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# A Innovative method for Image retrieval using perceptual textural features

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**Abstract :**

**Texture is a very important image feature extremely used in various image processing problems like Computer Vision ,Image Representation and Retrieval It has been shown that humans use some perceptual textural features to distinguish between textured images or regions. Some of the most important features are coarseness, contrast, direction and busyness. In this paper a study is made on these texture features. The proposed computational measures can be based upon two representations: the original images representation and the autocorrelation function (associated with original images) representation.**

Keywords : Texture features, Content Based Image Retrieval, Computational measures

## I. Introduction

Texture has been extensively studied and used in literature since it plays a very important role in human visual perception. Texture refers to the spatial distribution of grey-levels and can be defined as the deterministic or random repetition of one or several primitives in an image.

Texture analysis techniques can be divided into two main categories: spatial techniques and frequency-based techniques. Frequency based methods include the Fourier transform and the wavelet-based methods such as the Gabor model. Spatial texture analysis methods can be categorized as statistical methods, structural methods, or hybrid methods.

It is widely admitted in the computer vision community that there is a set of textural features that human beings use to recognize and categorize textures. Such features include coarseness, contrast and directionality.

## II. Autocorrelation function

The Auto correlation Function [1] denoted as $f(\delta i, \delta j)$ for an image I of nXm dimensions is defined as

$$f(\delta i, \delta j) = \frac{1}{(n-\delta i)(m-\delta j)} X \sum_{i=0}^{n-\delta i-1} \sum_{j=0}^{m-\delta j-1} I(i,j) I(i+\delta i, j+\delta j) \qquad (1)$$

For images containing repetitive texture patterns, the autocorrelation function exhibits periodic behavior with the same period as in the original image. For coarse textures, the autocorrelation function decreases slowly, whereas for fine textures it decreases rapidly For images containing orientation(s), the autocorrelation function saves the same orientation(s).

In this paper the test images are taken from Broadatz database [2] and the autocorrelation function is applied on original images shown in figure 1 . The original images are scaled in to nine parts and autocorrelation function is applied on the one of the scaled images randomly. Scaled images are shown in figure 2.

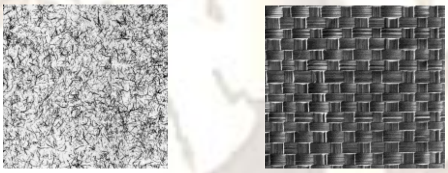
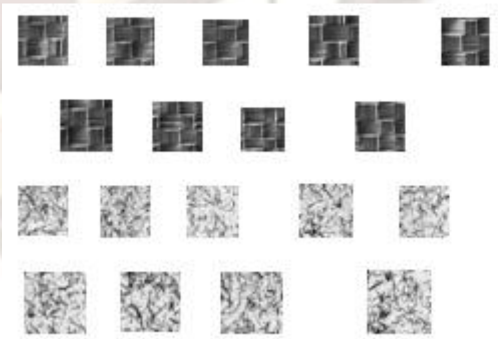


Fig :1 Original images from Broadatz Database

Any image of the scaled images can be selected and the autocorrelation function is applied on the scaled image.



Fig; 2 Scaled Images

Figure 3 shows the randomly selected scaled image from the scaled images and its histogram.

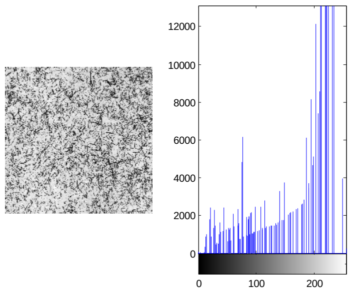



Fig :3 Randomly selected scaled image and its histogram

After applying the autocorrelation fucntion the image is shown in figure 4 and its equivalent histogram.

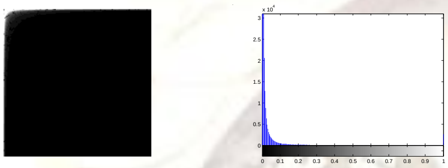


Fig:4 Autocorrelation applied on scaled image and its histogram

## III. Computational measures for Textural features

Perceptual features ave been largely used both in texture retrieval and content-based image retrieval (CBIR)[4] systems like:

• *IBM QBIC* system which implements Tamura features.

• *Candid* by the Los Alamos National Lab's by Kelly et alii using Laws filters .

• *Photobook* by Pentland et alii from MIT referring to Wold Texture decomposition model

The general estimation process of computational measures simulating human visual perception is as follows [3] .

Step :1 The autocorrelation $f(\delta i, \delta j)$ is computed on Image $I(i,j)$.

Step 2 : Then, the convolution of the autocorrelation function and the gradient of the Gaussian function is computed in a separable way

Step 3 : Based on these two functions, computational measures for each perceptual feature are computed

### A.Coarseness

Coarseness is the most important feature , it is coarseness that determines the existence of texture in an image. Coarseness measures the size of the primitives that constitute the texture. A coarse texture is composed of large primitives and is characterized by a high degree of local uniformity of grey-levels. A fine texture is constituted by small primitives and is characterized by a high degree of local variations of grey-levels. First we compute the first derivative of the autocorrelation function in a separable way according to rows and columns, respectively.Two functions $Cx(i,j) and\, Cy(i,j)$ are then obtained

$$Cx(i,j) = f(i,j) - f(i+1,j)$$
$$Cy(i,j) = f(i,j) - f(i,j+1) \qquad (2)$$

Second, we compute the first derivatives of the obtained functions $Cx(i,j)$and $Cy(i,j)$ in a separable way according to rows and columns. Two functions $Cxx(i,j)$ and $Cyy(i,j)$are then obtained

$$Cxx(i,j) = Cx(i,j) - Cx(i+1,j)$$
$$Cyy(i,j) = Cy(i,j) - Cy(i,j+1) \qquad (3)$$

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

$$Cx(i,j) = 0$$

$$Cxx(i,j) < 0 \qquad (4)$$
$$Cy(i,j) = 0$$

$$Cyy(i,j) < 0 \qquad (5)$$

Coarseness, denoted ,Cs is estimated as the average number of maxima in the autocorrelation function: a coarse texture will have a small number of maxima and a fine texture will have a large number of maxima. Let $Maxx(i,j) = 1$if pixel (i,j) is a maximum on rows and$Maxx(i,j) = 0$ if pixel is not a maximum on rows. Similarly Let $Maxy(i,j) = 1$ if pixel is a maximum on columns and $Maxy(i,j) = 0$ if pixel is not a maximum on columns. Coarseness can be expressed by the following equation:

$$Cs \frac{1}{1/2X(\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\frac{Maxx\ (i,j)}{n} + \sum_{j=0}^{m-1}\sum_{i=0}^{n-1} Maxy\ (i,j)/m} \qquad (6)$$

The denominator gives the number of maxima according to rows and columns. The more the number of maxima is high, the less the coarseness is and *vice-versa*.

### B. Contrast

Contrast measures the degree of clarity with which one can distinguish between different primitives in a texture. A well contrasted image is an image in which primitives are clearly visible and separable. Local contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. More precisely, given a pixel *p=(i,j)* and neighbor mask *W* X *W*of the pixel, local contrast is computed as

$$L\_Ct(i,j) = \frac{maxp\ \in WXW\,(P) - minp\ \in WXW\,(P)}{maxp\ \in WXW\,(P) + minp\ \in WXW\,(P)} \qquad (7)$$

We propose to measure the global contrast as the global arithmetic mean of all the local contrast values over the image:

$$G\_Ct = \frac{1}{m*n} \sum_{i=1}^{n} \sum_{j=i}^{m} L_{+}Ct(i,j) \qquad (8)$$

where *n*, *m* are the dimensions of the image.

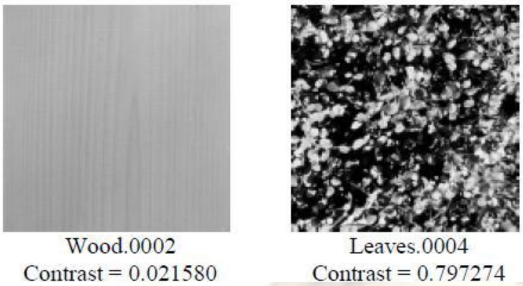



Fig. 5 The less and the most contrasted texture in the Vis Tex database.

In Figure 5 are shown the most and the less contrasted textures in Vis Tex texture database [5] as respect to the proposed measure

## C. Directionality

Regarding directionality,we want to estimate two parameters: the dominant orientation(s) and the degree of directionality. Orientation refers to the global orientation of primitives that constitute the texture. The degree of directionality is related to the visibility of the dominant orientation(s) in an image, and refers to the number of pixels having the dominant orientation(s).

*Orientation Estimation:* When considering the autocorrelation function, one can notice two phenomena concerning the orientation:
1. existing orientation in the original image is saved in the corresponding autocorrelation function;
2. the usage of the autocorrelation function instead of the original image allows
keeping the global orientation rather than the local orientation when one uses the original image.

It follows that the global orientation of the image can be estimated by applying the gradient on the autocorrelation function of the original image according to the lines Cx and according to the columns Cy . The orientation ϴ is given by

$$\theta = \arctan\left(\frac{Cy}{Cx}\right) \qquad (9)$$

We consider only pixels with a significant orientation. A pixel is considered as oriented if its amplitude is superior than a certain threshold t.

*Directionality Estimation:*For directionality, we consider the number of pixels having dominant orientation(s) $d$ . Let $\theta d(i,j) = 1$ if pixel(i,j) has a dominant orientation $\theta d$ and $\theta d(i,j) = 0$ if pixel (i, j) does not have a dominant orientation.We consider only dominant orientations $\theta d$ that are present in a sufficient number of pixels, and then more than a threshold t so that orientation becomes visible. Let us denote the number of non oriented pixels $N\theta nd$ The degree of directionality $N\theta d$ of an image can be expressed by the following equation:

$$N\theta d = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \theta d\,(i,j)}{(nXm) - N\theta nd} \qquad (10)$$

The more Nϴd is large, the more the image is directional. The more Nϴd is small, the more the image is nondirectional.

## IV. Experimental Results

The Computational perceptual features are used to retrieve the image. Figure 6 shows the window to select the query image. Among the available images the image is

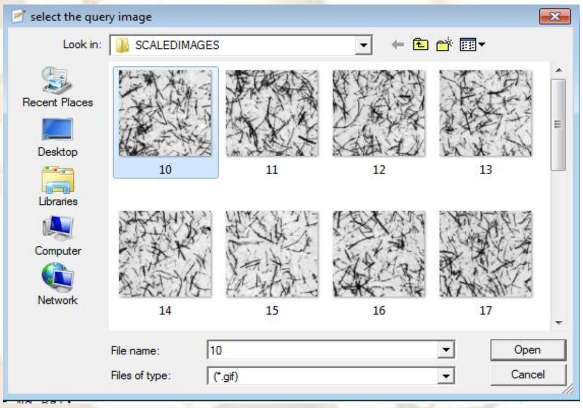



Figure 6 : Window to select query image

retrieved .In the figure 7 we can see the total number of retrieved images is Nine. Precision of the image retrieved is calculated as total number of relavent images / total number of images i.e Precision = 6/9 =0.667 in this example

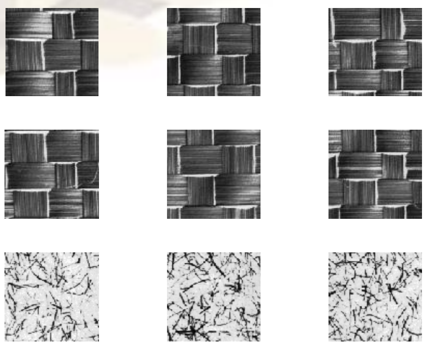


Figure 7 : Retrieved images

## V. Conclusion

An Innovative method is used to content based image retrieval using perceptual features of texture. The precision is calculated and shown experimentally that it is 0.6 to 0.8. And this method of image retrieval is effective compared to existing methods.

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