aspects related to it: Visual texture and Perceived texture. Visual texture is the underlying surface details that can be perceived visually. While perceived texture is defined as the surface details revealed through the sense of touch. In our daily life we encounter different objects having different textures. In order to judge the haptic feeling of these objects, we do not necessarily need to touch these objects. A picture of a surface may contain information related to the micro-geometry of the surface, and the micro-geometry somehow reflects the haptic feeling of the surface. But which haptic characteristics are associated with the visual characteristics is still an open for topic of debate.

The motivation for the current research is to find a relationship that exists between the two aspects of texture. This relationship can be used to simplify the haptic texture modeling and make the surface texture rendering more efficient. Current haptic texture modeling approaches make use of physical signals, captured from the textured surface, to make a haptic texture model [1]. This requires creation of models for every new surface. Other studies have shown that there exists a relationship between the visual and haptic texture [2], but a quantitative relation has not been proved yet. To find this relationship, first of all, haptic texture models will be created for a set of surfaces with varying physical properties. The visual texture can be found from an image with the help of various image features. A relationship will be established between the image feature space and the haptic texture space. This relationship is used to make the most similar perceptual haptic texture model of any new surface.

This paper is organized as follows. Section II and Section III describe the definition and the method used to build the image feature and haptic perceptual space. Section IV examines the relationship between the two spaces. Section V additionally discusses the adjective meaning of the space. An overall block diagram explains each step in Figure 1.

II. PERCEPTUAL HAPTIC TEXTURE SPACE

In the perceptual haptic texture space, the surfaces are represented as a set of points in an n-dimensional perceptual space. We use MDS (Multidimensional Scaling) analysis to represent the perceived texture of surface in perceptual space [3].

In order to find the dissimilarity between the surfaces, psychophysical experiments were performed to get the perceived distances among the surfaces. These perceptual distances are used to create a dissimilarity matrix. The dissimilarity matrix was used to perform Multidimensional Scaling (MDS) analysis. As a result, the location of samples in 2D perceptual space is found and the axes are labeled with adjectives to show the variations in perceived surface texture properties associated with the samples. The experiment is designed by the procedure outlined in a similar research [4].

1) Experiment details: A total of six participants took part in the experiment. A set of thirteen sandpaper

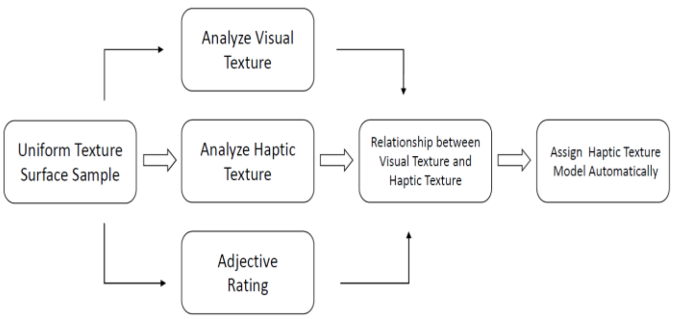

Figure 1 Block Diagram of the overall framework

samples (S_1,S_2, …,S_{13}) were used as uniform textured surfaces in the experiment.

In order to find the dissimilarity between samples, each participant performed a pairwise comparison for all sample pairs following the procedure for magnitude estimation without modulus. Since there were thirteen samples and each sample pair was presented four times, it resulted in (13x12=2) x4=312 pairwise comparisons.

2) Data Analysis: For each participant, the scores for each pair were averaged. Then score for every participant was mapped to a scale of 0 – 100. A scaling factor a_k was calculated for every participant *k*. Let S_{ij} represent the average score for the stimuli *(i, j)* where *i*, *j* takes on values between 1,2,3, … ,13 and $i \neq j$. The scaling factor for each participant was calculated as follows

$$a_k = \frac{100}{\max(S_{ij})} \quad (1)$$

The dissimilarity scores were averaged across all the six participants to get a dissimilarity matrix.

Using the dissimilarity matrix, classical MDS analysis was performed. Based on the Kruskal stress [3], two dimensional representation was selected for our perceptual space representation (0.16 for 2 dimensions which is considered fair [5]).

3) Results: The Euclidean distances in Perceptual Space are represented in two dimensions by the blue dots shown in Figure 3.

III. IMAGE FEATURE SPACE

In the image feature space, the visual texture of a surface is represented as the feature values calculated form an image of the surface. For the current study we focus on extracting the image features based on GLCM (Grey Level Co-occurrence Matrix) which is known to effectively reflect small surface texture.

After taking images of all the sandpaper samples, a GLCM matrix was formed for every image, which was used for extracting image features. The features were then analyzed to find the best texture features that were the most accurate representations of the surface textures in Section IV. Four features that showed the highest correlation with average particle size of the

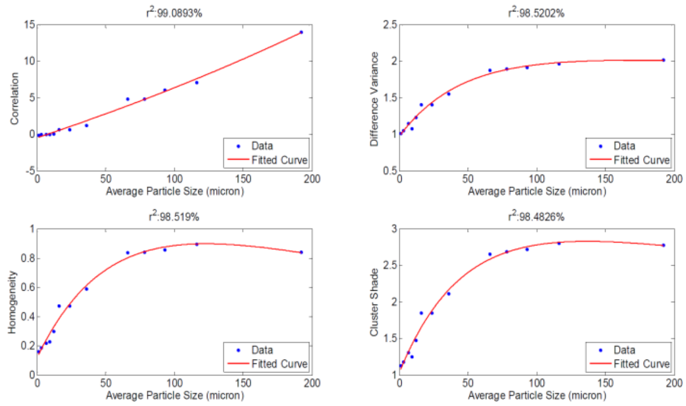

Figure 2 Image feature value against the particle size

sample are taken, and their values are plotted against the particle size as shown in Figure 2. It can be seen that the size of the particle is reflected in the image features.

IV. RELATION BETWEEN HAPTIC AND IMAGE SPACE

To find the relationship between the image feature space and perceptual space, the image feature values were linearly mapped to a scale of 0–100. After this, multiple linear regression was performed by using the location of samples in the perceptual space as input variables and the image feature values as output variables. The regression coefficients for all image features were normalized and the ratio for the regression coefficients was calculated. This ratio is represented in Figure 4 as the slope of the line for the image feature. Only the best four image features (energy, sum average, sum entropy, correlation) are presented. The length of the line represents the goodness of fit.

V. ADJECTIVE RATING

In order to reveal the relationship among the image features, adjectives, and the perceptual space, another psychophysical experiment was conducted. The method of adjective rating was used to find the list of adjectives that can be used to describe the haptic texture properties associated with the sandpaper samples. Six participants took part in this experiment.

In the method of adjective rating, the participants rate the similarity between the feel of the surface and an adjective pair. As a first step for adjective rating experiment, a list of adjectives was collected [4] that best described the feelings associated with all the samples. The resulting list of five adjective pairs obtained is Irritating – Pleasant, Flat – Bumpy, Sticky – Slippery, Hard – Soft and Rough – Smooth.

A GUI with five slide bars showing five adjective pairs on opposite sides of each slider was presented to the participants. The participants were asked to explore

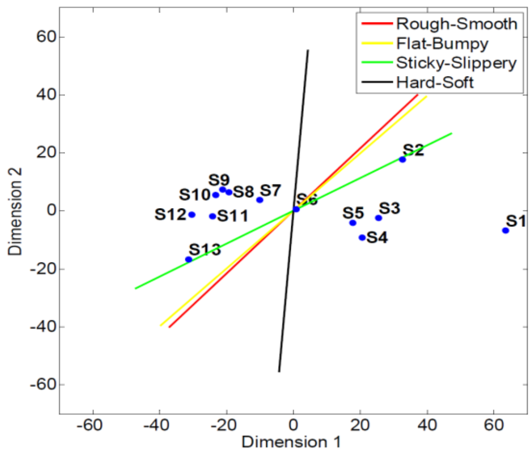

Figure 3 Multiple Linear Regression in Perceptual Space

a single sample and adjust the slider for each adjective pair in describing the feeling associated with the sample.

The final adjective rating representing the score was calculated by averaging the value from all the participants. The perceptual space along with the adjective pair regression results are shown in Figure 3.

Some of the image feature axis in the perceptual space reveal the same characteristics as shown by the adjective rating in Figure 4, suggesting a strong correlation between the image feature and the adjective pair.

Visual analysis between image feature axis and adjective pair axis in the perceptual space show that four image features (energy (f_1), sum average (f_{13}), sum entropy (f_{15}) and correlation (f_6)) have high correlation with the adjective pair Rough-Smooth, Flat-Bumpy, Sticky-Slippery, and Hard-Soft, respectively, as shown in Figure 4. The figure suggests that the image features can be used to estimate the perceptual adjectives, and vice versa.

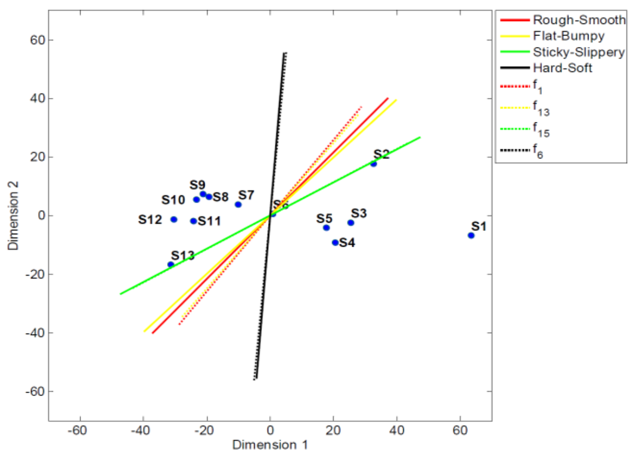

Figure 4 Correlated Image Features and Adjective pairs in Perceptual Space

In addition, we examined the adjective pairs which can describe the physical characteristics of a surface. To do this, the sample coordinates were projected on individual adjective pair axis as shown in Figure 5. The

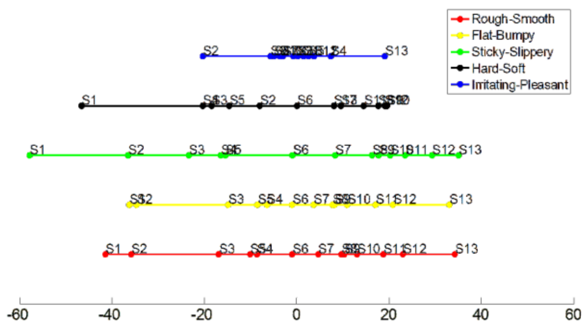

Figure 5 Sample Locations in Perceptual Space Projected on Adjective Axis

order of the samples was preserved in the case of the perceptual axis for Sticky-Slippery. In the case of adjective pairs Flat- Bumpy and Rough-Smooth all samples were in order except S_4 and S_5. In case of Hard-Soft and Irritating-Pleasant most of the samples were out of order. The result indicated that some adjective pairs could correctly reflect the average particle size of the sandpaper and that this data could be used to automatically generate a virtual textured surface having a specific perceived roughness or stickiness value by controlling the size of the micro bump of the surface.

VI. CONCLUSION

Our research concludes that visual features extracted from the image, if carefully selected, can reveal important physical characteristics related to surface texture. This research can help in standardization of haptic models, such that all the models are placed in the same perceptual space with the same parameters.

VII. ACKNOWLEDGEMENTS

논문은 미래창조과학부의 재원으로 한국연구재단의 지원을 받아 <실감교류 인체감응솔루션> 글로벌프론티어 사업으로 수행된 연구임(2012M3A6A3056074)

References

[1] Baumgartner, E., Wiebel, C. B. & Gegenfurtner, K. R. "Visual and Haptic Representations of Material Properties" Multisensory Research, 26, 429-455, 2013.

[2] Wu, J., Song, A. & Zou, C. "A novel haptic texture display based on image processing", IEEE International Conference on Robotics and Biomimetics, 1315-1320, 2007.

[3] Kruskal, J. B. "Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis", Psychometrika, Springer, 29, 1-27, 1964.

[4] Hwang, I. & Choi, S. "Perceptual space and adjective rating of sinusoidal vibrations perceived via mobile device", IEEE Haptics Symposium, 1-8, 2010

[5] Wickelmaier, F. "An Introduction to MDS", Sound Quality Research Unit, Aalborg University, Denmark, 2003.