Multiple Representations of Perceptual Features for Texture Classification and Retrieval

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ABSTRACT
Texture is a very important feature extremely used in various image processing problems. Human beings are used some texture based perceptual features to distinguish between textured images or regions. These Perceptual features 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 important perceptual features are coarseness, contrast, directionality and busyness. This paper proposed a new perception-based approach to content-based image classification and retrieval. The proposal is based on multiple representations: Original Image Representation and Autocorrelation Function Representation. The computational measures for textural features are computed both on original image and autocorrelated image. In order to validate these features measures, applied them for texture classification and retrieval on brodatz images. For texture classification, features computed on Multiple representation correctly classified the best matching class among the existing class in comparison with original representation based features and autocorrelation representation based features. K-Nearest Neighborhood classifier is used for this classification task. For texture retrieval, Multiple representation based features retrieved more number of relevant images in comparison with features derived from autocorrelation representation. Gower co-efficient of similarity is used to find the feature similarity between images in retrieval task. Thus this work attained good classification rate of 93.5% and better retrieval rate by using these estimated features on our approach.

Keywords
Multiple representations, perceptual features, texture, texture classification, texture retrieval.

1. INTRODUCTION
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 feature are widely used for extraction of specific image properties such as coarseness and presence of edges.

A number of texture analysis methods have been proposed [1]-[15]. Haralick [16] categorized texture analysis methods into statistical methods, structural methods, and hybrid methods [17]-[21]. 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 that the majority of the computational methods use mathematical features that have no perceptual meaning.

Among the various works that have been done in the field of texture analysis [22], this paper is interested in dealing with human visual perception. In the literature, some works related to perceptual texture analysis have been done [23]-[27]. Tamura *et al.* [28] and Amadasum *et al*. [29] 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.* [28] was based on the co-occurrence grey-level matrix (CGLM). The work of Amadasun *et al*. [29] 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*. [30] 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 is to evaluate the computational measures for perceptual textural features. First, proposed a new method to estimate a set of perceptual textural features. Second, application of this proposed perceptual model to texture classification and retrieval task. Our approach is to combine the features which are computed on both original images and the autocorrelation function and applied them for classification and retrieval task to obtain very good classification and retrieval rate. It should be noted that the study reported here was tested on a sample of 8 images (Figure.1) from Brodatz database [31].

The rest of this paper is organized as follows. In section 2, we present definitions of the set of perceptual textural features we are considering in this study; in section 3, the autocorrelation function on which our work is based is presented; in section 4, computational measures corresponding to the perceptual textural features are presented; in section 5, application of perceptual features to texture classification is presented with implementation result; in section 6, application of perceptual features to texture retrieval is presented with experimental result; in section 7 and 8, a conclusion and future work are given respectively.

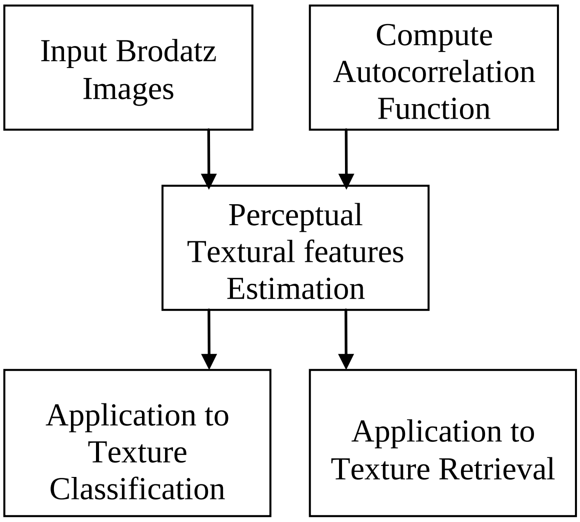


Figure 1: Block diagram of proposed system

Figure 1 shows the block diagram of this work. Autocorrelation function is represented on each input Brodatz image. Computational measures for perceptual textural features are computed both on original image and autocorrelation representation. The feature measures obtained from these two representations are combined and applied for texture classification and retrieval task.

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[32][33]. 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[34]. 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[35]. 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.

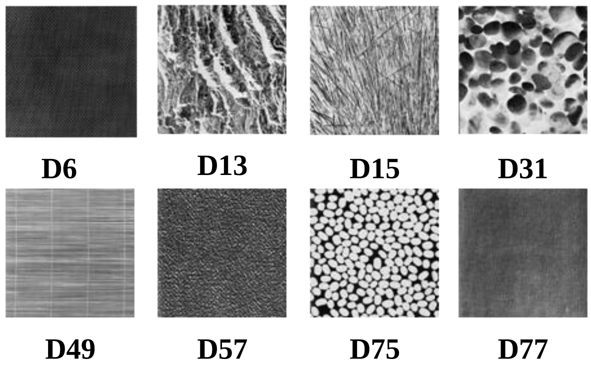


Figure 2: Brodatz images used in this work

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[18]:

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

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[36]-[38].

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

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

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

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

$\frac{1}{\alpha}$ is a parameter used to make C_s having sense against the quantity $\frac{M_a x N_t}{n x m}$.

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

$$\theta = \arctan G_y/G_x \quad (4)$$

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

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

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

$$B_s = 1 - C_s^{\frac{1}{\alpha}} \quad (6)$$

$\frac{1}{\alpha}$is a parameter used to make C_s having sense against the quantity 1.

5. APPLICATION TO TEXTURE CLASSIFICATION

This experiment was carried out to assess the performance of the perceptual features in texture classification task. Computational features presented in this paper are applied in classification task on Brodatz database. The samples used are D13, D57, D77, D6, D75, D49, D31, and D15. Three kinds of classifications are performed in this work namely original representation based classification, autocorrelation representation based classification and multiple representation based classification. Actual classification task is achieved by K-Nearest Neighborhood classifier.

5.1 K-Nearest Neighborhood classifier

This classifier is used to identify the best matching class among the existing class by using nearest neighbor method. The syntax of knnclassify is defined as follows

Class = knnclassify(Sample, Training, Group) (7)

Where,
Sample is the matrix whose values represent the set of features which are obtained during testing phase. Sample must have same number of columns as Training.
Training is the matrix whose values represent the set of features which are obtained during training phase.
Group is the vector whose distinct values define different class

5.2 Implementation

Texture classification consist of two phases namely training phase and testing phase. The database contain sample of 8 brodatz images. In training phase, each of these samples is divided into 9 nonoverlapping tiles to obtain 72 subimages of size 128 x 128 (8 images x 9 titles per image). During this phase, leaving out four subimages for each category at a time and training the classifier on the remaining five. 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. In testing phase, four untrained subimages for each class in the testing set are presented to the classifier to identify the best matching class.

5.3 Classification Based on 9 Subimages from Each class

5.3.1 Training phase for original representation

Each database image is divided into 9 subimages. Five subimages from each category are stored in training set and remaining goes for testing purpose. Computational measures for perceptual features are computed on training set images. Thus we are obtained the feature set based on original representation.

5.3.2 Training phase for autocorrelation representation

Each database image is divided into 9 subimages. Five subimages from each category are stored in training set and remaining. Autocorrelation function is computed on each image in the training set and perceptual features are estimated. Thus we are obtained the feature set based on autocorrelation representation.

5.3.3 Testing phase for original representation

Perceptual features are estimated on each image in the testing set and obtained the feature set. Knnclassifier is used to find the best matching samples for the testing set images among the existing class in the training set. This is achieved by passing the feature sets which are obtained during training and testing phase for original representation.

5.3.4 Testing phase for autocorrelation representation

Autocorrelation function is represented on each image in the testing set and features are estimated at a time. Thus obtained the feature set. Knnclassifier is used to find the best matching samples for the testing set images among the existing class in the training set. This is achieved by passing the feature sets which are obtained during training and testing phase for autocorrelation representation.

5.3.5 Testing phase for multiple representation

Perceptual features are estimated on each image in the testing set and obtained the feature set on original images. Then, Autocorrelation function is represented on testing set images and features are estimated at a time. Thus obtained the feature set on autocorrelation representation. Knnclassifier is used to find the best matching samples for the testing set images among the existing class in the training set. This is achieved by passing the feature sets which are obtained during training phase for original and autocorrelation representation and testing phase for multiple representations.

Classification results are shown in table I. It clearly shows that knnclassifier obtained very good accurate rate in testing phase for multiple representation in comparison with other testing phases. Accuracy rate is defined as follows

Accuracy rate=

$$\frac{\textit{Total number of correct matching class for testing class}}{\textit{Total number of subimages on testing set}}$$

Overall classification performances are shown in figure 3. On these three types of classification, multiple representation based classification shows better accuracy rate in comparison with other two types of classification. It clearly shows that we have obtained more number of correctly classified samples for each category by our approach.

5.4 Implementation Result

Table I: Classification Results

Classification Based on	Accuracy Rate
Original Representation	84.375
Autocorrelation Representation	81.25
Multiple Representation	93.75

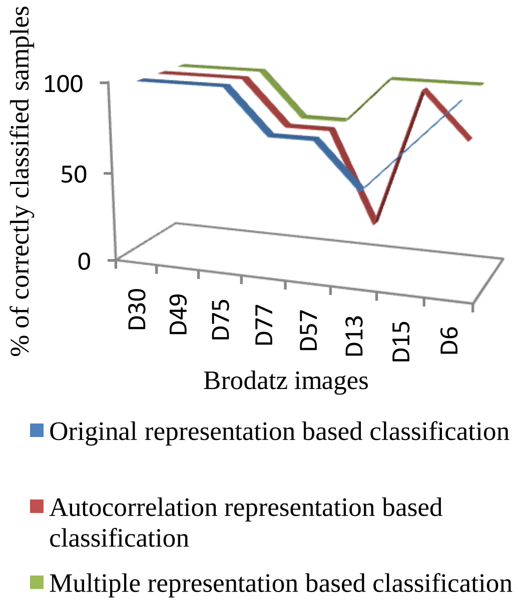


Figure 3: Performance measure of texture classification

6. APPLICATION TO TEXTURE RETRIEVAL

This experiment was carried out to assess the performance of the features in an actual retrieval task. Computational features presented in this paper are applied in texture retrieval on Brodatz database. The samples used are D13, D57, D77, D6, D75, D49, D31, and D15. Two kinds of retrieval are performed in this work. Retrieval performances are based on the number of subimages derived from each image in the database. Similarity measure used in this work is Gower coefficient of similarity.

6.1 Gower Coefficient of Similarity

The similarity between two texture images GS_{ij}, which are represented by i and j based on all features can be defined as

$$GS_{ij} = \frac{\sum_{k=1}^{4} s_{ij}^{(K)}}{4} \tag{7}$$

Where, $s_{ij}^{(k)}$ represent the similarity between two images on specific feature k.

Quantity $S_{ij}^{(k)}$ is defined as follows

$$S_{ij}^{(k)} = 1 - \frac{|x_{ik} - x_{jk}|}{R_k} \tag{8}$$

Where, x_{ik} is the feature k on given input image
x_{jk} is the feature k on jth image in the database
R_k is the difference between maximum and minimum value of feature k on feature set X.

Quantity R_k is defined as follows

$$R_k = \mathrm{Max}(X_k) - \mathrm{Min}(X_k) \tag{9}$$

6.2 Implementation

Retrieval task consists of training and testing phase. In training phase, perceptual features are estimated from original image representation and autocorrelation function representation. In testing phase, autocorrelation representation based retrieval and multiple representation based retrieval are carried out.

6.3 Retrieval Based on 9/25 Subimages from Each class

6.3.1 Training phase for original representation

In the database, each sample is divided into 9/25 subimages of size 128 x 128. Computational measures of perceptual features are estimated from these subimages. Thus obtained the feature set based on original representation.

6.3.2 Training phase for autocorrelation representation

In the database, each sample is divided into 9/25 subimages of size 128 x 128. Autocorrelation function is computed on subimages. Computational measures of perceptual features are estimated from these autocorrelated subimages. Thus obtained the feature set based on autocorrelation representation.

6.3.3 Testing phase for autocorrelation representation

Autocorrelation function is represented on the image which is given as input. Four features are estimated from this autocorrelated image. Gower coefficient of similarity is measured the similarity between these four features to the feature set which is obtained during the training phase for autocorrelation representation.

6.3.4 Testing phase for multiple representation

Four perceptual features are estimated from the image which is given as input. On that image, autocorrelation function is represented and four features are computed. Thus eight features are obtained. Similarity measurement is defined between these eight features to the feature sets which are obtained during the training phase for original representation and autocorrelation representation.

Retrieval results are shown in tables 1 and table 2. Table 1 shows the retrieval result for 9 subimages from each class. If there n images in the database, then the total number of retrievd images is 9*n. Table 2 shows the retrieval result for 25 subimages from each class. If the total number of images in the database is n, then the total number of retrieved images is 25*n. Retrieval rate is defines as follow,

$$\text{Retrieval Rate}=\frac{No.of\ Relevant\ images\ retrieved}{Total\ number\ of\ retrieved\ images}$$

Overall retrieval performances are shown in figure 4 and figure 5. In both kind of retrievals, multiple representation based retrieval shows better retrieval rate than autocorrelation based retrieval. It clearly shows that we have retrieved more number of relevant images for our approach.

6.4 Implementation result

Total No. of Images in Database	Total No. of Retrieved Images	No. of Relevant Images Retrieved Based on	
		A	B
18	162	130	154
27	243	161	197
36	324	222	275
45	405	284	343
54	486	341	410
63	567	422	491
72	648	478	556

A) Autocorrelation representation

B) Multiple representation

Table II: Retrieval result based on 9 subimages from each class

Total No. of Images in Database	Total No. of Retrieved Images	No. of Relevant Images Retrieved Based on	
		A	B
50	1250	993	1179
75	1875	1244	1562
100	2500	1790	2146
125	3125	2176	2635
150	3750	2801	3260
175	4375	3274	3789
200	5000	3806	4407

A) Autocorrelation representation

B) Multiple representation

Table III: Retrieval result based on 25 subimages from each class

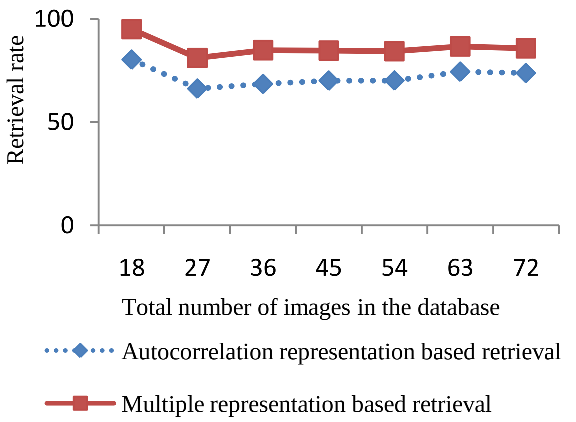


Figure 4: Performance measure of retrieval based on 9 subimages from each class

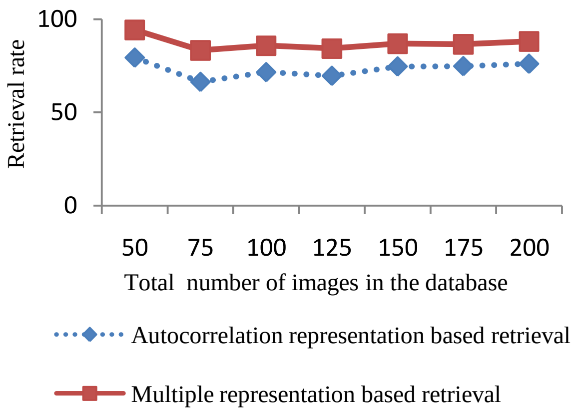
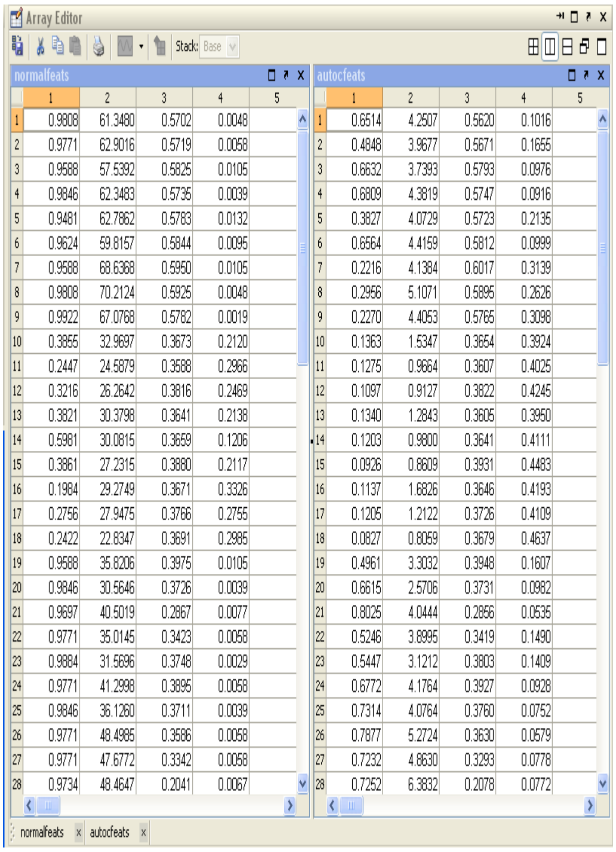


Figure 5: Performance measure of retrieval based on 25 subimages from each class



Array Editor

normalfeats

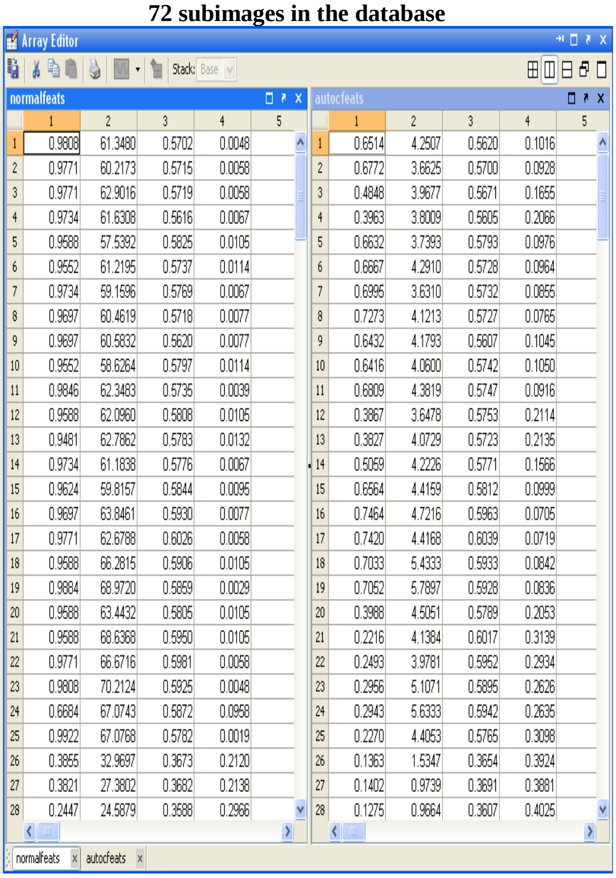
	1	2	3	4	5
1	0.9808	61.3480	0.5702	0.0048	
2	0.9771	62.9016	0.5719	0.0058	
3	0.9588	57.5392	0.5825	0.0105	
4	0.9846	62.3483	0.5735	0.0039	
5	0.9481	62.7862	0.5783	0.0132	
6	0.9624	59.8157	0.5844	0.0095	
7	0.9588	68.6368	0.5950	0.0105	
8	0.9808	70.2124	0.5925	0.0048	
9	0.9922	67.0768	0.5782	0.0019	
10	0.3855	32.9697	0.3673	0.2120	
11	0.2447	24.5879	0.3588	0.2966	
12	0.3216	26.2642	0.3816	0.2469	
13	0.3821	30.3798	0.3641	0.2138	
14	0.5981	30.0815	0.3659	0.1206	
15	0.3861	27.2315	0.3880	0.2117	
16	0.1984	29.2749	0.3671	0.3326	
17	0.2756	27.9475	0.3766	0.2755	
18	0.2422	22.8347	0.3691	0.2985	
19	0.9588	35.8206	0.3975	0.0105	
20	0.9846	30.5646	0.3726	0.0039	
21	0.9697	40.5019	0.2867	0.0077	
22	0.9771	35.0145	0.3423	0.0058	
23	0.9884	31.5696	0.3748	0.0029	
24	0.9771	41.2998	0.3895	0.0058	
25	0.9846	36.1260	0.3711	0.0039	
26	0.9771	48.4985	0.3586	0.0058	
27	0.9771	47.6772	0.3342	0.0058	
28	0.9734	48.4647	0.2041	0.0067	

autocfeats

	1	2	3	4	5
1	0.6514	4.2507	0.5620	0.1016	
2	0.4848	3.9677	0.5671	0.1655	
3	0.6632	3.7393	0.5793	0.0976	
4	0.6809	4.3819	0.5747	0.0916	
5	0.3827	4.0729	0.5723	0.2135	
6	0.6564	4.4159	0.5812	0.0999	
7	0.2216	4.1384	0.6017	0.3139	
8	0.2956	5.1071	0.5895	0.2626	
9	0.2270	4.4053	0.5765	0.3098	
10	0.1363	1.5347	0.3654	0.3924	
11	0.1275	0.9664	0.3607	0.4025	
12	0.1097	0.9127	0.3822	0.4245	
13	0.1340	1.2843	0.3605	0.3950	
14	0.1203	0.9800	0.3641	0.4111	
15	0.0926	0.8609	0.3931	0.4483	
16	0.1137	1.6826	0.3646	0.4193	
17	0.1205	1.2122	0.3726	0.4109	
18	0.0827	0.8059	0.3679	0.4637	
19	0.4961	3.3032	0.3948	0.1607	
20	0.6615	2.5706	0.3731	0.0982	
21	0.8025	4.0444	0.2856	0.0535	
22	0.5246	3.8995	0.3419	0.1490	
23	0.5447	3.1212	0.3803	0.1409	
24	0.6772	4.1764	0.3927	0.0928	
25	0.7314	4.0764	0.3760	0.0752	
26	0.7877	5.2724	0.3630	0.0579	
27	0.7232	4.8630	0.3293	0.0778	
28	0.7252	6.3832	0.2078	0.0772	

normalfeats autocfeats

Figure 5: Feature set obtained during training phase for 72 subimages in the database



Array Editor

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6	0.9552	61.2195	0.5737	0.0114	
7	0.9734	59.1596	0.5769	0.0067	
8	0.9697	60.4619	0.5718	0.0077	
9	0.9697	60.5832	0.5620	0.0077	
10	0.9552	58.6264	0.5797	0.0114	
11	0.9846	62.3483	0.5735	0.0039	
12	0.9588	62.0960	0.5808	0.0105	
13	0.9481	62.7862	0.5783	0.0132	
14	0.9734	61.1838	0.5776	0.0067	
15	0.9624	59.8157	0.5844	0.0095	
16	0.9697	63.8461	0.5930	0.0077	
17	0.9771	62.6788	0.6026	0.0058	
18	0.9588	66.2815	0.5906	0.0105	
19	0.9884	68.9720	0.5859	0.0029	
20	0.9588	63.4432	0.5805	0.0105	
21	0.9588	68.6368	0.5950	0.0105	
22	0.9771	66.6716	0.5981	0.0058	
23	0.9808	70.2124	0.5925	0.0048	
24	0.6684	67.0743	0.5872	0.0958	
25	0.9922	67.0768	0.5782	0.0019	
26	0.3855	32.9697	0.3673	0.2120	
27	0.3821	27.3802	0.3682	0.2138	
28	0.2447	24.5879	0.3588	0.2966	

autocfeats

	1	2	3	4	5
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2	0.6772	3.6625	0.5700	0.0928	
3	0.4848	3.9677	0.5671	0.1655	
4	0.3963	3.8009	0.5605	0.2066	
5	0.6632	3.7393	0.5793	0.0976	
6	0.6667	4.2910	0.5728	0.0964	
7	0.6995	3.6310	0.5732	0.0855	
8	0.7273	4.1213	0.5727	0.0765	
9	0.6432	4.1793	0.5607	0.1045	
10	0.6416	4.0600	0.5742	0.1050	
11	0.6809	4.3819	0.5747	0.0916	
12	0.3867	3.6478	0.5753	0.2114	
13	0.3827	4.0729	0.5723	0.2135	
14	0.5059	4.2226	0.5771	0.1566	
15	0.6564	4.4159	0.5812	0.0999	
16	0.7464	4.7216	0.5963	0.0705	
17	0.7420	4.4168	0.6039	0.0719	
18	0.7033	5.4333	0.5933	0.0842	
19	0.7052	5.7897	0.5928	0.0836	
20	0.3988	4.5051	0.5789	0.2053	
21	0.2216	4.1384	0.6017	0.3139	
22	0.2493	3.9781	0.5952	0.2934	
23	0.2956	5.1071	0.5895	0.2626	
24	0.2943	5.6333	0.5942	0.2635	
25	0.2270	4.4053	0.5765	0.3098	
26	0.1363	1.5347	0.3654	0.3924	
27	0.1402	0.9739	0.3691	0.3881	
28	0.1275	0.9664	0.3607	0.4025	

normalfeats autocfeats

Figure 6: Feature set obtained during training phase for 200 subimages in the database

7. CONCLUSION

A new perceptual model based on a set of computational measures corresponding to perceptual textural features namely coarseness, directionality, contrast, and busyness is proposed. Computational measures are based on multiple representations: original image representation and the autocorrelation function associated with original images. Coarseness was estimated as an average of the number of maxima. Contrast was estimated as a combination of the average amplitude of the gradient, the percentage of pixels having the amplitude superior to a certain threshold and coarseness itself. Directionality was estimated as the average number of pixels having the dominant orientation(s). Busyness was estimated based on coarseness. These four basic properties of texture 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. In order to validate the proposed set of computational feature measures, applied them in classification and retrieval task on brodatz images. In both applications, better results in terms of classification rate and retrieval rate were obtained by using these developed features based on our approach.

8. FUTURE WORK

The immediate prospect related to this work is consideration of other perceptual features such as regularity and complexity. Application of these additional computational feature measures with existing features for texture classification and retrieval on large set of images from other texture database.

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