

Perceptual Textural Features Corresponding to Human Visual Perception

Noureddine Abbadeni, Djemel Ziou and Shengrui Wang

Université de Sherbrooke

Faculté des Sciences / DMI

Sherbrooke, Québec

J1K 2R1, Canada

{abbadeni, ziou, wang}@dmi.usherb.ca

Abstract

The aim of this paper is to present a method to estimate perceptual textural features. Indeed, texture is an important image feature extremely used in image classification, recognition and retrieval problems. It has been shown that humans use some perceptual textural features to distinguish between textured images or regions. Among the most important perceptual textural features, we cite coarseness, contrast and orientation. After situating the problem and giving some definitions, we will present the computational measures derived from the auto-covariance function to estimate these perceptual textural features. Experimental results are then given and a strong correspondence between the computational measures proposed and the psychological measures is shown using a psychometric method.

Keywords

Texture, auto-covariance, human visual perception, coarseness, contrast, orientation, psychometrics.

1 Introduction

1.1 Texture analysis techniques

Texture is one of the most significant features which exist in the majority of images. It plays a very important role in human visual perception. Consequently, a lot of research has been done on texture in order to use it in image recognition and interpretation problems. Despite its crucial importance and ubiquity in image data, there is no formal, precise and universal definition of texture. Although, we can express some intuitive concepts related to texture. Texture can be regarded as the spatial distribution of the grey-levels in an image. It can be a deterministic or a random repetition of one or several primitives in an image. Primitives can be

small; in this case, we talk about microtextures. They can be large; in this case, we talk about macrotextures.

Texture analysis techniques have been used in many topics such as classification, segmentation and shape from texture [20], [11]. In a general way, we can divide various texture analysis methods into two large classes: statistical methods and structural methods [8], [9], [11], [13], [17], [20]. Statistical methods such as the co-occurrence matrix [8] are not adapted in the case of macrotextures since it does not capture the shape properties of objects. Structural methods which consist in two stages: 1. initially, the primitives of texture are determined; 2. then, the placement rules of these primitives are determined. Obviously, the structural methods are suitable in the case of macrotextures.

Since many natural textures contain statistical information as well as structural information, some works combine between the statistical methods and the structural methods to obtain hybrid methods [13].

1.2 Artificial vision and human vision

Texture analysis methods cited above are not drawbacks-free: statistical methods seem to give good results in the case of microtextures whereas in the case of macrotextures the results are worse. The reverse is true in the case of structural methods. The majority of the existing methods (statistical, structural or hybrid) have another drawback not less significant: the computational cost. Indeed, the majority of these methods require a significant computing time. At the opposite, human visual perception seems to work well for almost all the types of texture [2]. So the different textures in an image are usually and easily very apparent to a human observer, but automatic analysis of these patterns has been found to be very complex. It is widely believed that the most important properties that humans use to discriminate between textures are coarseness, contrast and orientation [2], [18]. It follows that, to simulate human visual

perception system, we must dispose of some techniques to estimate these perceptual features on image data. So this is what we are dealing with in this paper: which perceptual textural features humans use and how we can simulate them with computational measures ?

1.3 Organization of the paper

This paper is organized as follows: in Section 2, a brief summary of related work is given and our approach is depicted; in Section 3, the auto-covariance function is presented; in Section 4, the perceptual textural features considered in this study, namely coarseness, contrast and orientation, are defined; in Section 5, the computational techniques used to estimate each of these perceptual features is introduced; in Section 6, the corresponding computational results are presented; in Section 7, the correspondence between computational measures and human measures is shown; and finally, in Section 8, a summary of the paper and some related investigations are given.

2 Related work and our approach

In the literature, some works related to human visual perception have been done. Julesz [12] and Bergen et al. [3] studied human visual perception. Tamura et al. [18] and Amadasun et al. [2] proposed, each, computational measures for some textural features. They studied, then, the correspondence between the classification obtained with these computational measures and the classification made by human subjects. The work of Tamura et al. [18] was based on the co-occurrence grey-level matrix (CGLM). The work of Amadasun et al. [2] was based on a variant of the CGLM called neighborhood gray-tone difference matrix (NGTDM). The results they obtained with the computational measures were relatively good with respect to human classification. Ravishankar et al. [15] proposed a texture naming system, i.e. they try to determine the relevant dimensions of texture such as the three dimensional representations of color (RGB, HSI, etc.).

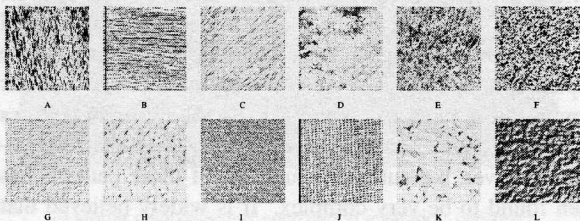


Figure 1: Sample of the test images.

The goal we are pursuing here fits within this framework except that we use a different technique to estimate these perceptual textural features and our objectives are specific. We want to estimate perceptual textural features using the auto-covariance function. Motivations behind the use of the auto-covariance function are given in the following section.

The study reported here was tested on a sample of images (Fig. 1) from Brodatz database [4]. This sample of images has been chosen to be largely representative. It must be noted that all these images contain only one type of texture. If we have images with different textured regions, segmentation techniques are required to determine texture edges. The segmentation problem is not addressed in this paper.

3 The auto-covariance function

The auto-covariance function $f(\delta_i, \delta_j)$ for an $n \times m$ image I is defined as follows [11]:

$$f(\delta_i, \delta_j) = \frac{1}{(n - \delta_i)(m - \delta_j)} \sum_{i=0}^{n-\delta_i-1} \sum_{j=0}^{m-\delta_j-1} I(i, j)I(i+\delta_i, j+\delta_j) \quad (1)$$

where $0 \leq \delta_i \leq n - 1$ and $0 \leq \delta_j \leq m - 1$. δ_i and δ_j represent the shift on rows and columns respectively.

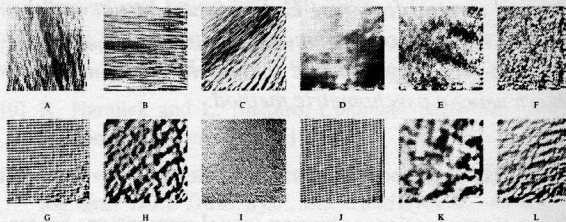


Figure 2: The auto-covariance function of images of Fig. 1.

The auto-covariance function exhibits some very interesting characteristics. Indeed, for images containing repetitive texture patterns, the auto-covariance function exhibits periodic behavior with the same period as in the original image (fig. 1 and fig. 2). For images containing orientation(s), the auto-covariance function saves the same orientation(s) (fig. 1 and fig. 2). For coarse textures, the auto-covariance function decreases slowly and presents few variations whereas for fine textures it decreases rapidly and presents a lot of variations (fig. 4). For orientation, if compared with the gradient method, we can see that the method with the auto-covariance function saves the global orientation(s) in the images rather than the pixel orientation as with the gradient method (fig. 3). Taking into account all these

facts, we have decided to use the auto-covariance function to estimate these perceptual features.

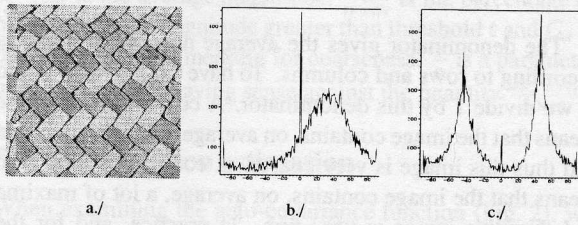


Figure 3: Orientation: a./original image, b./ orientation given by the gradient of the auto-covariance function, c./ orientation given by the gradient of original image.

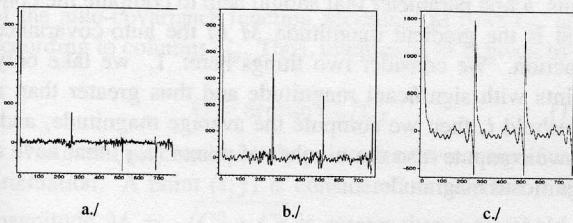


Figure 4: Variations of the auto-covariance function of images a./ *I*, b./ *F* and c./ *K*: the first three lines of the auto-covariance function

The results of the auto-covariance function computed on the images of (Fig. 1) are given in (Fig. 2). Note that the dynamic range of grey-levels of these images has been increased with histogram equalization in order to highlight the characteristics of this function. In these results, we can see that the auto-covariance function saves many characteristics of the original image such as orientation, period of repetition and coarseness. In the following, we will define these perceptual features and, then, we will show techniques to estimate them using the auto-covariance function.

4 Perceptual textural features: simple definitions

There are many perceptual features cited in literature such as contrast, orientation, coarseness, regularity, roughness and line-likeness [18], [2]. Here, we will focus on the most important perceptual features which are coarseness, contrast and orientation.

4.1 Coarseness

Coarseness is the most fundamental property and, in a certain sense, it is the coarseness which implies the texture¹. It measures the size of the primitives. A large texture consists of large primitives and requires therefore a high degree of local uniformity of grey-levels. A fine texture is made up of small primitives and requires therefore a high degree of local variation of the grey-levels.

4.2 Contrast

Contrast measures the degree of clearness with which one can distinguish between different textured areas in an image. An image is well contrasted if its different areas are clearly visible. Among the factors which influence contrast, we cite: grey-levels range dynamic, ratio of the black and the white in the image and the frequency of changes of intensity.

4.3 Orientation

Direction is a global property in an image area. It measures the dominant orientation in a textured area. An image can have one dominant orientation, several dominant orientations or no orientation, in this case, it is known as isotropic. The orientation implies the form of the primitives as well as their placement rules. Two primitives which differ only in orientation have the same direction.

5 Computational measures for perceptual textural features

5.1 General scheme

The general scheme of perceptual textural features estimation is shown in figure (Fig. 5). It consists of the following:

- The auto-covariance function $f(\delta_i, \delta_j)$ is computed on an input image *I* using equation (1).
- The auto-covariance function obtained is then convolved with the gradient of the Gaussian in a separable way, i.e., according to columns and rows. Two functions are thus obtained, C_x and C_y respectively.

5.2 Coarseness estimation

When examining the auto-covariance function (Fig. 2), we can point out two phenomena regarding coarseness: 1. the coarseness of primitives in the original image is saved in the corresponding auto-covariance function; 2. for fine textures,

¹Some works have used coarseness as the main indice to decide whether an image contains or does not contain texture.

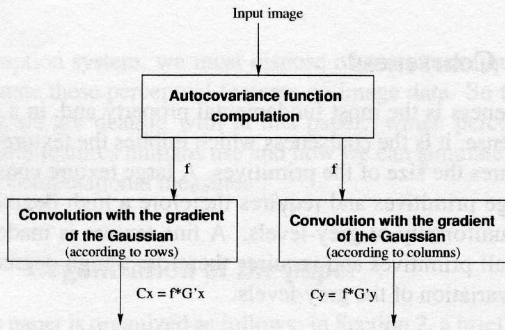


Figure 5: General scheme of the perceptual textural features estimation process.

the auto-covariance function exhibits a lot of variations and for coarse textures it exhibits less variations. So we can say that coarseness can be seen as the number of extrema of the auto-covariance function.

First, we compute the first derivatives of the auto-covariance function $f(i, j)$ in a separable way according to rows and columns. Two functions are obtained $C_x(i, j)$ and $C_y(i, j)$:

$$\begin{cases} C_x(i, j) = f(i, j) - f(i + 1, j) \\ C_y(i, j) = f(i, j) - f(i, j + 1) \end{cases} \quad (2)$$

Then, we compute the derivative of each of $C_x(i, j)$ and $C_y(i, j)$ in a separable way according to rows and columns respectively. Two functions are obtained $C_{xx}(i, j)$ and $C_{yy}(i, j)$:

$$\begin{cases} C_{xx}(i, j) = C_x(i, j) - C_x(i + 1, j) \\ C_{yy}(i, j) = C_y(i, j) - C_y(i, j + 1) \end{cases} \quad (3)$$

To detect maxima, we use the following equations (for rows and columns respectively):

$$\begin{cases} C_x(i, j) = 0 \\ C_{xx}(i, j) < 0 \end{cases} \quad (4)$$

$$\begin{cases} C_y(i, j) = 0 \\ C_{yy}(i, j) < 0 \end{cases} \quad (5)$$

Coarseness, denoted C_s , is thus estimated as the average number of maxima in the auto-covariance function: a coarse texture will have a small number of maxima and a fine texture will have a large number of maxima. Let $Max(i, j) = 1$ if point (i, j) is a maxima (either row maximum or column maximum) and $Max(i, j) = 0$ if point (i, j) is not a maxima. Coarseness C_s can be written as:

$$C_s = \frac{1}{\frac{1}{2} \times \left(\frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} Max(i, j)}{n} + \frac{\sum_{j=0}^{m-1} \sum_{i=0}^{n-1} Max(i, j)}{m} \right)} \quad (6)$$

The denominator gives the average number of maxima according to rows and columns. To have C_s between 0 and 1, we divide 1 by this denominator. A coarseness near one means that the image contains, on average, only few maxima and thus this image is very coarse. A coarseness near zero means that the image contains, on average, a lot of maxima and thus this image is very fine. In practice, and for the majority of textured images, C_s is between 0.01 and 0.2.

5.3 Contrast estimation

When examining the auto-covariance function (Fig. 2), we can point out that the covariance value is high for well-contrasted images and is low for not well-contrasted images. Thus, a first parameter that should help to compute the contrast is the gradient magnitude M of the auto-covariance function. We consider two things here: 1. we take only points with significant magnitude and thus greater than a threshold t , then we compute the average magnitude, and, 2. we compute also the number of points (i, j) that have a significant magnitude:

$$\begin{cases} C_x = f * G'_x \\ C_y = f * G'_y \end{cases} \quad (7)$$

$$M = \sqrt{C_x^2 + C_y^2} \quad (8)$$

where G'_x and G'_y are the partial derivatives of the Gaussian according to rows and columns and $*$ represents the operation of convolution.

Let $t(i, j) = 1$ if point (i, j) has a magnitude greater than threshold t $t(i, j) = 0$ if point (i, j) has a magnitude less than threshold t . Let N_t denotes the number of points having a magnitude greater than threshold t :

$$N_t = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} t(i, j) \quad (9)$$

The average magnitude M_a is given by:

$$M_a = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} M(i, j) \times t(i, j)}{N_t} \quad (10)$$

We found also that coarseness may play a role in contrast. So coarseness may be used as another parameter to enhance contrast of coarse textures since coarse textures have generally small magnitude.

So, we propose the following formula to estimate contrast C_t :

$$C_t = \frac{M_a \times N_t \times C_s^{\frac{1}{\alpha}}}{n \times m} \quad (11)$$

M_a is the average magnitude, $\frac{N_t}{n \times m}$ is the percentage of pixels having a magnitude greater than threshold t and C_s is the computational measure for coarseness. $\frac{1}{\alpha}$ is a parameter used to make C_s having sense against the quantity $\frac{M_a \times N_t}{n \times m}$.

5.4 Orientation estimation

When examining the auto-covariance function (Fig. 2), we can point out two phenomena regarding orientation: 1. the orientation in the original image is saved in the corresponding auto-covariance function; 2. using the auto-covariance function allows to save the global orientation rather than the local orientation obtained if the original image is used. So, instead of using the original image, we use the corresponding auto-covariance function. It follows that the global orientation can be estimated as the orientation of the gradient of the auto-covariance function according to rows C_x and according to columns C_y . Thus, orientation Θ is given by:

$$\Theta = \arctan C_y / C_x \quad (12)$$

Note that we consider only points that have a significant orientation. A point (i, j) is considered as oriented if the magnitude $M = \sqrt{C_x^2 + C_y^2}$ is greater than a threshold t . We have used the same threshold as in the estimation of contrast.

Also, we want to classify images according to their degree of directionality. To accomplish this, we consider the number of points N_{Θ_d} having the dominant orientation Θ_d . Let $\Theta_d(i, j) = 1$ if point (i, j) have the dominant orientation Θ_d and $\Theta_d(i, j) = 0$ if point (i, j) does not have the dominant orientation Θ_d . The degree of directionality is given by N_{Θ_d} :

$$N_{\Theta_d} = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \Theta_d(i, j) \quad (13)$$

The more N_{Θ_d} is larger the more the image is directional. The less N_{Θ_d} is smaller the more the image is non directional.

6 Computational results

Table (tab. 1) gives the results concerning coarseness C_s , Contrast C_t and the degree of directionality N_{Θ_d} computed on the auto-covariance function of images of (Fig. 1) using equation (6), equation (11) and equation (13) respectively.

These computational results indicate that the most coarser images are K, H, D, C, L and F and the less coarser images are G, F, A, E, B and I ; the most contrasted images

are J, A, B, F, L and I and the less contrasted images are G, E, C, D, K and H ; the most directional images are B, G, A, J, C and F and the less directional images are L, I, D, E, K and H . Below, we will make compare these computational rankings with the psychological rankings.

In the following section, we will compare these computational results reported in this section with psychological ones made by human subjects. This comparison is based on a psychometric method which will be presented first.

7 Correspondence between computational rankings and psychological rankings

Psychological experiments were conducted to study the correspondence between the rankings obtained with our computational measures and the rankings done by human subjects. 30 human subjects have participated in these experiments and only few of them (11) were working in the field of pattern recognition and computer vision. Two objectives were pursued with these psychological experiments:

- the first objective was to see at which extent the computational rankings correspond to the psychological rankings and thus to see if the computational measures are valid.
- the second objective was to see if the textural features studied here were related to each other.

7.1 Psychometric method

The psychometric method used to compare rankings is described in [7] and was used also by [2]. This method consist of the following:

1. Given that n objects are ranked in r different rankings according to some features. First, a quantity called the sum of rank values is computed using the following equation:

$$S_i = \sum_{k=1}^n f_{ik} R_k \quad (14)$$

i represents the i^{th} image and varies between 1 and n . k represents the rank and varies between 1 and n . f_{ik} represents the number of human subjects that give the i^{th} object the rank k (the frequency of giving the rank k to the i^{th} object). R_k is in the reverse order to k and is given by the following equation:

$$R_k = n - k + 1 \quad (15)$$

Image	A	B	C	D	E	F	G	H	I	J	K	L
C_s	0.022	0.015	0.028	0.031	0.021	0.022	0.024	0.041	0.014	0.022	0.052	0.025
C_t	0.160	0.103	0.030	0.029	0.039	0.093	0.041	0.024	0.053	0.268	0.028	0.060
N_{Θ_d}	2058	3677	1221	817	794	1093	2276	401	842	1540	684	899

Table 1: C_s , C_t and N_{Θ_d} of images of (Fig. 1).

Once the sum of rank values S_i computed, they are ordered decreasingly. The object with the higher sum of rank values S_i is given position 1, the object with the second higher sum of rank values S_i is given position 2 and so on.

2. Once the human rankings are obtained, we must determine the correspondence between the human rankings and the computational rankings. To do this, we use the well-known Spearman coefficient r_s of rank correlation defined as:

$$r_s = 1 - 6D/n(n^2 - 1) \quad (16)$$

where D is the sum of squared differences and is defined as:

$$D = \sum_{i=1}^n d_i^2 \quad (17)$$

where d_i is the difference between the ranks assigned to the i^{th} object in two different rankings m and l and is defined as:

$$d_i = (k_{mi} - k_{li}) \quad (18)$$

The value of r_s is between 1 and -1 . A value of 1 indicates that there is a total correspondence between the two rankings. A value of -1 indicates that there is a total disagreement between the two rankings. A value of 0 indicates that the rankings are orthogonal.

7.2 Correspondence between psychological and computational rankings

Table (tab. 2) gives the psychological rankings done by human subjects of coarseness, contrast and degree of directionality.

Table (tab. 4) gives the the rank correlations r_s , computed with equation (16), between human measurements and computational measurements. These results show that there is strong correlation between computational coarseness ranking and psychological coarseness ranking ($r_s =$

Table 2: Human rankings of textures according to perceptual textural features.

Rank (k)	Coarseness	Contrast	Direction
1	K	F	C
2	L	J	B
3	H	A	A
4	D	L	J
5	G	B	G
6	C	D	L
7	F	C	E
8	J	E	I
9	A	G	F
10	E	K	D, H, K
11	B	I	-
12	I	H	-

0.954), between computational contrast ranking and psychological contrast ranking ($r_s = 0.769$) and between computational degree of directionality ranking and psychological degree of directionality ranking ($r_s = 0.821$).

Table (tab. 3) gives the computational rankings obtained by the techniques introduced above of C_s (computational coarseness), C_t (computational contrast) and N_{Θ_d} (computational degree of directionality).

For coarseness, the correspondence is quiet perfect ($r_s = 0.954$) and the only relatively notable difference is in the case of image L which was ranked at the rank $k = 2$ in the psychological ranking and at the rank $k = 4$ in the computational ranking. The other disagreements, for coarseness, are not significant (the difference $d_i = 1$).

For contrast, the correspondence is less than in the case of coarseness but it is very good ($r_s = 0.769$). The disagreements occur mainly in the case of image I ($d_i = 5$), image D ($d_i = 4$) and image F ($d_i = 3$). For image I , the reason of the difference is that this image has a very high magnitude but a very small coarseness. Humans tend to classify such images as low contrasted. For image F , the reason of the difference is that this image has both magnitude and coarseness quiet similar to images A , B and J and thus they have relatively the same degree of contrast. For image D , the difference is due mainly to the low magnitude of this image.

Table 3: Computational rankings of textures according to perceptual textural features.

Rank (k)	C_s	C_t	N_{Θ_d}
1	K	J	B
2	H	A	G
3	D	B	A
4	L	F	J
5	C	L	C
6	G	I	F
7	A, F, J	G	L
8	-	E	I
9	-	C	D
10	E	D	E
11	B	K	K
12	I	H	H

For Direction, the correspondence is very good ($r_s = 0.821$). The main disagreements occur for images C ($d_i = 4$), G ($d_i = 3$) and E ($d_i = 3$). This is due mainly to the fact that, in human rankings, not all the images are classified as directional by people. This means that, for such images, the sum of rank values S_i will be very small and thus the corresponding rank will be higher. For example, for image E , only 7 human subject among 30 have classified it as directional.

As a conclusion, we can say that the proposed computational measures C_s , C_t and N_{Θ_d} are strongly correlated with the psychological measures coarseness, contrast and direction respectively and thus simulate well human visual perception of textures.

Table 4: Rank correlation between computational rankings and human rankings of textures.

Coefficient r_s	Coarseness	Contrast	Direction
C_s	0.954	-0.122	-0.233
C_t	-0.573	0.769	0.597
N_{Θ_d}	-0.433	0.545	0.821

7.3 Relatedness of perceptual features to each other

Table (tab. 5) gives the values of rank correlation between human rankings of textures. We can point out that, on one hand, there is no correlation between coarseness and contrast and between coarseness and direction (-0.174 and -0.290 respectively), on the other hand, there is an important correlation between contrast and direction (0.430). In

fact, when the contrast is very low, the orientation will not be visible.

Table 5: Rank correlation between human rankings of textures.

Coefficient r_s	Coarseness	Contrast	Direction
Coarseness	-	-0.174	-0.290
Contrast	-	-	0.430
Direction	-	-	-

Table (tab. 6) gives the values of rank correlation between computational rankings of textures. The precedent remarks can be emphasized here. In fact, on one hand, there is a very low correlation between coarseness and contrast and between coarseness and direction (-0.541 and -0.409 respectively), on the other hand, there is a more important correlation between contrast and direction (0.748).

Table 6: Rank correlation between computational rankings of textures.

Coefficient r_s	C_s	C_t	N_{Θ_d}
C_s	-	-0.541	-0.409
C_t	-	-	0.748
N_{Θ_d}	-	-	-

The same remarks can be made when examining table (tab. 4) and correlation between C_s and contrast, C_s and direction, C_t and coarseness, C_t and direction, N_{Θ_d} and coarseness, and N_{Θ_d} and contrast.

Globally, the results we obtained here are satisfactory and, if compared with the results obtained by Tamura et al. ([18]) and Amadasun et al. ([2]), are more accurate. The main differences are: first, we have found that coarseness is quiet orthogonal with contrast whether [18] and [2] found some correlation between the two features; second, we have found there is an important correlation between contrast and direction whether [18] found that contrast is quiet orthogonal with direction ([2] did not consider direction in his work). It should be noted that we have not used the same sample of test images; [18] and [2] themselves did not use the same sample of test images.

8 Summary and further investigations

In this paper, we have shown new techniques to estimate perceptual textural features namely coarseness, contrast and direction using the auto-covariance function. Coarseness was

estimated as the number of maxima in the auto-covariance function. Contrast was estimated as the combination of the average magnitude of the gradient of the auto-covariance function, the percentage of pixels having magnitude greater than a given threshold and coarseness. Orientation was estimated as the orientation of the gradient of the auto-covariance function; the degree of directionality was estimated as the number of pixels having the dominant orientation. Experimental results and comparison with psychological measures show that there is a strong correspondence between the techniques presented and the psychological measures. The experimental comparison shows also that coarseness is quiet orthogonal to both contrast and direction whereas contrast is relatively well correlated with direction. The immediate prospects related to this work are the following: 1. considering other perceptual features such as busyness, regularity and complexity; 2. applying these perceptual features in texture-based image retrieval.

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