

## Suitability of Texture Analysis Methods for Perceptual Texture

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### ABSTRACT

Image texture analysis has been widely used as object recognition methods in the field of computer vision. Most features extracted from conventional texture analysis metrics, however, were found unrelated to the visual appearance. In the present study, psychophysical data on “coarseness” were used to examine the suitability of conventional image-texture metrics, including co-occurrence matrices, run length, grey level difference method and neighbouring grey level dependence statistics. The results showed that a few features obtained from the conventional metrics were in close correlation with “coarseness”. However, these metrics are not concerned with any human visual system.

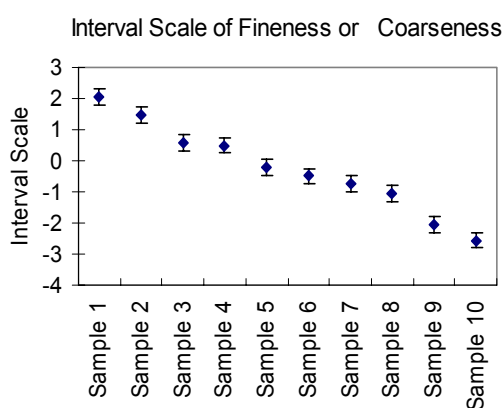
### 1. INTRODUCTION

Image texture analysis has attracted considerable attention over the last few decades. A large number of studies have been carried out according to three categories issues: *texture classification*, *texture segmentation* and *texture synthesis*<sup>1</sup>. *Texture classification* refers to the process of grouping images of texture into classes, where each resulting class contains similar patterns according to some similarity criterion. *Texture segmentation* refers to the process of dividing an image into homogeneous regions according to some homogeneity criterion. *Texture synthesis* is often used for image-compression applications and computer graphics, where the goal is to render object surfaces to make them as realistic as possible. As these issues focus mainly on texture, little attention has been given to the texture analysis regarding human perception. Although accuracy of classification, segmentation and synthesis are specified by humans, the features obtained from image-texture metrics such as energy and entropy are not perceived. It is more convenient to analyse features based on human perceptual texture such as coarseness and contrast for further uses of the image-texture metrics, such as prediction of human perception.

### 2. EXPERIMENT

#### 2.1. Visual assessment

Coarseness is one of the keywords for perceptual texture<sup>2</sup> and has been of interest to industries such as textiles and paints. In a psychophysical experiment on coarseness, fifteen observers were presented with 10 real fabrics of 10×10 cm in size under a D65 simulator in a VeriVide viewing cabinet. The observers were asked to assess the coarseness of each fabric using a rank order method<sup>3</sup>, i.e. each observer ranked the fabrics in order of coarseness. Each observer conducted the assessment twice for the repeatability test. The experimental results show a mean repeatability value of 0.95 calculated by correlation coefficient. The experimental data were converted into Z scores as the scale values (coarseness). The less the Z score, the coarser texture of the fabric. Figure 1 shows the scale values of the 10 fabrics, where the error bars indicate the precision of each scale value, which was determined by the 95% confidence interval.



**Figure 1:** The scale values (coarseness) with the 95% confidence interval. Sample 1 is the finest and Sample the coarsest.

## 2.2. Extraction of texture features

The 10 fabrics used in the visual assessment were captured using a NikonD1x digital camera under the illuminant box DidEye system with a uniform diffuse light<sup>4</sup>. Each image was black-white with a size of 500×300 pixels, as shown in Figure 2. Texture features were extracted from the images using 4 approaches; co-occurrence matrices<sup>5</sup>, run length<sup>6</sup>, grey level difference method, and neighbouring grey level dependence statistics.

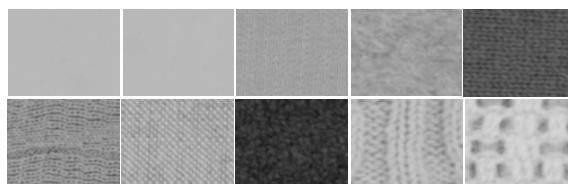


Figure 2: The images of the 10 fabrics used in this experiment.

### Co-occurrence matrices

Co-occurrence matrices is one of the most well known and widely used methods. This method is based on the repeated occurrence of grey level configurations (pixel values) in the texture. The occurrence of grey level configuration is determined by a matrix of frequencies  $P_{\phi,d}(i, j)$ , which indicates how frequently two nearest-neighbouring pixels with grey levels  $i$  and  $j$  appear in the image separated by a given distance  $d$  (defined as the number of pixels) in a direction  $\phi$  of  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  or  $135^\circ$ . An example of co-occurrence matrix computation for  $P_{0^\circ, 1}(\phi = 0^\circ \text{ and } d=1)$  is given in Figure 3. The co-occurrence matrix reveals certain properties about the spatial distribution of the grey levels in a texture image. Haralick *et al.*<sup>5</sup> has proposed a set of 14 measures of textural features that can be computed from the co-occurrence matrices. In this experiment, 4 features (energy, entropy, contrast and correlation) were computed at direction parameter  $\phi = 0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  with distance parameter  $d = 1 \sim 11$ .

image				$0^\circ$	Matrix			
0	0	1	1		4	2	1	0
0	0	1	1	$\begin{pmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{pmatrix}$				
0	0	1	1					
0	2	2	2					
2	2	3	3					

Figure 3: A 4x4 image with four grey levels, 0 to 3 and co-occurrence matrix ( $d=1, \phi = 0^\circ$ )

### Run Length

Texture features can be based on computation of continuous probability of the length and grey level of the primitive in the texture. Run length matrix  $P(i,j)$  describes the number of times that the image contains a run of length  $j$ , in a given direction, consisting of points having grey level  $i$  (or lying in the grey level range  $i$ ). The example in Figure 4 shows an image having four grey levels (0-3) and the resulting grey level run length matrices for a directions  $\phi=0^\circ$ <sup>6</sup>. Using the run length, 5 features (short run emphasis, long run emphasis, run length non-uniformity, grey level non-uniformity and run percentage) were computed at direction parameter  $\phi=0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$ .

Image				Grey level	Run length				
0	1	2	3		$0^\circ$	1	2	3	4
0	2	3	3	$\begin{matrix} 0^\circ & 1 & 2 & 3 & 4 \\ 0 & 4 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 2 & 3 & 0 & 0 & 0 \\ 3 & 3 & 1 & 0 & 0 \end{matrix}$					
2	1	1	1						
3	0	3	0						

Figure 4: An example of the run length matrices ( $\phi = 0^\circ$ )

### Grey Level Difference Method

This statistic (first order) method compute features based on absolute differences between pairs of grey levels in an image. For any given distance  $d = (\Delta x, \Delta y)$ , let  $f' = (x, y) = |f(x, y) - f(x + \Delta x, y + \Delta y)|$ . Grey level difference method matrix is the probability of the density function of  $f'$  in a given direction. Figure 5 is an example that shows an image having four grey levels (0-3) and a matrix for a directions  $\phi=0^\circ$  and distance  $d = 1$ . In order to extract useful number of information from the texture, four features (contrast, angular second moment, entropy, and mean) were calculated at  $d=1 \sim 9$ .

Image				Grey level difference
0	1	2	3	
0	2	3	3	$\begin{matrix} 0^\circ & 0 & 1 & 2 & 3 \\ P(l) & 3 & 5 & 1 & 3 \end{matrix}$
2	1	1	1	
3	0	3	0	

Figure 5: An example of grey level different method matrix ( $d=1, \phi = 0^\circ$ )

### Neighbouring Grey Level Dependence Statistics

This approach uses directional independent feature by considering the relationship between an element and all its neighbour elements at once instead of one direction at the one time to reduce the calculation required in processing an image. This matrix  $P(i,j)$  can be considered as frequency counts of grey level variation of a processed image. The array is  $N_g \times N_r$  where  $N_g$  is the number of possible grey levels and  $N_r$  is the number of possible neighbours to a pixel in an image. If the image function  $f(i,j)$  is discrete, then it is convenient to compute  $P$  matrix by counting the number of the times the difference between each element  $f(i,j)$  and its neighbours is equal to certain number  $a$ , at a certain distance  $d$ . Figure 6 shows the example of matrix  $P$  computed from an image having four grey levels (0-3) at the distance  $d=1$  and the difference between its neighbour is equal to 0 ( $a=0$ ). For the purpose of achieving useful texture information, five features (small number emphasis, large number emphasis, second moment, number non-uniformity, and entropy) were computed at the combination of  $(d,a) = (1,1), (1,6), (1,10), (2,1), (2,6),$  and  $(2,10)$  for this experiment.

		Image								
		1	1	2	3	1				
		0	1	1	2	2				
		0	0	2	2	1				
		3	3	2	2	1				
		0	0	2	0	1				
Grey Levels	NGLDM number ( $N_r$ )									
	0	1	2	3	4	5	6	7	8	
	0	0	0	1	0	0	0	0	0	0
	1	0	0	1	1	0	0	0	0	0
	2	0	0	0	0	4	1	0	0	0
3	0	1	0	0	0	0	0	0	0	

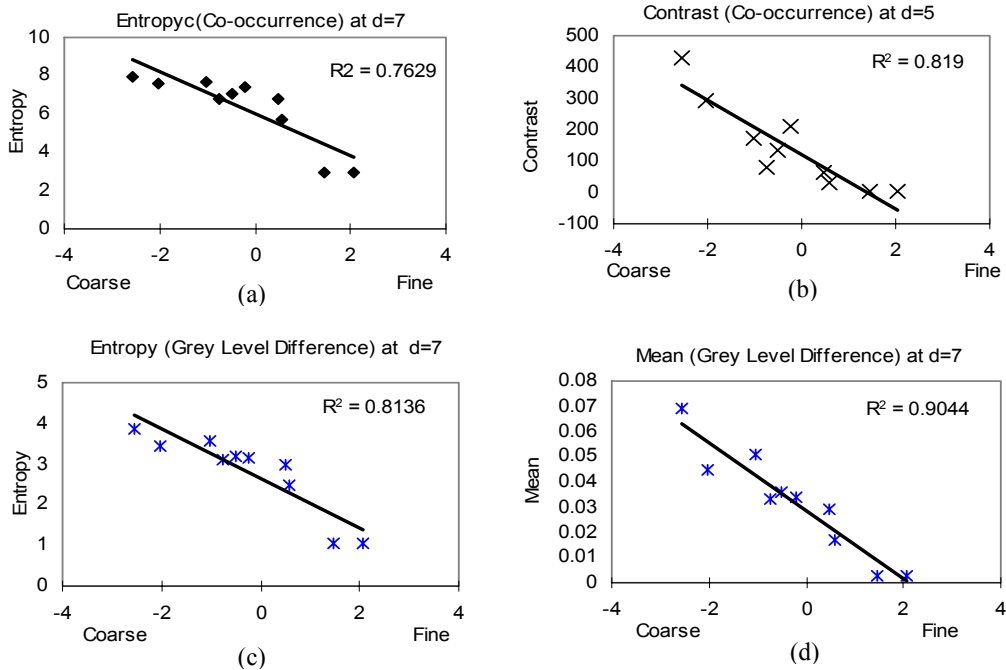
Figure 6: An example of the neighbouring grey level dependence statistics matrix

### 3. RESULTS

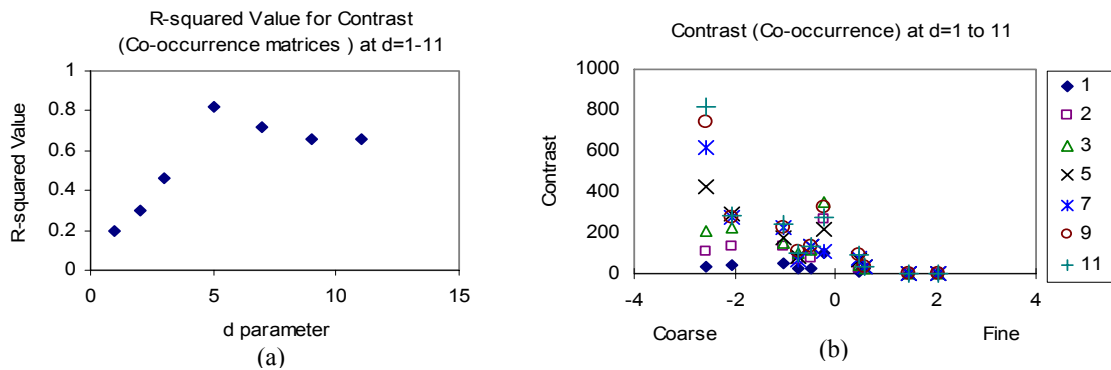
Figure 7 shows some of the results plotted the features extracted from the image-texture metrics against the scale value in terms of coarseness, obtained from the visual assessment as shown in Figure 1. The visual assessment result in Figure 1 shows that there were very clear coarseness differences between samples. However, features extracted from the run length and neighbouring grey level difference statistics showed the poor correlation with the perceptual texture. Two features out of four features from the co-occurrence matrices; the entropy at  $d = 7$  and the contrast at  $d = 5$  at  $\phi = 0^\circ$ , and two features out of four features from the grey level difference method; the entropy at  $d = 7$  and mean at  $d = 7$  at  $\phi = 0^\circ$ , showed good correlation with the perceptual texture, as shown in Figures 7 (a) to (d). However, these features changed as the parameters varied. Although the feature described the perceptual texture very well at a particular parameter, the other parameters did not always show good correlation, as shown in Figure 8 (a); R-square values between contrast from Co-occurrence matrices and perceptual texture changed, when  $d$  parameter vary from 1 to 11. Especially, large variations in the features with different  $d$  values were in the coarse textures chosen by visual assessment, as shown in Figure 8 (b).

### 4. DISCUSSION AND CONCLUSION

Although the co-occurrence matrices and the grey level difference method described the perceptual texture very well at particular  $d$  values, the features change with  $d$  values. For the human perception, the perceived texture can change with viewing conditions such as distance between an observer and samples, because of characteristics of our eyes, e.g. the contrast sensitivity of human perception<sup>7</sup>. Contrast sensitivity is the ability of the visual system to discriminate spatial information of luminance and chromatically defined form. It is affected by the angular display size. For example, perceived texture of a sample is coarse in a close distance, but the same sample could perceive as fine texture from a far distance. This means that features of the image-texture metrics and human perception change with the different scales; namely  $d$  values defined in terms of a number of pixels and characteristic of our eyes. However there are no correlation between  $d$  value and the characteristic of our eyes. The  $d$  values which showed the good correlation with the perceptual texture in this experiment, can not describe perceptual texture, when the viewing condition or samples is changed. Because of this difficulty, the co-occurrence matrices and the grey level difference method are not reliable methods to describe perceptual texture. Therefore, an image-texture metric that takes into account the human vision system would be required.



**Figure 7:** The relationship between the features computed the image-texture metrics and the perceptual texture. (a) Entropy from the co-occurrence matrices vs coarseness from the psychophysical experiments (b) Contrast from the co-occurrence matrices vs coarseness (c) Entropy from the grey level difference method vs coarseness (d) Mean from the grey level difference method vs coarseness



**Figure 8:** (a) R-square value for contrast from the co-occurrence matrices (b) Variation of contrast from the co-occurrence matrices with  $d = 1, 2, 3, 5, 7, 9,$  and  $11$

## References

1. M. Tuceyran and A.K. Jain, "Texture analysis", in The Handbook of Pattern Recognition and Computer Vision (2<sup>nd</sup> Eds.), C.H. Chen, L.F. Pau and P.S.P. Wang, chapter 2, 235-276, World Scientific Publishing Co., 1998
2. H. Tamura, S. Mori and T. Yamawaki, "Textural Features Corresponding to Visual Perception", IEEE Trans. Systems, Man, and Cybernetics. Vol. SMC-8, No.6, 460-472 (1978).
3. P. G. Engeldrum, "Psychophysical Scaling: a toolkit for imaging systems", Optics & Photonics News, Imcotek Press; USA (2000).
4. M.R. Luo, G.H. Cui and C. Li, "British Patent: Apparatus and method for measuring colour (DigiEye system)", Derby University Enterprise Limited, October 2001.
5. R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural features for image classification", IEEE Trans. Systems, Man, and Cybernetics, SMC-3, 610-621 (1973).
6. M. M. Galloway, "Texture Classification using Grey Level Run Length", Computer Graphics and Image Processing, 4, 172-179 (1975).
7. P.G.J. Barten, "Contrast sensitivity of the human eye and its effects on image quality", The Society of Photo-Optical Engineers, Washington, US, (1999).