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Image Repossession Based on Content Analysis Focused by Color, Texture and Pseudo-Zernike Moments features of an Image

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ABSTRACT

In this we propose a new and efficient technique to retrieve the images based on Dominant Color, texture and Pseudo Zernike moments to achieve the higher retrieval efficiency and performance. First an image is uniformly divided into 8 partitions. After the above partition, the centroid of the each partition is selected as its quantized color. Texture of an image is obtained by using steerable filter. Shape feature of an image is obtained by using Pseudo Zernike moments. The combination of the Dominant color, Texture and Pseudo Zernike moments provide a robust feature set for image retrieval. Euclidean distance of color, texture and shape features is used in the retrieving the similar images. The efficiency of the proposed method is demonstrated with results.

Keywords Image retrieval, dominant color, texture, steerable filter, shape, pseudo Zernike moments.

1.INTERODUCTION

Now a days people are interested in using digital images. So the size of the image database is increasing enormously. Lot of interest is paid to find images in the database. There is a great need for developing an efficient technique for finding the images. In order to find an image, image has to be represented with certain features. Color, texture and shape are three important visual features of an image.

Content based image retrieval (CBIR)[1] has become a prominent research topic because of the proliferation of video and image data in digital form. Increased bandwidth availability to access the internet in the near future will allow the users to search for and browse through video and image databases located at remote sites. Therefore fast retrieval of images from large databases is an important problem that needs to be addressed. Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. CBIR is an important alternative and complement to traditional text based image searching and can greatly enhance the accuracy of the information being returned. It aims to develop an efficient visual Content based technique to search, browse and retrieve relevant images from large scale digital image collections. Most proposed CBIR techniques automatically extract low level features (e.g. color, texture, shapes and layout of objects) to measure the similarities among images by comparing the feature differences. Color is one of the most widely used low-level visual features and is invariant to image size and orientation [1]. As conventional color features used in CBIR, there are color histogram, color correlogram, and dominant color descriptor (DCD). Color histogram is the most commonly used color representation, but it does not include any spatial information. Color correlogram describes the probability of finding color pairs at a fixed pixel distance and provides spatial information.. Therefore color correlogram provides better retrieval performance in comparison to color histogram. DCD is MPEG-7 color descriptors [4]. DCD describes the salient color distributions in an image. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution [5]. In [6],Yang et al. presented a color quantization method for dominant color extraction, called the linear block algorithm (LBA), and it has been shown that LBA is efficient in color quantization and computation. For the purpose of effectively retrieving more similar images from the digital image databases (DBs), Lu et al.[7] uses the color distributions, the mean value and the standard deviation, to represent the global characteristics of the image, and the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system. In [3,9] HSV color is used as feature descriptors of an image. Here HSV color space is quantized with non-equal intervals. H is quantized into 8-bins, S into 3-bins and v into 3-bins. So color is represented with one dimensional vector of size 72 (8X3X3). Instead of using 72 color Feature values to represent color of an image, it is better to use compact representation of the feature vector. For simplicity and with out loss of generality the RGB color space is used in this paper.

Texture is also an important visual feature that refers to innate surface properties of an object and their relationship to the surrounding environment. Many objects in an image can be distinguished solely by their textures without any other information. There is no universal definition of texture. Texture may consist of some basic primitives, and may also describe the structural arrangement of a region and the relationship of the surrounding regions [5]. In our approach we have used the texture features using steerable filters.

Shape feature has been extensively used for retrieval systems [10, 11]. Image retrieval based on visually significant points [12, 13] is reported in literature. In [14], local color and texture features are computed on a window of regular geometrical shape surrounding the corner points. General purpose corner detectors [15] are also used for this purpose. In [16], fuzzy features are used to capture the shape information. Shape signatures are computed from blurred images and global invariant moments are computed as shape features.

In this we propose a new and efficient technique to retrieve the images based on Dominant Color, texture and Pseudo Zernike moments The rest of this paper is organized as follows the section 2 outlines proposed method. The section 3 deals with experimental setup.

The section 4 presents results. The section 5 presents conclusions.

2. PROPOSED METHOD

Only simple features of image information can not get comprehensive description of image content. We consider the dominant color, texture and shape features combining not only be able to express more image information, but also to describe image from the different aspects for more detailed information in order to obtain better search results. The proposed method is based on dominant color, texture and shape features of image

Retrieval Algorithm

Step1: Step1: Uniformly divide each image in the database and the target image into 8-coarse partitions as shown in Fig.1.

Step2: For each partition, the centroid of each partition is selected as its dominant color.

Step3: Obtain texture features by using steerable filter.

Step4: Obtain shape feature by using pseudo Zernike moments.

Step5: Construct a combined feature vector for color, texture and shape.

Step6: Find the distance between feature vector of query image and the feature vector of target images using weighted and normalized Euclidean distance.

Step7: Sort the Euclidean distances.

Step8: Retrieve first 20 most similar images with minimum distance.

2.1 Dominant Color feature Representation

In general, color is one of the most dominant and distinguishable low-level visual features in describing image. Many CBIR systems employ color to retrieve images, such as QBIC system and Visual SEEK. In theory, it will lead to minimum error by extracting color feature for retrieval using real color image directly, but the problem is that the computation cost and storage required will expand rapidly. So it goes against practical application. In fact, for a given color image, the number of actual colors only occupies a small proportion of the total number of colors in the whole color space, and further observation shows that some dominant colors cover a majority of pixels. Consequently, it won't influence the understanding of image content though reducing the quality of image if we use these dominant colors to represent image. DCD contains two main components: representative colors and the percentage of each color. DCD can provide an effective, compact, and intuitive salient color representation, and describe the color distribution in an image or a region of interesting. But, for the DCD in MPEG-7, the representative colors depend on the color distribution, and the greater part of representative colors will be located in the higher color distribution range with smaller color distance.. DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution. We will adopt a new and efficient dominant color extraction scheme to address the above problems [6, 7].

2.2 Extraction of Dominant color of an image

The selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, the RGB color space is used. Firstly, the RGB color space is uniformly divided into 8 coarse partitions, as shown in Fig. 1. If there are several colors located on the same partitioned block, they are assumed to be similar.

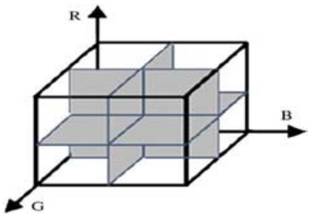


Fig.1. The Division of RGB color space

After the above coarse partition, the centroid of each partition is selected as its quantized color. Let X = (X^R, X^G, X^B) represent color components of a pixel with color components Red, Green, and Blue, and C_i be the quantized color for partition i. The average value of color distribution for each partition center can be calculated by

$$\bar{x}_i = \frac{\sum_{x \in C_i} x}{\sum_{x \in C_i} 1}$$

After the average values are obtained, each quantized color can be obtained by using below formula

$$C_i = \left(\bar{X}_i^R, \bar{X}_i^G, \bar{X}_i^B\right)(1 \le i \le 8)$$

In this way the Dominant color of an image will be obtained. We check each survived color, if its percentage is less than threshold T_m, it will be merged into the nearest color. In our paper, we set the $T_d$as 25 and $T_m$as 6%. As a result, we obtain a set of dominant colors, and the final number of dominant colors is constrained to 4–5 on average.

2.3 Extraction of Texture of an image

Most natural surfaces exhibit texture, which is an important low level visual feature. Texture recognition will therefore be a natural part of many computer vision systems. In this paper, we propose a texture representation for image retrieval based on steerable filters.

Steerable filter is a class of filters in which a filter of arbitrary orientation is synthesized as a linear combination of a set of “basis filters” [17]. The edge located at different orientations in an image can be detected by splitting the image into orientation sub-bands obtained by the basis filters having these orientations. It allows one to adaptively “steer”a filter to any orientation, and to determine analytically the filter output as a function of orientation.

The steering constraint is

$$F_\theta(m,n) = \sum_{k=1}^{N} b_k(\theta) A_k(m,n)$$

Where $b_k(\theta)$ is the interpolation function based on the arbitrary orientation θ which controls the filter orientations. And the basis filters $A_k(m,n)$ are rotated version of impulse response at θ.

The structure of steerable filter is illustrated in Fig.2.

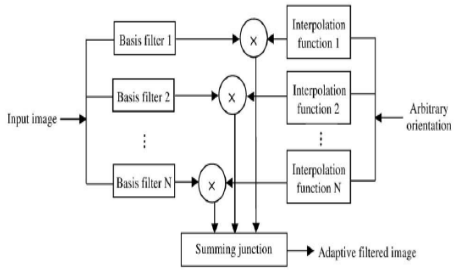


Fig.2. Structure of steerable filter

In general, we usually adopt 4–6 oriented sub-bands to extract image texture information when applying steerable filter to analyze digital images. In this paper, we extract the texture feature from four oriented sub-bands for the filtered image in different orientations. we use the mean μ and standard deviation σ of the energy distribution of the filtered images $S_i(x,y)$(i = 1,2,3,4 represent horizontal orientation, rotation of 45°,vertical orientation, and rotation of −45°,respectively), by considering the presence of homogeneous regions in texture images. Given an image I(x,y), its steerable filter decomposition is defined as:

$$S_i(x,y) = \sum_{x_1}\sum_{y_1} I\left(x_1, y_1\right) B_i(x - x_1, y - y_1)$$

Where B_i denotes the directional bandpass filters at orientation i=1,2,3,4. The energy distribution $E_i(x,y)$ of the filtered images $S_i(x,y)$ is defined as

$$E_i = \sum_x \sum_y |S_i(x,y)|$$

The mean (μ_i) and standard deviation (σ_i) are found as follows:

$$\mu_i = \frac{1}{MN} E_i(x,y)$$

$$\sigma_i = \sqrt{\frac{1}{MN}\sum_x \sum_y (S_i(x,y) - \mu_i)^2}$$

where M, and N is the width and height of image I(x,y) respectively. So, the corresponding texture feature vector of the original image I(x,y) should be defined as:

$$F_T = (\mu_1, \sigma_1, \mu_2, \sigma_2, \mu_3, \sigma_3, \mu_4, \sigma_4)$$

2.4 Shape feature representation

Shape is known to play an important role in human recognition and perception. Object shape features provide a powerful clue to object identity. Image shape descriptors, as used in existing CBIR systems, can be broadly categorized into two groups, namely, contour- and region-based descriptors [2]. Contour-based shape descriptors use the boundary information of object shapes. Early work implemented object shapes via Fourier descriptors [1,2]. Exploiting only information from the shape boundaries, contour-based shape descriptors thereby ignore potentially important information in the shape interior. In region-based methods, shape descriptors utilize information from both boundaries and interior regions of the shape. As the most commonly used approaches for region-based shape descriptors, moments and function of moments have been utilized as pattern features in a number of applications [1,2].

2.5 Pseudo-zernike moments

Pseudo-Zernike moments consist of a set of orthogonal and complex number moments [18]which have some very important properties. First, the pseudo- Zernike moments' magnitudes are invariant under image rotation. Second, pseudo-zernike moments have multilevel representation capabilities. Third, pseudo-zernike moments are less sensitive to image noise. In this paper, the pseudo-Zernike moments of an image are used for shape descriptor, which have better features representation capabilities and are more robust to noise than other moment representations.

Pseudo-Zernike moments consist of a set of complex polynomials [24] that form a complete orthogonal set over the interior of the unit circle, $x^2+y^2 \le 1$. If the set of these polynomials is denoted by $\{V_{nm}(x,y)\}$, then the form of these polynomials is as follows

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)\exp(jm\theta)$$

Where $\rho = \sqrt{x^2+y^2}$, $\theta = \tan^{-1}(y/x)$. Here n is a non-negative integer, m is restricted to be $|m| \le n$. Like any other orthogonal and complete basis, the pseudo-Zernike polynomial can be used to decompose an analog image function f(x,y):

$$f(x,y) = \sum_{n=0}^{\infty} \sum_{\{m:|m|\le n\}} A_{nm} V_{nm}(x,y)$$

Where where $A_{nm}$is the pseudo-Zernike moments of order n with repetition m. given a digital image of size M x N, its pseudo-zernike moments are computed as

$$\hat{A}_{nm} = \frac{n+1}{\pi} \sum_{i=1}^{M} \sum_{j=1}^{N} h_{nm}(x_i, y_j) f(x_i, y_j)$$

Where the value of I and j are taken such that $x_i^2 + y_j^2 \le 1$. In this research, we adopt the following formulas which are used to compute pseudo-zernike moments of images:

$$\hat{A}_{nm} = \frac{n+1}{\pi} \sum_{i=1}^{M} \sum_{j=1}^{N} V^*_{nm}(x_i, y_j) f(x_i, y_j) \Delta x \Delta y$$

Pseudo-Zernike moments are not scale or translation invariant. In our work, the scaling and translation invariance are firstly obtained by normalizing the image, and then $|\hat{A}_{nm}|$ is selected as shape feature set for image retrieval.

The pseudo-zernike moments based shape feature vector is given by

$$F_S = \left(|\hat{A}_{00}|, |\hat{A}_{10}|, |\hat{A}_{11}|, |\hat{A}_{20}|, \cdots, |\hat{A}|_{54}, |\hat{A}|_{55}\right)$$

3. EXPERIMENTAL SETUP

After the color, texture and shape feature vectors are extracted, the retrieval system combines these feature vectors, calculates the similarity between the combined feature vector of the query image and that of each target image in an image DB, and retrieves a given number of the most similar target images.

3.1 Color feature similarity measure

The color feature of query image Q is $F_CQ = \{(C_i,P_i), i = 1, ..., N_Q\}$ and the color feature of each target image I in an image DB is $F_CI = \{(C_i,P_i), i = 1, ..., N_I\}$, we define a new color feature similarity as follows.

$$S_{Color}(Q,I) = \sum_{i=1}^{N_Q} \sum_{j=1}^{N_I} d_{ij} S_{ij}$$

Where N_Q and N_I denote the number of the dominant colors of the query image Q and the target image I respectively: denotes the Euclidean distance between the dominant color C_i^Q of query image Q and the dominant color C_i^I of the target image I.

3.2 Texture feature similarity measure

The texture feature similarity is given by

$$S_{Texture}(Q,I) = \left(\sum_{i=1}^{4} \left[\left(\mu_i^Q - \mu_i^I\right)^2 + \left(\sigma_i^Q - \sigma_i^I\right)^2 \right] \right)^{1/2}$$

Where μ_i^Q and σ_i^Q denotes the texture feature of query image Q, μ_i^I and σ_i^I denote the texture feature of the target image I.

3.3 Shape feature similarity measure

We give the shape feature similarity as follows:

$$S_{Shape}(Q,I) = \left(\sum_{i=0}^{5} \sum_{j}^{i} \left(|\hat{A}_{ij}^Q| - |\hat{A}_{ij}^I| \right)^2 \right)^{1/2}$$

where $|\hat{A}_{ij}^Q|$ and $|\hat{A}ij^I|$ denote the shape feature of the query image Q and the target image I respectively.

So the distance used for computing the similarity between the query feature vector and the target feature vector is given as

$$S(I,Q) = w_C S_{Color}(Q,I) + w_T S_{Texture}(Q,I) + w_S S_{Shape}(Q,I) \quad w_C + w_T + w_S = 1$$

where W_C, W_T, W_S is the weight of the color, texture, and shape features respectively. So finally we define the similarity as:

$$S'(Q,I) = \frac{S(I,Q) + S(Q,I)}{2}$$

When retrieving images, we firstly calculate the similarity between the query image and each target image in the image DB, and then sort the retrieval results according to the similarity value.

4. EXPERIMENTAL RESULTS

The experiments were carried out as explained in sections 2 and 3. The results are benchmarked with some of the existing systems using the same database [15]. The quantitative measure is given below

$$p(i) = \frac{1}{100} \sum_{1 \le j \le 1000,\, r(i,j) \le 100,\, ID(j) = ID(i)} 1$$

Where *p(i)* is precision of query image I, ID(i) and ID(j) are category ID of image I and j respectively, which are in the range of 1 to 10. the r(i, j) is the rank of image j. This value is percentile of images belonging to the category of image i , in the first 100 retrieved images.

The average precision *pt* for category ***t***(1≤t≤10) is given by

$$p_t = \frac{1}{100} \sum_{1 \le i \le 1000,\, ID(i) = t} p(i)$$

The comparison of proposed method with other retrieval systems is presented in the Table 1. These retrieval systems are based dominant color, combination of dominant color, GLCM texture.

Our proposed retrieval system is better than these systems in all categories of the database.

Table 1. Comparison of average precision obtained by proposed method with other retrieval techniques.

Class	Dominant color	Dominant color and GLCM Texture	Proposed method
Africa	0.21	0.27	0.467
Beaches	0.35	0.36	0.417
Buildings	0.5	0.25	0.436
Buses	0.22	0.52	0.435
Dinosaurs	0.29	0.91	0.988
Elephants	0.24	0.38	0.473
Flowers	0.73	0.89	0.683
Horses	0.25	0.47	0.747
Mountains	0.18	0.3	0.403
Food	0.29	0.32	0.41
Average	0.326	0.467	0.545

The experiments were carried out on a Core i3, 2.4 GHz processor with 4GB RAM using MATLAB. Fig. 3 shows the image retrieval results using Dominant color, texture and pseudo-zernike moments proposed method. The image at the top left- hand corner is the query image and the other 19 images are the retrieval results. The performance of a retrieval system can be measured in terms of its recall (or sensitivity) and precision (or specificity). Recall measures the ability of the system to retrieve all models that are relevant, while precision measures the ability of the system to retrieve only models that are relevant. We have tested the performance with a Corel image Gallery. Corel images have been widely used by the image processing and CBIR research communities.

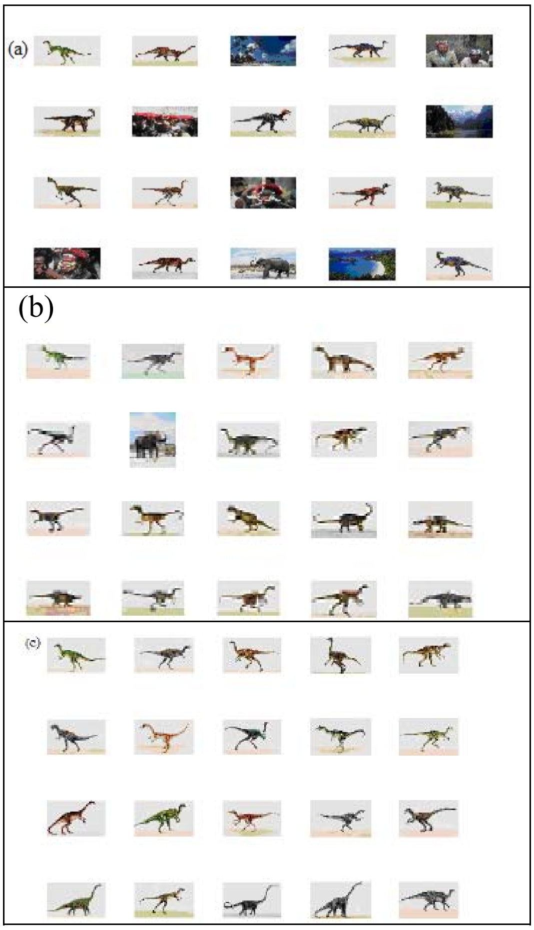
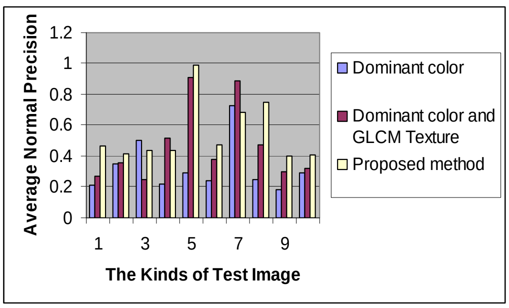


Fig.3 The image retrieval results (dinosaurs) using different techniques (a) retrieval based on Dominant color (b) retrieval based on Dominant color and GLCM texture (c) retrieval based on proposed method (Dominat color, texture and pseudo-zernike moments image).

The following graph showing the Comparison of average precision obtained by proposed method with other retrieval systems



6. CONCLUSION

In this paper, a CBIR method has been proposed which uses the combination of dominant color, texture and pseudo-zernike moments shape descriptor. The proposed method yielded higher average precision and average recall. In addition, the proposed method almost always showed performance gain of average retrieval time over the other methods. As further studies, the proposed retrieval method is to be evaluated for more various databases.

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