An Analysis of Haptic Based Image Classification

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Abstract

This paper presents an image texture classification approach by using visual features and the haptic characteristics of image surface texture. In this study, thirteen sandpaper samples are used to create dataset. GLCM (Grey Level Co-occurrence Matrix) features were extracted for each image in the dataset. The haptic properties of each texture image were calculated using an adjective rating experiment. We have used four different algorithms were used for the visio-haptic classification. The algorithms were trained by using the image features as inputs and the haptic properties (adjective rating scores) as response variables. Out of the four algorithms, the cross-validation results for Neural Networks showed the highest classification accuracy of 80%. Such an approach can be readily used to predict haptic properties based on image features of textured surfaces.

1. Introduction

The haptic representation of an object requires two things, the geometric model and a haptic properties model. Geometric modelling can be done with standard computer graphics algorithms. To model haptic properties such as, haptic texture, stiffness etc.; designers commonly utilize complex tools to collect this data or manually tune the model by feeling the surface. For haptic textures, a new approach is now being developed that uses high resolution photographs and image classification to automatically assign the requisite texture model [1]. According to ref [2], there is a connection between haptic and image texture. Traditionally, image classification focuses on macro details of a photograph. However, an image also contains micro geometry information that relates to the haptic feeling of the surface.

This research is a continuation of [3], in that study psychophysical experiments were conducted to find the adjective rating pairs. These pairs highlight the perceptual characteristics of the individual haptic textures. We have employed four machine learning algorithms for haptic texture classification. K-Nearest Neighbor and Decision Tree represent the classic, while Neural net and Deep learning epitomize the prevalent image classification algorithms. It must be noted that due to the nature of haptic textures, our approach is different from pure image classification. Here the response variable for all the algorithms is the selected adjective rating pairs.

2. Dataset

To create image dataset, we have used samples of sandpapers as they have a uniform surface and surface properties remain constant throughout the surface. We can differentiate sandpapers with their grit number because every sandpaper with distinct grit number has a different average particle size and surface roughness, this provides a good measure as a ground truth. A total of 13 sandpapers are used in this study. Figure 1 shows the images of sandpapers.

Images are captured by a mobile phone (Lumia 925) camera. Each sample is rotated by an angle of 90° after capturing one image. As a result, for each sample, four images were captured by rotating it at an angle of 0°, 90°, 180° and 270°. To induce further variation, images were captured under three lighting conditions. I) Normal room light, II) placing a light source directly above the sample surface and III) placing a light source at an angle of 20° with the sample surface.

In each image, uniform surface texture covered an area of 1600 × 1600 in camera pixels. To reduce non-uniformness in the small region of the surface, each image was cropped into five smaller images of sizes 800 × 800. The four corners and one from the center as shown in the Figure 2. Thus, a total of 780 images were generated from the 13 sandpaper samples (13 samples × 5 cropped images × 4 angles × 3 light conditions). All 13 samples were named as S1, S2, …, S13 in increasing order of grit number.

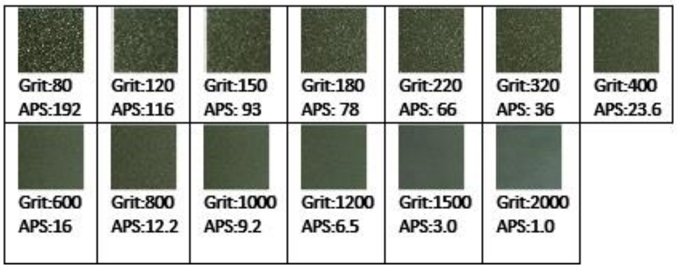

Figure 1. 13 sandpaper samples with their grit number and average particle size (APS) in μm

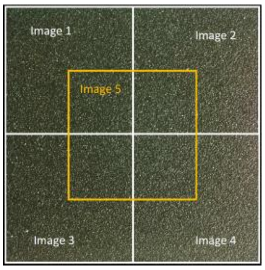

Figure 2. Image crop procedure

3. Experiment

A psycophysical experiment was conducted by Noman et al. in [3], using the same dataset as in this study, to find out a perceptual space where the sandpaper samples were placed based on the dissimilarities between them. Furthermore, an adjective rating experiment was carried out to find out the perceptual characteristics related to each sample. The perceptual space, along with the regressed adjective-pair line are shown in Figure 4. Five adjective pairs were used in that study. It was reported that three out of the five adjective pairs mostly preserved the order of the sample (according to the grit number). These three adjective pairs will be used in the current study. The selected adjective pairs are rough-smooth, flat-bumpy and sticky slippery (Figure 4).

4. Image Feature Extraction

After generating a dataset, image features are extracted from the dataset. For this purpose, GLCM (Grey Level Co-occurrence Matrix) features are calculated for each image. GLCM proposed by Haralick et al. [4] is the most widely used the method to extract features from a surface for texture recognition. GLCM matrix is calculated by considering the neighboring pixels of a given pixel. There are two control parameters in selecting these neighbors; direction and distance to the neighboring pixels. In this study, four directions (0°, 45°, 90° and 135°) and two distances (1 and 2 pixels) were used. Afterwards, 44 image features were calculated, 22 for each distance value.

Since, a 44 dimensional feature vector would most likely cause overfitting, therefore, the dimensionality of feature vector was reduced using the the approach proposed in [5], i.e., using multidimensional scaling technique. The dimensionality was reduced from 44 to 15.

5. Classification Algorithms

As a next step, classification algorithms were applied to the features extracted in the last step to classify each image with respect to its image features. However, the labels provided to the images came from the adjective rating experiment. Thus, the classification was based on an amalgam of haptic and visual (images) information. The image features were used as input variables, while, the adjective rating scores were used as response variables for the algorithms. The algorithms used in the current study are I) Decision Tree, II) Deep Learning, III) K-Nearest Neighbor and IV) Neural Net. RapidMiner Studio v7.4 software was used to carry out this study.

Table 1

Algorithm	**Parameter**	**Value**
Decision Tree	Criterion	Accuracy
	Pre-Pruning	Disable
	Maximal depth	-1
Deep Learning	Activation	Rectifier
	No. of hidden layers	2
	Size of hidden layers	100 each
K-NN	Weighted Vote	Enable
Neural Net	No. of hidden layers	2
	Size of hidden layers	25

6. Results and Discussion

Results are calculated by applying the classification algorithm on the data set. Table 2 shows the percentage accuracy for each algorithm.

Table 2: Results

Algorithm	Accuracy
Decision Tree	69.23 %
Deep Learning	71.92 %
K-NN	80.0 %
Neural Net	81.54 %

Figure 3, provides the percentage accuracy of each algorithm with respect to each individual sample.

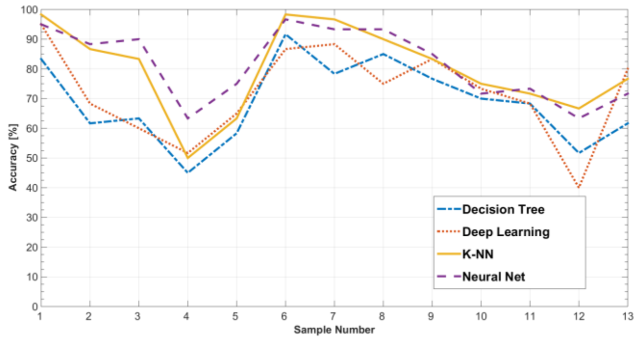

Figure 3. Percentage accuracy for each sample

As we can see from the Figure 3, most of the samples were classified correctly most of the time but few of them got low percentage during classification. The reason is, some samples are having similar features as of their neighboring samples. Figure [4] is showing the perceptual distance of dissimilarity between the samples. The samples having low distance to its neighbors in the perceptual space got lower accuracy in classification.

7. Conclusion

In the current research, haptic property based image classification was carried. Four different classification algorithms were used to classify the haptic properties of sandpaper samples based on their image features. The highest accuracy, of 80% for neural networks, shows that such a hybrid technique of classification can be successfully used in haptic classification.

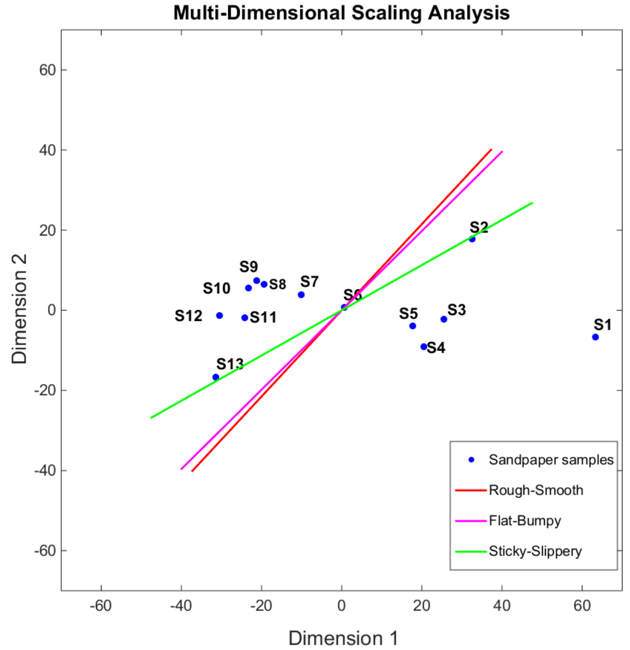

Figure 4. Multiple Linear Regression in Perceptual Space

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