An Efficient Approach of Content Based Image Retrieval using Texture, Color and Shape Features of an Image

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Abstract: *retrieval of an image is an extra powerful and green for dealing with enormous photograph database. content based photograph retrieval (CBIR) is a one of the picture retrieval technique which makes use of consumer visible capabilities of an photograph together with color, form, and texture functions and so forth. it permits the quit user to offer a query photograph so one can retrieve the saved photos in database in keeping with their similarity to the question photograph. on this work, content based totally image retrieval is done by means of combining the two functions including color and texture. Color capabilities are extracted by way of using HSV histogram, color correlogram and color second values. Texture capabilities are extracted through segmentation based fractal texture analysis (SFTA). The accuracy of color histogram based totally matching can be accelerated by way of the use of shade coherence vector (CCV) for successive refinement. The velocity of shape based retrieval may be enhanced by way of considering approximate form in place of the exact form. The principle goal this work is classification of photo the use of SVM algorithm.*

Keywords— *Image Retrieval; Content based image retrieval; HSV color histogram; color correlogram; color moments; SVM Algorithm; Relative Standard Derivation; Fractal Texture features.*

I. INTRODUCTION

Digital images are used in a huge variety of programs such as geography, medical, structure; advertising, layout, military and albums. We've a few difficulties in looking and organizing the biggest amount of snap shots in databases. the retrieval of photos is divided into strategies, which can be textual content primarily based and content based totally picture retrieval. in CBIR device, it is normal to organization the photo functions in three major classes: color, texture and shape. Coloration is by way of some distance the maximum commonplace visible function utilized in cbir, ordinarily because of the simplicity of extracting color records from snap shots. a digital photograph on this context is a fixed of pixels. each pixel represents a shade. colorations may be represented the use of exclusive shade spaces

depending at the requirements utilized by the researcher or depending on the software along with crimson-green-blue (rgb), hue-saturation-cost (hsv), yiq or yuv and so on. this paper additionally affords an method to retrieve pictures thru an automated segmentation approach. this lets in us to get approximate facts approximately the shape of the regions in the pix. form description or representation is an crucial issue each in object recognition and category. The segmentation is accomplished thru a stochastic algorithm the usage of the brightness of the regions underneath analysis.

2. RELATED WORK

Image retrieval in CBIR based totally at the visible functions along with texture, color and form. Texture analysis, is generally a very time-eating technique. Studies in texture analysis are very crucial, due to the fact this is used to improve the discriminatory capacity of the extracted image capabilities. so that it will as it should be capture the textural traits of an photo, texture evaluation algorithms use filter out banks or co-occurrence grey level matrices (GLCM) have to bear in mind multiple orientations and scales. the SFTA works a lot faster in terms of characteristic extraction time, when in comparison to Gabor and heraldic techniques.

2.1 Texture feature representation

The primary goal of the SFTA is to extract texture feature in an photograph which ends in the formation of a function vector. haussdorf fractal size approach is used in SFTA. To find choicest threshold otsu set of rules is used. for real world photographs it is cautioned in that the otsu approach offers a better selection of thresholds. it is said that otsu approach the picture is believed to be composed of only two areas: item and heritage, and the exceptional threshold is the only that maximize the between-classes variance of the two regions. The otsu method is likewise extendable to multilevel thresholding. Extraction of texture features may additionally deliver time consuming method. Solve this time eating problem by using enforcing sfta algorithm

Figure 2: Images are having different color in same class

Texture features is required here for the below reasons such as

1. Each class has set of images these color is independent but these texture information is dependent from one to one is shown in Figure 2.
2. Images are having same color with different texture is shown in Figure 3.

Figure 3: Images are having same color in different classes

An enhanced input RGB image is converted into Grayscale image I. SFTA texture method applied multilevel Otsu thresholding on Grayscale image I for decomposing the segmented image in several parts. This is achieved by selecting pairs of thresholds (lower threshold t_l and upper threshold t_u) using Two Threshold Binary Decomposition (TTBD). SFTA feature vector correlate with the number of binary images acquired in TTBD phase. If the standard total number of extracted threshold is 4, we acquire 8 different binary images. Each binary image has three feature vectors that depict the *boundaries fractal dimension*. The purpose of fractal measurement is used to narrate the boundaries complexity and segmented image structures. An extracted vector features are fractal dimension, mean gray level, and size of area image. SFTA algorithm has been explained given below in figure 4.
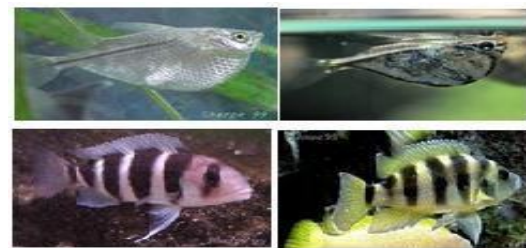
Require: Grayscale image I and number of threshold n_t.

Ensure: Feature vector V_{SFTA}.

1: T ← MultiLevelOtsu (I, n_t)
2: T_A\{\{t_i, t_i+1\}: t_i, t_i+1∈ T, i∈ [1..|T|-1]\}
3: T_B\{\{t_i, nl\}: t_i∈ T, i∈ [1...

4: i0
5: for \{\{t_l, t_u\}: \{t_l, t_u\} ∈ TA ∪ TB\} do
   Ib **TwoThresholdSegmentation** (*I* ,*tl*,*tu*)
6:      Δ(x, y) **FindBorders** (I_b)
7:      V_{SFTA}[i] **BoxCounting** (Δ)
8:      V_{SFTA}[i+1] **MeanGrayLevel**(*I*, I_b)
9:      V_{SFTA}[i+2] PixelCount(I_b)
10:       i i+3
11: **end for**
12: **return** *VSFTA*

Figure 4: SFTA Algorithm

2.2   Color feature representation

It has been reported that the HSV color space gives the best color histogram feature, among the different color spaces. For the initial process of histogram matching, we use the HSV color space. The HSV color space is preferred for

Manipulation of hue and saturation since it yields a greater dynamic range of saturation.
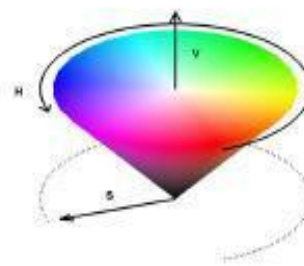

Figure 5: HSV Cone

Figure 5 illustrates the single hex cone HSV color model. The top of the hex cone corresponds to V = 1, or the maximum intensity of colors. The point at the base of the hex cone is black and here V = 0. Complementary colors are 180° opposite one another as measured by H, the angle around the vertical axis V, with red at 0°. The value of S is a ratio, ranging from 0 on the center line vertical axis V to 1 on the sides of the hex cone. Any value of S between 0 and

1 may be associated with the point V = 0. The point S = 0, V = 1 is white. Intermediate values of V for S = 0 are the grays. Note that when S = 0, the value of H is irrelevant. From an artist's viewpoint, any color with V = 1, S = 1 is a pure pigment whose color is defined by H. Adding white and black corresponds to decreasing S without changing V and corresponds to decreasing V without changing S respectively. Tones are created by decreasing both S and V.

Coloration coherence vector is double color histograms which consist of coherent vector and incoherent vector. we define a coloration's coherence as the degree to which pixels of that color are participants of big further-colored regions. we talk to those full-size regions as coherent areas, and take a look at that they're of good sized significance in characterizing Images. Our coherence classifies pixels as both coherent and incoherent. Coherent pixels are part of a few tremendous contiguous locations, at the same time as incoherent pixels are not. a coloration coherence vector represents this category for each coloration inside the image. this notion of coherence allows us to make exceptional differences that cannot be made with simple color histograms.

the preliminary level in computing a CCV [13] is just like the computation of a shade histogram. First blur the image barely via replacing pixel values with the average fee in a small nearby community consisting of the eight adjacent pixels. Outline the coloration area with simplest n wonderful hues inside the photograph. The following step is to categories the pixels within a given color bucket as both coherent and incoherent. A coherent pixel is part of a huge group of pixels of the equal color, whilst an incoherent pixel isn't. After phrases determine the pixel organizations via computing related components. When that is entire, each pixel will belong to precisely one connected aspect. Classify pixels as both coherent and incoherent depending on the size of its connected issue. a pixel is coherent if the size of its connected component exceeds a set value τ; otherwise, the pixel is incoherent.**2.3   HSV color Histogram**

Color feature is one of the most important things to access the image. The color of an image is represented from the famous color spaces like RGB, XYZ, YIQ, L*a*b, U*V*W, YUV and HSV [1]. HSV color space gives the best color histogram feature, among the different color spaces [1]. HSV color space is represented by three components such as Hue (H), Saturation(S), and Value (V).

$$H = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \right\}$$

$$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)]$$

$$V = \frac{1}{3}(R+G+B)$$

Where i denotes the color bin in the color histogram. N denotes the total number of bins used in color histogram and H[i] denotes the total number of pixel of color I in an image. Generally, every pixel in an image will be in favor to color histogram bin. So that, in the image color histogram, each bin value gives the number of pixels those have the same corresponding color.

Algorithm

The computation of HSV color histogram has been done by using following steps as,

Step1: Convert RGB color image into HSV color space.

Step 2: Color quantization is carried out using color histogram by assigning 8 levels to hue, 2 levels to saturation and 2 levels to value for give a quantized HSV space with 8x2x2=32 histogram bins.

Step3: The normalized histogram is obtained by dividing with the total number of pixels.

2.4   Shape feature retrieval

Shape is an important visual feature and it is one of the basic features used to describe image content. However, shape representation and description is a difficult task. This is because when a 3-D real world object is projected onto a 2-D image plane, one dimension of object information is lost. As a result, the shape extracted from the image only partially represents the projected object. To make the problem even more complex, shape is often corrupted with noise, defects, arbitrary distortion and occlusion. Further it is not known what is important in shape. Current approaches have both positive and negative attributes; computer graphics or mathematics use effective shape representation which is unusable in shape recognition and vice versa. In spite of this, it is possible to find features common to most shape description approaches.

Basically, shape-based image retrieval consists of measuring the similarity between shapes represented by their features. Some simple geometric features can be used to describe shapes. Usually, the simple geometric features can only discriminate shapes with

large differences; therefore, they are usually used as filters to eliminate false hits or combined with other shape descriptors to discriminate shapes. They are not suitable to stand alone shape descriptors. A shape can be described by different aspects [15]. These shape parameters are Mass, Center of gravity(Centroid) , Mean, Variance, Dispersion, Axis of least inertia, Digital bending energy, Eccentricity, Circularity ratio, Elliptic variance, Rectangularity, Convexity, Solidity, Euler number, Profiles, Hole area ratio, etc. Some of these are described as follows.

Mass is the no. of pixels contained in one class. It is given as

$$mass = \sum_{xy} h(x, y)$$

where

$$h = \begin{cases} 1 & if \ s(x, y) \in c \\ 0 & if \ s(x, y) \notin c \end{cases}$$

Centroid is also called as the center of mass; h is a mask of cluster c over image S(x, y).

Centroid are defined as:

$$x_c = \frac{\sum_{xy} x * h(x, y)}{mass}$$

$$y_c = \frac{\sum_{xy} y * h(x, y)}{mass}$$

The mean and variance features of the class c are computed over the original image I considering the resulting segmentation S, and they are respectively denoted by μ_c and $\sigma^2_{c..}$

Dispersion is the sum of the distances of each region of a class from the class Centroid. The distance is calculated by Euclidean distance formula. The dispersion can be given as

$$Disp = \sum dist (O_c , O_{i,c})$$

Where, dist $(O_c, O_{i,c})$ is the Euclidean distance

O_c= Centroid of the class c

$O_{i,c}$= Centroid of region I of class c

Algorithm for shape Retrieval
Step1: read the image
Step2: convert it from RGB to grayscale
Step3: determine the range and number of classes.
Step4: calculate the number of pixels i.e. mass belonging to each class.

Step5: calculate the Centroid and dispersion for each class.
Step6: compare Centroid of each class of query image with the Centroid of each class from database image and extract out that class.
Step7: compare that class's mass and dispersion with respective class.
Step8: increase the count if it satisfies certain threshold.
Step9: consider second class and repeat steps 6-8 till all classes get over.
Step10: take another image from the database and repeat the comparison.

3. EXPERIMENTAL RESULTS

In proposed approaches, the image database contains 400 images, in database images, 100 images are used for testing and remaining 300 images are used for training. An input query image and total number of returned images are desired by the user. Features for query image are extracted by using the co-ordinates (x_c, y_c) of the STFBA and HSV color models.

Both color and shape retrieval algorithms are implemented in MATLAB with the database of 570 images. All the images are stored in JPEG format with size 384×256 or 256×384. There are six different categories; which includes 100 horse, 100 rose, 100 dinosaur, 100 bus, 100 elephants and 70 bikes. To evaluate the performance of the image retrieval algorithm we use the two most well known parameters; precision and recall.

$$recall = \frac{relevant \quad retrieved}{all \quad relevant}$$

$$precision = \frac{relevant \quad retrieved}{all \quad retrieved}$$

The machine is accomplished with 10 snap shots from every of the six categories and calculated the average precision and common bear in mind parameters for they all. The effects received the use of shape and color based for unique class of pix is shown in table-i. Retrieval results images with query photograph of form and shade primarily based are shown in determine 3a-b and 4a-b respectively. The mixture of color and shape for unique forms of pix is given in table-ii and corresponding result snap shots are proven in determine 5a-b. in both tables common accuracy of the proposed method is about extra than 70 % which is much greater than the histogram based totally approach.

4. CONCLUSION

CBIR is a process to go looking the applicable picture in database photograph when new or question photo is given through the user. on this paper, we use mixed texture, color and shape capabilities. to classify the question photo function vector with schooling samples the use of svm algorithm and preferred deviation is used here for similarity measurement. Overall performance dimension is calculated through the usage of precision and do not forget operations. the purpose of this paper become to enhance the accuracy (precision) of a CBIR software via permitting the gadget to retrieve greater photographs just like the supply photo. the brand new algorithms beneath research and also the recently published ones appear to be extraordinarily invasive on the picture. additionally each new algorithm is always seen to have positive regions in which it works high-quality and negative. the proposed methodology had extended the common precision from a mean of 44% to a mean of 72%.

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