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A Modified Shape Feature Extraction Technique for Image Retrieval

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Abstract *– Semantic based Image retrieval is an emerging research area and is currently the mainstay in variety of applications or domains. In recent times, there exists a lot of gap between the high level semantics and low level features. The process of Features extraction is Application-specific or options are limited. In this paper, we propose a new Modified Shape Descriptor (MSD) feature extraction technique which is used as descriptive feature to discriminate Objects in an image database. In Object recognition after initial Pre-processing, feature extraction is the next crucial step which determines the efficiency of the technique or method. In our approach, a test image is taken from the database, which is then divided into 8x8 Blocks each; shape structure is detected using edge detection technique with Threshold method to generate the shape feature vector. Then, texton-based texture, color features are extracted using the existing Multi-texton Histogram (MTH) method. To form the final discriminating feature vector for that image in total, three features are extracted namely shape, texture and color for that particular image to form a discriminating feature vector which this then stored in a feature library. When a query image is given Euclidean distance between the query image and the test images feature values available in the feature library are computed. Based on the similarity characteristics top-k images are retrieved. Our proposed method gives better results when compared with other existing techniques.***

Index Terms *– Content-based image retrieval, Pattern Recognition, Image Retrieval, Multi-texton Histogram, Shape Descriptor.*

I. INTRODUCTION

The Now days, the database of stored images is growing at an enormous rate and the image retrieval process is a time consuming task even though processing capabilities have increased at an unbelievable speed with multi-core technologies. In computer vision and pattern recognition, new methodologies are evolving in the feature extraction stage, which yield better results than the old traditional methods. These features are extracted without segmenting an image is the active topic and this area is an active area in the image retrieval methodology.

Three categories of image retrieval methods. a) Text-based b) content-based c) semantic-based methods. Image retrieval is an important topic in the field of pattern recognition and artificial intelligence. An image retrieval system is a computer system for browsing, searching and retrieving images from a very large database of digital images or web.

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Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools.

A paradigm shift in the goals of the next-generation CBIR researchers is necessary of which Image retrieval in the coming years is major research area. The need of the hour is to establish how this technology can reach out to the common man in the way text retrieval techniques have. Methods for visual similarity, or even semantic similarity (if ever perfected), will remain techniques for building systems. What the average end-user can hope to gain from using such a system is a different question altogether. For some applications, visual similarity may in fact be more critical than semantic. For others, visual similarity may have little significance. Under what scenarios a typical user feels the need for a CBIR system, what the user sets out to achieve with the system, and how she expects the system to aid in this process are some key questions that need to be answered in order to produce a successful system design. Unfortunately, user studies of this nature have been scarce so far.

II. LITERATURE REVIEW

The text-based approach can be traced back to 1970s [4]. Since the images need to be manually annotated by text descriptors, it requires much human labour for annotation, and the annotation accuracy is subject to human perception. In early 1990s, researchers had built many content- based image retrieval systems, such as QIBC, MARS, Virage, Photobook, FIDS, Web Seek, Netra, Cortina [5], Visual SEEK [6] and SIMPLIcity [7]. Since the indexes are directly derived from the image content, it requires no semantic labeling [8].In general, the research of CBIR techniques mainly focuses on two aspects: part-based object retrieval [16–19] and low-level visual feature-based image retrieval [20–23].One problem with all current approaches is the reliance on visual similarity for judging semantic similarity, which may be problematic due to the semantic gap [Smeulders et al. 2000] between low-level content and higher-level concepts. Image tile-based approach using Histogram proposed a method within a multiresolution multi-grid framework [P. S.

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Hire math and Jagadeesh Pujari] Guang-Hai Liu ,LeiZhang , Ying-KunHou,, Zuo-Yong Li , Jing-YuYang proposed multi texton histogram technique five textons by identifying textures and storing the texture and color feature which better than GLCM and TCM.

Later he proposed microstructures of identifying the edge orientation The Modified Shape Description (MSD are defined based on shape and edge orientation similarity, and the MSD is built based on the underlying colors in micro textures with similar edge orientation. With micro-structures serving as a bridge, the MSD extracts features by simulating human early visual processing and it effectively integrates color, texture, and shape and color layout information as a whole for image retrieval. Specifically, it has only 82 vectors for full color images,

A new feature extractor and descriptor, namely multi-texton histogram (MTH), for image retrieval. MTH can be viewed as an improved version of TCM. It is specially designed for natural image analysis and can achieve higher retrieval precision than that of EOAC [27] and TCM [26]. It integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram, and can represent the spatial correlation of color and texture orientation. Lowe [28] has suggested a very effective algorithm, called scale-invariant feature transform (SIFT), in computer vision to detect and describe local features in images. It has been widely used in object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, etc.; Banerjee et al. [29] implemented edge-based features for CBIR. The algorithm is computationally attractive as it computes different features with limited number of selected pixels. The TCM is proposed in [26] can describe the spatial correlation of textons for image retrieval. It has the discrimination power of color, texture and shape features

Luo et al. [30] developed a new algorithm called color edge co-occurrence histogram (CECH), which is based on a particular type of spatial- color joint histogram. This algorithm employs perceptual color naming to handle color variation, and pre-screening to limit the search scope (i.e. size and location) of the object.

III. METHODOLOGY

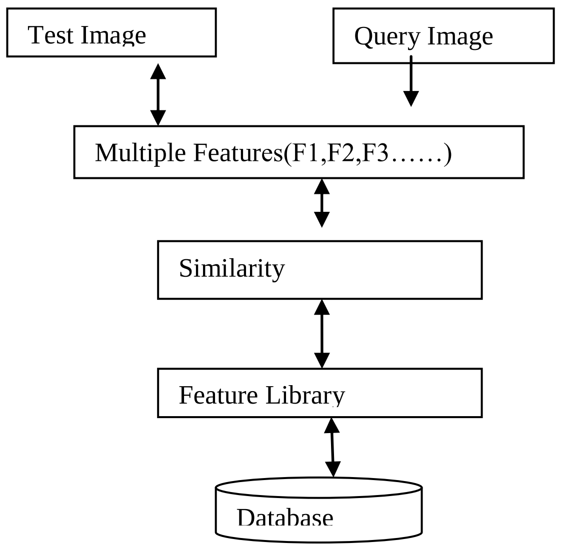

FIGURE: 1. ARCHITECTURE FOR MULTI-FEATURES EXTRACTION IN IMAGE RETRIEVAL.

Among the statistical approaches autocorrelation functions, texture edgeness, structural elements, spatial moments, spatial gray level co-occurrence probabilities, gray level run-length and autoregressive models are commonly used. Here spatial gray level and Texture edgeness approach is used.

Shape Feature: Various low-level visual features can be extracted from the images and stored as image indexes. The query is an image example that is indexed by its features, and the retrieved images are ranked with respect to their similarity to the query image. Image retrieval approach by introducing a new image feature detector and descriptor namely the Modified Shape Description (MSD) descriptor, it is very efficient for image retrieval. The proposed method is extensively tested on Corel datasets with 15,000 images.

a. Shape Feature Extraction:

The image is divided into 8x8 blocks and the two neighbouring blocks are considered simultaneously to determine the structure of the object. Here Edge Elements Extraction by Thresholding technique is used. Most of the edge detection techniques have two steps: (i) finding the rate of change of gray levels, i.e. the gradient of the image, and (ii) extracting the edge elements for which gradient exceeds a predefined threshold.

There are various methods for obtaining the gradient g’ (row, column). A binary image e (row, column) where pixels (row, column) contains a label ‘1’ if g (row, column) is an edge pixel or a label ‘0’ otherwise. So edge (row, column) may be obtained as

$$\text{Edge (row, column)}=\begin{cases}1 \ if\ g'(row,column) > t\ (row,column)\\ 0\ if\ g'(row,column) \leq t\ (row,column)\end{cases} \quad (1)$$

So, the image subset Se contains only edge elements of g (row, column). Here t (row, column) is the threshold at the pixel (r, c) and can be found out using the relation:

$$T\ (r, c) = \Phi th \quad (row, column, Qp(row, column)) \qquad (2)$$

Where Qp (row, column) denotes the set of features at pixel (row, column). Depending on the variables to determine t (row, column), the threshold is called global (or space-invariant), local (or space-variant) and adoptive. In brief, the edge extraction technique then reduces the selection of threshold that transforms Tth: g’ $(row,column) \rightarrow e(row,column)$

The operator Tth satisfies the following two conditions

1. Tth is not invertible since it is not one-one
2. Tth can take any value t (row, column) as threshold from the interval [min row, column {g’ (row, column)}, max row, column {g’ (row, column)}].

The Same Strategy is implemented using the Formula

$$Igy=0.2989*Ir+0.5870*Ig+0.1140*Ib \qquad (3)$$

The above equation is the Craig’s formula for converting RGB color image to gray scale image. The image I is converted to gray scale image gy and same procedure is used as in [12].

b. Texture Feature Extraction:

Texture Feature: Texture features corresponding to human visual perception are very useful for parameterization of appearance of object and its subsequent recognition [Tamura et al. (1978)]. Textural features can also be used to estimate orientation and depth of object surface [Horn (1986)]. In an intensity image this roughness is recorded as tonal or intensity variation over a neighbourhood. In most cases this variation appears as a repetitive arrangement of some basic pattern.

Basic patterns of large size are indicative of coarser texture. Similarly basic patterns of small size are indicative of finer texture.

c. Algorithm For Texture Feature Extraction:

Input: Image (I)
Output: Feature Vector (F)
Algorithm:
// binning

- Quant <- zeros(A,B);
- For i=1:1000
- Read the RGB image
- Divide the values with 255

Quant

0	0	0	0	0	...	...	0
0	0	0	0	0	..	0	0
0	0	0	0	0	0	0	....
0	0	0	0	0	0	0	0
0	0	0	0	...	..	....	...

A X B

//Dividing values into 72 bins //Rounding the value of r1

- Step1: p<-round(r1*(8));

if (p > 7)
p<-7; //Rounding the value of g1
• Step 2: q<-round (g1*(3)); if (q > 2)
q<-2; //Rounding the value of b1
• Step 3: r <- round(b1*(3/));
if(r > 2) r<-2;
• Step 4: Quant(i,j) <- 9 * p + 3 * q + r+1;
Quantization:

12	9	8	2	0	...	...	...
71	9	1	8	33	..	...	...
2	30	30	71	8	...	....	....
3	8	27	9	33	8	32	55

//Texture image extraction

- Consider the 3 x 3 matrix from quantized image.
- Compare the 1st value in matrix with rest of the values.
- If the value occurred at least 3 times, then that matrix is considered as texture.
- Else, consider the next value and repeat the process.
- Pvalues <- Quant(i:i+2,j:j+2);
- for q <- 1 to 9
- f=0;
- for r <- 1 to 9
- if(PValues(q) == PValues(r))
- f=f+1;
- end
- end

// texture image

- if(f >= 3)
- Final(i:i+2,j:j+2)=Quant(i:i+2,j:j+2);
- end.

Texture and Color Quantization:

Algorithm for Color Feature Extraction:

Color Feature: Any pixel in the image can be described by three components in a certain color space (for instance, red, green, and blue components in RGB space, or hue, saturation, and value in HSV space) or CLUT (Color Look Up Table) or Lab, a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. The HSV color space is selected during color feature extraction due to its ability for easy transformation from RGB to HSV and vice versa. Since HSV color space is natural and approximately perceptually uniform, the quantization of HSV can produce a collection of colors that is also compact and complete.

d. Algorithm for Color Feature Extraction:

Input: Image (I)
Output: Feature Vector (F)
Step 1: for I = 1 to 1000
Step 2: Read an RGB image I of size A x B
Step3: Divide each value with 255// normalization
//then values are reduced to 0-1
then divide the values into 10 bins
//construction of color feature vector
Step 4:
CF (Color (i,j) x 10) <- CF(Color(i,j) x 10) +1;
//Here count of pixel value is obtained and stored in CF array
Go to step1

e. **Retrieval Phase:** In the retrieval phase, the top 12 images are retrieved using KNN algorithm and performance results are computed.

IV. EXPERIMENTAL RESULTS:

The proposed approach is tested on a general purpose image database with 1000 images from COREL. The 1000 images are classified to 10 categories with 100 images each. Three images are randomly selected from each category (e.g., Elephant, Flower, Horse etc.). A retrieved image represents a correct match if and only if it belongs to the same category as the query image. The average precision is calculated through evaluating the top 20 returned results.

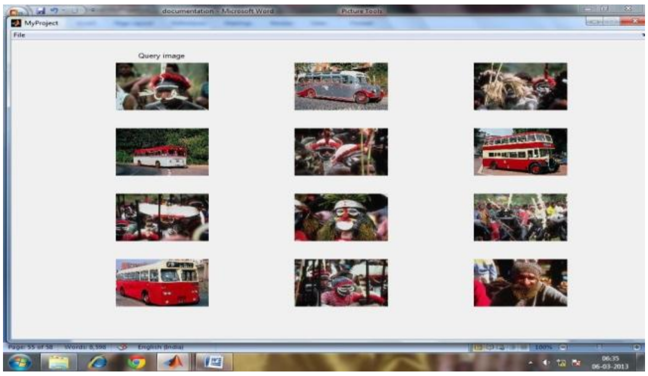

FIGURE: 2 COMPARISON GRAPH FOR RECALL FOR RETRIEVED IMAGES

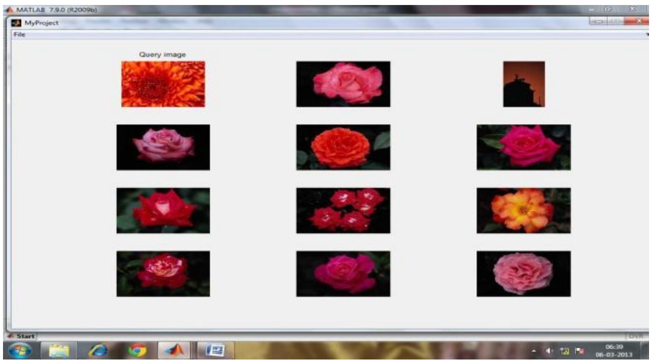

FIGURE 3: COMPARISON GRAPH FOR RECALL FOR RETRIEVED IMAGES

Performance Evaluation: The measures used for testing our algorithm are:

$$\text{Precision} = \frac{\text{Number of Retrieved Relevant}}{\text{Total Number of Retrieved}} \quad (4)$$

$$\text{Recall} = \frac{\text{Number of Retrieved Relevant}}{\text{Total Number of Possible Relevant}} \quad (5)$$

There is also a combined measure of recall and precision called van Rijsberger's measure. The formula is given below:

Eff= 1 – [(1 + b2) x Precision x Recall]/[b2 x Precision + Recall] (6)

Where Eff = van Rijsbergers measure,b = relative importance to the user of recall and precision, Using this measure, the system can be tested in the case of user pays more attention to either the recall or the precision. For example if b = 2, the user is twice as interested in recall as in precision. If b = 0, the user is not interested in recall so E = 1 – P. If b =0, the user is not interest in precision so E = 1 – R.

TABLE I. :COMPARISON OF MSD AND MTH WITH SHAPE FEATURES

S.No.	Category	Two feature(C=72,T=6) MSD			Three feature(Color Shape+Texture)		
		Precision	Recall	E	Precision	Recall	E
1	Elephant	0.75	0.09	0.160	1	0.223	0.370
2	Flower	1	0.1	0.178	1	0.204	0.340
3	Glass	0.833	0.12	0.214	0.98	0.206	0.341
4	Horse	0.833	0.1	0.178	1	0.222	0.370
5	Racecars	1	0.12	0.214	1	0.224	0.372
Average values		0.883	0.106	0.189	1	0.216	0.359

TABLE II. :COMPARISON OF THREE FEATURES

S.No	Category	CLUT		Two feature(C=72,T=6)			Three feature		
		Precision	Recall	Precision	Recall	E	Precision	Recall	E
1	Elephant	0.636	0.078	0.75	0.09	0.16	1	0.223	0.37
2	Flower	0.881	0.098	1	0.1	0.178	1	0.204	0.34
3	Glass	0.686	0.09	0.833	0.12	0.214	0.98	0.206	0.341
4	Horse	0.909	0.09	0.833	0.1	0.178	1	0.222	0.37
5	Racecars	0.08	0.12	1	0.12	0.214	1	0.224	0.372
Average values		0.808	0.388	0.883	0.106	0.189	0.996	0.216	0.359

TABLE III. :COMPARISON OF PRECISION FEATURES

Category	CLUT	Two feature(C=72,T=6) MSD	Three feature(color +Shape+Texture)
	Precision	Precision	Precision
Elephant	0.636	0.75	1
Flower	0.881	1	1
Glass	0.686	0.833	0.98
Horse	0.909	0.833	1
Racecars	0.08	1	1
Average values	0.808	0.883	0.996

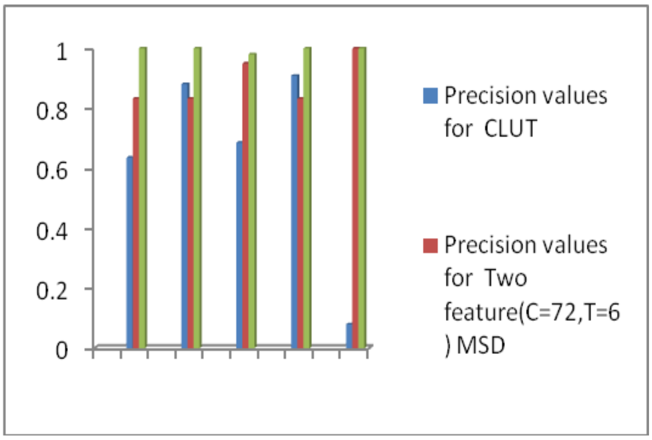

Figure 4: Comparison Graph for Precision values for Retrieved images

TABLE IV. COMPARISON OF RECALL FEATURES

Recall values for our Approach			
Category	CLUT	Two feature(C=72,T=6) MSD	Three feature(color +Shape+Texture)
Elephant	0.078	0.09	0.223
Flower	0.098	0.1	0.204
Glass	0.09	0.12	0.206
Horse	0.09	0.1	0.222
Racecars	0.12	0.12	0.224
Average values	0.388	0.106	0.216

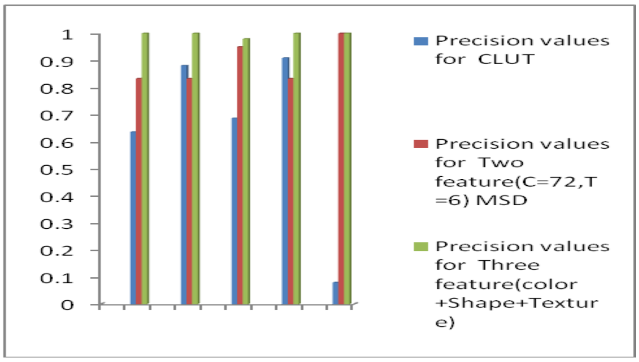

FIGURE 5: COMPARISON GRAPH FOR RECALL FOR RETRIEVED IMAGES

V. CONCLUSION

From the above Experimental results, it can be concluded that three features of an image shape, texture and color using CLUT(Color Look Up Table) provides a good discriminative power and also as Observed the precision and recall values improved over MTH or micro structure descriptor (MSD) methods. In the case of CLUT feature extraction when the database size increases the precision and recall values fall to a lower value because of Color Saturation Property So we can conclude that when the database increases in size relatively more the number of features could offer better precision and recall values.

So to achieve good image retrieval efficiency CLUT method is sufficient and necessary.

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