Multiple Representations of Perceptual Features for Texture Classification

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ABSTRACT
Texture Classification plays a vital role in medical image, remote sensing image, pattern analysis for the past three decades. Eventhough it is three decades problem, still having a lot of scope in pattern analysis. Textural features corresponding to visual properties of texture are highly desirable for two reasons; they will be optimum in terms of feature selection and will be applicable to all kinds of textures. Some of the perceptual features are coarseness, contrast, direction and busyness. The aim of this paper is to present a new method to estimate these perceptual features. The proposal based on two representations: Original Image Representation and Autocorrelation Function Representation. These estimated perceptual features measures are applied to classification on large image data set, the well-known Brodatz database using k-nearest neighborhood classifier.

Keywords
Texture, perceptual features, autocorrelation, k-nearest neighborhood classifier, human visual perception.

1. INTRODUCTION
Texture is an important item of information that human use in analyzing a scene. Literally, 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.

A number of texture analysis methods have been proposed [1]-[9]. Haralick [10] categorized texture analysis methods into statistical methods, structural methods, and hybrid methods [11]-[15]. The drawbacks of almost all of these approaches are that they do not have general applicability and computational cost involved, either in terms of memory requirement, computation time or implementational complexity. In comparison, human visual perception seems to work perfectly for almost all types of textures. The reason for this mismatch between computational methods and human vision is, the majority of the computational methods use mathematical features that have no perceptual meaning easily comprehensible by users.

Among the various works that have been done in the field of texture analysis [16], this paper is especially interested in those dealing with human visual perception. In the literature, some works related to perceptual texture analysis have been done [17]-[20]. Tamura *et al.* [21] and Amadasum *et al*. [22] proposed, each, computational measures for some textural features such as coarseness, contrast, direction, busyness, regularity and complexity. They studied, then, the correspondence between the classification obtained with these computational measures and classification made by human subjects. The work of Tamura *et al.* [21] was based on the co-occurrence grey-level matrix (CGLM). The work of Amadasun *et al*. [22] was based on the 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*. [23] 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, HIS, etc).

The objective of this paper falls is to identify a best class among the existing class. First, propose a new method to estimate a set of perceptual textural features. Second, application of this proposed perceptual model to texture classification. Furthermore, to improve accuracy rate, propose to use two representations: the original images representation and the autocorrelation function representation. It should be noted that the study reported here was tested on a sample of 8 images (Figure.1) from Brodatz database [24].

The rest of this paper is organized as follows. In section II, we present definitions of the set of perceptual textural features we are considering in this study; in section III, the autocorrelation function on which our work is based is presented; in section IV, computational measures corresponding to the perceptual textural features are presented; in section V, application of perceptual features to texture classification is presented; in section VI, implementation and results of our work is presented; in section VII, a conclusion is given.

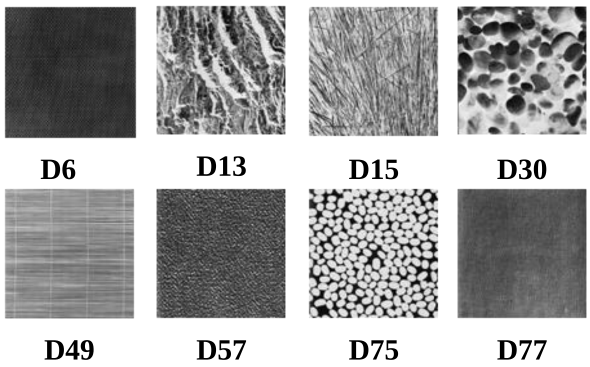

Figure 1: Sample of Test Images From BRODATZ database

2. PERCEPTUAL TEXTURAL FEATURES
In our work, we have considered four perceptual features. In the following, we give conceptual definitions of each of these features.

Coarseness is the most important feature that determines the existence of texture in an image. Coarseness measures the size of the primitives that constitute the texture[25][26]. A coarse texture is composed of large primitives and 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.

Directionality is a global property in an image. Directionality measures the degree of visible dominant orientation in an image[27]. An image can have one or several dominant orientation(s) or no orientation at all. In the latter case, it is said isotropic. The orientation is influenced by the shape of primitives as well as by their placement rules.

Contrast measures the degree of clarity with which one can distinguish between different primitives in a texture[28]. A well-contrasted image is an image in which primitives are clearly visible and separable. The contrast is influenced by the grey-levels in the image, the ratio of white and black in the image and the intensity change frequency of grey-levels.

Busyness refers to the intensity changes from a pixel to its neighborhood; a busy texture is a texture in which the intensity changes are slow and gradual. Therefore busyness is related to spatial frequency of the intensity changes in an image. If intensity changes are very small, they risk to be invisible. Consequently, the amplitude of the intensity changes has also an influence on busyness. Busyness has a reverse relationship with coarseness.

3. AUTOCORRELATION FUNCTION REPRESENTATION

The autocorrelation function of an image can be used to assess the amount of regularity as well as fineness of the texture present in the image, denoted as $f(\delta_i, \delta_j)$. For an n x m image I is defined as follows[12]:

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

where $1 \le \delta_i \le n$ and $1 \le \delta_j \le m$. δ_i and δ_j represent shift on rows and columns, respectively.

This function is related to the size of the texture primitive. If the texture is coarse, then the autocorrelation function will drop of slowly; otherwise, it will drop off very rapidly. For regular textures, the autocorrelation function will exhibit peaks and valleys.

4. COMPUTATIONAL MEASURES FOR PERCEPTUAL FEATURES

The general estimation process of computational measures simulating human visual perception is as follows[29]-[31].

1) The autocorrelation *f(i, j)* is computed on image *I(i ,j)*.
2) Then, the convolution of the autocorrelation function and the gradient of the Gaussian function are computed in a separable way (according to rows and columns). Two functions are then obtained.
3) Based on these functions, computational measures for each perceptual features are computed as described in the following subsections.

For multiple representations, the computational measures presented in the following are computed on both the original images and the autocorrelated images.

4.1 Coarseness Estimation

When considering the autocorrelation function, we can notice that coarseness is saved in the corresponding autocorrelation function. Therefore, number of extrema in the autocorrelation function determines coarseness of a texture.

Coarseness, denoted C_s, is estimated as the average number of maxima in the autocorrelated images and original images. A coarse texture will have a small number of maxima and a fine texture will have a large number of maxima. Coarseness C_s can be written as

$$C_s= \frac{1}{0.5 \text{ x } \left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{m} Max_x(i,j)}{n} + \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} Max_y(i,j)}{m}\right)} \tag{2}$$

4.2 Contrast Estimation

If the image is well-contrasted, the value of autocorrelation function decreases quickly; otherwise, it decreases slowly. Therefore, amplitude M of the gradient of the autocorrelation function determines contrast.

Contrast, denoted C_t, is estimated as the product of the average module M_a of the gradient of the autocorrelation function, the percentage of points $\frac{N_t}{n \text{ x } m}$ having a module greater than a threshold t and the coarseness C_s. Coarseness is introduced here to reflect the fact that a coarse texture is more clearly visible than a fine texture. So contrast is given by

$$C_t= \frac{M_a \text{ x } N_t \text{ x } C_s^{\frac{1}{\alpha}}}{n \text{ x } m} \tag{3}$$

4.3 Direction Estimation

Two parameters are estimated here: the orientation θ and the degree of directionality. The Orientation θ is estimated as the orientation of the gradient of the autocorrelated image or original image. It is given by

$$\theta= \arctan G_y/G_x \tag{4}$$

The degree of directionality N_{θ_d} is estimated as the number of points having the dominant orientation θ_d. The dominant orientation θ_d is the orientation of the largest number of pixels in an image having a module greater than a threshold t. N_{θ_d} can be expressed as follow

$$N_{\theta_d}= \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} \theta_d(i,j)}{n \text{ x } m} \tag{5}$$

4.4 Busyness Estimation

Busyness is related to coarseness in the reverse order, that is when the coarseness is high, the busyness is low. So busyness is estimated by using coarseness as follow

$$B_s=1-C_s^{\frac{1}{\alpha}} \tag{6}$$

5. APPLICATION TO TEXTURE CLASSIFICATION

This experiment was carried out to assess the performance of the features in an actual classification task. Computational features presented in this paper are applied in texture classification on Brodatz database. The samples used are D13, D57, D77, D6, D75, D49, D30, and D15. Each of these images of Brodatz database was divided into 9 nonoverlapping tiles to obtain 72 subimages of size 128 x 128 (8 images x 9 titles per image).

K-Nearest Neighbourhood Classifier is used to identify the best matching class based on these estimated perceptual features. In the classification, the technique of training on the data was employed, in this case leaving out four samples for each category at a time and training the classifier on the remaining five. After that four untrained samples for each class were presented to the classifier to identify. Thus, training set and testing set contains 40 (8 images x 5 titles per image) and 32 (8 images x 4 titles per image) subimages respectively.

6. IMPLEMENTATION AND RESULTS

The classification results are shown in Table 1 and Table 2. Overall, the table shows that better classification results were obtained using the features developed and presented in this correspondence. Moreover the computation of the features is less expensive. Furthermore with regard to memory requirement, the method described here has considerable advantage.

6.1 Original Image Classification

In the training phase, perceptual features are estimated from the original subimages. In the testing phase, subimages stored for validation are given as input. Perceptual textural features are estimated. K-nearest neighborhood classifier is used to compare the computational measures of features from testing and training phase and to find the accuracy rate.

6.2 Autocorrelated Image Classification

Autocorrelation Function is computed on subimages meant for training. In the training phase, perceptual features are estimated from the autocorrelated subimages. In the testing phase, subimages stored for validation are given as input. Autocorrelation function is compute on these subimages, and then Perceptual textural features are estimated. Classification rate is achieved by classifier.

6.3 Multiple Representation Classification

In the training phase, perceptual textural features are estimated from original and autocorrelation function representation. In the testing phase, subimages stored for validation are given as input. Perceptual features are estimated from these both representations and obtain the accuracyrate.

Table 1: Classification Results

Classification Based on	Accuracy (percent)
(A) Original Representation	84.375
(B) Autocorrelation Representation	81.25
(C) Multiple Representation	93.75

Table 2: No. of Correctly Classified Samples per Category on Testing Set

	D 15	D 30	D 49	D 75	D 6	D 77	D 57	D 13
A	3	4	4	4	4	3	3	2
B	4	4	4	4	3	3	3	1
C	4	4	4	4	4	3	3	4

Overall Classification performances and extracted features are shown in Figure 2 and Figure 3 respectively. We have attained very successful results for classification by using these computed perceptual features on selected brodatz images. In comparison, Multiple representation shows more accuracy rate than those obtained by Original and Autocorrelation Representation.

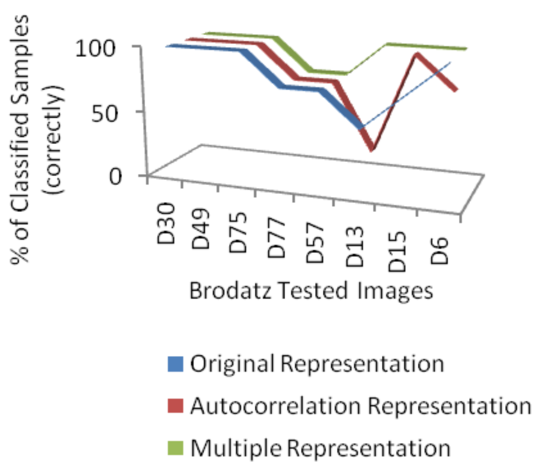

Figure 2. Performance Measure for Classification

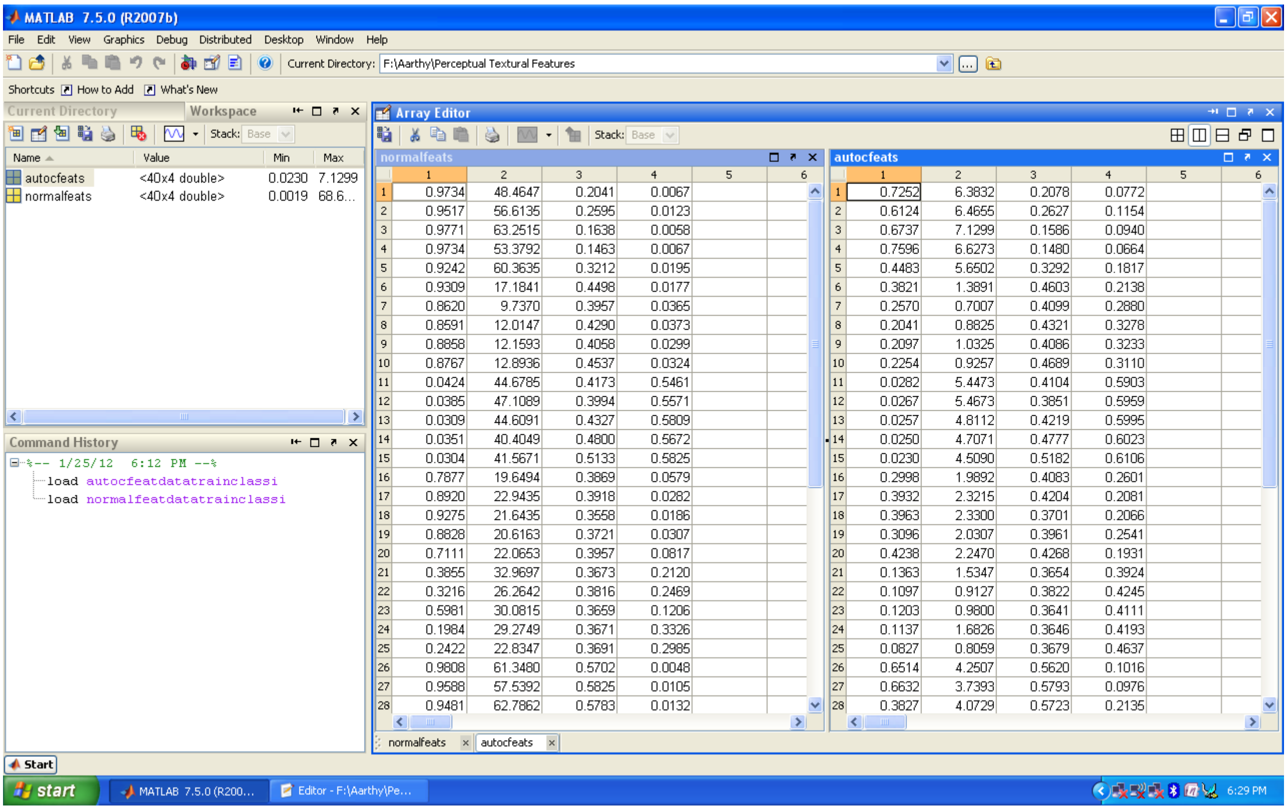

Figure 3. Exaction of Features on Original and Autocorrelation Function Representation

7. CONCLUSION

In our work, an attempt has been made to develop measures that correspond to some textural properties. Four basic properties of texture, namely: coarseness, contrast, directionality, busyness were conceptually defined. The conceptual expressions were put into computational forms. In this approach, autocorrelation function was computed for a given image, and the features were derived from these autocorrelated and original images. Finally improved results in terms of classification accuracy were obtained for multiple representation using these developed features. The immediate prospect related to this work is consideration of other perceptual features such as regularity and complexity.

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