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A New Frame Work for Content Based Image Retrieval Based on Rule Based Motifs on Full Texton Images

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ABSTRACT

This paper derives new framework for content based image retrieval (CBIR) by deriving color features and texture features. This paper initially transforms the RGB color plane image into HSV color plane and derives the individual histograms on H, S and V planes. This paper derives rule based dynamic motif matrix (RDMM) on full texton index (FTi) index images of V-plane. The FTi overcomes the disadvantages and ambiguity issues in indexing textons of earlier methods. The RDMM overcomes the ambiguity issues arise especially when two or more pixels of the 2x2 grid exhibit the similar intensity levels and this reduces overall retrieval rate. This paper integrated the co-occurrence features derived on RDMM-FTi with histogram features of pure color model. The proposed framework is tested on popular color databases and also compared with state of art models of texton and motif based methods based on average precision rate (APR) and average recall rate(ARR). The experimental results indicate the efficacy of the proposed method over the existing methods.

Key words : Texton, Dynamic motif, Co-occurrence, Color features, rule based.

1. INTRODUCTION

The term Texture represents the properties of an object surface. The texture measures the attributes of an image surface with respect to changes in certain directions, scales and intensity levels. Texture also extracts the significant information about structural arrangements of a surface. Texture also derives important information based on relationship between adjacent structural elements. The attributes of a texture derives information based on the behavior of group of pixels surrounded by distance d instead of a single pixel. The most of the work on LBP [1] and its variants are concentrated on gray level image processing applications. The LBP features are also derived on three individual color channels [2, 3]. Later the LBP histograms are derived for each channel in YCBCr color space and applied PCA to reduce the dimensionality in deriving feature vector [4]. This method [4] obtained high results in face recognition when compared with gray level features. The local color vector binary pattern (LCVBPs) [5] is derived in the literature for face recognition and it is more effective. The LBP is extended to color features and this has resulted in deriving various variants of LBP with color information [6-8]. In addition to the texture and color features the shape features also provides a good amount of useful information for image retrieval. The LBP and its variants are basically derived on a 3x3 neighborhood and can be extended to 5x5 or 7x7 neighborhood and they basically capture the relationship between central pixel and sampling points. In the literature other local patterns also played a crucial role, which are derived on a 2x2 grid. The motif and texton based methods falls into this category and they derived different patterns on 2x2 grid.

The texton based methods [9-12] attained good results in texture classification and also on CBIR. A texton is derived if and only if two or more pixels in the grid exhibit the similar intensities. The motif based methods derive a structure based on scanning sequence on a 2x2 grid. The motif based methods [13-16] played a key role in CBIR and in other applications. This paper derives a rule based dynamic motif matrix (RDMM) on full texton index image (FTi) (RDMM-FTi) and the feature of this descriptor is integrated with color features to derive a feature vector. This paper is organized as follows: the section 2 and 3 deals with the related work and methodology, the section 3 and 4 deals with results and conclusions.

2. RELATED WORK

The textons represents a pattern derived on a micro grid. The texton represents the relationship and behavior of adjacent pixels in the gray scale domain. The complex patterns of an image can be easily derived from textons, which represents the simple patterns. In the literature texton based methods are used for CBIR. The TCM [17] derived textons only with three and four identical pixels over a 2x2 grid. The TCM [17] has defined only five textons as shown in the Figure 1. The textons are detected by moving the 2 x 2 grid in an overlapped manner and this process requires a fusing operation to derive a final texton image in TCM. The TCM assigned a zero value to the pixels which are not part of texton formation and other pixels (which are part of the textons defined by TCM) retain the same grey level value. The TCM derived a co-occurrence matrix and computed GLCM features for CBIR.

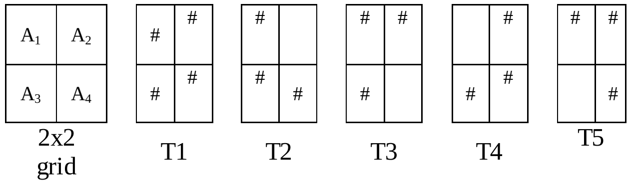


Figure 1: The five types of textons defined by in TCM.

In the literature to overcome the complex fusing operations of TCM the Multi Texton Histogram (MTH)[18] is proposed. The MTH defined only few textons with two identical grey level values as shown in Figure .2. And MTH does not considered the textons with three and four identical pixels. The MTH divided the image initially into 2X2 grids, to overcome the fusing operation of TCM. In MTH approach the RGB color space is quantized in to 64 colors. The MTH frame work identified four types of textons T6, T7, T8 and T9 on a 2x2 grid and they are shown in Fig.2. The common property of these four textons types are they consist of two identical pixels in the 2x2 grid.

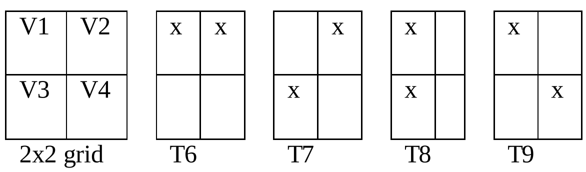


Figure 2: The four types of textons used on MTH.

The MTH assigned a zero value to entire 2X2 grid of four pixels if it is not defined any texton. The 2x2 grids remain same if any one of the four textons is detected with in the grid. The MTH derived multi texton histogram over the image and the histogram features are used for CBIR. The MTH creates ambiguity in identifying texton types due to its derivation of limited number of texton types with two identical pixels over a 2X2 grid [9, 19].

The TCM and MTH defined only few texton types and they retained original grey level values of the pixels which are part of texton formation. Thus they have not replaced the 2x2 grid with texton indexes. Thus the original dimension of the image and grey level range of the image is not reduced in TCM. However, MTH reduces the dimension of the image into N/2* M/2. Very recently we have proposed a full texton matrix (FTM)[19] and integrated it with H,S and V color histograms for CBIR of color images.

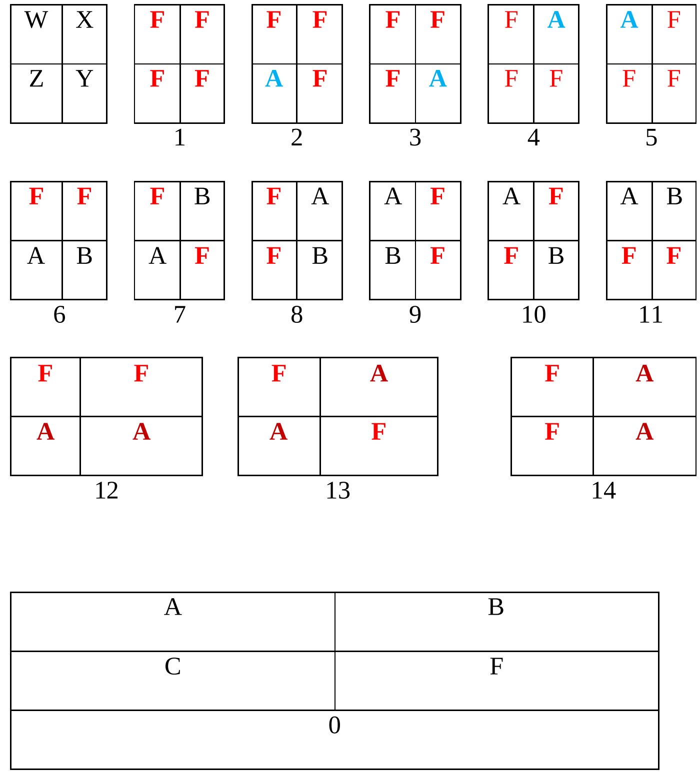


Figure 3: The defined texton types of FTM on a 2x2 grid.

In Figure 3 of FTM the A, B, C and F represents the different gray levels of the 2x2 grid. The FTM defined all possible structures over a 2X2 grid and thus overcomes the disadvantages of TCM and MTH. The FTM initially divided the image texture into micro grids of size 2X2. Based on the similar pixels with the same grey level values, the FTM assigned a Full Texton Index (FT_i) and the 2X2 grid is replaced with the FT_i value. The FT_i defined all possible textons over a 2x2 grid. Each texton type of FT_i is given a unique index ranging from 0 to 14. The FT_i quantizes the image of size N*M into N/2*M/2 and transforms the image with FT_i values ranging from 0 to 14. The FTM replaces the 2*2 grid with FT_i, since it has defined full range of texton types without any ambiguities. This is the major achievement of FT_i over TCM and MTH and other existing texton frameworks. The FTM approach derived a co-occurrence matrix on FT_i image and derived GLCM features for efficient CBIR.

3. PROPOSED METHOD

In the literature the region based methods divides the image into macro regions and macro regions into micro regions. The size of macro region will be more than micro region. This paper proposes a different approach. This paper initially divides the texture image into micro region of size 2*2 and replaces each micro region with an FT_i. Then this research divides again the image into micro region of size 2*2. The pixels of 2x2 local micro regions represent a structure derived on a 2x2 grid by FT_i.

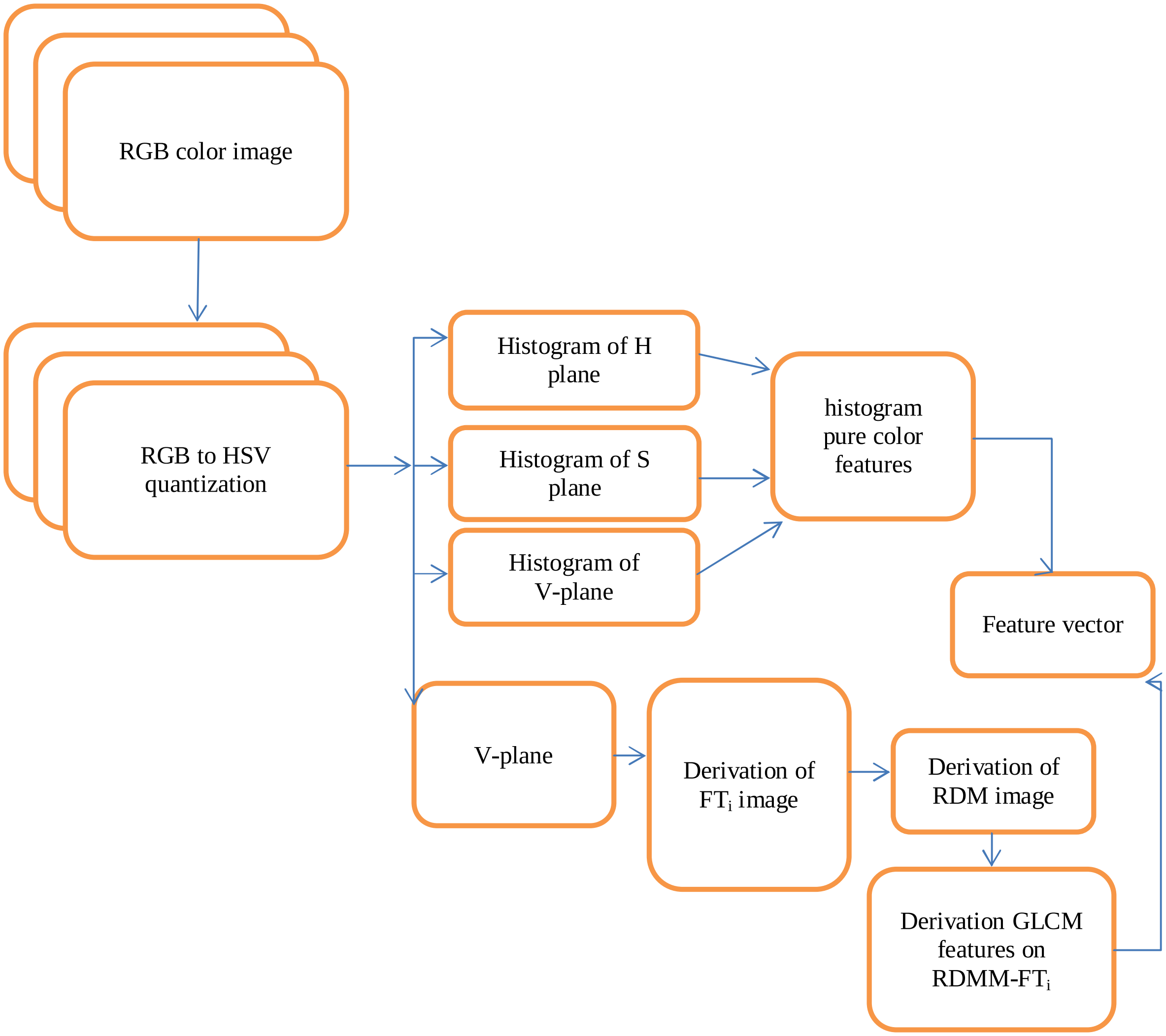


Figure 4: Framework of the proposed color based RDMM-FTi framework.

The research derives the rule based dynamic motif (RDM) index on each 2*2 grid of FTi image and replaces the 2*2 grid with RDM index. The proposed framework initially transforms the color texture image into HSV color plane. In the first step it computes the histograms of the H, S and V-color planes individually. In the second step it derives the FTi image on V- plane and derives RDMM on FTi image. The GLCM features derived on RDMM are integrated with the individual histograms of H, S, and V color plane to derive feature vector. The framework of the proposed RDMM-FTi is given in Figure 4.

One of the primary works on motif is motif co-occurrence matrix (MCM) [20]. The MCM always initiates the scanning from top left most corner of the 2x2 grid. The scanning process continues by visiting the remaining three pixels exactly once based on incremental differences with the initial scan position pixel value. The MCM defines only five types of structures and assigns an index to each scanning structure.

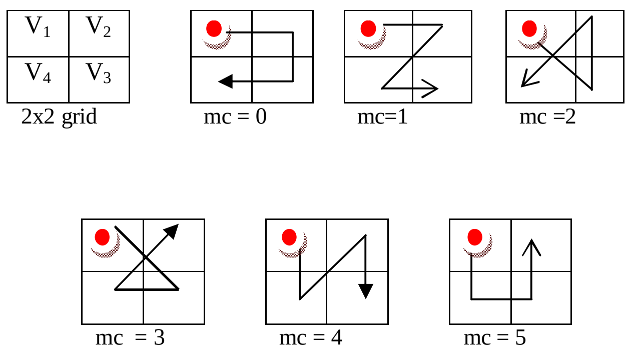


Figure 5: A 2x2 grid and six Peano motifs.

To derive the complete motif information on the 2x2 grid dynamic motifs (DM) are proposed in the literature [16] in which initial scanning position is not fixed as in the case of MCM. The DM initiates the scanning process on the 2x2 grid from the pixel location whose gray level values is least. The DM derives 24 unique motif indexes or different structures as shown in Figure 6.

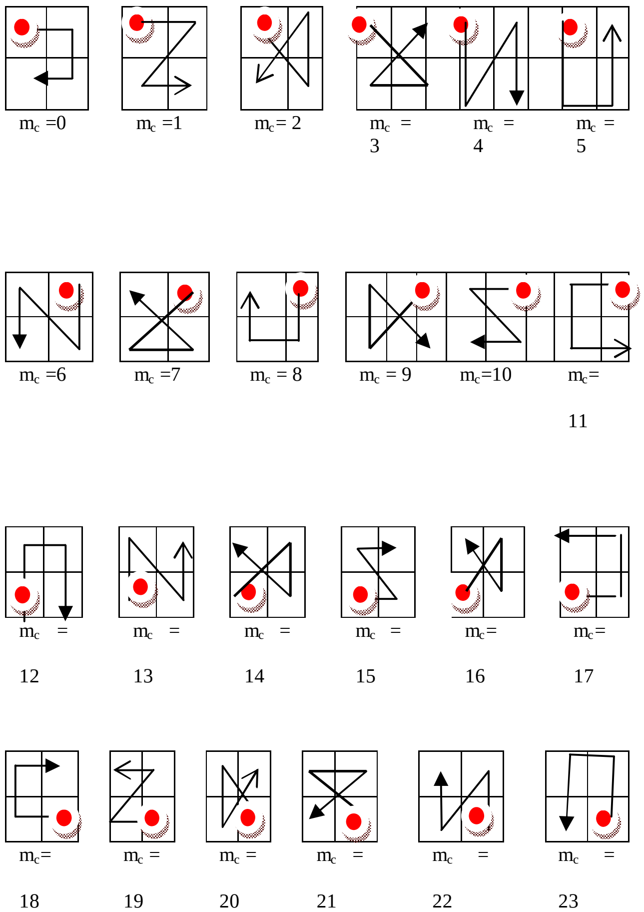


Figure 6: Dynamic motif patterns.

The disadvantage with MCM is, it is initial scanning position is fixed and thus it may not derive the complete motif information on a 2x2 grid.

This paper after a thorough investigation on DM, found that though DM, defines complete set of motifs, however they are not unique. The DM and also MCM fails in giving unique indexes to motif or peano scan motif (PSM) patterns whenever two or more pixels of the 2x2 grid represents the same brightness or intensity values, i.e. the DM and MCM creates ambiguity in assigning unique indexes. The DM and MCM also fail in deriving a unique structure or code for these frequent instances that may appear in the texture images (Figure 7 to Figure 10). This factor may reduce retrieval rate since the same DM / MCM may give two or more different codes or indexes for the similar type's values. The proposed rule based dynamic motif (RDM) address this issue and derives unique PSM indexes by defining rules in scan directions especially whenever two or more pixels exhibits the same intensity values on 2x2 grid of motif.

The MCM creates ambiguity when two or more pixels other than top left most pixels have identical values. This phenomenon is explained with the following figures (Fig.7 and Fig.8). The MCM always initiates the scan from top left most pixel location.

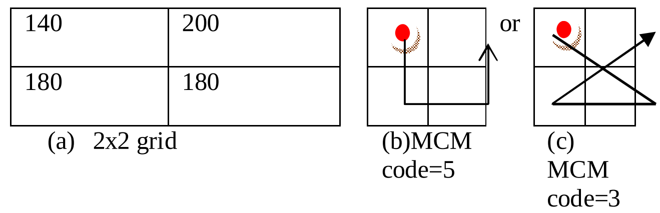


Figure 7: The ambiguity issues in MCM.

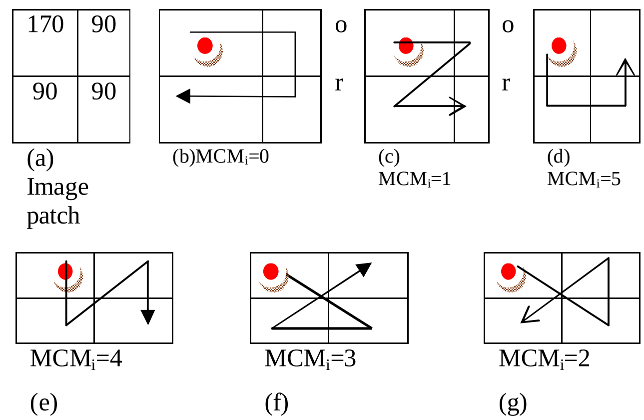


Figure 8: The ambiguity in MCM when three pixels have identical values.

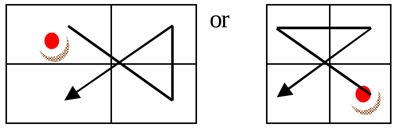
The Figure 7 consists of two identical pixels on the 2x2 grid. In this case the MCM starts scanning from the top left most corner and confuses to reach/scan the next immediate position because the pixels P3 and P4 exhibits the same intensity levels. The MCM can scan in the form of Figure 7(b) or 7(c) by replacing the 2x2 grid with MCM index 5 or 3. The Fig.8 is a more serious case in which all three or four pixels of 2x2 grids possess the same intensity levels. In this case the ambiguity or confusing factor of MCM is tripled and it can scan the 2x2 grid in any one of the six forms displayed in Fig.8(b) or 8(c) or 8(d) or 8(e) or 8(f) or 8(g). That is the MCM can replace the 2x2 grid with MCM code 0 or 1 or 2 or 3 or 4 or 5. In both cases as shown in Fig.7 and 8 the MCM completely fails in deriving a unique code. That means for the same grid of 2x2 as shown in Figure 7 and 8 and other instance where two or pixels contains the same values of brightness, the MCM derives two or more MCM codes or structures and this factor reduces the overall retrieval rate and also significantly affects the classification rate. In the literature so far no body addressed this factor.

The Figure 7 represents two pixels with identical values other than initial scan position of a 2x2 grid may occur in many instances of texture image. The other possibilities of this instance are shown in Figure 9.

The dynamic motif derives 24 different scanning patterns especially when all four pixels of the 2x2 grid exhibit the identical values since peano scan can be initiated from any position in DM. In the same way dynamic motif derives 2 and 6 different motifs when 2 and 3 pixels of the 2x2 grid represents exactly the similar gray values as shown in Figure 9 and 10 respectively. This phenomenon reduces the overall retrieval rate in DM since the above patterns with 2 or more pixels of the 2x2 grid with identical pixel values are unable to derive a unique code or unique structure.

45	65
75	45

(a) 2x2 grid

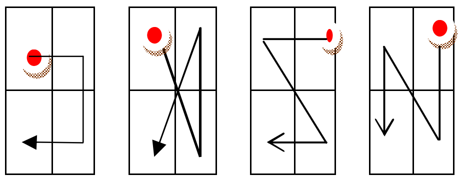


(b) DMi =2 or (c) DMi =21

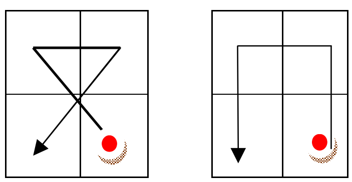
Figure 9: The ambiguity issues in DM.

109	109
125	109

(a)



(b) DMi =0 (c) DMi = 2 (d) DMi =10 (e) DMi =7



(f) DMi =21 (g) DMi =23

Figure 10: The 2x2 grid with 3 identical pixels: Ambiguity issues in DM.

This research addressed this important and crucial factor of MCM and DM by deriving rules on DM & MCM that controls the peano scan motif when two or more pixels in the grid exhibits the similar values. The derivation of unique indexes is very important and crucial for any motif frame works especially for MCM and DM because the 2x2 grid is replaced with motif indexes. If this index is not unique or does not represent a unique structure then overall performance will be degraded significantly. This factor is not addressed so far in the literature. This paper addressed this, using two rules that controls the scanning behavior especially when two or more pixels represents the similar values on a 2x2 grid. The advantage of this rule based DM(RDM) is, it derives only a unique code or structure even in the case of multiple pixel locations exhibits the similar gray level values. The RDM starts scanning the 2x2 grid from the pixel location whose gray level value or code is minimum and continuous scanning based on the incremental difference with the initial position. If two or more pixels exhibit the same grey level values or code, the proposed RDM derived two rules to resolve the conflict or ambiguity in scanning the grid as given below.

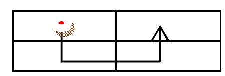
Rule 1 for RDM: If a pixel on the top row and bottom row exhibits the same grey level value or code then scanning preferences is given to top row pixel.

Rule 2 for RDM: If a pixel on the left column and right column exhibit same vale, then the scanning preference will be given to the left most pixel.

These two simple rules on the dynamic motif and MCM over comes the ambiguity issues shown in the above Fig.7 to Figure 10. The advantage of RDM is it derives a unique structure and it is explained with the help of the Figure 11 and Figure 12. For the Figure 7 and 8 of MCM, the proposed RDM derives only one unique code/ structure as shown below in Figure 11.The proposed RDM derives a unique code even whenever four pixels of the 2x2 grid exhibits the same gray level values, whereas the DM and MCM derives 24 and 6 different motif indexes respectively (Figure.12(a), 12(b)). The unique structure for the Figure 12(c) or Fig.9(a) is derived by RDM based on the rule 1, which says the scanning process will be given priority to the top row pixel whenever the top row and bottom row pixels exhibits the same values. In the similar way for the Figure 12 (e) or Figure 10(a) with three identical pixel values, the proposed RDM derives only unique structure or code as shown in Figure.12(f) instead of 6 different codes as in the case of dynamic motifs.

140	200
180	180

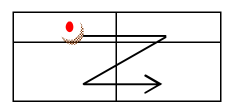
(a)2x2 grid of Figure.7(a)



(b)RDM-scan direction RDM_i =5 Rule1

170	90
90	90

(a)2x2 grid of Figure.8(a)

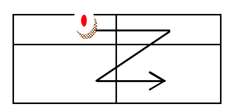


(b)RDM with unique index RDMi =1 Rule1 &2

Figure 11: the derivation of unique index by RDM for Fig.7 and 8 of MCM.

10	10
10	10

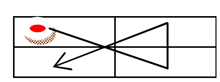
(a)2x2 grid with 4 identical pixels.



(b)RDMi for Figure 10 =1 Rule1 &2

45	65
75	45

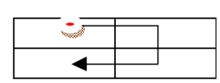
(a)2x2 grid of Figure 10(a)



(b)RDMi for Figure 10 (C)=2 Rule1

109	109
125	109

(a)2x2 grid of Figure 10(a)



(b)RDMi for Figure 10 (c)=0 Rule1&2

Figure 12: Resolving ambiguity issues of DM by RDM.

This framework finally reduces the original dimension of the image into N/4*M/4 with values ranging from 0 to 23. This paper derives a co-occurrence matrix on RDM index image derived on FTi image and this is named as RDM matrix- FTi (RDMM-FTi). The RDMM-FTi measures the occurrence frequencies of RDM-FTi at a distance d. This paper computed the six gray level co-occurrence matrix (GLCM) features namely i) Homogeneity or Angular Second Moment (ASM) ii) Energy iii) Contrast iv) Correlation v) Local Homogeneity or Inverse Difference Moment (IDM) vi) Prominence feature on RDMM-FTi with a distance d=1 and 2 and on each distance value, this research derived six RDMM-FTi with an angle of rotation 0o, 45o, 90o, 135o, 180o, 225o. This leads a total of 6x6=36 GLCM features for each distance value. The feature vector is derived by integrating the color features derived from individual color plane histogram (H, S and V) with gray level features derived from RDMM-FTi.

Contribution of this paper

This paper has conferred a new method for CBIR by integrating color features, with shape features derived by RDMM using FTi and finally GLCM features on this. The main involvements in the current paper are as follows:

1. Derivation of simple rules on motif to overcome the ambiguity issues of earlier motif based methods.
2. Derivation of simple rules on motif that controls the path of peano scans whenever two or more pixels exhibits the same gray level values.
3. Derivation of unique index for all kinds of motif frame works.
4. Derivation RDM on full texton index image.

4. RESULTS AND DISCUSSIONS

This paper used five bench mark databases to test the retrieval performance of the proposed framework and also compared the proposed method with the other popular existing methods based on Tetons and PSMs. This paper used Manhattan distance measure to compare the similarities in between query and database images. The feature vector is computed on all database images individually and placed in a database and also on query image [19, 21]. The image with least distance value is considered as relevant image. This paper used precision and recall as the evaluation measures to test the efficacy of the proposed and existing methods. This paper retrieved the top 20 similar images for each query image.The precision gives the ratio between the numbers of relevant images retrieved versus the total number of images retrieved. The recall measures the ratio between numbers of relevant images retrieved versus the total number of relevant images in the database i.e. number of images in each category of the database for the query image. This paper computed average precision rate (ARR) and average recall rate (ARR) for comparison purpose. The five popular databases used in this research are Corel-1k [22] and Corel-10K databases [23], MIT-VisTex database [24], Holidays dataset [25] and CMU-PIE database [26] and brief discussion about these databases and the number of different classes or categories, the number of images per class and the number of images considered in each class are given in our previous paper [21]. The sample images of these databases are shown in the following figures. This paper computed APR and ARR on the proposed method and on the existing methods using the above affordable databases and results are plotted in terms of graphs from the figures 13 to 17. This work in figure 23, displayed the top 20 retrieved images for one of the query image from each database.

The precession and recall curves of Figure 18 to 22 clearly indicate that the proposed frame work is better than other methods. In terms of precession on corel-1k and 10k databases, the proposed method accuracy has been increased by 8%, 7% and 2% when compared to the other popular texton based methods TCM, MTH and CHFTiCM. The proposed method also exhibited high accuracy in terms of APR by 5% and 3%, when compared to existing Motif based methods MCM and DMM on Corel data bases. The same trend is repeated on the remaining databases. The ARR has shown same tendency on all databases.

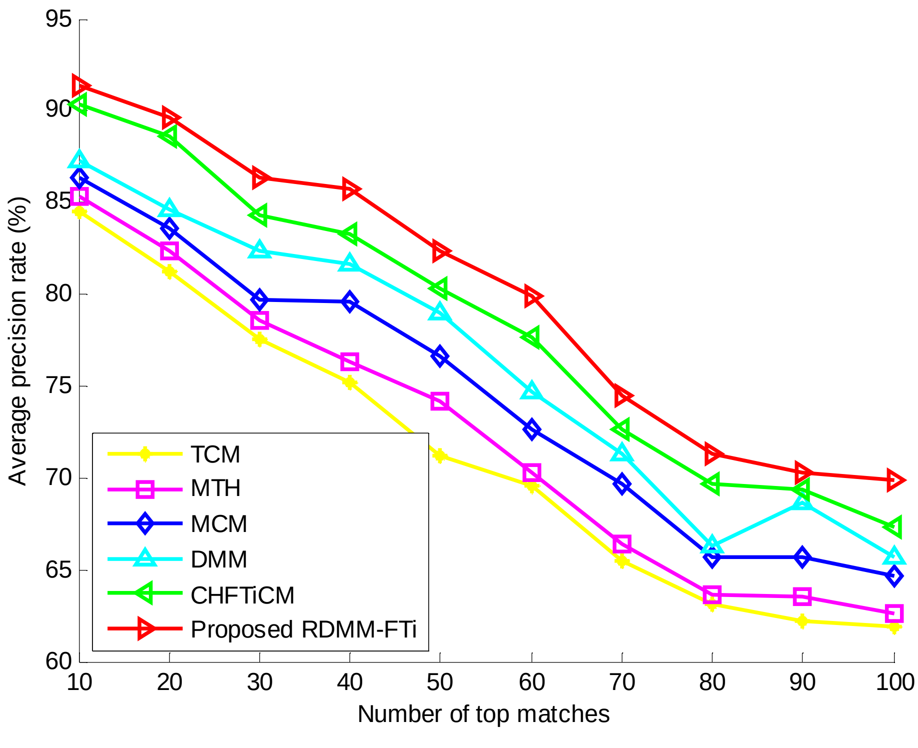
Figure 13: Corel-1K database sample images.

Figure 14: Corel-10K database sample images.

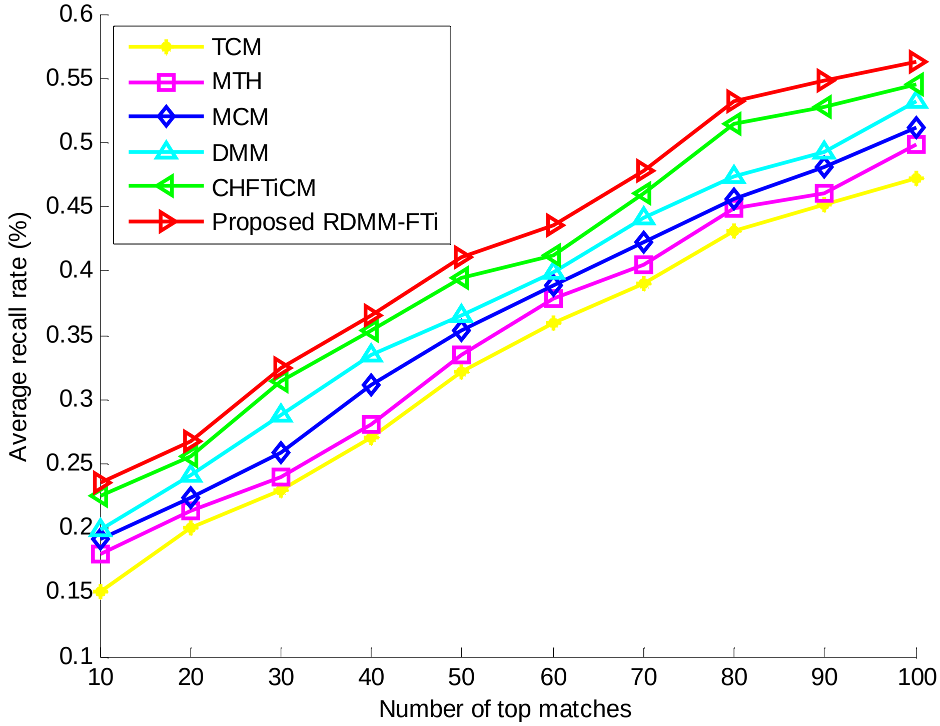
Figure 15: The sample textures from Holidays database.

Figure 16: The sample textures from MIT-VisTex texture.

Figure 17: The sample facial images from CMU-PIE database.

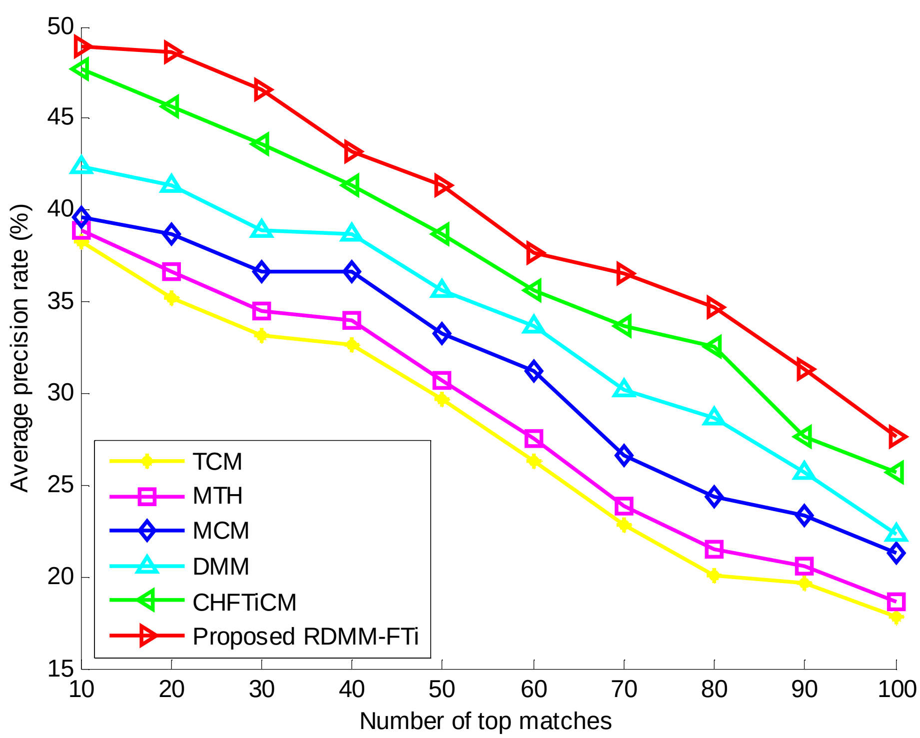


(a) APR.

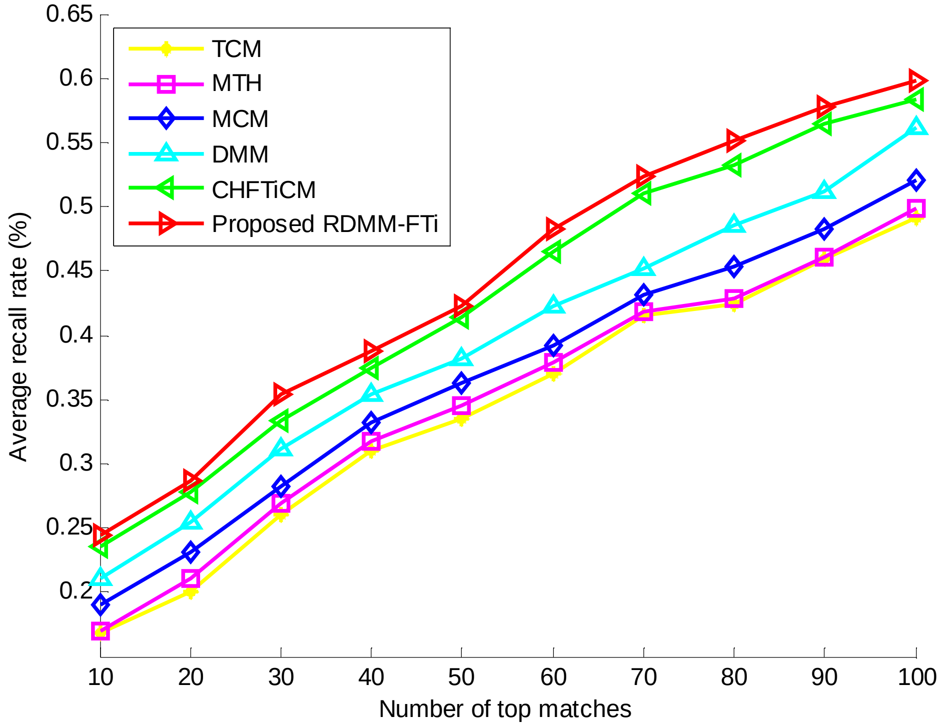


(b) ARR.

Figure 18: Comparison of over Corel-1k database using (a) APR (b) ARR.

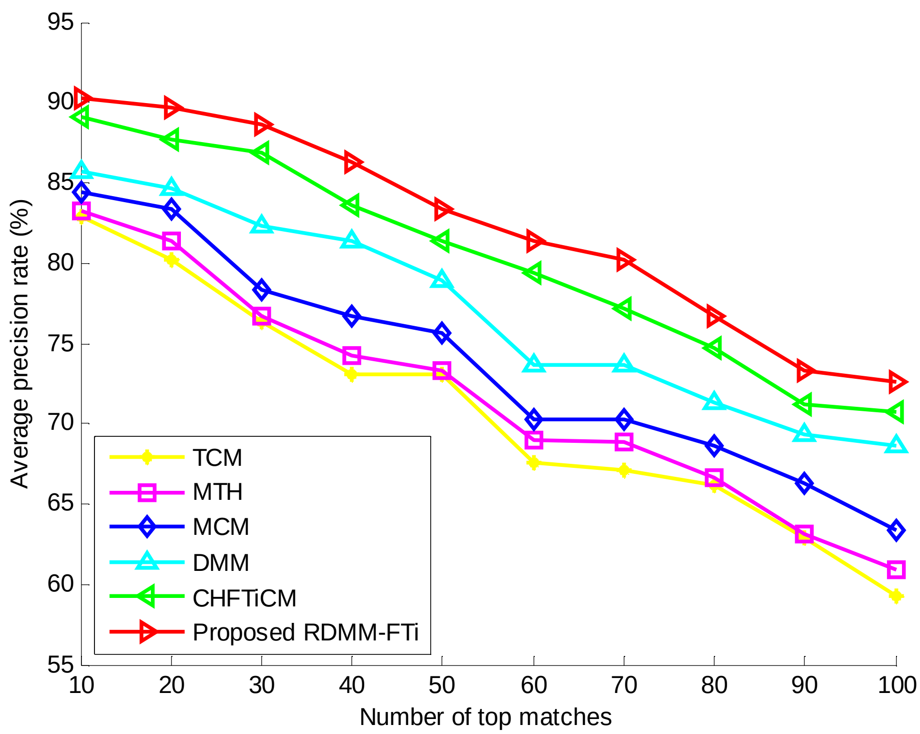


(a) APR.

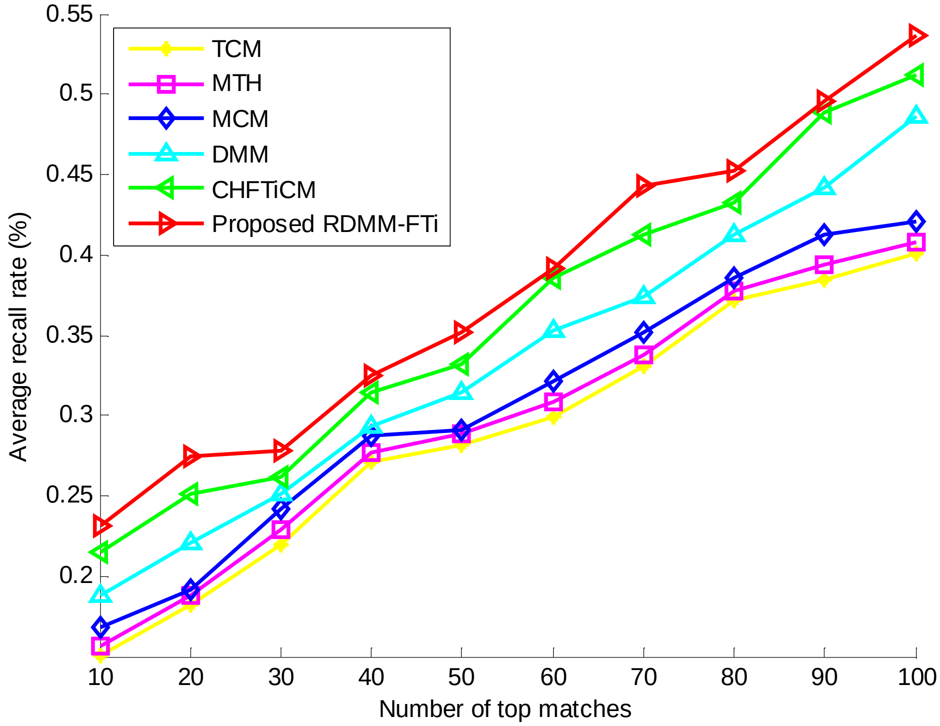


(b) ARR.

Figure 19: Comparison over Corel-10k database using (a) APR (b) ARR.

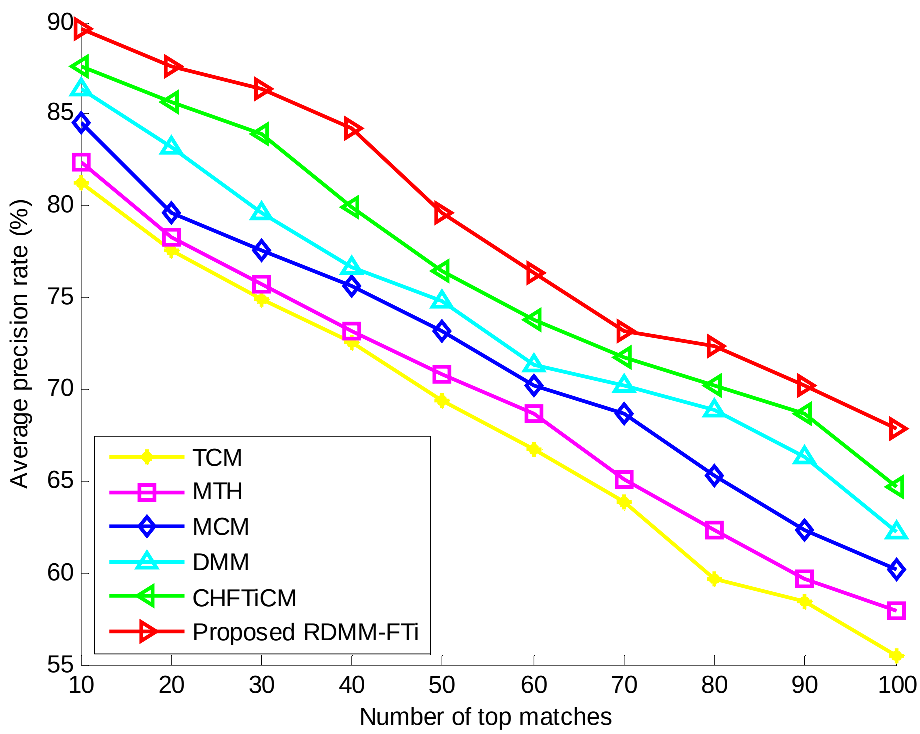


(a) APR.

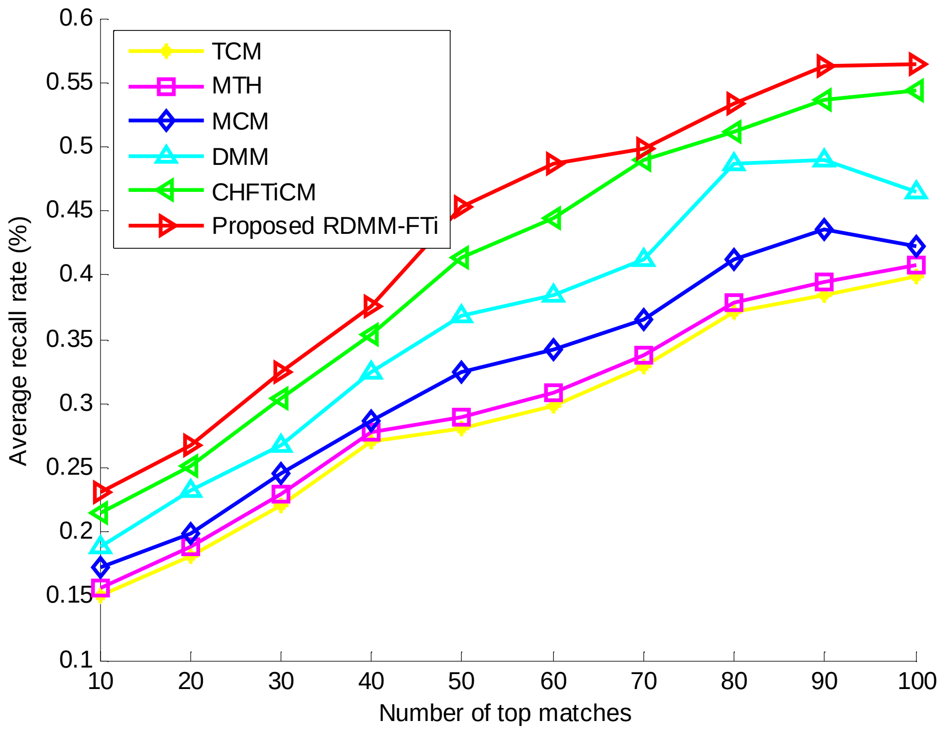


(b) ARR.

Figure 20: Comparison over Holidays database using (a) APR (b) ARR.

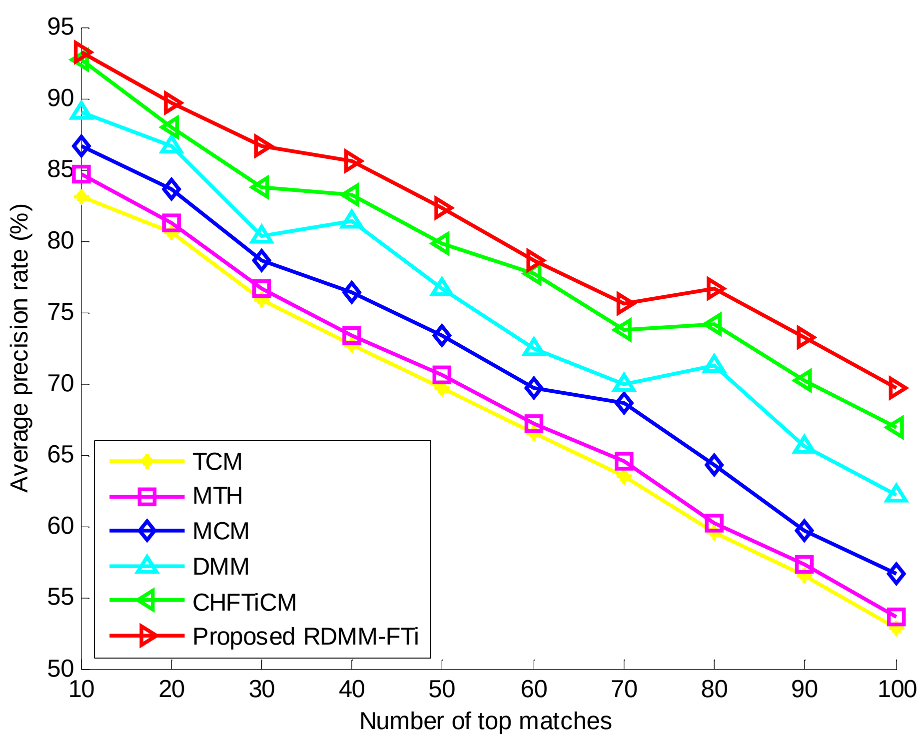


(a) APR.

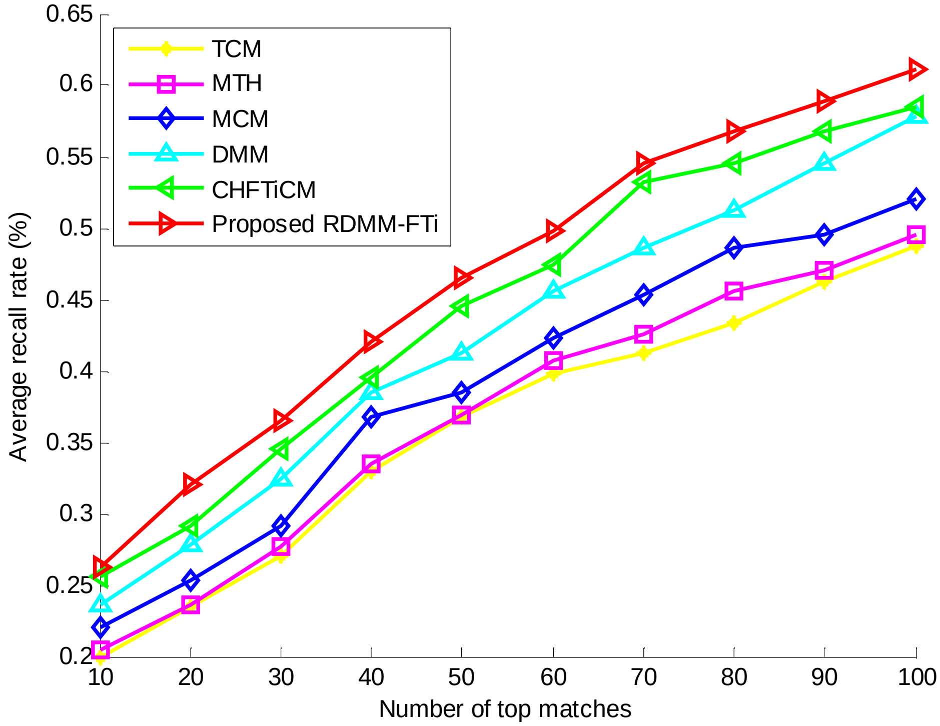


(b) ARR.

Figure 21: Comparison over MIT-VisTex database using (a) APR (b) ARR.

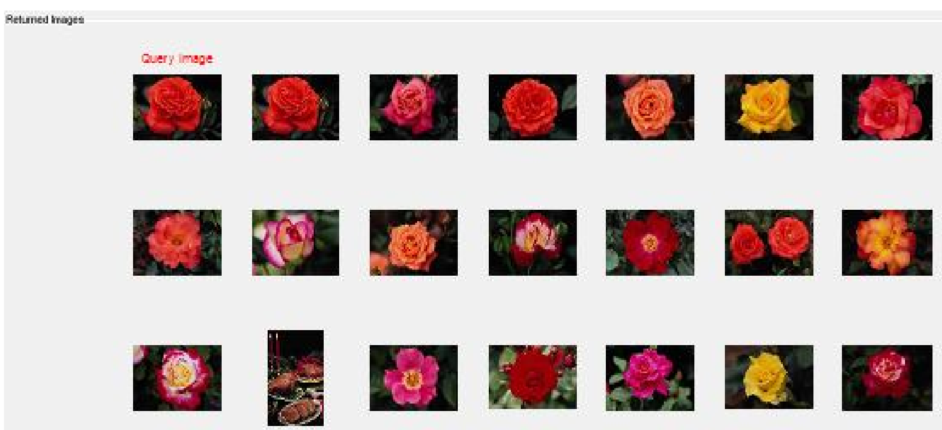


(a)APR.

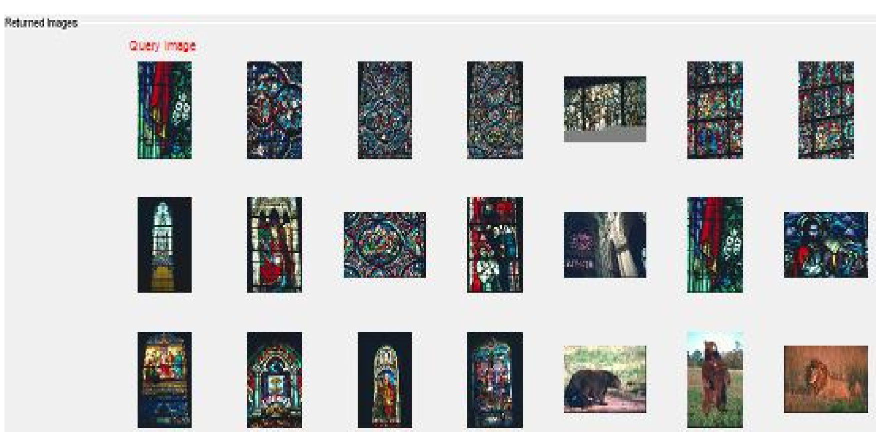


(b) ARR.

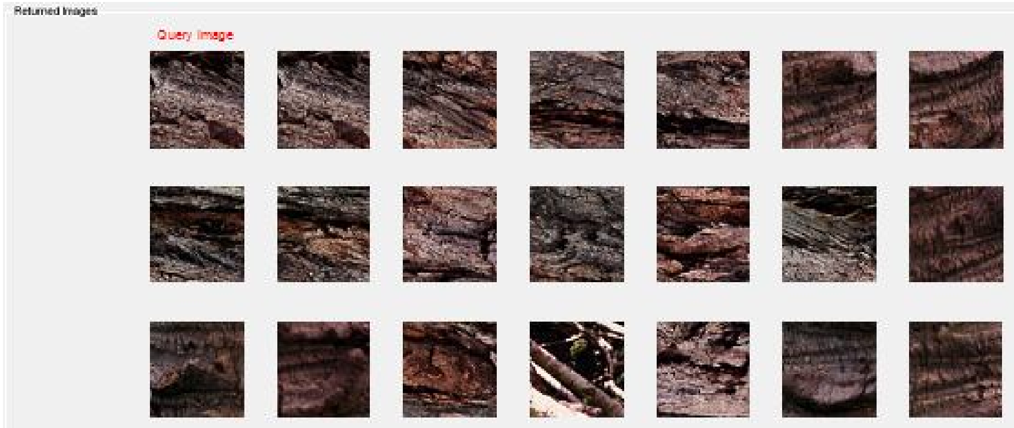
Figure 22: Comparison over CMU-PIE database using (a) APR (b) ARR.



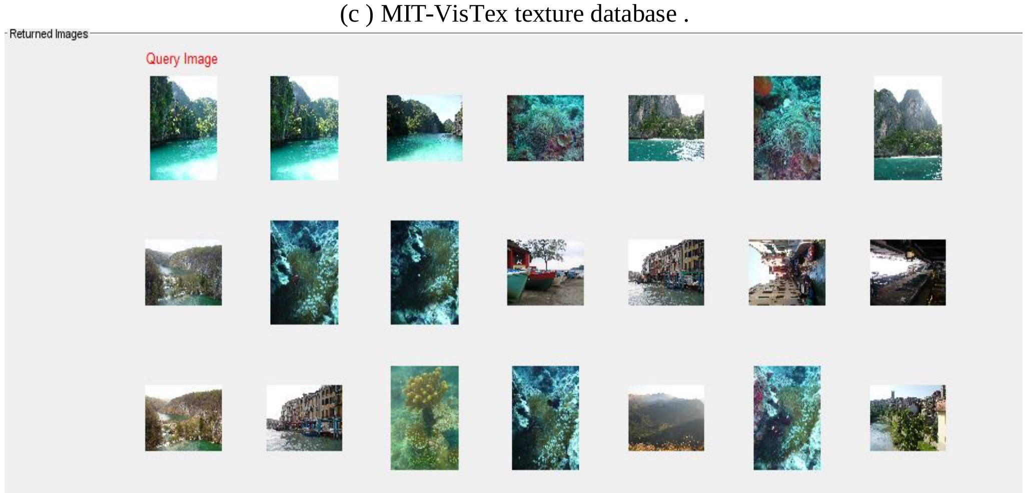
(a) Corel 1k.



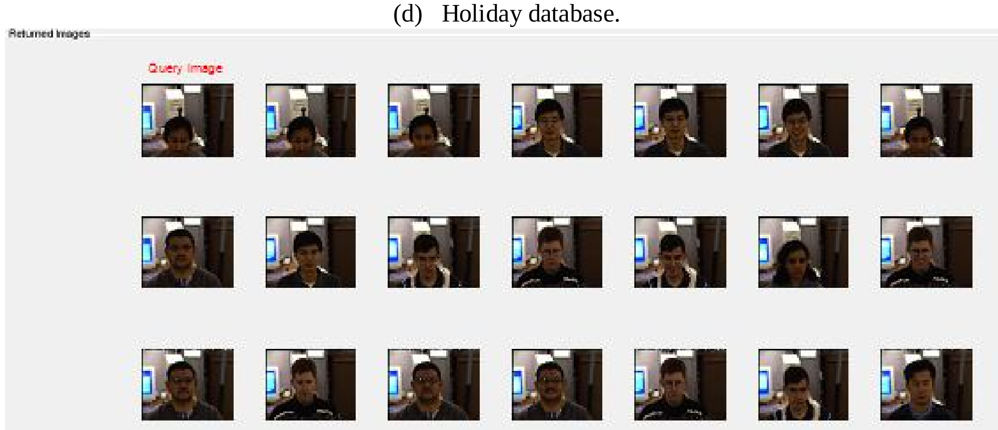
(b) Corel 10k.



(c) MIT-VisTex texture database .



(d) Holiday database.



(e) CMU-PIE database.

Figure 23: Top 20 retrieved images of considered databases.

5. CONCLUSION

This paper initially derives the individual color histograms of H, S and V plane. The proposed frame work initially divides the V-plane of the image into 2x2 grids and derives full texton index image. Full texton index over comes the complex fusing operations of TCM and ambiguity issues in MCM. This paper derives the rule based dynamic motif (RDM) on full texton image. The disadvantages of all earlier motif frameworks is they derive different structures or codes for the same 2x2 grid whenever two or more pixels exhibits the same intensity levels. This results a simple mismatch and affects significantly the overall retrieval rate. The rules derived for RDM guides the peano scan motif in a unique way whenever two or more pixels of the 2x2 grid exhibits the same gray level. The derived rules make the proposed framework more efficient and increase overall retrieval rate. This paper integrates the pure color features with GLCM features derived on the proposed RDMM-FTi to derive the feature vector. The experimental results on the popular databases exhibits the performance of the proposed method over the existing texton, and motif based methods.

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