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Image Retrieval Using Combination of Texture and Shape Features

N.Puviarasan[1], Dr.R.Bhavani[2], A.Vasanthi[3]

Associate Professor, Dept. of Computer Science and Engineering, Annamalai University, Chidambaram [1]

Professor, Dept. of Computer Science and Engineering, Annamalai University, Chidambaram [2]

PG Student, Dept. of Computer Science and Engineering, Annamalai University, Chidambaram [3]

Abstract: The purpose of this research paper is retrieval of images from the image database using Content Based Image retrieval (CBIR) technique. It uses a novel approach which is a combination of texture and shape features. The K-means clustering and Fuzzy C-means clustering are used for segmenting the images. Then, the 5 Haralick texture features and 7 shape features are extracted. The extracted features are combined together. In our experiment, Corel database of image containing 1000 having 10 categories each of which has 100 images is used. The results are compared with other existing methods and it is found that the proposed combined features are better in retrieval of images than the other methods. Euclidean distance and Hausdroff distance are used for similarity measurements in the proposed CBIR method.

Keywords: CBIR, K-means clustering, Fuzzy C-means clustering, Euclidean distance, Hausdroff distance

I. INTRODUCTION

In recent time, due to the growth of powerful processors and the cheapest nature of memories, the deployment of huge image databases supporting a wide range of applications have now become achievable. Databases possessing art works, satellite and medical images have a great potential in attracting more and more users in diverse fields like geographical, architecture, advertising, medicine, fashion design and publishing. Accessing the desired and relevant images from large image databases in an efficient manner is now a great necessity.

II. RELATED WORK

This paper [1] proposes CBIR system which exploits the local color and texture options of chosen images sub-blocks and world color along with form options of the images. A combined color and texture feature is computed for every region, the form options are computed from the string bar graph descriptor.

This paper [2] proposes CBIR which combines color and texture features. HSV color space and Gabor texture features are used in this paper. Canberra distance is used for similarity measurement. This paper [3] presents an approach for the image retrieval based on the combination of text-based and content-based features. Color moment and Co-occurrence matrix are used for the extraction of color feature and texture features.

In this paper [4] the local region of image is represented by local maximum edge binary patterns which are evaluated by taking into consideration the magnitude of local difference between the central pixel and its neighbours. This paper [5] uses structure elements descriptor to describe color and texture features.
The accuracy of color histogram based matching can be increased by using Color Coherence Vector (CCV) for successive refinement. The speed of shape based retrieval can be enhanced by considering approximate shape rather than the exact shape. In addition to this a combination of color and shape based retrieval is also included to improve the accuracy of the result in [6].

In this paper [7], a content-based image retrieval method based on an effective consolidation of color and texture features is proposed. Pseudo Zernike chromaticity distribution moment in opponent chromaticity space is applied to extract the color feature. A method for image retrieval based on fractal coding characters is used in [8]. A statistical method based on kernel sensitivity estimation is applied for analysing fractal coding techniques.

This paper [9] discusses a novel content based image retrieval system based on compounding of framelet transform with gray level co-occurrence matrix (GLCM).
Its growth is due to some causes such as in many large image databases, conventional methods of image indexing are used. These traditional methods of image indexing proceeds by storing an image in the databases and relating it with a keyword or number that associate with a categorized description, have become obsolete. They have been proven that these methods are insufficient, laborious and extremely time consuming.

In CBIR, each image is stored in the database and its features are extracted and matched with query image features. It possesses two steps: feature extraction and matching. The first step involves the process of extraction of image features to a distinguishable extent. The second step proceeds by matching of extracted query image features with the features of images stored in the database to yield a result which is visually similar.

III. PROPOSED WORK

The median filtering is applied in the proposed work for removing the noise, where the value of an output pixel is found by the median of the neighbourhood pixel. The sensitivity to outliers is much less for median than the mean.

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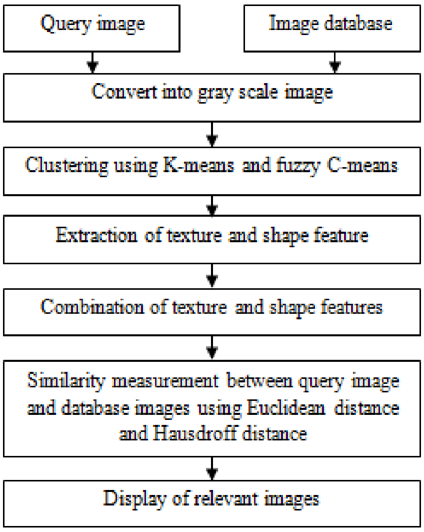

Figure 1: Block diagram of the proposed CBIR Method

Thus, median filtering is most suited to remove the outliers while preserving the sharpness of the image. The schematic diagram of proposed work is shown in Figure 1. As a first step, the input query image is converted into gray scale image. The images are segmented using Fuzzy C-means and K-means clustering to group similar images. The purpose of segmentation is to support for the extraction of efficient features. Then, Tamura and Haralick features for texture and shape moment invariants for shape are extracted and the proposed method is a combination of texture and shape features. The extracted features from the query image and database images are compared using the similarity measurements like Euclidean distance and Hausdroff distance.

IV. SEGMENTATION

The next step is the application of a suitable clustering technique to cluster individual pixels into groups that exhibit homogeneous properties. To select the suitable clustering technique, K-means and fuzzy C-means methods are applied on median filtered noise removed images. Then, the performance of two methods is compared.

A. *K-MEANS CLUSTERING*

The K-means method aims to minimize the sum of squared distances between all points and the cluster centre [10]. This procedure consists of the following steps:

(1) Choose K initial cluster centres $z_1(1)$, $z_2(1)$, ...$z_k(1)$.
(2) At the k-th iterative step, distribute the samples x among the K clusters using the relation,

$$x \varepsilon C_j(k) if \parallel x - z_j(k) \parallel < \parallel x - z_i(k) \parallel \quad (1)$$

for all i = 1,2, ...K; i ≠ j; where $C_j(k)$ denotes the set of samples whose cluster centre is $z_j(k)$.

1. Compute the new cluster centres $z_j(k + 1)$, j = 1,2,....K such that the sum of the squared distances from all points in $C_j(k)$ to the new cluster centre is minimized. The measure which minimizes using the sample mean of $C_j(k)$. Therefore, the new cluster centre is given by

$$z_j(k+1) = \frac{1}{N_j}\sum_{x\varepsilon C_j(k)} x, j = 1,2, \dots K \quad (2)$$

where N_j is the number of samples in $C_j(k)$.

2. If $z_j(k + 1) = z_j(k)$ for j = 1,2,3,....K then the algorithm has converged and the procedure is terminated. Otherwise goto step 2. It is obvious in this description that the final clustering will depend on the initial cluster centres chosen and on the value of K. The latter is of the most concern since this requires some prior knowledge of the number of clusters present in the data, which in practice is highly unlikely.

B. *FUZZY C-MEANS CLUSTERING*

Fuzzy C-means clustering (FCM) is an iterative algorithm that produces optimal partitions based on minimization of the following objective function [11],

$$J_m = \sum_{i=1}^{g}\sum_{j=1}^{n}(\mu_{ij})^m \parallel X_j - V_i \parallel \quad (3)$$

where X_j (j = 1, 2... n) is the data point; V_i is the fuzzy centroid; μ_{ij} is the degree of membership of X_j in cluster i ; c is the number of clusters that needs to be determined in advance; n is the number of data points to be clustered; and m is the fuzziness index, which is set to a value greater than one. The norm operator ‖.‖ represents the Euclidean.

C. *COMPARISON OF SEGMENTATION METHODS*

To study the performance measure of cluster based segmentation methods, the following quality measures are used.

(1) Structural Content (SC)

$$SC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N} Ip(j,k)^2}{\sum_{j=1}^{M}\sum_{k=1}^{N} Op(j,k)^2} \quad (4)$$

(2) Normalised Correlation coefficient (NCC)

$$NCC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N} Ip(j,k) Op(j,k)}{\sum_{j=1}^{M}\sum_{k=1}^{N} Ip(j,k)^2} \quad (5)$$

(3) Mean square error(MSE)

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[Ip(i,j) - Op(i,j)]^2 \quad (6)$$

(4) Peak signal to noise ratio(PSNR)

$$PSNR = 20 \log_{10}\left[\frac{255*255}{\sqrt{MSE}}\right] \quad (7)$$

The above four parameters are calculated based on the input image $Ip(x, y)$ and segmented image $Op(x, y)$.

Table 1: Comparison of K-means and Fuzzy C-means clustering

No. Of clusters	*K - means* SC	NCC	PSNR	*Fuzzy C - means* SC	NC	PSNR
4	1.1879	0.6834	34.4330	1.1255	0.7155	34.9834
5	1.2078	0.7266	35.4351	1.1121	0.7456	35.8901
6	1.5122	0.7356	35.5910	1.2345	0.7255	35.9961
7	1.6122	0.7786	35.6176	1.2522	0.7534	36.4567
8	1.7123	0.7834	35.8631	1.2671	0.7678	36.5632

The K-means and Fuzzy C-means clustering are developed using MATLAB. The table 1 compares the two clustering methods used for image segmentation. It is found that

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FCM clustering produces fairly higher accuracy by giving more PSNR value.

V. FEATURE EXTRACTION

Tamura and Haralick features are texture features. Shape moment invariants are shape features. The extraction process of texture and shape is presented in the following sections.

A. *TAMURA FEATURES*

There are 6 different Tamura features: coarseness, contrast, directionality, line likeness, regularity and roughness [12]. The first three features are used since they are strongly correlated with human perception [13]. Hence, in this paper the same first three features are extracted and used.

B. *HARALICK FEATURES*

Gray-level co-occurrence matrix (GLCM) gives the relative frequencies of occurrence of gray level combinations among pairs of image pixels. This matrix considers relationships of image pixels in different directions, such as horizontal, vertical, diagonal and anti-diagonal. Suppose the input image has M and N pixels in the horizontal and vertical directions respectively. Suppose that the grey level appearing at each pixel is quantized to Z levels, Assume N_x = 1,2,3....M is a horizontal space domain and N_y = 1,2,3,....N is a vertical space domain and G = 0,1,2,...Z be the set of Z quantized gray levels [3].

In a given distance (d) and direction θ, the GLCM is calculated using gray scale pixel i,j expressed as the number of co-occurrence matrix elements as follows [14].

$$P(i,j|d,\theta) = \frac{P(i,j|d,\theta)}{\sum_i \sum_j P(i,j|d,\theta)} \tag{8}$$

Haralick proposed 14 kinds of GLCM parameters [15] among which the following 5 parameters are mainly used.

1. MOMENT OF INERTIA (CONTRAST)

$$I = \sum_i \sum_j (i-j)^2 P(i,j) \tag{9}$$

Moment of inertia will have a large value for images which have a large amount of local spatial variation in gray levels and a smaller value for images with spatially uniform gray level distributions.

2. ENERGY :

$$E = \sum_i \sum_j [(P(i,j))]^2 \tag{10}$$

Energy is the measure of gray distribution uniformity of image. The coarser the texture is, the more energy it contains

3. ENTROPY :

$$H = \sum_i \sum_j [P(i,j)] \log P(i,j) \tag{11}$$

Entropy is a measure of the amount of information of an image. Entropy relates to the texture information. If there is no texture information, the entropy is zero.

4. CORRELATION :

$$C = (d,\theta) = \frac{\sum_{i,j}(i-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x \sigma_y} \tag{12}$$

Where

$$\mu_x = \sum_i \sum_j iP(i,j), \mu_y = \sum_i \sum_j jP(i,j) \tag{13}$$

$$\sigma_x^2 = \sum_i \sum_j (i-\mu_x^2)P(i,j),$$

$$\sigma_y^2 = \sum_i \sum_j (i-\mu_y^2)P(i,j) \tag{14}$$

Correlation is used to measure the degree of similarity of the elements in GLCM.

5. HOMOGENITY :

$$H_o = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|} \tag{15}$$

Homogeneity feature returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

C. *SHAPE FEATURES*

Moment invariant is region-based object shape representation. Suppose R is the binary image, the p+q central moments of R form as [16]:

$$\mu_{p,q} = \sum_{(x,y)\epsilon R}(x-x_c)^p(y-y_c)^q \tag{16}$$

(x_c, y_c) is the center of the object. For scale-independent nature, central moments can be standardised as:

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_{0,0}^{\gamma}}, \gamma = \frac{p+q+2}{2} \tag{17}$$

Based on these moments, Hu bring forward seven moments of transformation, rotation and scale independence:

$$\Phi_1 = \mu_{2,0} + \mu_{0,2} \tag{18}$$

$$\Phi_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^2 \tag{19}$$

$$\Phi_3 = (\mu_{3,0} - 3\,\mu_{1,2})^2 + (\mu_{3,0} - 3\,\mu_{2,1})^2 \tag{20}$$

$$\Phi_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{0.3} + \mu_{2,1})^2 \tag{21}$$

$$\Phi_5 = (\mu_{3,0} - 3\,\mu_{1,2})(\mu_{3,0} + \mu_{1,2})\left[(\mu_{3,0} + \mu_{1,2})^2 -\right.$$

3μ0,3+ μ2,12+ (μ0,3–3 μ2,1)(μ0,3+ μ2,1)[μ0,3+ μ2,12– 3μ3,0+μ1,22] (22)

$$\Phi_6 = (\mu_{2,0} - \mu_{0,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{0,3} + \mu_{2,1})^2\right] + 4\,\mu_{1,1}(\mu_{3,0} + \mu_{1,2})(\mu_{0,3} - 3\,\mu_{2,1}) \tag{23}$$

$$\Phi_7 = 3(\mu_{2,1} - \mu_{0,3})(\mu_{3,0} + \mu_{1,2})\left[(\mu_{3,0} + \mu_{1,2})^2 -\right.$$

3μ0,3+ μ2,12+ (μ0,3–3 μ2,1)(μ0,3+ μ2,1)[μ0,3+ μ2,12– 3μ3,0+μ1,22] (24)

All feature vectors are normalised to original sequence using gaussian normalisation method. Then, Haralick texture feature vectors and shape feature vectors are combined.

VI. SIMULARITY MEASUREMENT

A. *EUCLIDEAN DISTANCE*

This distance matrix is mostly used for similarity measurement in image retrieval because of its efficiency and effectiveness. It measures the distance between two vectors of images by calculating the square root of the sum of the squared absolute differences and it can be calculated as

$$\delta d = \sqrt{\sum_{i=1}^{n}(|Q_i - D_i|)^2} \tag{25}$$

where Q and D are the query feature vector and database feature vector respectively.

B. THE HAUSDROFF DISTANCE

Given two finite point sets A = a1, a2, ...a_p and B = b1, b2, ...b_q, the Hausdroff distance is defined as

$$H(A,B) = \max(\, h(A,B), h(B,A)\,) \qquad (26)$$

where

$$h(A,B) = \max_{a\epsilon A} \min_{b\epsilon B} \| a-b \| \qquad (27)$$

and ‖.‖ is some underlying norm on the points of A and B. h(A,B) is the function for directed hausdroff distance from A to B. This function discovers the point a ϵ A, which is farthest from any point of B and calculates the distance from a to its neighbourhood in B.

VII. EXPERIMENTAL RESULTS

The proposed method is tested by using the Corel database of images, which is freely available for researchers (Wang et al., 2000). The database consists of 1000 images having 10 categories each of which has 100 images. The categories are people, beaches, buildings, buses, dinosaurs, elephants, roses, horses, mountains, and food. All these categories are used for the experiments. All the images are in the RGB color space. They are in the JPEG format with a size of 256x384 and 384 x 256 pixels.

A. EVALUATION MEASUREMENTS

The effectiveness of the image retrieval is based on the performance of the feature extraction and similarity measurement. In this section we describe the performance metrics which have been adopted not only to evaluate the effectiveness of image retrieval but also to make sure of the stability of the results.

B. PRECISION

The precision in image retrieval is the measurement of the retrieved relevant images to the query of the total relevant images.

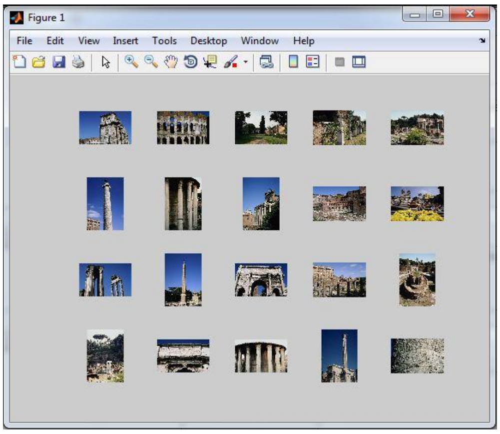

Figure 2: Retrieved images

C. RECALL

The recall in image retrieval is the measurement of the retrieved relevant images to the total database images.

The table 2 shows the average precision values of different groups of images in Corel database for different existing separate features like Tamura features, Haralick 14 features and the 7 shape moment invariants. From the table 2, it is found that the proposed method of combination of Haralick 5 features and 7 shape moment invariant features give better results than the other methods. The similarity measurement is done using Euclidean distance and Hausdroff distance. The average precision values are shown in table 3. It is observed that the Euclidean distance gives better results.

Table 2: Average Precision values for Corel database

Distance	Tamura features	Haralick features	shape moments	Proposed method
Euclidean	0.63	0.67	0.74	0.89
Hausdroff	0.58	0.64	0.71	0.82

Table 3: Average Precision and Recall values of image retrieval for each category using Euclidean and hausdroff distance

Category of images	Euclidean		Hausdroff	
	precision	recall	precision	recall
African	0.764	0.645	0.712	0.624
Beaches	0.673	0.533	0.641	0.511
Building	0.721	0.682	0.692	0.643
Buses	0.755	0.694	0.708	0.649
Dinosaurs	0.734	0.673	0.698	0.613
Elephant	0.684	0.596	0.651	0.545
Roses	0.630	0.590	0.599	0.556
Horses	0.771	0.678	0.743	0.624
Mountains	0.624	0.540	0.594	0.520
Food	0.732	0.610	0.692	0.596

VIII. CONCLUSION

In this paper, the query image is processed to remove the noise using median filtering. Then, segmentation is done using K-means clustering and Fuzzy C-means clustering to group the similar images. After comparing the two segmentation methods in terms of quality measures like SC, NCC and PSNR, it is found that FCM clustering is better than K-means clustering. Then Tamura texture features, Haralick 14 features, 7 shape moment invariant features are extracted. The proposed combination of Haralick 5 texture features and 7 shape moment invariants is generated for all types of features. Finally, similarity measurements are done using Euclidean distance and Hausdroff distance. The proposed combined features are better in the retrieval than the separate feature. Among the two similarity measurement methods, it is found that Euclidean distance gives better results than the Hausdroff distance.

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