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Content Based Image Retrieval using Color and Full Texton Index Co-occurrence Matrix (FTiCM) Features

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Abstract*: In this paper a powerful feature descriptor is derived based on color and texture features. This paper initially transforms the RGB color image into HSV color apace. The color histograms are derived on H, S and V color planes. The structural features are derived on V-color space by dividing into micro girds of size 2x2 and each micro grid is replaced with full texton index (FTi). The FTi's are extracted based on shape of the texton derived from four, three and two identical pixels. The proposed full textons represents all possible patterns on a 2x2 grids and this representation over comes the disadvantages and ambiguity of TCM and MTH approach. The texture features are derived on the FTi image by computing co-occurrence matrix and by deriving gray level co-occurrence matrix (GLCM) features. The GLCM features derived from Full Texton Index co-occurrence Matrix (FTiCM) are integrated with the histogram features derived on the individual color planes. The proposed color histogram-full texton co-occurrence matrix (CHFTiCM) model is experimented on Corel-1k, Corel-10k, MIT-VisTex, Holidays and CMU-PIE and Holidays datasets. The performance of the proposed CBIR is measured in terms of average retrieval rate (ARR) and average precision rate (APR) and compared with the state-of-art methods. The results indicate the superiority of the proposed method over the existing methods.

***Index Terms*: RGB, HSV, V-color space, texton, MTH, TCM.**

I. INTRODUCTION

The goal of content based image retrieval (CBIR) is to provide the user an efficient way to access, browse and retrieve images from the given database. In CBIR, the images are indexed by intensity level contents derived from texture, color and structure or shape. These image contents are referred as image features and generally represented in numeric values. These features derived from query image are compared with features of database images using a distance function and the most similar image(s) are retrieved from the database images. The CBIR methods are basically divided into two groups. i) The methods based on global features ii). based on local features. The most common global feature extraction method is color histogram [1] such as domain color descriptors and color layout descriptors. The color histograms are based on the spatial relationship among sampling or neighboring pixels. Later color auto correlegram was developed for CBIR [2]. The global features based methods are computationally efficient, invariant to image size and rotation and also robust to image noise to some extent. Recently the local based methods emerged as strong and powerful candidates for the CBIR. The global based methods are inadequate to handle issues related to occlusion, changes in: illumination, local features/shapes etc. One of the powerful local based texture descriptor is local binary pattern (LBP) derived by Ojala et al. [3]. These local descriptors are robust to certain level of illumination changes, geometric transformation, distortions and occlusion to some extent. These local descriptors have many applications [4-10]. The two popular methods of feature extractions i.e. the global and local methods have limitations and advantages when compared to each other. Color is the powerful image feature and it is popularly used because the color features are invariant to orientation and size. The color histogram represents global color distribution of an image and it determines the joint probability of intensities of color channel. The shape features of an object also provide the rich information. The shape features derived on a local grid are popular among texture classification, face recognition and CBIR [11]. The shape features derived on micro regions of size 2x2 or 3x3 derive simple patterns and based on these simple patterns/ shape one can derive complex structures. There is no unique definition for texture however texture represents the object surface. The texture features represents smoothness, uniformity, angular movement, coarseness regularity and randomness etc. The texture features can be derived based on structural, spectral [12] and statistical approaches. This research integrated structural features derived on micro regions with GLCM features to derive efficient and precise texture features of the image. After an in-depth study on the current literature on color, texture, shape and statistical features on texture analysis, classification and CBIR, this research found that in many cases the satisfactory results are not noticed by considering a single set of feature. This paper observed that by concatenating or integrating the two or more feature sets will give good results. The texture features were combined with color features for color image retrieval [13]. The present research also noticed two major problems associated by integrating different features: the feature vector size will be growing to huge extent when compared to individual features especially i.) color histograms are combined with other set of features ii.) Fusing the different set of features into one collected from different modalities.

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The first disadvantage makes the process of CBIR is slow and especially whenever the image database is large. The retrieval rate may be dropped by second disadvantage i.e. if the integration of features is not done carefully.

This paper derives an integrated approach by fusing the local and global descriptors. In this paper the global color histograms are fused with local texture features derived on the FTi images. The global features are extracted in this research by computing histograms in the individual color plane. The local features are extracted from a micro grid of size 2x2 by deriving full texton patterns. The micro grids are replaced with FTi. The GLCM features are derived on FTi image and this integrates the texton with statistical features of texture.

This paper is organized as follows: the section one describes the introduction. The section two describes the related work. The section three elaborates the proposed method. The section four presents results and discussions with major contribution of the paper. The conclusions are presented in section five.

II. RELATED WORK

The texton played one of the important roles in CBIR. The textons are derived on a local micro grid of size 2x2. The textons represents the simple patterns on a micro grid and with these simple patterns one can represent the complex patterns. In the literature the texton co-occurrence matrix (TCM) [14] and multi-texton histogram (MTH) [15] were derived for CBIR. A texton is formed if and only if two or more pixels of the grid have exactly identical gray level values. The TCM derives only five texton types on a 22 micro grid. Out of these four textons will have three identical pixels denoted as T2, T3, T4 and T5 and one texton with all four identical pixels denoted as T1 (Fig.1).

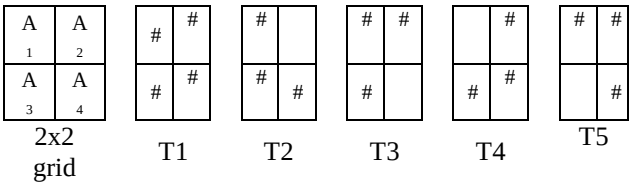


Fig.1: The five types of textons used in TCM.

The TCM identifies the texton pattern in an overlapped manner on a 2x2 grid. In fact TCM scans the image five times to identify the five types of texton patterns and in each scan the TCM identifies one of the texton patterns. The TCM forms the final texton image by fusing the five texton type images. If a texton type is identified then TCM approach places a zero in the pixel location of the 2x2 grid, which is not part of the texton pattern. And the intensity levels of the 2 x 2 grid are unchanged in the pixel locations which are part of the texton. Later in the literature the MTH [40] approach is introduced. The MTH approach derived texton patterns with two identical pixels on a 2x2 grid as shown in Fig.2 and the texton patterns are denoted with indexes from T6 to T9. The MTH overcomes the fusing operation of TCM approach by dividing the image into micro grids of size 2x2. The texton patterns are identified in each 2x2 grid. The MTH approach retains the 2x2 grid without changing the pixel gray level intensities whenever a texton pattern of MTH is identified. The entire 2x2 grid is assigned a value zero if no texton type of MTH is identified.

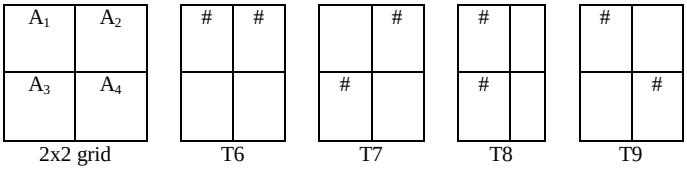


Fig. 2: The four types of textons used on MTH.

The co-occurrence matrix measures the occurrence of pixel pairs, located at a particular distance and specific direction. The size of co-occurrence matrix depends on the size of gray levels. The values in the GLCM ranges from 0 to m where m is the maximum number of times a specific pixel pair appeared with a distance d and the rotation angel □. The process of computation of co-occurrence pixel pair is shown in Fig.3 (a) and 3(b). The Fig.3 (a) displays the original image grey level matrix. The Fig.3 (b) displays the GLCM of Fig. 3(a) with distance 1 and □ = 0o. In Fig. 3(b) i.e. in GLCM the topmost row and leftmost column which are displayed in red color, indicates the grey level values of the original matrix 3(a) (0 to 3). For each pair (0,0), (0,1), ..(0.4),..(1,0)…(1,4)……(4,4), the co-occurrence has been calculated. For the pair (1,1) and (2,1) with a distance 1 and with an angle of rotation 0o, the occurrence pairs in original matrix are shown in red and blue colors respectively and such occurrences are reported four and three times respectively. Therefore in GLCM for the pixel pair (1,1) and (2,1) the values 4 and 3 are placed.

1	1	0	0	2
0	3	2	1	0
0	1	1	1	3
3	3	0	2	1
0	2	1	1	3

Fig.3(a): Original matrix .

Pixel pair	0	1	2	3
0	1	0	3	1
1	2	4	0	2
2	0	3	0	0
3	1	0	1	1

Fig.3(b): GLCM for Fig.3(a)

Fig.3: The computation of GLCM for a distance d=1 and angle of rotation 0o.

III. PROPOSED METHOD

Images can be broadly divided into three types. The first one is black and white image. The black and white images only contain two intensity levels i.e. black and white. The second type of images is known as gray level images. The gray level image can have range of intensities from 0 to g under one band. The third types of images are known as color images. The color images will have multiple bands for each pixel and contain a range of intensity for each band.

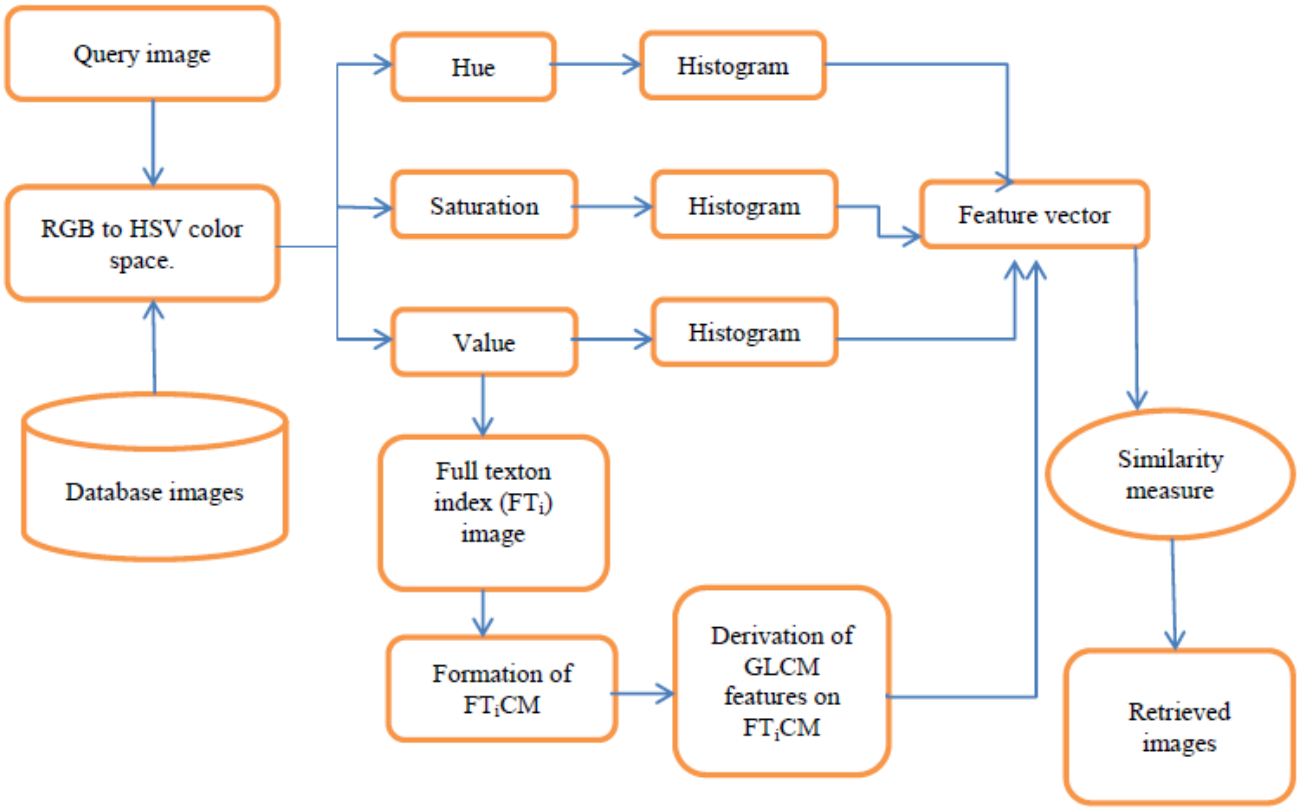


Fig.4: Frame work of proposed CHFTiCM method.

The popular and the most generally used color model is RGB. The RGB has three color bands called red, green and blue. And the RGB used additive color mixing. The other type of color model is HSV color space where H, S and V stand for Hue, Saturation and Value respectively. HSV is often used by artists because color, intensity and brightness can be extracted individually in HSV color space than in terms of additive or subtractive color components as in the case of RGB and other color models. This paper constructed histograms for all three components of HSV individually. The histogram features extracts the global information.

After a careful study and thorough investigation on TCM and MTH, this paper observed the following demerits in these approaches:

i. The TCM has only defined the texton patterns with three and four identical pixels and ignored completely the patterns with two identical pixels.
ii. The TCM requires a fusing operation to derive the final texton image which is a time consuming.
iii. The MTH derived only few texton patterns with two identical pixels.
iv. The MTH derives ambiguity in identifying textons when three or more pixels exhibited exactly the same intensity level (Fig.5). In Fig. 5(a) the MTH identifies the 2 x 2 grid with texton type T6 and T9 and in figure 5(b) the MTH recognizes the 2x 2 grid with two texton patterns namely T7 and T8. This is mainly because the MTH approach ignores the texton patterns with three identical pixels.
v. The TCM and MTH approaches have not defined full textons patterns on a 2x2 grid.
vi. Most of the approaches based on textons have not replaced the 2x2 texton micro grids with texton indexes. The reason for this, they have derived only few number or partial number of texton patterns. Further, the replacement with texton indexes is not possible in TCM due to fusing operation.
vii. The existing texton methods derived a framework mainly to assign a zero value to the 2 x 2 grids which are not forming any textons or those pixels which are not part of textons.

This paper addressed these disadvantages by deriving full textons.

85	85
92	85

(a) Texton type T6 and T9 MTH

15	15
15	25

(b)Texton type T7 and T8 in MTH

Fig. 5: Ambiguity in identifying texton types in MTH.

This paper derives full texton indexes that include all the patterns with four, three and two identical pixels on a micro grid of size 2x2. The V- component holds the gray scale information; therefore value component is used for extraction of local features in this paper. The proposed method transforms the V-plane of the texture image into a full texton index (FTi) image in the following way. The proposed FTi derives 14 textons shapes on the micro grid of size 2x2 (Eqn.1). The FTI framework initially divides the image into sub grids of size 2x2 (Fig.6). The sub grids are replaced by the corresponding FTi as derived in equation 1.

In the equation 1, G represents the sub grid and W, X, Y and Z represents the position of the pixels of the 2x2 grid and G(I) represents the gray level intensity of the pixel position I of the 2x2 grid. This paper quantized the gray level intensities of V-plane by transforming, it into an FTi image. The proposed FTi framework reduces the original image of size NxM into N/2 x M/2 and replaces each micro grid with FTi ranging from 0 to 14.This paper derives gray level co-occurrence matrix (GLCM) on FTi image and this derives a Full texton index co-occurrence matrix(FTiCM). This paper computed four FTiCM with a distance factor 'd' of 1, 2 3 and 4. Further, this paper derived four GLCMs for each distance value by rotating the image with 0o, 45o, 90o and 135o. This paper computed the following six GLCM features namely Homogeneity or Angular Second Moment (ASM), Entropy, contrast, Prominence feature, correlation, Local Homogeneity or Inverse Difference Moment (IDM) for each d value and on each rotation on FTiCM. Thus this FTiCM derives 4x4x6 =96 features on each image. These features represents the texton (structural) and statistical information of the image texture.

Finally the feature vector is generated by concatenating the histograms of HSV color space with FTiCM features. These features are named as CHFTiCM features.

$$FT_{I(x,y)} = \begin{cases} 0\ G(J) \neq G(K) \neq G(L) \neq G(M) \\ 1\ G(J) = G(K) = G(L) = G(M) \\ 2G(J) = G(K) = G(L) \neq G(M) \\ 3G(J) = G(K) = G(M) \neq G(L) \\ 4G(J) = G(L) = G(M) \neq G(K) \\ 5G(K) = G(L) = G(M) \neq G(J) \\ 6G(J) = G(K) \neq G(L) \neq G(M) \\ 7G(J) = G(L) \neq G(K) \neq G(M) \\ 8G(J) = G(M) \neq G(K) \neq G(L) \\ 9G(K) = G(L) \neq G(J) \neq G(M) \\ 10G(K) = G(M) \neq G(J) \neq G(L) \\ 11G(L) = G(M) \neq G(J) \neq G(K) \\ 12G(J) = G(K) \neq G(L) = G(M) \\ 13G(J) = G(L) \neq G(K) = G(M) \\ 14G(J) = G(M) \neq G(K) = G(L) \end{cases} \quad (1)$$

15	26	48	48	68	63
53	62	81	48	68	68
56	56	63	45	48	52
56	51	63	23	48	48
78	49	36	36	17	48
86	78	36	64	58	58

(a)Sample image patch.

1	2	4
3	8	4
7	3	11

(b)FTi Image of (a)

Fig. 6. The transformation frame work of V-plane image in to aFTi image.

The proposed algorithm is given below and a flow chart of the frame work has been given in Fig.4.

Input: query image
Output: retrieval of similar images from the database.
Algorithm begin
Convert the RGB image into HSV color plane.
Quantize Hue (H), saturation (S) and Value (V) bins and Compute the histogram of H,S and V color space.
Divide the V-color space into micro girds of size 2x2.
Replace the micro grids with FT indexes (FTi)
Compute co-occurrence matrix on FTi image and this becomes FTiCM.
Compute GLCM features for d=1,2,3 and 4 with angle of rotation of 0o,45o,90o and 135o on FTiCM.
Construct feature vector of all images in the database (CHFTiCM) by concatenating the features of individual color histograms (CH) (step2) with features of FTiCM (Step 6).
Construct the feature vector of query image.
Compare the feature vector of query image and feature vector of database images using similarity distance measures.
Sort the distance measure values in ascending order and display the corresponding images of first best matches.
End of the algorithm

IV. Results and Discussions

This section presents a brief discussion about databases used for the retrieval, the state-of-art methods used for comparison purpose and the similarity measured. To test the efficacy of the proposed descriptor, this paper used five bench mark color databases images and a brief discussion on these databases and sample images of these databases are given below (Fig.7 to Fig. 11).

A.*Description of the databases*

The Corel-1k [16] and Corel-10K databases [17] consists of natural images. The Corel-1K consists of images with 10 categories and each category consists of 100 images. The Corel-1K database includes image categories of buildings, elephants, buses, flowers, mountains, food, hills , Africans , dinosaurs and beaches. The size of the images is either 256x384 or 384x256. The Corel-10K database consists of 80 categories and in each category the number of images are varying and in total it consists of 10,800 images. The image size of Corel-10K database is 120x80. This paper considered 40 categories of images and in each category it has chosen 20 images. This results a database size of 40x20 =800 images of Corel-10K. The MIT-VisTex database [18] consists of a large amount of colored images with 40 different categories. The size of each image is 512x512. This paper considered 16 images under each category. This leads the size of database as 640 (16x40) images. This paper also used the Holidays dataset [19]. This data set consists of 500 image groups and mostly these images consist of set of images with personal holiday's photos (large variety of scene types: natural, man-made, water and fire effects, etc). The remaining ones were taken on purpose to test the robustness to various attacks: rotations, viewpoint and illumination changes, blurring, etc. The CMU-PIE database [20] contains facial images captured under varying pose, illuminations, expression and lighting with a size of 648 x 486, with 15 different categories. Each category consists of varying number of images.

This paper considered all fifteen categories and under each category considered 15 images.

B. *Similarity measure and query matching*

Feature extraction process is carried out on all the database images and query image and a feature vector data is computed for the entire database images. The similarity measure between query image versus the database images computed by this research using two distance measures: Euclidean and Manhattan distance measure.

Manhattan distance measure:

$$d(db_i, q) = \sum_{l=1}^{V} \left| F_{DBi}(l) - F_q(l) \right| \quad (14)$$

Euclidean distance measure:

$$D(db_i, q) = \sum_{l=1}^{V} \left(\left| F_{dbi}(l) - F_q(l) \right|^2 \right)^{1/2} \quad (15)$$

Where D(dbi,q) measures the distance between database image i (dbi) and query image q. V represents the total number of features in the features vector. Fdbi(l) and Fq(l) are the feature vector 'l' of ith database image and query image respectively. The best relevant image will have the shortest distance.

C. *Evaluation measures*

The precision and recall are used as evaluation measures. In each experiment each image of the database is used as query image and image retrieval is performed and retrieval performance is evaluated. And average performance is noted down. For each retrieval 20 most similar images are retrieved. The precision measures the ratio between the number of relevant images retrieved versus the total number of images retrieved (n) (Eqn.8). The recall measures the ratio between number of relevant images retrieved versus the total number of relevant images in the database (Nic) i.e. number of images in each category 'c' of the database for the query image (Eqn.9).

$$P(i,n) = {}^{\text{Number of relevant iamges retrieved}}/_{n} \quad (8)$$

$$R(i,n) = {}^{\text{Number of relevant iamges retrieved}}/_{N_{ic}} \quad (9)$$

Average precision and recall are given in equation 10 and 11.

$$P_{avg}(J,n) = \frac{1}{N_{ic}} \sum_{i=1}^{N_{ic}} P(i,n) \quad (10)$$

$$R_{avg}(J,n) = \frac{1}{N_{ic}} \sum_{i=1}^{N_{ic}} R(i,n) \quad (11)$$

Where, J denotes the number of categories. The total precision and total recall for the entire database are calculated as.

$$P_{total}(n) = \frac{1}{N_c} \sum_{i=1}^{N_c} P_{avg}(J,n) \quad (12)$$

$$R_{total}(n) = \frac{1}{N_c} \sum_{i=1}^{N_c} R_{avg}(J,n) \quad (13)$$

Where Nc is the total number of categories exist in the database.

D. *Results and discussions*

This paper measured the capabilities of the proposed method on an aforementioned five color database using the above performance measures and graphs are plotted. The present method derived features from color and full texton and statistical features of texture. This paper measured the APR and ARR on the proposed CHFTiCM frame work using the Manhattan and Euclidean distance similarity measures on each database and listed out in Table 1 and Table 2. The Manhattan similarity measure, shown good results when compared to Euclidean distance measure. In rest of the paper Manhattan distance measure is used.

Table 1: APR values using Euclidean and Manhattan distances when number of top matches are 10 for CHFTiCM method.

Distances/ Database	Corel -1k	Corel-10k	MIT-VisTex	Holidays	CMU-PIE	Average
Manhattan	90.32	47.68	89.15	87.64	92.73	81.5
Euclidean	87.63	40.12	81.68	82.16	90.53	76.4

Table 2: ARR values using Euclidean and Manhattan distances when number of top matches are 10 for CHFTiCM method.

Distances/ Database	Corel -1k	Corel-10k	MIT-VisTex	Holidays	CMU-PIE	Average
Manhattan	0.225	0.135	0.215	0.201	0.242	0.20
Euclidean	0.211	0.124	0.210	0.185	0.231	0.19

The existing methods based on color and textures have been compared with the proposed method. To derive the same from the existing methods i.e., LBP, CS-LBP ,LDP, LTP, BLK-LBP, DLEP and LTrP, this work concatenated RGB color histogram of 18 bins for each band i.e. 24 bins with the feature vectors of LBP[3], CS-LBP [21],LDP[22], LTP[23], BLK-LBP[24], DLEP [25] and LTrP[26] separately.

This paper retrieved for each query image different number of images from the database and performance is computed using the performance measures APR and ARR. The Fig. 12, 13, 14, 15 and 16 shows the performance of the proposed method verses the existing methods using similarity measures APR and ARR according to the number images retrieved on the data bases COREL-1k, COREL-10K, Holidays, MIT-VisTex and CMU-PIE respectively. Retrieval performance is presented based on the number of top matches during experiment for each database image. The precision and recall graphs clearly indicated the high performance of the proposed method over the existing methods and the research concatenated the color histograms with the features of the existing methods to maintain the comparison levels. From these results it is noted that the presented frame work of this paper is more advantageous in terms of average precision, recall and accuracy than the existing methods.

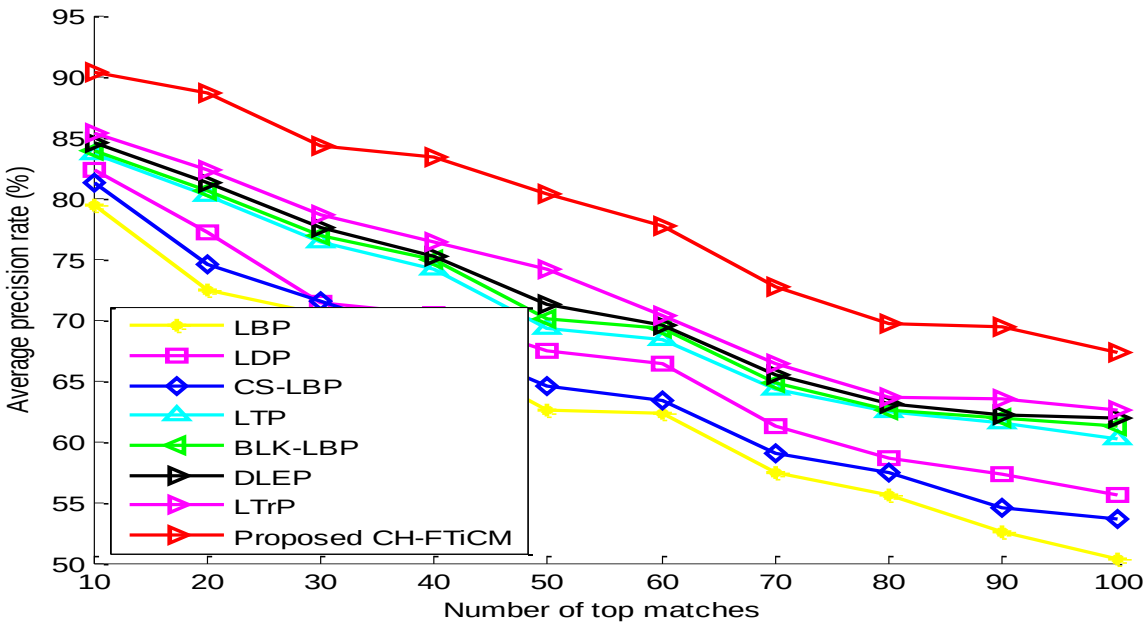
Fig. 7: Corel-1K database sample images.

Fig. 8: Corel-10K database sample images.

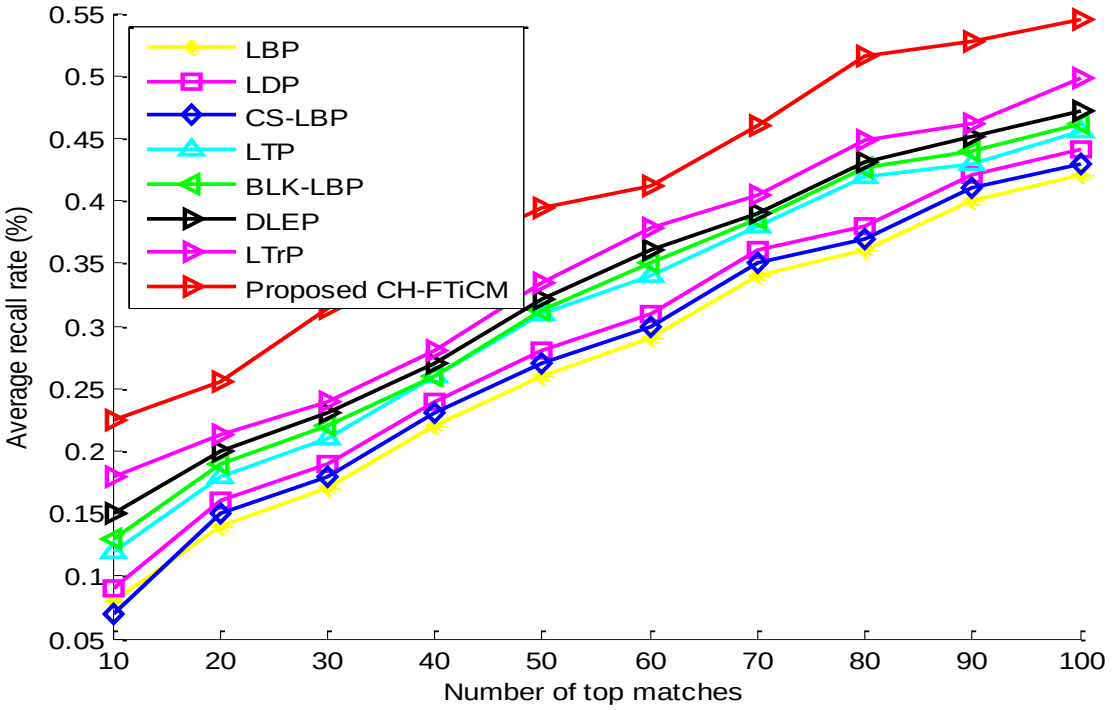
Fig. 9: The sample textures from Holidays database.

Fig. 10: The sample textures from MIT-VisTex texture.

Fig. 11: The sample facial images from CMU-PIE database.

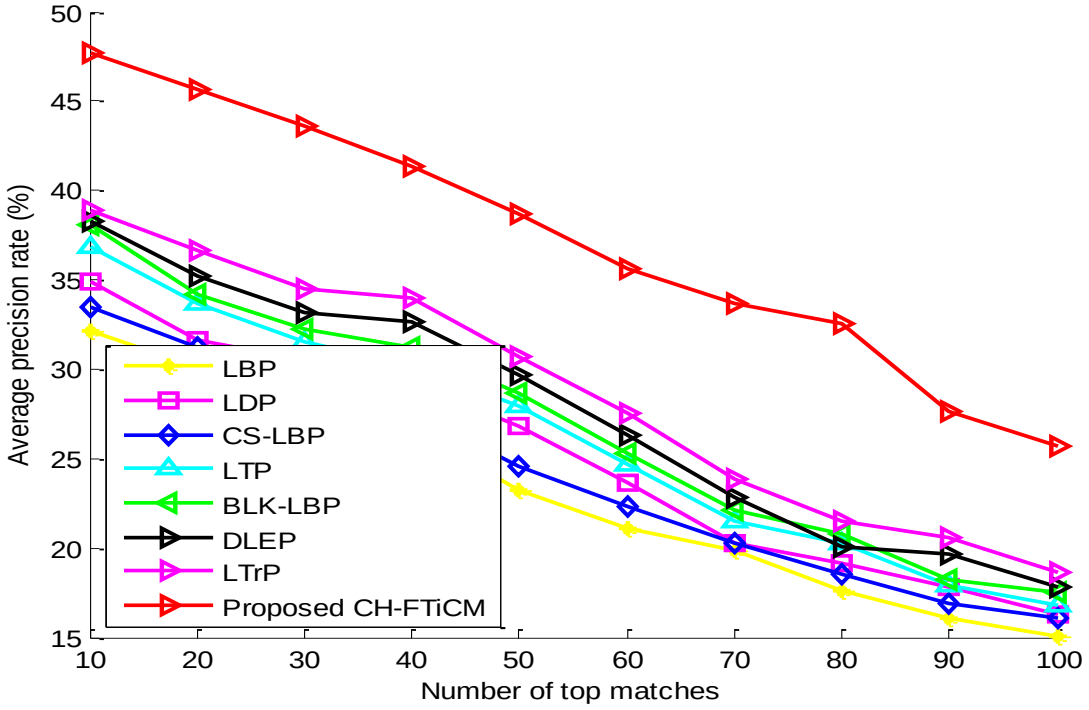


(a) APR.

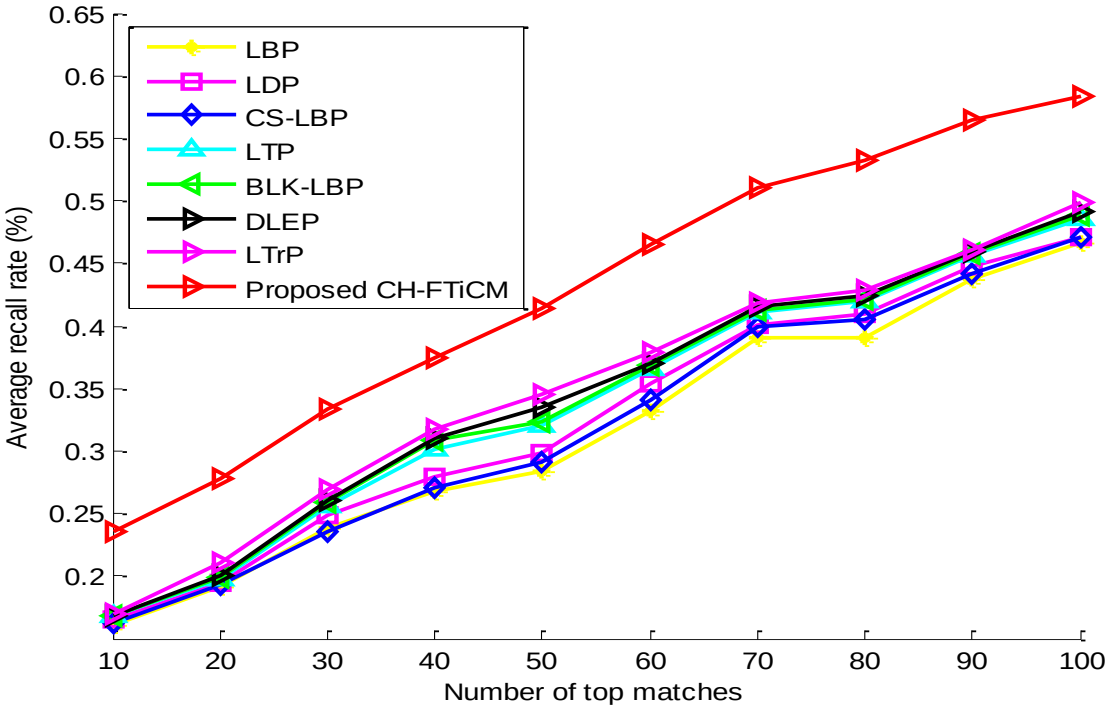


(b) ARR.

Fig.12: Comparison of over Corel-1k database using (a) APR (b) ARR.

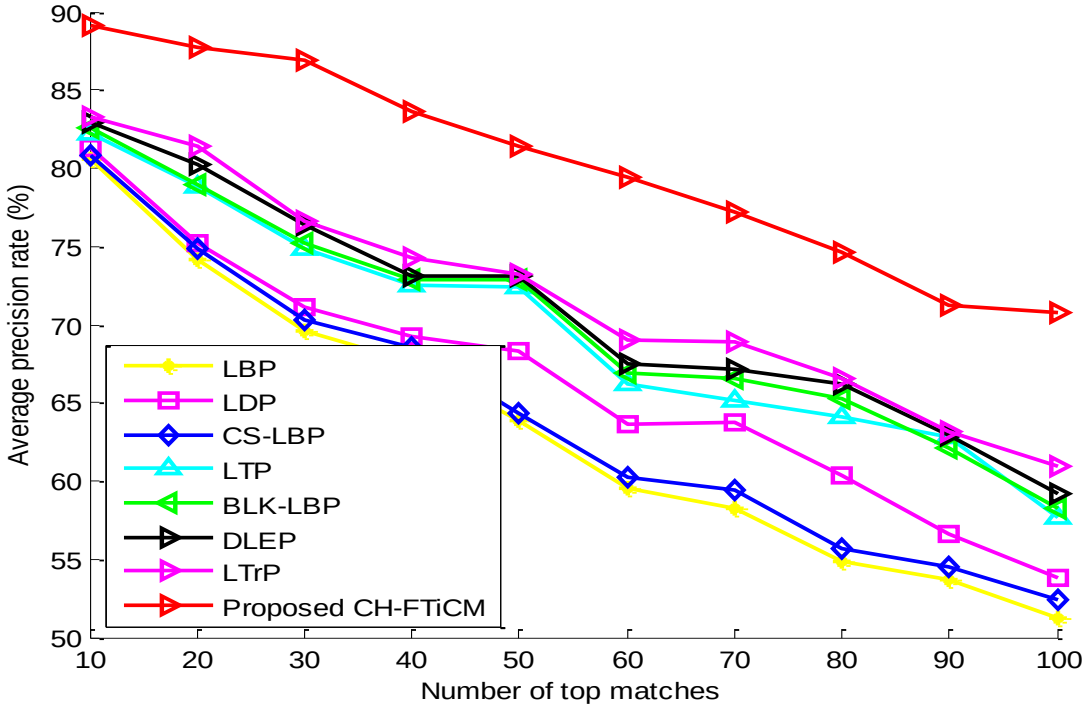


(a) APR.

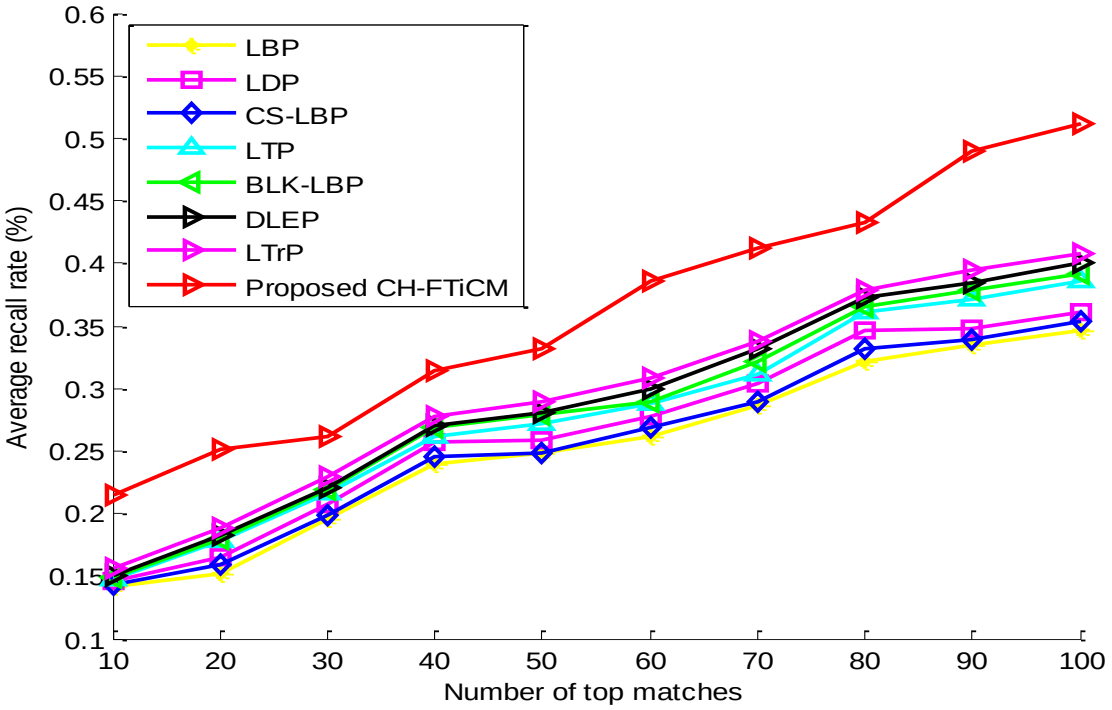


(b) ARR.

Fig.13: Comparison over Corel-10k database using (a) APR (b) ARR.

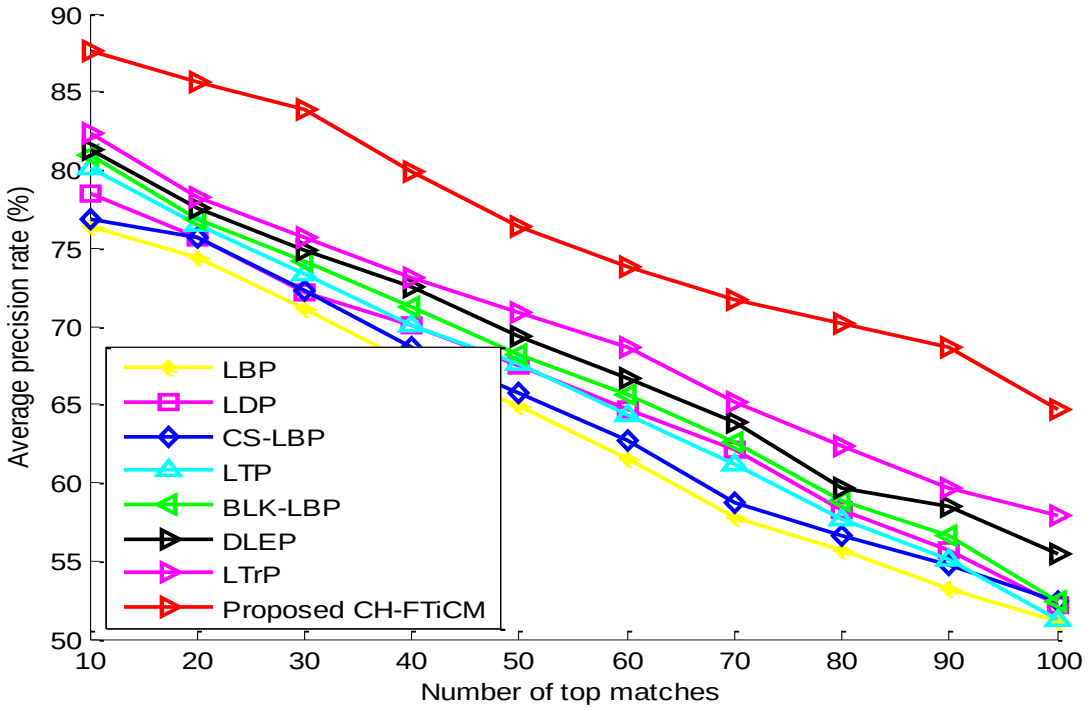


(a) APR.

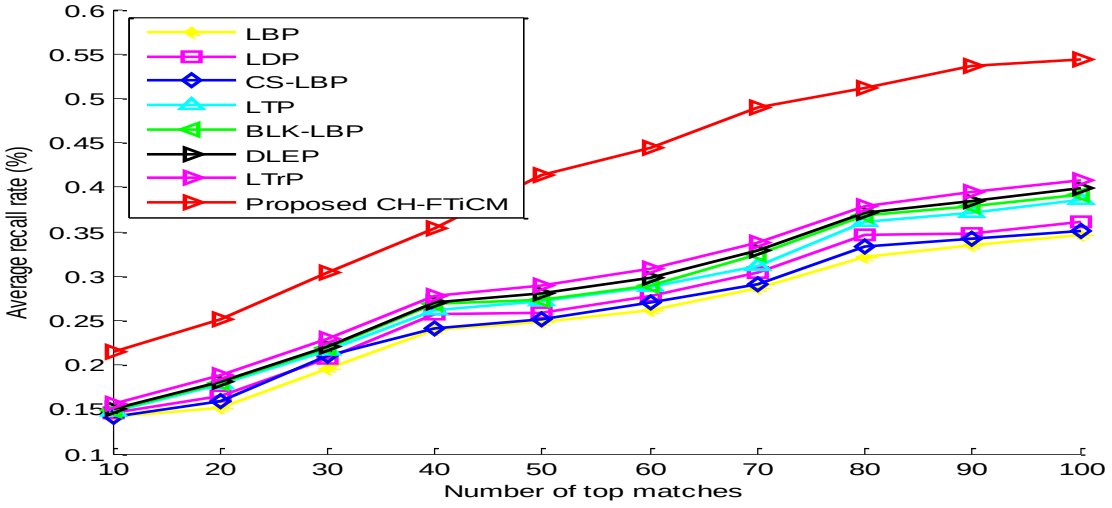


(b) ARR.

Fig.14: Comparison over Holidays database using (a) APR (b) ARR.

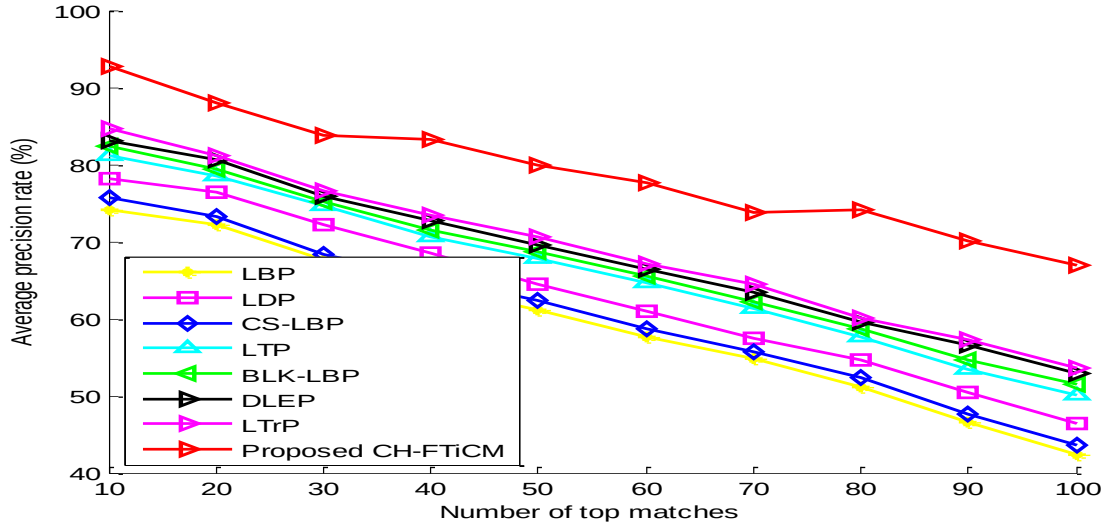


(a) APR.

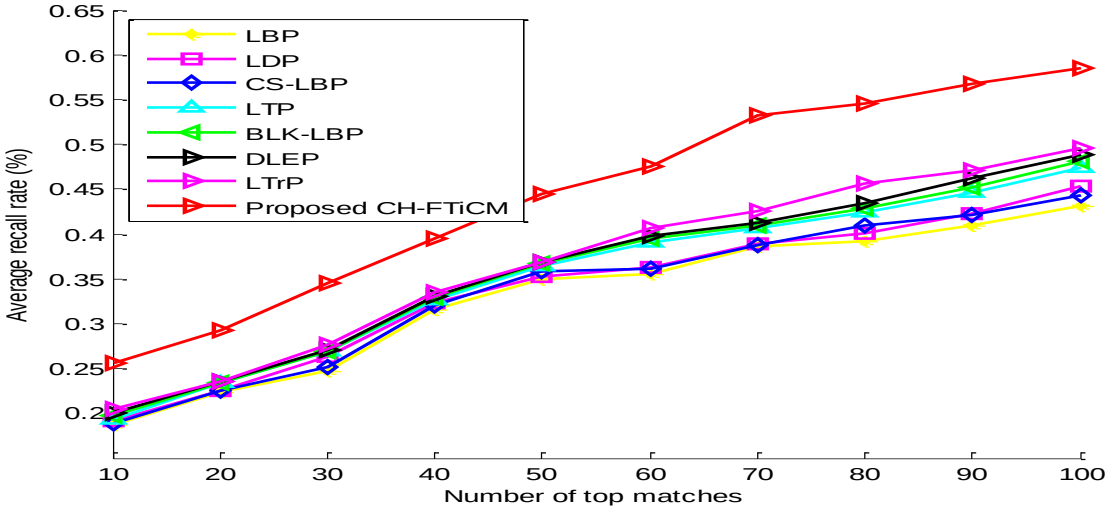


(b) ARR.

Fig.15: Comparison over MIT-VisTex database using (a) APR (b) ARR.



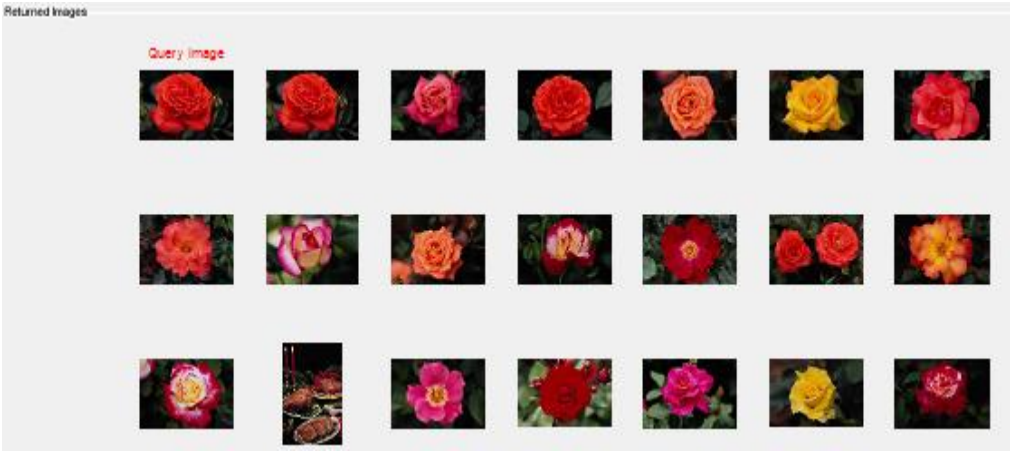
(a)APR.



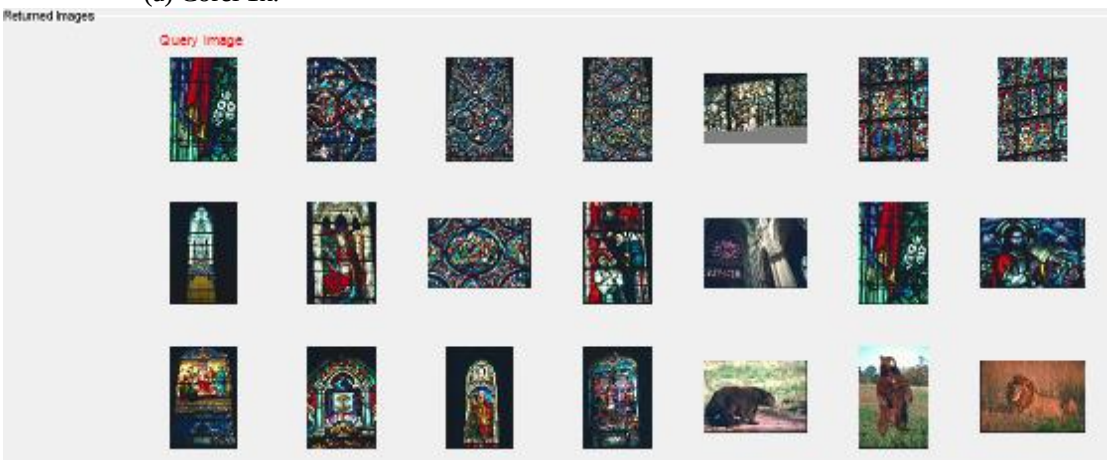
(b) ARR.

Fig.16: Comparison over CMU-PIE database using (a) APR (b) ARR.

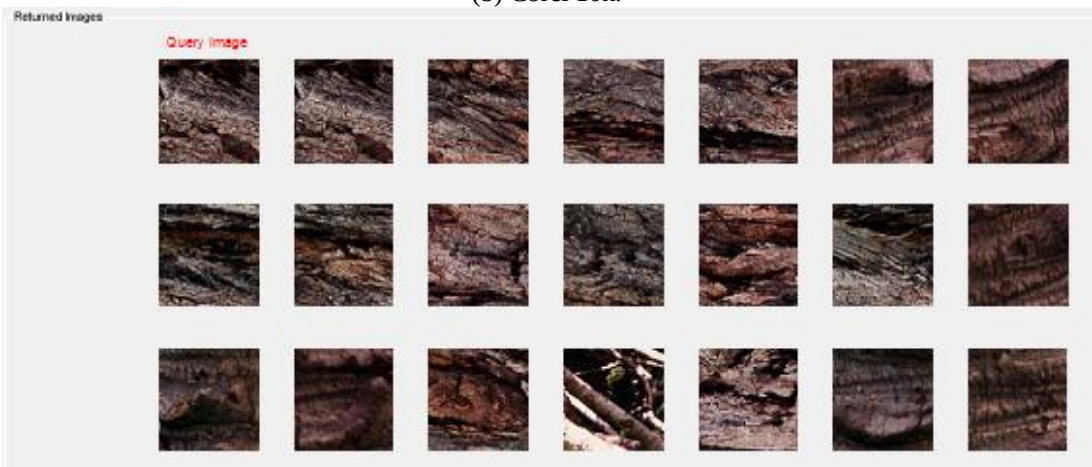
This work also displayed the top 20 retrieved images for one of the query image from each database in Fig. 17.



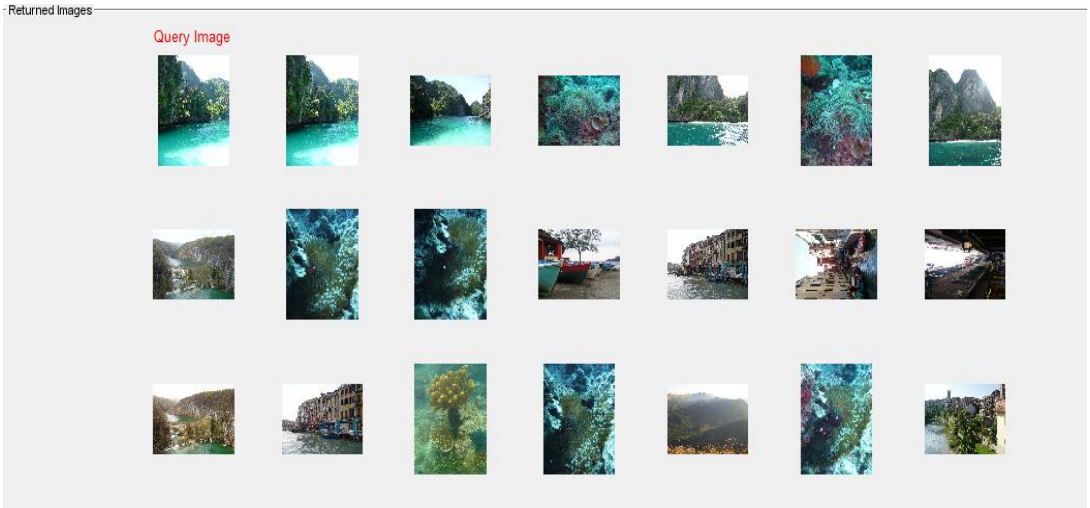
(a) Corel 1k.



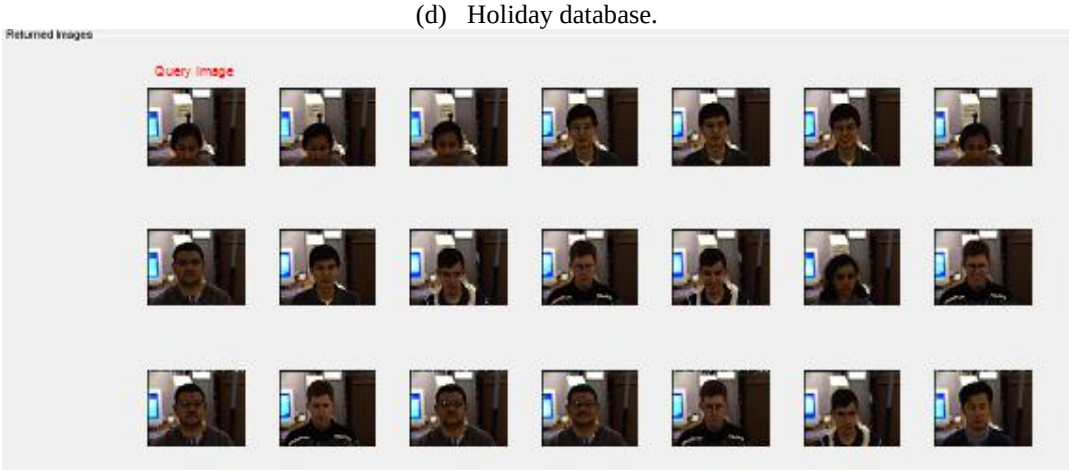
(b) Corel 10k.



(c) MIT-VisTex texture database .



(d) Holiday database.



(e) CMU-PIE database.

Fig. 17: Top 20 retrieved images of considered databases.

Main contribution

This paper has conferred a new method for CBIR based on color, full texton and statistical features of texture. The main involvements in the current paper are as follows:

1. A new feature vector called full texton index co-occurrence matrix (FTiCM) has been proposed.
2. The proposed FTiCM integrated the full texton features with GLCM features of the image texture.
3. The FTi mage is different form TCM and MTH and the proposed framework replaces the 2x2 grid with FTi.
4. Color information in the form of histograms is derived on Hue (H), Saturation (S) and Value (V) components of HSV.
5. The GLCM features extracted on FTiCM have combined with histogram features of H, S and V to form a feature vector.

V. CONCLUSIONS

A feature descriptor CHFTiCM is proposed for color texture image retrieval in this paper. The proposed frame work utilizes the global features in the form of individual H,S,Vcolor histograms and local features with FTiCM. This paper replaces each 2x2 grid of the V-plane with the full texton index and derives a co-occurrence matrix and derives six GLCM features with varying distances and angle of rotation. The HSV color space is used to extract color, brightness and value features respectively. The full texton derives all possible texton patterns on a 2x2 grid and it overcomes the fusing problems associated with TCM and ambiguity issues arises in MTH. The TCM and MTH approaches have not replaced the 2x2 grids with texton indexes due to the limited number of textons. Further the derivation of GLCM on FTi image derives the co-occurrence relation among the neighboring texton indexes. The GLCM features derived on the FTiCM derives the structural statistical information of the local texture.

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