Complexity Perception of Texture Images

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Abstract. Visual complexity perception plays an important role in the fields of both psychology and computer vision: it can be useful not only to investigate human perception but also to better understand the properties of the objects being perceived. In this paper we investigate the complexity perception of texture images. To this end we perform a psycho-physical experiment on real texture patches. The complexity of each image is assessed on a continuous scale. At the end of the evaluation, each observer indicates the criteria used to assess texture complexity. The most frequent criteria used are regularity, understandability, familiarity and edge density. As candidate complexity measures we consider thirteen image features and we correlate each of them with the subjective scores collected during the experiment. The performance of these correlations are evaluated in terms of Pearson correlation coefficients. The four measures that show the highest correlations are energy, edge density, compression ratio and a visual clutter measure, in accordance with the verbal descriptions collected by the questionnaire.

Keywords: Image complexity · Psycho-physical experiment · Color image features · Texture

1 Introduction

Visual scenes are composed of numerous textures, objects, and colors. Texture helps us to understand the visual world. It provides a cue to the shape and orientation of a surface, to segmenting an image into meaningful regions, and to classifying those regions in terms of material properties [1]. Human texture processing has not yet been fully understood given its complexity and the involvement of mechanisms at different levels. Researches have addressed the problem of texture processing using both artificial and natural materials [2]. Investigating the complexity of real texture images can provide new insights in understanding how humans perceive texture and if the material recognition influences such process. Some studies of visual complexity perception deal with real world images [3] but little research has been carried out into the visual complexity of texture images.

Depending on the specific task and the application domain, different definitions of image complexity are possible. From a purely mathematical point of view,

V. Murino et al. (Eds.): ICIAP 2015 Workshops, LNCS 9281, pp. 119–126, 2015.
DOI: 10.1007/978-3-319-23222-5_15

Kolmogorov [4] defines the complexity of an object as the length of the shortest program that can construct the object from basic elements, or description language. Snodgrass et al. [5] refer to the visual complexity as the amount of detail or intricacy in an image. Birkhoff [6] relates the image complexity to visual aesthetics. Heaps and Hande [7] define complexity as the degree of difficulty in providing a verbal description of an image. Visual complexity is in general represented by a multi-dimensional space, where according to Oliva et al. [3], quantity of objects, clutter, openness, symmetry, organization and variety of colors modulate the shape of the complexity space for the case of real-world scenes.

In a previous work [8] we have studied the image complexity perception of real world images. In particular we have investigated how different image features, based both on color and spatial properties, correlate with the collected subjective data. We have found that features that work on grayscale values better correlate with subjective data than features developed to measure color properties, suggesting that color does not influence significantly the perception of image complexity when real world scenes are considered. In this kind of images, in fact the lightness component provides enough information about the semantic content.

Recently, Guo et al. [9,10] have considered the perception of texture complexity. They identified five low-level characteristics that are used by humans to perceive the visual complexity of textures: regularity, roughness, directionality, density, and understandability. Visual complexity is a function of not only each individual characteristic but also of interactions between them. The authors conclude that visual complexity perception is related to the objective characteristics of a texture as well as respondents subjective knowledge.

In this paper we investigate the complexity perception of texture images. To this end we perform a psycho-physical experiment on real texture patches. During the experiment no explicit definition of *complexity* was provided to the observers. The complexity of each image is assessed on a continuous scale. At the end of the evaluation, each observer was asked to fill out a questionnaire indicating the criteria used to assess texture complexity. To find out if objective measure can predict subjective scores, we here consider thirteen image features that measure colors as well as other spatial properties of the images. We correlate each of them with the subjective scores collected during the experiment and we evaluate the performance of these correlations in terms of Pearson correlation coefficients. In Section 2 the experimental set up is described, while in Section 3 the thirteen objective measures are listed. Finally in Section 4 we report the correlation results and the analysis of the verbal descriptions.

2 Subjective Experiment

The aim of this experiment is to assess the complexity perception of real texture images. In this evaluation, both bottom-up and top-down cognitive mechanisms may be active. In our experiment we intentionally gave as little guidance as possible about the definition of complexity with the aim to elucidate if some common criteria in perceiving complexity can be extracted from the experimental data.

Fig. 1. Thumbnails of the texture images chosen to sample each of the 54 classes in the VisTex data set, ordered from the less complex (top left) to the most complex (bottom right), according to the subjective scores.

Participants and Stimuli

A group of 17 observers with normal or corrected-to-normal visual acuity and normal color vision took part in the experimental session. All the observers were recruited in the Department of Informatics System and Communication of the University of Milano Bicocca. Their ages ranged from 23 to 50 years old.

The 54 images used as stimuli belong to the VisTex25 data set [11]. This data set consists of 864 images representing 54 classes of natural objects or scenes captured under non-controlled conditions with a variety of devices. From each of the 54 classes, one image has been chosen.

Experimental Setup

The images are individually shown on a web-interface. They are shown in a random order, different for each subject. The subjects report their complexity judgments (scores) by dragging a slider onto a continuous scale in the range [0-100]. They can look at the stimuli for an unlimited time. The position of the slider is automatically reset after each evaluation. A grayscale chart is shown to calibrate the brightness and the contrast of the monitor. Ishihara color test have been preliminarily presented to the observers for estimating color vision deficiency. Nine training images are presented to the observers prior to the 54 test ones. These images have been used to train the subjects about the range of complexity to be evaluated. The corresponding data has been discarded and not considered as experimental data. At the end of the test, the observers were asked to verbally describe the characteristics of textures that affect their evaluation of visual complexity perception.

We have applied Z-score and outliers detection to obtain the final Mean Opinion Scores (MOS) of each image. The raw complexity score r_{ij} for the i-th subject ($i = 1, ...14$ in case of color images or $i = 1, ...17$ in case of grayscale images) and j-th image ($j = 1, ...29$) was converted into Z scores:

$$z_{ij} = \frac{r_{ij} - \bar{r_i}}{\sigma_i} \tag{1}$$

where $\bar{r_i}$ is the average of the complexity scores over all images evaluated by the subject, and σ_i is the standard deviation. The Z scores were then averaged across subjects after the removal of the outlier scores. A score for an image was considered to be an outlier, and thus removed from the average computation, if it was outside an interval of width two standard deviations about the average score for that image.

3 Objective Measures

In what follows we list and briefly describe the candidate complexity measures here considered. The first four of them work on grayscale images. They measure properties of the Grey Level Co-occurrence Matrix (GLCM), which is one of the earliest techniques used for image texture analysis. In particular GLCM is capable of identifying the repetition, uniformity, disorder, contrast, and heterogeneity within images. In this work the MATLAB function *graycoprops* is used:

- $\mathcal{M}_1$: Contrast, it is a measure of the intensity contrast between a pixel and its neighbor over the whole image.
- $\mathcal{M}_2$: Correlation, it is a measure of how correlated a pixel is to its neighbor over the whole image.
- $\mathcal{M}_3$: Energy, it is the sum of squared elements in the GLCM.
- $\mathcal{M}_4$: Homogeneity, it measures the closeness of the distribution of elements in the GLCM with respect to the GLCM diagonal.

Measures from $\mathcal{M}_5$ to $\mathcal{M}_8$ describe image features associated to frequency, edge density, compression and number of regions:

- $\mathcal{M}_5$: Frequency factor, it is the ratio between the frequency corresponding to the 99% of the image energy and the Nyquist frequency.
- $\mathcal{M}_6$: Edge density [12], it is obtained applying the Canny edge detector to the grayscale image.
- $\mathcal{M}_7$: Compression Ratio, it is here evaluated as the ratio of the image JPEG compressed with Q factor = 100 and the full size uncompressed image.
- $\mathcal{M}_8$: Number of regions calculated using the mean shift algorithm [13].

Measures from $\mathcal{M}_9$ to $\mathcal{M}_{11}$ evaluate mainly color image properties:

$\mathcal{M}_9$: Colorfullness : it is the simplified version of the metric proposed by [14], that consists in a linear combination of the mean and standard deviation of the pixel cloud in the color plane.

$\mathcal{M}_{10}$: Number of colors [15]: measures the number of distinct color in the image. RGB values are first quantized by removing the least significant bits, then these values are indexed and the number of unique index values are counted.

$\mathcal{M}_{11}$: Color harmony [15,16]: it is based on the perceived harmony of color combinations. It is composed of three parts: the chromatic effect, the luminance effect, and the hue effect.

We underline that these measures were not specifically developed to predict subjective complexity. However some of them have shown to successfully predict image complexity for particular set of stimuli or tasks.

We also consider two clutter measures developed by Rosenholtz et al. [17]. They attempt to measure the efficiency with which the image can be encoded while maintaining perceptual image quality. The MATLAB implementation provided by the authors has been used:

$\mathcal{M}_{12}$: Feature Congestion: three clutter maps for the image, representing color, texture and orientation congestion are evaluated across scales and properly combined to get a single measure.

$\mathcal{M}_{13}$: Subband Entropy: it is related to the number of bits required for subband image coding: the less cluttered an image is, the more it is redundant and the more efficiently it can be encoded.

4 Results

In Figure 1 the 54 stimuli are shown in increasing order of complexity, according to MOS. We can notice that images with regular pattern and symmetries have been judge as less complex, while images with more details and less ordered structures have been judged as more complex.

In Table 1 the verbal descriptions of the observers, are summarized in terms of the most frequent criteria used to assess texture complexity. We underline that each observer could have used more than one criteria. Table 1 shows that the major texture characteristics considered are regularity, understandability, familiarity and edge density. While regularity and edge density can be associated to bottom-up cognitive mechanisms, understandability and familiarity are related to top-down processes. Moreover, several observers have reported both types of criteria, confirming that bottom-up and top-down mechanisms interfere in perception.

To find out how the objective metrics described in Section 3 predict subjective scores, we have correlated each of them to the MOS using a logistic regression function. The correlation performance is expressed in terms of Pearson Correlation Coefficient (PCC), reported in Table 2. We observe that in general the

Table 1. Summary of verbal description

Criterium	Frequency
Regularity	60%
Understandability	47%
Edge Density	33%
Familiarity	13%

Table 2. PCC of the 13 objective metrics

	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$	$\mathcal{M}_5$	$\mathcal{M}_6$	$\mathcal{M}_7$	$\mathcal{M}_8$	$\mathcal{M}_9$	$\mathcal{M}_{10}$	$\mathcal{M}_{11}$	$\mathcal{M}_{12}$	$\mathcal{M}_{13}$
PCC	0.43	-	0.53	0.42	0.35	0.58	0.50	0.47	0.24	0.44	-	0.55	0.44

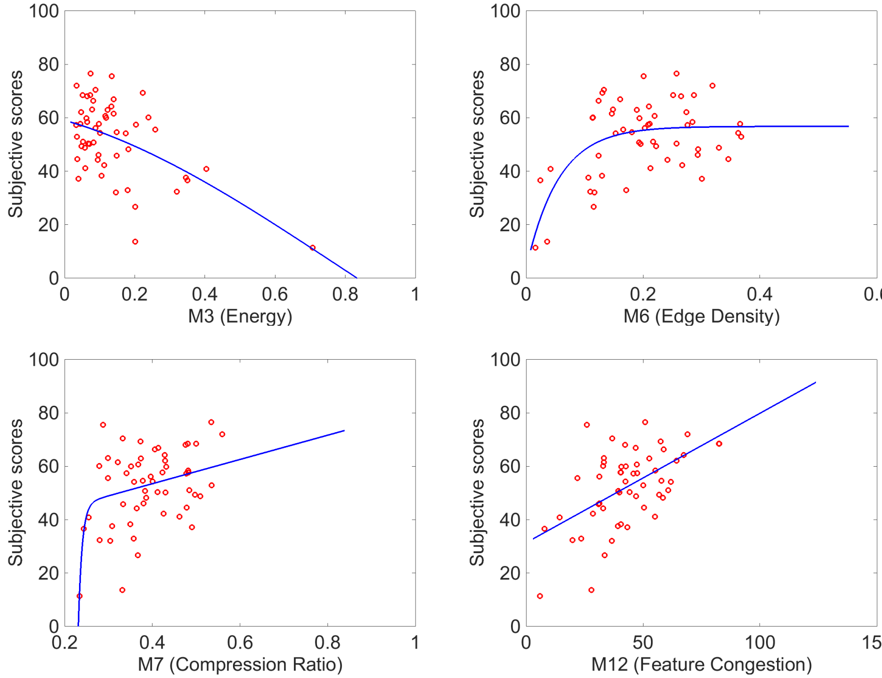

Fig. 2. Logistic correlations of the four metrics with the highest PCC.

metrics do not perform very well. For measures $\mathcal{M}_2$ (Correlation) and $\mathcal{M}_{11}$ (Color harmony) we were not able to find a significant correlation and thus we do not report in Table 2 the corresponding PCCs. Only four of them show PCC greater or equal to 0.5. These four metrics are: $\mathcal{M}_3$ (Energy), $\mathcal{M}_6$ (Edge density), $\mathcal{M}_7$ (Compression ratio) and $\mathcal{M}_{12}$ (Feature Congestion). We plot in Figure 2 the corresponding logistic correlation functions.

Taking into account the criteria that came out from the observers (Table 1), we can easily associate the verbal description *edge density* with the metric $\mathcal{M}_6$. The description *regularity* could be described by $\mathcal{M}_3$ and $\mathcal{M}_6$ but also by the measure of visual clutter $\mathcal{M}_{12}$. We recall that this measure combines color, luminance contrast, and orientation energy. With respect to the *understandability* and *familiarity* criteria, none of the considered metric is able to capture these top-down concepts. This fact could partially explain the low correlations found.

5 Conclusions

In this work we provide insight into the texture complexity perception, with the aim to underline if some common criteria in perceiving complexity can be extracted from the experimental data. The results of our analysis give a hint about the main aspects that should be considered when formulating a model to predict texture complexity. In particular we have identified some low level features (such as edge density) that play an important role. However how to integrate them within a model that also take into account top down mechanisms is still an open problem. As future research we will investigate if a combining of several single measures is able to predict the subjective perception of texture images. Moreover another important issue that will be address is to evaluate the role of color in texture complexity perception. To this end we plan to perform a further experiment with the same stimuli here considered, but in their gray-scale version to compare the results.

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