Performance Analysis on Texture Based Image Retrieval using Perceptual Model and MOGG

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***Abstract* - The rise of interest in techniques for retrieving images on the basis of automatically-derived features such as color, texture and shape are increasing and this technology is named as Content Based Image Retrieval. In this paper, texture hasbeen used as feature and feature extraction was done by using Perceptual model and Mixtures of Generalized Gaussian Distribution. The perceptual features taken for analysis are Coarseness, Contrast, Directionality and Busyness. The Brodatz Database images are taken for analysis. The precision, recall and time are used as metrics to compare the performance of these methods.**

Keywords: Content Based Image Retrieval, Mixtures of Generalized Gaussian Distribution, BrodatzDatabase

1. INTRODUCTION

Content based image retrieval, a techniquewhich uses visual contents to searchimages from large scale image databases according to users' interests, has been anactive and fast advancing research area since the 1990s. During the past decade,remarkable progress has been made in both theoretical research and systemdevelopment. However, many challenging research problems like speed and accuracy of the retrieval system thatcontinue to attract researchers from multiple disciplines.

Textureplays an important role in many machine vision tasks like surface inspection, scene classification, and surface orientation and human visual perception. Texture is characterized by the spatial distribution of gray levels in a neighborhood. Thus, Texture cannot be defined for a point. The ability to match and retrieve texture similar images is an important factor in differentiating the areas on images with same color (such as leaves, sky ,etc).

Tamura feature is a statistical method. Image texture such as the degree of contrast, coarseness, directionality and regularity [Tamura et al,1978], or periodicity, directionality and randomness [Liu and Picard, 1996]. In recent years attention to Gaussian is quite increasing[5,11,4].Mixtures of Generalized Gaussian is an extension of Generalized Gaussian and it has parameters like mean, variance, weight and shape parameter. The similarity measure used was Kullback-Leibler divergence.

II. RELATED WORK

Texture features play an important role in computer vision and image processing. There are many available texture basedimage retrieval system in the academic arena [2,3,10].Abbadeni. N,D. Ziouand S.Wang[1] estimated perceptual textural features namely coarseness, contrast, directionality, and busyness based on auto covariance function. Liu. F and R.W Pichard[8] here an image model with a new set of features that address the challenge of perceptual similarity. It is useful for use in large collections. Manjuth. B. S and Ma. W. Y[6] used Gabor wavelet features for texture analysis and focuses on a multiresolution representation based on Gabor filters. Minh[4], here a new wavelet based texture retrieval method that is based on accurate modeling of the marginal distribution of wavelet coefficients using Generalized Gaussian Density(GGD).

III. FEATURE EXTRACTION

Feature extraction is the basis for CBIR. Here, we have used texture feature extraction. Texture refers to visual patterns with properties of homogeneity that do not result from the presence of only single color or intensity. Textures are represented by texels, which are then placed into a no. of sets, depending on how many textures are detected in the image.Tree, clouds, water, bricks and fabrics are the examples of texture.Micro textures refer to textures with small primitives while macro textures refer to textures with large primitives [12].

Texture analysis techniques have been used in several domains such as classification, segmentation, shape from texture and image retrieval[10,8,6,3].Typically texture features include contrast, uniformity, coarseness, roughness, frequency, density and directionality[1,8].If the features extracted from the images are presented as multidimensional points, thedistances between corresponding multi-dimensional points can be calculated. Cosine and KLD are the distance measure used in this paper.

PRATICAL APPLICATIONS OF CBIR

- Crime prevention
- The military
- Architectural and Engineering design
- Fashion and Interior design
- Medical diagnosis
- Cultural heritage
- Home entertainment
- Web searching

Sample Images

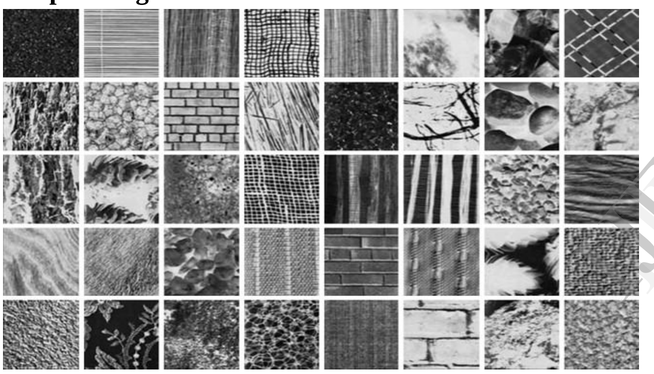

Fig. 1. Images of Brodatz Database[11]

IV. METHODOLOGY

A. Perceptual Textural Features

The perceptual textural features used are coarseness, contrast, directionality and busyness.

(1)*Coarseness*

Coarseness is a measure of granularity of the texture. A coarse texture is composed of large primitives and is characterized by a high degree of local uniformity of grey-levels. Coarseness is saved in this auto correlation function. For coarse textures it presents few local variations

Coarseness C_s is expressed by equation:

$$Cs=\frac{1}{\frac{1}{2}*\left(\frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} Max_x(i,j)}{n}+\frac{\sum_{j=0}^{m-1}\sum_{i=0}^{n-1} Max_y(i,j)}{m}\right)} \qquad (\mathbf{1})$$

Let $Max_x(i, j)= 1$ if pixel (i,j) is a maximum on rows and $Max_x(i, j)= 0$ if pixel (i,j) is not a maximum on rows. Similarly, Let $Max_y (i,j)= 1$ if pixel (i,j) isa maximum on columns and $Max_y (i,j)= 0$ if pixel (i,j) is not a maximum on columns.

(2)*Directionality*

Directionality is a global property in an image. It measures the degree of visible dominant orientation in an image.The degree of directionality is related to the dominant orientation(s) in an image, and refers to the number of pixels having the dominant orientation(s).

The degree of directionality $N\ominus_d$of an image can be expressed by the following equation

$$N\ominus_d=\frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\ominus d(i,j)}{(n*m)-N\ominus nd} \qquad (2)$$

$\ominus_d$ represents dominant orientation.

(3)*Contrast*

Contrast measures the degree of clarity with which one can distinguish between different primitives in a texture.

$$M_a=\frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} M(i,j)*t(i,j)}{Nt} \qquad (3)$$

Where M_a represents the average amplitude.M(i,j) is the amplitude of pixel (i,j), $N_t$the number of pixels having an amplitude superior to threshold t.

(4)*Busyness*

Busyness refers to the intensity changes from a pixel to its neighborhood. Busyness is a reverse relationship of coarseness.

$$Bs = 1 - C_s^{1/\alpha} \qquad (4)$$

Where C_s represents the computational measure coarseness ($1/\alpha$ is a quantity used to make C_s significant).

B. Mixtures Of Generalized Gaussian Distribution

The general Gaussian Distributions for a univariant random variable $X \in R$ is defined in its form

$$p\left(\frac{x}{\mu},\sigma,\beta\right)=\frac{\left(\beta\frac{\sqrt{\Gamma\left(\frac{3}{\beta}\right)}}{\sqrt{\Gamma\left(\frac{1}{\beta}\right)}}\right)}{2\sigma\Gamma\left(\frac{1}{\beta}\right)}\exp(-A(\beta)\left|\frac{x-\mu}{\sigma}\right|^{\beta}) \qquad (5)$$

$$\text{where}\,\mathbf{A}(\boldsymbol{\beta})=\left[\frac{\boldsymbol{\Gamma}\left(\frac{3}{\boldsymbol{\beta}}\right)}{\boldsymbol{\Gamma}\left(\frac{1}{\boldsymbol{\beta}}\right)}\right]^{\boldsymbol{\beta}/2}$$

$\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ represents mean and standard deviation.
Parameter $\boldsymbol{\beta} \geq \mathbf{1}$ controls the pdf and determines whether the distribution is peaked or flat. The larger the value of β ,the flatter the pdf, and the smaller β is, the more peaked the pdf is around its mean.
The message length that encodes the wavelet coefficients in a given subband is given by,

$$\mathbf{MessL} \cong -\mathbf{\log p}(\bar{\theta}) + \frac{1}{2}\mathbf{\log}|\mathbf{I}(\bar{\theta})| + \frac{c}{2}\left(\mathbf{1} + \mathbf{\log}\frac{1}{12}\right) - \mathbf{\log p}\left(\frac{x}{\bar{\theta}}\right) \quad (6)$$

Where, $\mathbf{p}(\bar{\boldsymbol{\theta}}), \mathbf{I}(\bar{\boldsymbol{\theta}}), \mathbf{p}\left(\frac{x}{\bar{\theta}}\right)$ denote the prior distribution of the parameters $\bar{\theta}$.

1. The Mean (μ_k) is obtained by,

$$\mu_k = \frac{\sum_{i=1}^{n} p\left(\frac{\theta k}{xi}\right)|x_i - \mu_k|\beta_k -^{2} x_i}{\left(\sum_{i=1}^{n} p\left(\frac{\theta k}{xi}\right)|x_i - \mu_k|\beta_k -^{2}\right)} \quad (7)$$

2. The Standard Deviation (σ_k) is obtained by,

$$\sigma_{k=}\ \beta_k\, A(\beta_k) \frac{\sum_{i=1}^{n} p(\frac{\theta k}{xi})|x_i - \mu_k|\beta_k}{\sum_{i=1}^{n} p(\frac{\theta k}{xi})} \quad (8)$$

3. The shape parameter (β_k) is obtained by,

$$\beta_k = \beta_k - (\delta^2 \log\left(\frac{p\left(\frac{x}{\bar{\theta}}\right)}{\gamma\beta_k^2}\right) - (\gamma\log(p(\frac{x}{\bar{\theta}})/\delta\beta_k \quad (9)$$

IV.THE SEQUENCE OF IMPLEMENTATION:

1. Brodatz database are of 11 classes of 8 images each. So totally 88 images.
2. Each database has separate coding part for test and train images.
3. First the images are undergone pre-processing stage where Perceptual model and Wavelet modelling are calculated.
4. Features are extracted from Perceptualmodel and MOGG.
5. They are converted into double format.
6. The features are extracted from query image given by the user.
7. The distance between query image and trained images are calculated using the distance measures.
8. The distance are stored in a one-dimensional matrix.
9. First three minimum values are extracted and regarding picture is obtained from trained database.
10. Time, precision, and recall are taken for performance analysis.

V. EXPERIMENTAL RESULTS

A. Performance Metrics

The metrics evaluatedfor performance evaluation are:

1. Time.
2. Precision.
3. Recall.

Time

Time is always important to do a process in minimum amount of time. Time also plays a vital role in the performance evaluation.

Time, here calculated, includes training time, retrieval time, and the time to calculate the distance measure.

Precision

Precision is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images. Precision P measures the accuracy of the retrieval.

$$\text{Precision} = \frac{No.\_of\_relevant\ \_images\ \_retrieved}{Total\ \_no\_of\_images\ \_in\_retrieved}$$

Recall

Recall is the number of relevant and retrieved images divided by the number of relevant images in the database for the considered query, measures the ability of a model to retrieve all relevant images.

$$\text{Recall} = \frac{No\_of\_revevant\ \_images\ \_retrieved}{Total\ \_no\_of\_relevant\ \_images\ \_in\_database}$$

B. Performance Evaluation

The level of retrieval accuracy achieved by a system is important to establish its performance. If the outcome is satisfactory and promising, it can be used as a standard in future research works.

The Performance analysis shown in the tables and graphs, gives the result thatMOGG is the best method by comparing both methods with the time value, precision and recall.

Tech	Image 3	Image 5	Image 6
Perceptual method	24.2342	23.10532	25.0052
MOGG	10.4321	9.04321	11.53210

Table 1: Computing time (secs) with cosine distance measure in perceptual method and KLD in MOGG model.

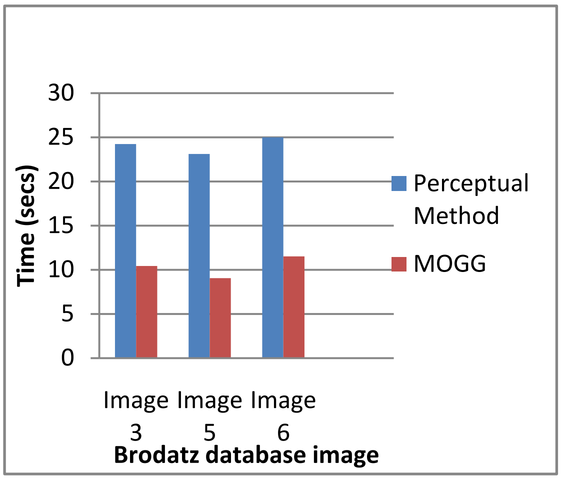

Fig 2: Retrieval time values from the image 3, image 5, image 6 in Perceptual method and MOGG model with cosine and KLD distance measure.

Tech	Image 3(%)	Image 5(%)	Image 6(%)
Perceptual method	60	33	100
MOGG	60	100	100

Table 2: Computing precision (%) with cosine distance measure in perceptual method and KLD in MOGG model.

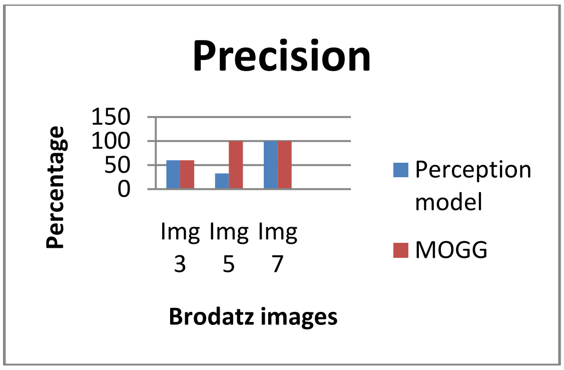

Fig 3: Precision values for the image 3, image 5, image 6 in Perceptual method and MOGG model with cosine and KLD distance measure.

Tech	Image 3(%)	Image 5(%)	Image 6(%)
Perceptual method	25	12.5	37.5
MOGG	25	37.5	37.5

Table 3: Computing recall (%) with cosine distance measure in perceptual method and KLD in MOGG model.

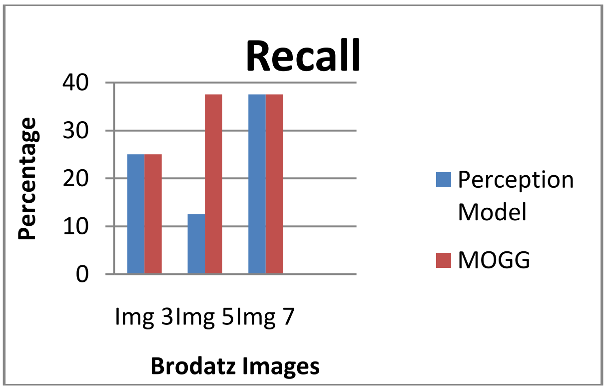

Fig 4:Recall values for the image 3, image 5, image 6 in Perceptual method and MOGG model with cosine and KLD distance measure.

VI. CONCLUSION

In this paper, Texture based image retrieval is done and the feature extraction was done by using Perceptual model and MOGG. The distance measures used are cosine and KLD. The perceptual features extracted are Coarseness, Contrast, Directionality and Busyness.we have maintained two stuff that is Training and Testing phase.In Training phase, We trained all the images in the Database by the process of Feature Extraction.In Testing phase, the Feature of the selected current image was extracted and compared with feature database.Finally, we got therelevant images from the database by the process of feature matching.The images are grouped into 11 classes of 8 images each class for a total of 88 images.

The analysis result shows thattime,precision and recall values of MOGG is faster than Perceptual Model.

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