Journal of Theoretical and Applied Information Technology
15th December 2016. Vol.94. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# CONTENT BASED IMAGE RETRIEVAL USING MULTI REGION FEATURES

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## ABSTRACT

In this paper an integrated method that brings together the image features form color, shape and texture is proposed for content based image retrieval (CBIR). The present paper converts the color image in to HSV color space and derives color histograms. The V color space of the image is divided into non over-lapping region of size 9x9. Each region is sub divided into nine non overlapped sub-regions and a feature vector is derived on each sub region. These feature vectors of each sub region compresses the 9x9 multi-region into 3x3. To derive shape feature, textons are computed on each 2x2 grid and the image is converted into "multi region texton matrix" (MRTM). The gray level co-occurrence matrix (GLCM) features are derived on MRTM and the image retrieval is performed on five categories of Wang database images by combining color histograms and the GLCM features of MRTM. The proposed method of CBIR is compared with GLCM and texton co-occurrence method (TCM) and results indicates the efficacy of the proposed method.

**Key words:** *Texton, HSV, GLCM features, sub regions*

## 1. INTRODUCTION

The exhaustive, low priced and efficient technological growth of image capturing devices made the availability of huge digital image databases or libraries. These digital libraries are expanding drastically day by day. The handling and accessing of these data base images by human annotations is impractical and it has led to the automatic search mechanisms and it has created a demand for content based image retrieval (CBIR) models. The traditional text based image retrieval models, retrieves an image using the key words that are used to annotate the images in the database. This is replaced by the content based image retrieval (CBIR) methods. In CBIR an image is retrieved by the visual contents of the image i.e. color, shape, texture and spatial distribution of intensities (low level features) etc. These low level features can be local, region or global. A good literature survey was conducted on CBIR and is available in [1-4]. The color is one of the significant feature of the CBIR and one of the simple color based CBIR is the color histogram [5]. The retrieval performance of this generally limited due to its low discrimination power mainly on immense data. To improve this various color descriptors are proposed in the literature using neural networks [6], DCT- domain vector quantization [7], supervised learning [8] and color edge co-occurrence histograms [9].

The natural images are visualized by their rich content of texture mosaic and color. The texture descriptors are based on grey scale variation and they can also integrate with color component of image retrieval (IR). It is very difficult to give unique definition to texture and it is one of the significant and salient features for CBIR. The texture based image retrieval is reported in the literature based on the characteristics of images in different orientations [10, 11, 12, 13]. Extraction of texture features on wavelets [14], wavelet transform based texture features [14] and correlagrams [15] are also proposed for efficient IR. The performance of the correlograms [15] is further improved using genetic algorithms (GA) [16]. The integrated methods that combines the color histograms with texture features [17, 18] and correlograms with rotated wavelets [19] attained a good IR rate.

The region of interest (ROI), based methods are more effective in deriving the user specifications. The disadvantage of this type of retrieval is, user

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

has to specify the region of interest (ROI), and based on this the features are derived on this ROI and compared with the database images. The main drawback of ROI based methods [20, 21, 22, 23] is that it only compares the blocks having similar spatial locations. Therefore blocks that are not part of ROI are not retrieved. In the method [22] the ROI are not directly identified by the user. These methods [20 21, 24] fail to provide a detailed level of relative locations similarity measure and also they increase computational complexity. Recently various pattern based features i.e. local maximum edge patterns [25], local tetra patterns [26] and directional local extreme patterns [27] are proposed for natural images. The pattern based features are also proposed for retrieving of medical images i.e. directional binary wavelet pattern [28], local mesh patterns [29] and local ternary co-occurrence patterns [30]. The block based methods using LBP texture descriptors are proposed by Takalo et al. [31] for CBIR. The CBIR on region of interest (ROI) using center symmetric local binary pattern (CS-LBP) which is on extension of LBP [32] is also proposed [33]. The present paper divides the image into multi regions and evaluates the features on each sub region instead of from each pixel. This provides the detailed relative location similarity and reduces the computational complexity. The present method is not based on ROI.

The preset paper is organized in the following way. The brief review of image retrieval, literature survey are given in section one. The second section describes the proposed IR frame work by elaborating multi region, texton and the derivation of MRTM model. The third section describes the results and discussions. The fourth section gives the conclusions.

## 2. PROPOSED FRAME WORK

### 2.1. The HSV (Hue, Saturation, Value) Color Space:

HSV closely corresponds to the human visual perception of color. The HSV color space can be represented as a three-dimensional hexacone, where the central vertical axis represents intensity which takes a value between 0 and 255 (Shapiro & Stockman, 2001). Saturation is the depth or purity of color. For zero saturation, as we move higher along the intensity axis, we go from black to white through various shades of gray. On the other hand, for a given intensity and hue, if the saturation is changed from zero to one, the perceived color changes from a shade of gray to the most pure form of the color represented by its hue. When saturation is near zero, all pixels, even with different hues, look alike and as we increase the saturation towards one, they tend to get separated out and are visually perceived as the true colors represented by their hues. Thus, the effect of saturation may be considered as that of introducing visual shadows on the image for any given value of hue and intensity.

### 2.2 Multi Region model

This paper initially divides the image into non-overlapped multi regions. Again each multi region is sub divided into sub regions. The region based features of the present paper encodes rectangular regions' intensities by average operator, and the resulting features describe diverse micro and regional structures of images. Based on this multi region features, textons are derived to represent shape descriptors. The sequence of simple Haar-like rectangle features are used in face recognition applications. The Haar-like features encode differences in average intensities between two rectangular regions, and they can be calculated rapidly through integral image [34]. The disadvantage of this complete Haar-like feature set is they are large and contains a mass of redundant information. To resolve this boosting algorithm is introduced to select a small number of distinctive rectangle features. The use of cascade structure [34] and extended set of Haar features with improved boosting algorithm [35] further speeds up the computations. Many other Haar like features [36] are also proposed including rotated Haar-like features [37], census transform [38], sparse features [39], etc. However, these Haar-like rectangle features seem too simple, and the detector often contains thousands of rectangle features for considerable performance. The large number of selected features leads to high computation costs both in training and test phases. The present multi region (MR) IR model derives a single value for each rectangular sub region. The advantage of the present method is they reduce the overall dimension space of the derived features. A region consists of set of sub regions, where each sub region represents the local neighborhood and also the micro features. One of the main concerns of the region based methods is how effectively they derive region features that hold the significant local and micro features. The MR model captures the dominant features on a large scale rectangular structure and the sub region features are estimated on grey level values of a local neighborhood. The small feature

Journal of Theoretical and Applied Information Technology
15th December 2016. Vol.94. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

set of multi region can make the overall process to be simple.

The region based methods are more applicable when working with images of large size and especially in real time environment. The present paper considered a region of size 9x9 and sub divided into 3 non overlapped sub-regions of size 3x3 and a feature vector is derived on each sub region. The present paper derived a single feature from each sub region i.e. the average gray level value of that sub region. There are several advantage of this average operator on each sub-regions: (1) It is more robust than LBP; (2) it encodes not only microstructures but also macrostructures of image patterns, and hence provides a more complete image representation than the basic LBP operator; and (3) MR model with average operator can be computed very efficiently using integral images. That's why the MR feature extraction can also be very fast: 4) MR features are more discriminative than Haar-like features and original LBP features. The transformation process of multi-region of size 9x9 into a region of size 3x3 is shown in Fig. 1.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 90 | 70 | 15 | 40 | 75 | 65 | 78 | 90 | 15 |
| 65 | 10 | 75 | 25 | 90 | 19 | 25 | 45 | 55 |
| 15 | 28 | 10 | 19 | 25 | 12 | 13 | 18 | 15 |
| 65 | 25 | 34 | 15 | 26 | 38 | 48 | 46 | 75 |
| 15 | 26 | 35 | 48 | 98 | 10 | 23 | 54 | 65 |
| 87 | 75 | 48 | 15 | 29 | 63 | 14 | 18 | 96 |
| 42 | 13 | 16 | 18 | 26 | 29 | 27 | 26 | 38 |
| 80 | 76 | 94 | 89 | 17 | 69 | 92 | 64 | 99 |
| 75 | 48 | 66 | 52 | 71 | 13 | 98 | 68 | 92 |

*Fig. 1 (a) The sub region of multi region.*

| | | |
|---|---|---|
| 42 | 41 | 39 |
| 45 | 38 | 49 |
| 57 | 43 | 67 |

*1 (b) The transformed multi region image*

| | | |
|---|---|---|
| 4 | 5 | 5 |
| 4 | 3 | 4 |
| 4 | 4 | 4 |

*1(c ) quinary multi region image*

The present paper quantized the multi region neighborhood into quinary or five elements ranging from 1 to 5 i.e. {1, 2, 3, 4, 5} by using thresholds among the centre pixel (center sub region of MR) and the neighboring pixels (neighboring sub region of MR) based on the following equation 1.

$$R(i,j) = \begin{cases} 1 \; P(i,j) < w \; a & R(i,j) \le a \\ 2 \; P(i,j) < w \; a & R(i,j) > a \\ 3 & R(i,j) = w \\ 4 \; P(i,j) > \; w \; a & R(i,j) > \; b \\ 5 \; P(i,j) > \; w \; a & R(i,j) \le b \end{cases} \qquad (1)$$

Where w is the grey level value of the centre pixel of the multi region and R (i,j) is the neighboring pixel grey level value a and b are the two thresholds.

The aim of this quinary multi region texture element representation {1, 2, 3, 4,5} is to deal precisely and accurately with regions of natural images in the presence of dissimilar digitization process and noise. This quinary quantization on MR features also help to extract more local texture information from the pixels and also to represent textons efficiently.

### 2.3 Computation of Multi Region Texton Matrix (MRTM)

The fundamental element of an image or in a raster screen is the pixel. A pixel is represented by its two dimensional co-ordinate positions and with a value that represents its brightness. It is found that, it is very difficult to obtain satisfactory results, of image processing, by designing algorithms that process the images based on pixel levels. More over this processing system fail in representing the shape component totally. Therefore inorder to improve the image retrieval performance, the present paper presents the texton based methods. Julesz [40] proposed the concept of textron's twenty years back and they represent the relationship between pixels in the form of shape component, however defining a texton is still a difficult task. Texton is one of the popular and significant shape primitives and is defined with certain placement rule. The textons represents the emergent and dominant patterns on a local neighborhood. The previous step generates a multi-region based texture image with five quantized levels or patterns {1,2,3,4,5}. The present step evaluates the textons on this. The texton based models are widely used in texture classification [41, 42], image retrieval [43, 44], face recognition [45, 46], age classification [47], facial expression recognition [48, 49] and image segmentation [50]. The reason for this popularity is due to the maintenance of close relationship with image attributes and local distribution of textons.

The image features have a close relationship with textons and color diversification. The difference of textons may form various image

Journal of Theoretical and Applied Information Technology
15th December 2016. Vol.94. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

features. If the textons in image are small and the tonal differences between neighboring textons are large, a fine texture may result. If the textons are superior and holds quite a few pixels then it results a coarse texture and it also depends on scale [51]. In the image if the textons are large and contains a small number of texton categories, then a shape may result. There can be numerous types of textons in image. In this paper, we only classify and make use of seven special types of textons that holds all the four or two neighboring pixels on a 2 x 2 windows or grid. The pixels of the grid are denoted as V, W, X and Y. The seven types of textons are denoted as $S_1$, $S_2$, $S_3$, $S_4$, $S_5$, $S_6$ and $S_7$ (Fig.2).

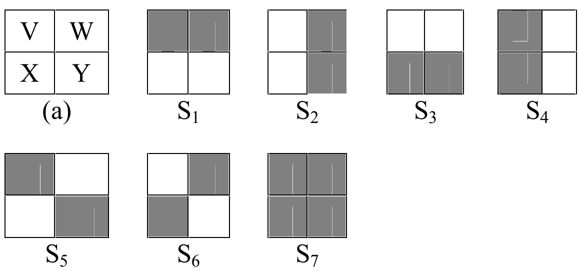
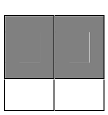



Fig.2: The texton patterns used in this paper (a) 2x2 window of the image $S_1$ to $S_7$ : different texton patterns.

| | | | | |
|---|---|---|---|---|
| 2 | 4 | 2 | 5 | 1 |
| 2 | 1 | 1 | 2 | 5 |
| 4 | 1 | 1 | 5 | 3 |
| 2 | 5 | 2 | 5 | 1 |
| 1 | 4 | 4 | 3 | 1 |

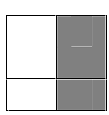
*a) Quantized Quinary Multi Region Image*

$S_1$



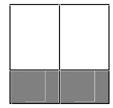
| | | | | |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 4 | 4 | 0 | 0 |

$S_2$



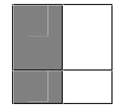
| | | | | |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 5 | 0 |
| 0 | 0 | 0 | 5 | 1 |
| 0 | 0 | 0 | 0 | 1 |

$S_3$



| | | | | |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 4 | 4 | 0 | 0 |

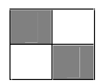
$S_4$



| | | | | |
|---|---|---|---|---|
| 2 | 0 | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 5 | 0 |
| 0 | 0 | 0 | 5 | 0 |
| 0 | 0 | 0 | 0 | 0 |

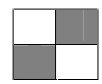
*a) Detection Of Textons $S_1$, $S_2$, $S_3$, $S_4$ On Quinary Multi Region Image Of (A)*

S5



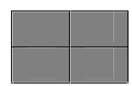
| | | | | |
|---|---|---|---|---|
| 0 | 0 | 2 | 5 | 0 |
| 0 | 1 | 0 | 2 | 5 |
| 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |

S6



| | | | | |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 5 |
| 0 | 1 | 0 | 5 | 0 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |

S7



| | | | | |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |

*(C) Computation Of Textons $S_5$, $S_6$ And $S_7$ On Quinary Multi Region Image Of (A)*

| | | | | |
|---|---|---|---|---|
| 2 | 0 | 2 | 5 | 0 |
| 2 | 1 | 1 | 2 | 5 |
| 0 | 1 | 1 | 5 | 0 |
| 0 | 0 | 0 | 5 | 1 |
| 0 | 4 | 4 | 0 | 1 |

d) Formation of MRTM (Final Texton image) using $S_1$, $S_2$, $S_3$, $S_4$, $S_5$, $S_6$ and $S_7$.

*Fig. 3: Computation Of MRTM From Quinary Multi Region Image.*

The process of texton identification is shown in Fig.3. The present paper used the seven types of textons to detect every grid. A particular texton

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

detection process is performed on a 2 x 2 grid in overlapped manner (shifting right by one column position then row by one position down) and if the texton is detected the pixels of textons are kept with original values and others are replaced with zeros. The same process is repeated for all seven categories and it is shown in Fig 3. The MRTM (final texton) image (Fig. 3d) will be formed by combining these seven types of texton images (Fig. 3b & 3c).

### 2.4 Computation of GLCM Features on MRTM

On MRTM image, the co-occurrence matrix is formed with a distance D and with an angle $0^0$,$45^0$,$90^0$ and $135^0$. This results a multi-region texton co-occurrence matrix (MRTCM) and this process of formation is shown in Fig.4. The GLCM features i.e. entropy, energy, contrast, local homogeneity and correlation (equations 2,3,4,5 and 6) are computed on MRTCM with $0^0$,$45^0$,$90^0$ and $135^0$ orientations and average feature values of these orientation are listed in the feature library. In order to extract color information the present paper also quantized the original image using HSV color space.

| | | | | |
|---|---|---|---|---|
| 2 | 0 | 2 | 5 | 0 |
| 2 | 1 | 1 | 2 | 5 |
| 0 | 1 | 1 | 5 | 0 |
| 0 | 0 | 0 | 5 | 1 |
| 0 | 4 | 4 | 0 | 1 |

4(A) MRTM Of Fig. 3(D).

| | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 0 | R(0,0) | R(0,1) | R(0,2) | R(0,3) | R(0,4) | R(0,5) |
| 1 | R(1,0) | R(1,1) | R(1,2) | R(1,3) | R(1,4) | R(1,5) |
| 2 | R(2,0) | R(2,1) | R(2,2) | R(2,3) | R(2,4) | R(2,5) |
| 3 | R(3,0) | R(3,1) | R(3,2) | R(3,3) | R(3,4) | R(3,5) |
| 4 | R(4,0) | R(4,1) | R(4,2) | R(4,3) | R(4,4) | R(4,5) |
| 5 | R(5,0) | R(5,1) | R(5,2) | R(5,3) | R(5,4) | R(5,5) |

4(B)

$$R(0^O, d = 1) = \begin{bmatrix} 2 & 2 & 1 & 0 & 1 & 1 \\ 0 & 2 & 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 2 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$R(45^O, d = 1) = \begin{bmatrix} 1 & 4 & 0 & 0 & 0 & 1 \\ 0 & 1 & 2 & 0 & 0 & 1 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$R(90^O, d = 1) = \begin{bmatrix} 2 & 1 & 0 & 0 & 2 & 0 \\ 2 & 2 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathrm{R}(135^O, d = 1) = \begin{bmatrix} 2 & 1 & 0 & 0 & 2 & 0 \\ 1 & 1 & 0 & 0 & 0 & 2 \\ 1 & 2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 1 \end{bmatrix}$$

4(c)

***Fig.4.*** *The Flow Chart Of The Multi Region Texton Co-Occurrence Matrix (MRTCM): A) MRTM Of Fig. 3(D) (B) The MRTCM Image (C) Four Directional MRTCM.*

$$\mathrm{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ii})P_{ii} \qquad (2)$$

$$\mathrm{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ii})^2 \qquad (3)$$

$$\mathrm{Contrast} = \sum_{i,j=0}^{N-1} P_{ii}\,(i-j)^2 \qquad (4)$$

$$\mathrm{Local\ Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ii}}{1+(i-j)^2} \qquad (5)$$

$$\mathrm{Correlation} = \sum_{i,j=0}^{N-1} P_{ii}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (6)$$

where $P_{ij}$ is the pixel value in position (i,j) of the texture image, N is the number of gray levels in the image, μ is $\mu = \sum_{i,j=0}^{N-1} iP_i$ mean of the texture image and $\sigma^2$ is $\sigma^2 = \sum_{i,j=0}^{N-1} P_i\,(i-\mu)^2$ variance of the texture image.

### 2.5 Image Retrieval Algorithm

The proposed algorithm is given below

Input: Query image Output: Retrieval of similar images

1. Convert the RGB image into HSV color space.
2. Divide the v-color space image into non overlapped regions of size 9 x 9.
3. Divide the region in to sub regions and derive feature vector based on average operator.
4. Quantize each region into quinary values based on thresholds.
5. Compute multi-region texton matrix (MRTM) by deriving textons on each 2x2 grid.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6. Derive multi-region texton co-occurrence matrix (MRTCM) with various distances.
7. Compute GLCM features on MRTCM.
8. Compute the histograms for H, S and V color spaces.
9. Construct feature vector by concatenating histograms for H, S and V color spaces with MRTCM features.
10. Compare the features of query image with the images in the database using similarity measurement.
11. Retrieve the images based on nearest distance or best matches.

### 2.6 Query Matching

The present retrieval model selects 16 top images from the database images that are matching with query image. And also experimented with more number of top images and retrieval performance is measured. This is accomplished by measuring the distance between the query image and database images. The present paper used Euclidean distance as the distance measure and as given below

$$D_{s}(T_n, I_n) = \left(\sum_{i,j=1} \left|f_i(T_n) - f_j(I_n)\right|^2\right)^{1/2} \quad (7)$$

Where $T_n$ query image, $I_n$ image in database;

The database image is used as the query image in our experiments. If the retrieved image belongs to the same category as that of query image we say that the system has suitably identified the predictable image otherwise the system fail to find the image. The performance of the present model is evaluated in terms of precision and recall rate. Precision is the ratio of number of retrieved images ($I_{NR}$), vs the number of relevant images retrieved ($I_{RR}$). The recall is the ratio of total number of relevant images in the database ($I_{TR}$) vs $I_{RR}$.

$$\text{Precision - P} = ( I_{RR} / I_{NR} ) \quad (8)$$

$$\text{Recall –R} = ( I_{RR} / I_{TR} ) \quad (9)$$

## 3. RESULTS AND DISCUSSION

In order to efficiently investigate the performance of the present retrieval model, we have considered the WANG database [52]. Wang is a subset of Corel stock photo database. In the WANG database the images have been manually chosen. This data base consists of 5 classes of images and 100 images per each class. The present paper used these 5 classes of images for relevance assessment. For a query image the relevant images are assumed to be the remaining 99 images of the same class. The images from all other classes are treated as irrelevant images. The hefty size of each class and the heterogeneous image class contents made WANG data base as one of the popular database for image retrieval.

The present paper compute GLCM features on MRTCM using various distance values: $D$ = 1, 2, . . . , 7. The average precision and recall rates of all classes of images are computed based MRTCM features and color histograms and listed in Tables 1 and 2. The best performance of MRTM with color histograms was obtained when $D$ = 4.
The retrieval performance of the MRTCM is compared with GLCM[54], color correlogram [53] and texton co-occurrence matrix [43]. The present paper selected 60 images of the same category or class as query images (one by one) and computed precession and recall rates by selecting top 16, 25, 35, 45, 55,65,75,85 and 95 images. The average precession rates of GLCM, CCG and TCM are ranging from 38% to 45%, 39% to 46% and 60% to 64% for number of images retrieved $I_{NR}$=16 (Table 1 & 2). The average precession and recall rates are plotted in graphs (Fig. 5 and 6) by varying $I_{NR}$. The present paper also computed image retrieval accuracy as defined below (equation 10).

$$\text{IR accuracy A} = ((\text{precession} + \text{recall}) /2 ) \quad (10)$$

The average IR accuracy graph with varying number of matches considered ($I_{NR}$) is plotted (Fig. 7). The proposed MRTCM achieved best performance when compared to the existing three methods. Fig.8 shows five examples of retrieval images, i.e. one image from each class, by the proposed method with D=4 for $I_{NR}$ =16 and top left most image is the query image. The image classes of dinosaur, buses and beaches exhibits more of shape and texture features that's why they have shown high retrieval rate when compared to other two classes of images.

**Journal of Theoretical and Applied Information Technology**
15th December 2016. Vol.94. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 1: Average Precision Rate Of All Classes Of Images With Various Distance Measures For $I_{RR}$ =16.*

| | Distance parameter | | | | | | |
|---|---|---|---|---|---|---|---|
| Methods | D=1 | D=2 | D=3 | D=4 | D=5 | D=6 | D=7 |
| GLCM | 0.38 | 0.41 | 0.42 | 0.45 | 0.44 | 0.43 | 0.43 |
| CCG | 0.39 | 0.41 | 0.44 | 0.46 | 0.45 | 0.44 | 0.43 |
| TCM | 0.60 | 0.61 | 0.63 | 0.64 | 0.63 | 0.61 | 0.62 |
| MRTCM with color histograms | 0.65 | 0.66 | 0.68 | 0.72 | 0.71 | 0.67 | 0.64 |

*Table 2: Average Precession Rate On Each Class Of Images For D=4 For $I_{RR}$ =16.*

| Methods | Image category and the precision (%). | | | | | |
|---|---|---|---|---|---|---|
| | Africa | Beach | Monumen | Buses | Dinosaurs | Average |
| GLCM | 0.39 | 0.42 | 0.44 | 0.48 | 0.5 | 0.45 |
| CCG | 0.4 | 0.43 | 0.46 | 0.49 | 0.52 | 0.46 |
| TCM | 0.61 | 0.6 | 0.66 | 0.67 | 0.7 | 0.64 |
| MRTCM with color histograms | 0.64 | 0.65 | 0.74 | 0.77 | 0.79 | 0.72 |

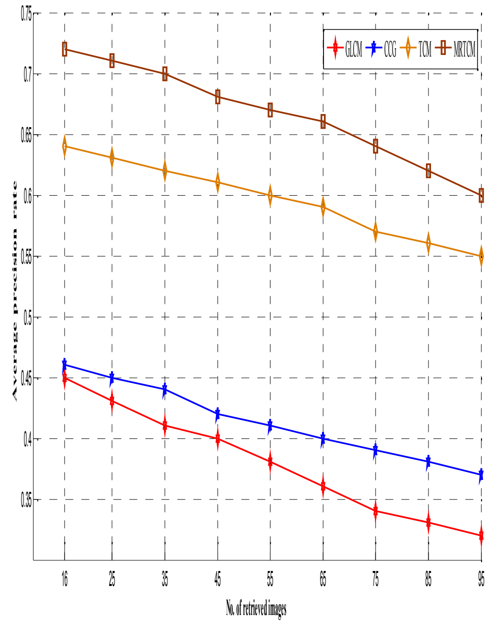



*Fig. 5: Average Performance Curve (Precision) Using GLCM, TCM And MRTCM Method With D=4.*

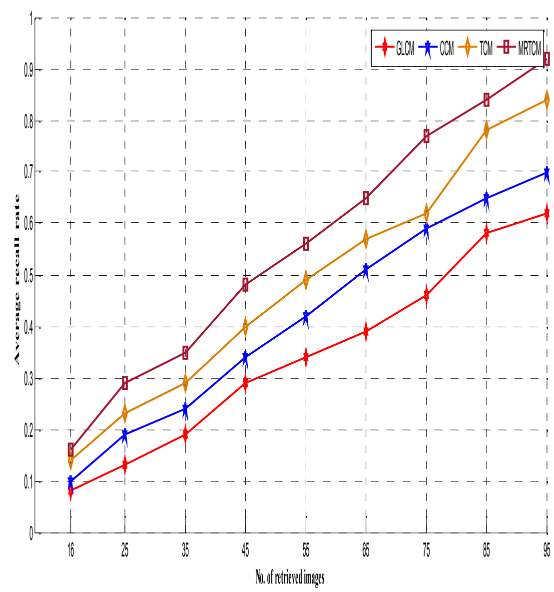



*Fig. 6: Average Performance Curve (Recall) Using GLCM, TCM And MRTCM Method With D=4.*

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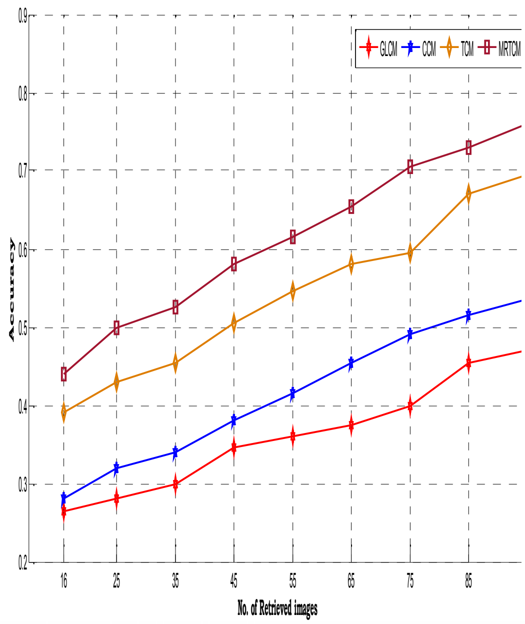


*Fig. 7: Accuracy Graph Of GLCM, CCM, TCM And MRTCM Methods.*

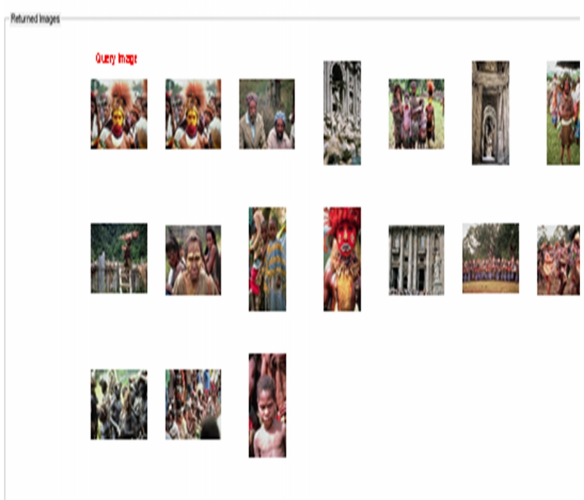


*Fig. 8 (A): Retrieved African Images.*

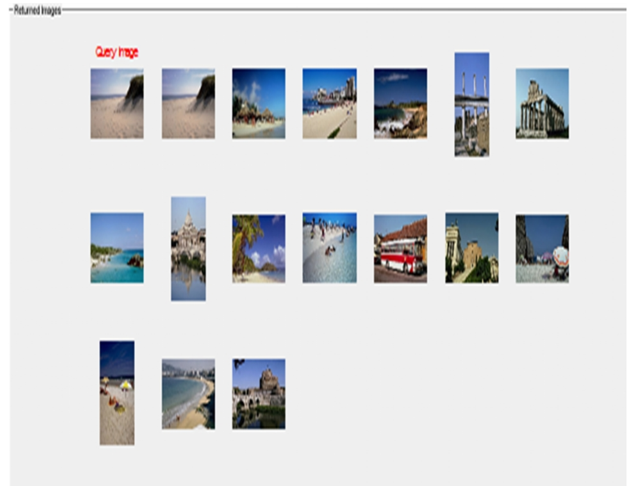


*Fig. 8 (b): Retrieved beach sand images.*

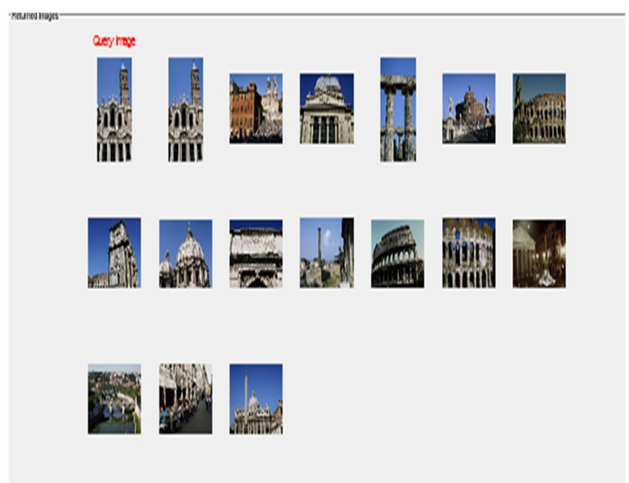


*Fig. 8 (C): Retrieved Monuments.*

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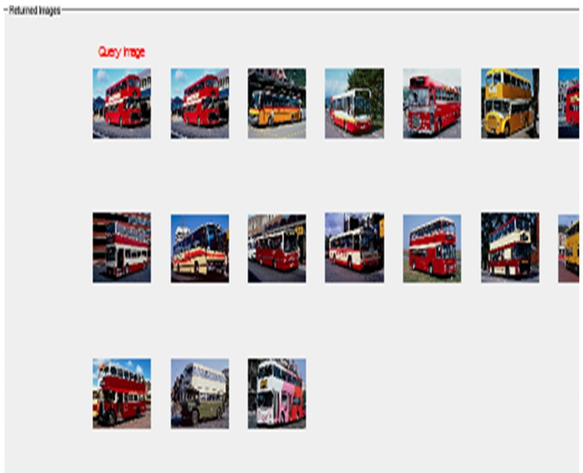


*Fig. 8(D): Retrieved Busses.*

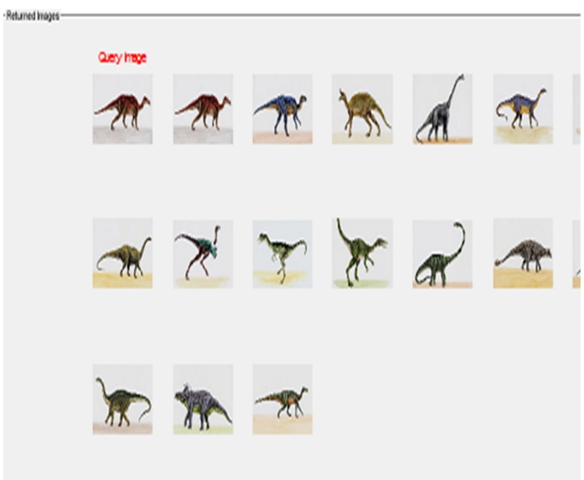


*Fig. 8(E): Retrieved Dinosaurs.*
*Fig. 8(A) To 8(E): Example Of Image Retrieval Using Integrated Scheme Of MRTCM With Color Histograms On The Five Classes. The Top-Left Image Is The Query Image, The Correct Images Do Not Include Query Image Itself.*

## 4. CONCLUSIONS

This paper presents a new integrated feature descriptor MRTCM for CBIR. The present method integrated the HSV color histograms features with the GLCM features derived on MRTCM. The multi region approach reduced overall dimensionality by deriving features on each region instead of micro regions. The textons on multi regions derived the structure of the image. Finally the texture features are computed by deriving the GLCM features on MRTCM. The present method and other existing methods are tested on WANG database using the precision and recall rates. The GLCM features on MRTCM are derived using various distances and for d=1 to 7. The present method yielded a good IR rate.

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