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IMAGE RETRIEVAL USING COLOR AND STRETCHED TEXTONS OF RULE BASED MOTIF

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ABSTRACT

By deriving color and texture attributes, this paper develops a new framework for content-based image retrieval (CBIR). The individual histograms on the H, S, and V planes are calculated in the first step. This paper primarily divided the 3x3 window into four overlapped micrograms of size 2x2. On each micro grid, it has derived Rule-based Dynamic motif (RM) indexes. The RM extracts all probable Motifs on a 2x2 grid by overcoming all possible ambiguities. This process transforms the 3x3 window into a 2x2 grid and each grid value represents the shape, and texture features more efficiently and precisely. On this transformed grid of 2x2, this paper applied Stretched Texton (ST) patterns. The ST patterns consider the magnitude relationship among the pixels that are part and not part of texton formation. This aspect is not considered in the earlier methods. The co-occurrence features are derived from RM-ST matrix (RMSTCM). The feature vector is derived by fusing features of RMSTCM with the histogram features of color components of H, S, and V. The suggested framework is related with the other methods of significance. The outcomes specify the efficacy of the RMSTCM.
Keywords: *Histograms; Texture; Stretched Textron's; Motifs; Co-Occurrence Feature* .

1. INTRODUCTION

The retrieval effectiveness of a CBIR system is meaningfully derived by the feature representation and similarity assessment. Numerous techniques have been suggested to address the well-known "semantic gap" issues, that arises between machines and humans [1,2]. Though there are various methods developed for feature extraction, however the efficient CBIR is continues to be one of the most exciting problems.

The retrieval performance of the search process will suffer due to the problem with text-based image retrieval [3]. To search the database for images, the Query by Image Retrieval (QBIR) module, which extracts the contents of the images, has become essential [3,4].

There were numerous local and global elements like histogram-based methods to express the image qualities and content for various earlier content-based techniques [5]. For the extraction of color and texture features in [6], primitives and colony filters are utilized. In their work, an image is broken up into numerous smaller pieces, and the color moments of each block are retrieved according to an existing method [7]. A clustering method and a predetermined color feature vector approach are used to group these moments into several classes [8]. Each digital value will serve as a representation of the distance between each digital image, however, up until recently, we were unable to extract an exact value from each of the images we searched specifically [9]. The method of communication used between the point nodes of the image is defined in some studies [10]. These methods typically work well for textures with one color and for items that stand out against the background [11]. The features derived from color moment are combined histograms of colors by Xue and Wanjun [12]. They claimed that index sorting outperformed other methods [12]. The integrated methods based on two or more attributes like color or texture or structural or statistical features are proposed for CBIR as well as texture classification [13,14,15,16]. The Gabor descriptors and color moments of the images were employed, to derive precise texture's features [17]. They used Euclidean distance to calculate similarity after normalizing the features. They claimed that compared to the earlier traditional procedures, the suggested method had greater retrieval accuracy [18].

The SVM (Support Vector Machine) classifier was utilized by Lohite et al. [19] to maximize the outcome by utilizing the images' frequently used color, texture, and edge attributes. A CBIR technique for visual words called WATH (weighted average of triangular histograms) was presented by Mehmood et al. [20]. A novel approach by Rashno et al. [21] involves splitting the input color image into subsets in the neutrosophic (NS) domain. Wavelet features, dominant color descriptors (DCDs), histograms, statistic components, and wavelet characteristics are retrieved for each segment. Then, images are retrieved using these features.

Local mean differential excitation pattern (LMDeP), a new feature descriptor that can generate reliable features, was introduced by Kumar et al. [22]. To address this gap and to progress the performance, Sarwar et al. [23] suggested an approach based on the bag-of-words (BoW) model. Rana et al. [24] proposed for picture retrieval by fusing texture features that were nonparametric with color and shape features. The SIFT and LIOP descriptors were combined visually to increase CBIR performance, according to Yusuf et al. In the literature binary robust invariant scalable keypoints (BRISK) was developed to derive efficient features for classification[25]. A technique for retrieving images that uses the YCbCr color scheme along with a DWT and canny edge histogram was developed by Ashraf et al. [26]. Two extended versions of motif co-occurrence matrices (MCM) are computed and integrated in vijayakumar et al's [27] study to enhance CBIR performance.

The section one of this paper gives the introduction. The section two expounds the adopted method with its background. The chapter three and four presents the elaborated results with discussion and conclusions

2. PROPOSED METHOD

The methods based on Motif played an important role mostly in CBIR and to some extent in texture classification [35, 28, 29,15,2]. MCM [35] is one of the most important works on CBIR. MCM derived significant local features by applying a scanning mechanism on a 2x2 grid. The MCM scanning process starts from the left most corner of the top row of 2x2 grid (Fig. 1). Based on incremental variations with the initial scan location pixel value, the scanning procedure continues by viewing the next three pixels exactly once. Each scanning structure depicted in Fig. 1 is assigned an index by the MCM, defining just five structural types or scanning patterns. The MCM is considered as static, since always the scanning position begins from top left corner. To make it dynamic, "Dynamic Motif (DM) [30]" is proposed in the literature.

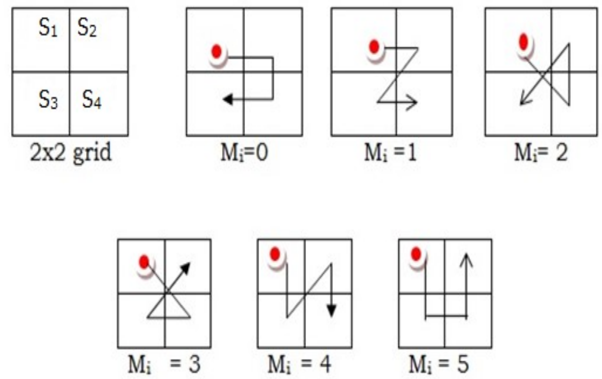

*Figure 1: A 2*2 Grid with MCM Patterns*

The DM generates comprehensive motif information on the 2x2 grid, in which the starting point for scanning is not fixed as in MCM. The scanning operation on the 2x2 grid is started by the DM from the pixel with the lowest grey level value. As seen in Fig. 2, the DM generates 24 distinct motif indexes or structures.

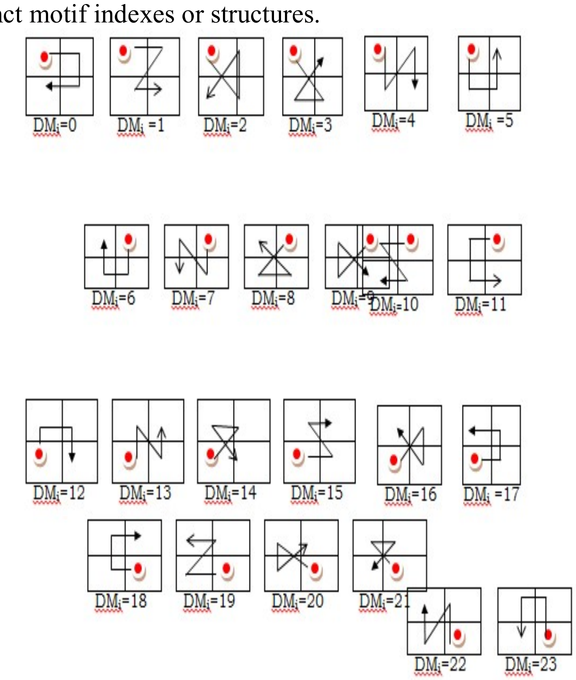

Fig 2 DM- Patterens

After conducting a thorough review of DM, this study discovered that while DM defines a comprehensive set of motifs, they are not unique. This process is explained in the following figures 3 and 4.

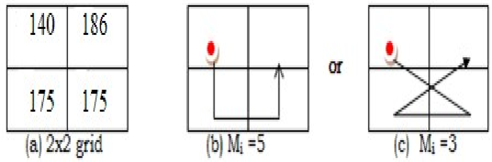

Fig. 3: The problems associated with MCM

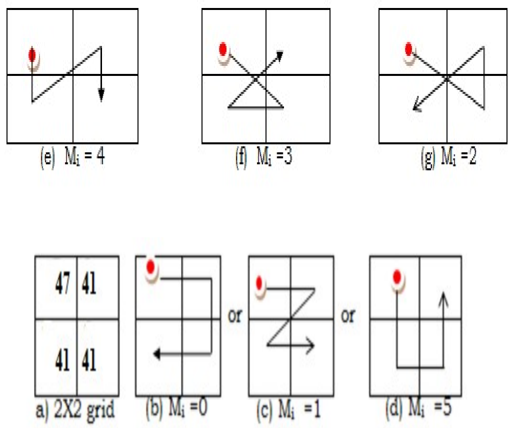

Fig.4: Ambiguity of MCM: three identical pixels

The 2x2 grid, Fig. 3 comprises of two identical pixels (V3 and V4). The MCM gets confused about reaching/scanning the next immediate spot after the initial position. This will result a non-unique index for the grid i.e., 5 or 3, as shown in Fig. 3(b) or 3(c). The example shown in Fig.4 is more significant, as all three pixels in a 2x2 grid have the same intensity levels. MCM's ambiguity or perplexing factor is tripled in this scenario, and thus it results six different forms: Fig.4(b), 4(c), 4(d), 4(e), 4(f), or 4(g) (g) and thus MCM can represent this grid with any of 5 different indexes (0 to 5). For Fig. 3(a), the DM also generates two different motifs patterns/ indexes 3 or 5. The DM also generates six different motifs or structures for Fig. 4(a) (DM index 6 or 8 or 19 or 22 or 16 or 17). The DM results 24 alternative scans, specifically once all pixels of the 2x2 grid possess the similar value. From the above it can be concluded that the DM and MCM derives lot of ambiguity in framing the structural patterns and this factor may reduce the retrieval rate and thus have a considerable impact on overall performance.

The ambiguity issues of DM and MCM are addressed by the Rule-based Dynamic Motif (RM) [28]. The benefit of this RM is that it only generates a single index or structure even when several pixel locations have similar grey level values. The RM scans the 2x2 grid starting at the pixel with the bottommost grey level value and endures scanning on the incremental difference based on the rules given below.

Rule 1 for RM: A pixel in both bottom and top rows holds the exactly similar value or attribute, the top row pixel is given scanning priority.

Rule 2 for RM: If a pixel in the right and left columns has the same value, scanning priority is given to the pixel on the left.

The ambiguity issues illustrated in MCM and DM are resolved by these two basic rules on the RM (Fig 5). The benefit of RM is that i) it generates a unique structure.

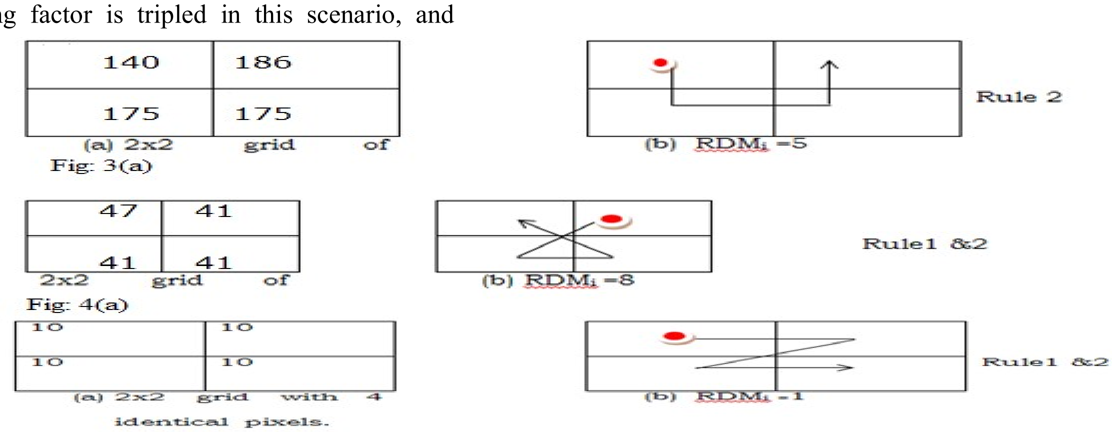

Fig: 5 Resolving ambiguity issues 0fmcm and DM by RDM

Even when all four pixels of the 2x2 grid have identical grey level values, the RM generates a unique index, but the DM and MCM generate 24 and 6 distinct motif indexes, respectively (Fig.5). The RM derives the unique structure for all variations of Fig. 5. The above illustrations

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explore ii) the efficacy of RM in overcoming the uncertainty issues of earlier motif methods. iii) The derivation process of unique structure using two simple rules. iv) the improvement of the overall retrieval rate.

The other popular method on the 2x2 grid, that derives the most important local structural features is the texton [31,32,33,34]. The initial work on textons is the "Texton Co-occurrence Matrix (TCM)" [36] and later many methods are derived on textons [31,32,33,34] and they have shown significant results and improvements in CBIR and Classification. The derivation of structural patterns of a texton is completely different from Motifs. A texton identifies a structure on a 2x2 grid when at least two co-ordinates of the grid hold alike grey levels.

The Texton Cooccurrence Matrix (TCM) derived structural patterns with three identical pixels, this has resulted only 5-patterns [36]. A Cooccurrence Matrix is derived from the final texton image. The major drawbacks of TCM are 1) it needs to scan the image five times to extract the final texton image. 2) It completely ignored the textons with 2 identical grey level values.

The other popular approach Multi Texton Histogram (MTH) derived four textons based on two identical pixel values [37]. The MTH addressed the fusing problem of TCM by dividing the image into micrograds of size 2*2. The MTH created ambiguity since it derived only a few textons with 2-similar pixels.

The uncertainty issues of MTH and fusion operations of TCM are studied in-depth by the other popular framework of textons "Complete Texton Matrix (CTM)" [33]. The advantage of CTM is it has derived textons with 4, 3, and 2 identical pixels. The structural patterns derived by CTM are shown in Fig.6.

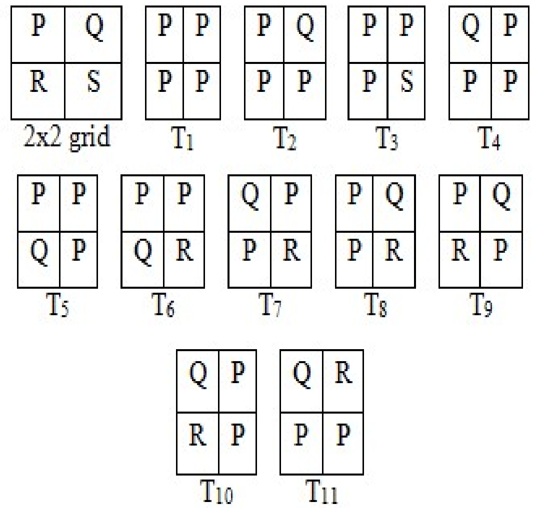


Fig: 6 CTM: textons and indexes

Recently we have explored the stretched texton (ST) co-occurrence matrix STCM [43] that takes into account the magnitude relationship. And these textons with magnitude relations are called as stretched texton. And the stretched texton is measured for textons with three and two identical pixels, with the following two facts:

Fact 1: The 2x2 micro grids with three identical pixels exhibit only two different grey levels g1 and g2. The magnitude relationship between g1 and g2 derives the following three cases: and STCM explored this.

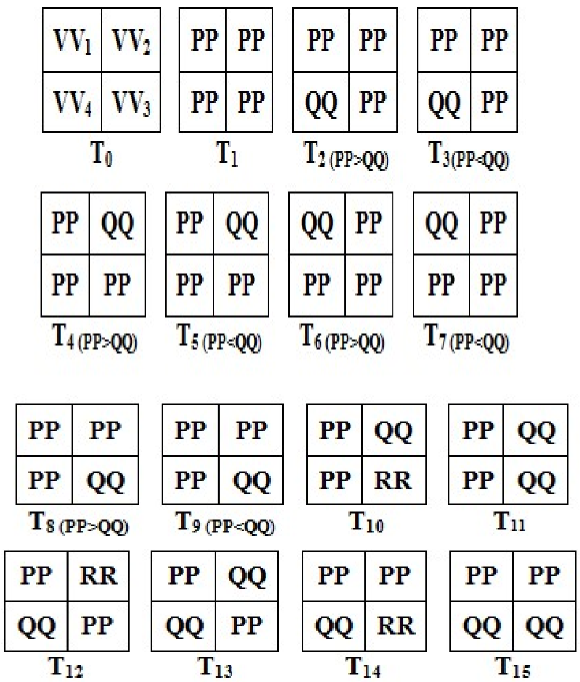
Case 1: C1: g1 > g2;

Case 2: C2: g1 < g2;

Case3: C3: g1 == g2; (this case is not possible with the three identical pixels; in such case it leads to the 2x2 grid with four identical pixels).

Fact 2: There will be only three grey levels g1, g2 and g3 on 2x2 micro for textons with only two identical pixels.

The structural patterns of STCM are depicted in Fig. 7. The STCM derives 19 structural patterns with indexes ranging from 0 to 18 (fig 7).The indexes 0 to 9 and 10 to 18 of fig. 7 represents the stretched textons with three identical pixel (fact 1) and two identical pixels respectively (fig 7).



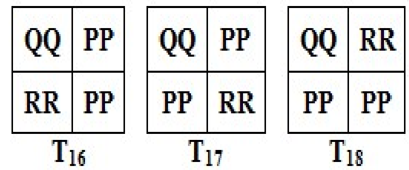


Fig. 7: stretched texton patterns

In a color image, each pixel is represented by numerous bands. Each band is represented by a range of intensity levels. The RGB and HSV color models are the most popular and widely utilized. Red, green, and blue color bands make up the RGB color scheme. The HSV model is also popular because it is preferred by most artists. This is due to the HSV extracting individual brightness, color, and intensity without any additive or subtractive color components. In this paper, the color images are quantized in the HSV model and distinct histograms of HSV are computed and used to signify color features. The grey scale information is stored in the V-component and it is employed to compute local features using RMSTCM.

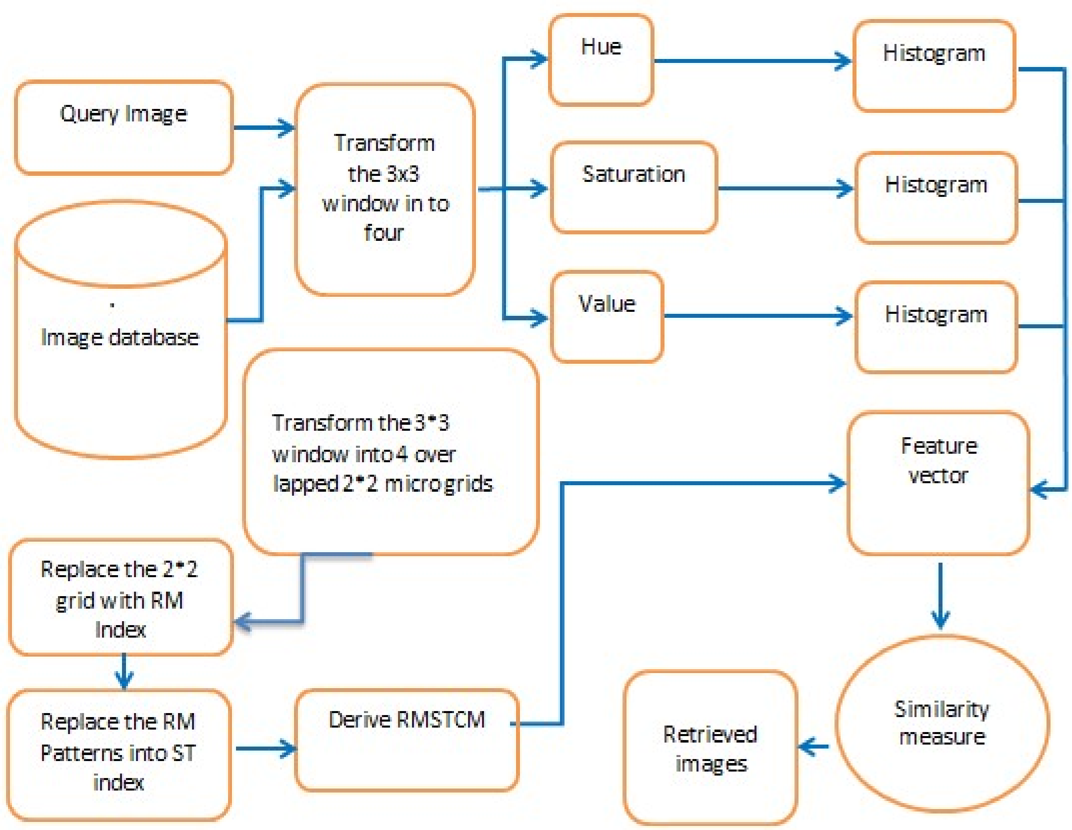


Fig- 8 Framework Of RMSTCM

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This paper initially divides the 3*3 neighborhood into four 2*2 grids and substitutes each grid with a RM index. Thus the 3*3 window is transformed into a 2*2 grid, where each pixel represents the structural patterns derived from RM. The ST pattern is applied on this 2*2 grid and it is replaced with the ST index. The center Pixel of 3*3 window of the input image is replaced with the derived RMST index. Thus this value represents the strong structural pattern derived from ST and RM indexes. This process is applied on the image. This process transforms the input image into a Rule-based Motif Stretched Texton (RMST) index image. The GLCM is derived on RMST and thus the input image is transformed further into RMST-Cooccurrence Matrix (RMSTCM). Thus the derived GLCM features represent the textural feature and strong structural features derived from the combination of the rule-based motifs and stretched textons. The six grey level co-occurrence matrix (GLCM) features are generated on RMSTCM and the features include: Correlation; Contrast; Homogeneity; Entropy; Energy; Inverse Difference Moment (IDM). This paper derived the features on RMSTCM with different angles of rotation. The feature vectors derived from RMSTCM are fused with color histograms HSV, to derive the concluding feature space of RMSTCM.

2.1 The research contribution

1. Generation of powerful structural features, where each feature represents the strong structural information derived from stretched textons and rule-based motifs.
2. The exploration of textural information in the form of GLCM features on strong structural information.
3. The fusing of color histograms with strong structural and statistical information.

3. RESULTS AND DISCUSSIONS

The databases used to evaluate classification or retrieval systems are an important parameter. The following measures are to be considered in choosing the databases i) the selected databases should contain a wide variety of classes ii) each class in the training and testing database should have many images. iii) the natural images should be included in image databases. This paper chose Corel-1K [38], Corel-10K [39], grayscale Broadtaz texture [40], colour Broadtaz texture [41], and MIT-VisTex [42]. The images of these databases are captured against different backgrounds and sample images are shown from fig. 9 to 13. The description of these databases is given in our earlier papers [reference of STCM, TTCM].

Fig. 9. Corel-1k Database Sample Images

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Fig. 10. Images of : Corel-10k

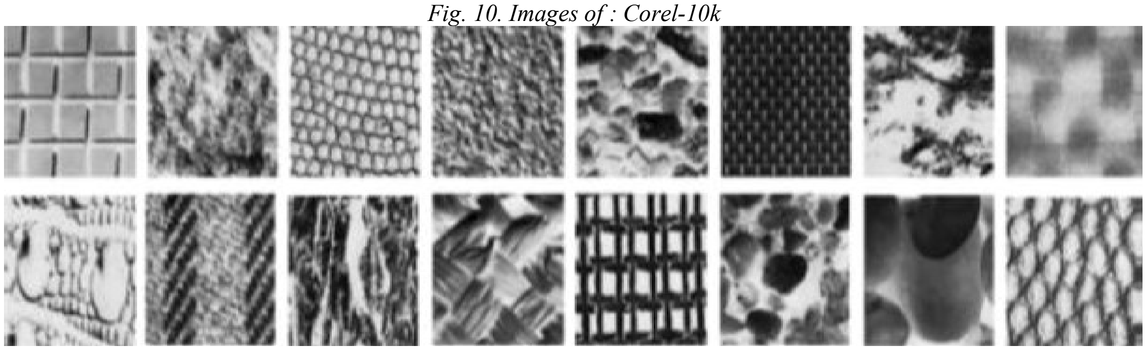

Fig. 11. Images of Brodatz

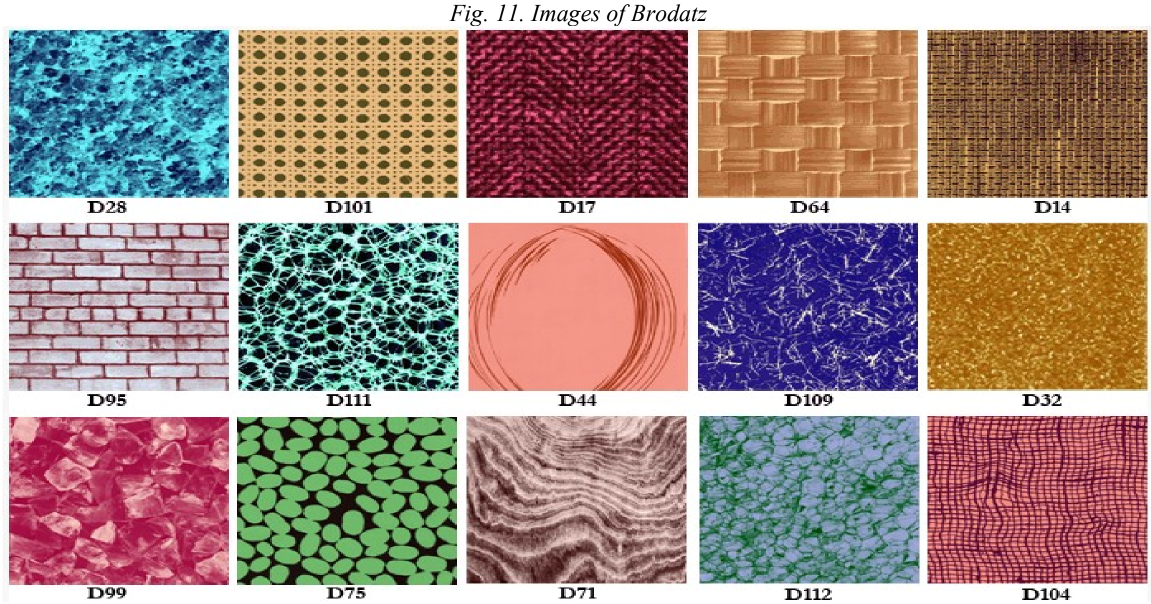

Fig. 12. Images of color-Brodatz

Fig. 13. Images of MIT-Vistex

This paper derived feature vector on images of databases and query. This research used Manhattan distance measures to compare query and database images. The distance measure is applied on the derived color and structural features of RMSTCM on the query and images in the dataset. The dissimilarity index between the images is computed. The images in the top 'N' lower measure index are sorted and considered for the top 'N' recovered images. The retrieval measures ("average precision rate (APR) and average recall rate (ARR)") are used to evaluate the performance of the proposed scheme and also on existing CBIR frameworks in the current paper. This paper evaluated retrieval performance by treating each database image as a query and computed average performance. Each retrieval retrieves 20 similar images.

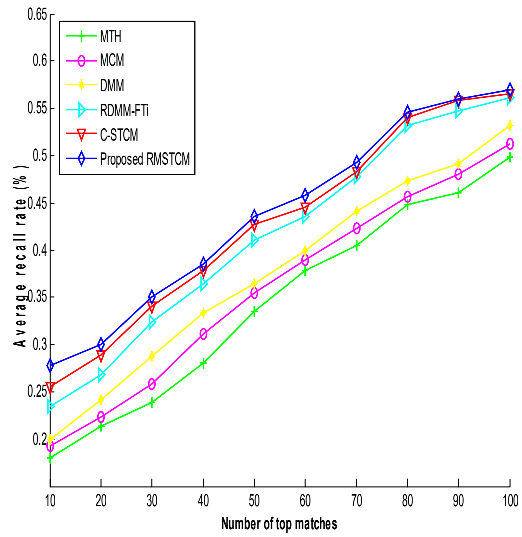

Fig.15 Graph- Corel-1K - ARR.

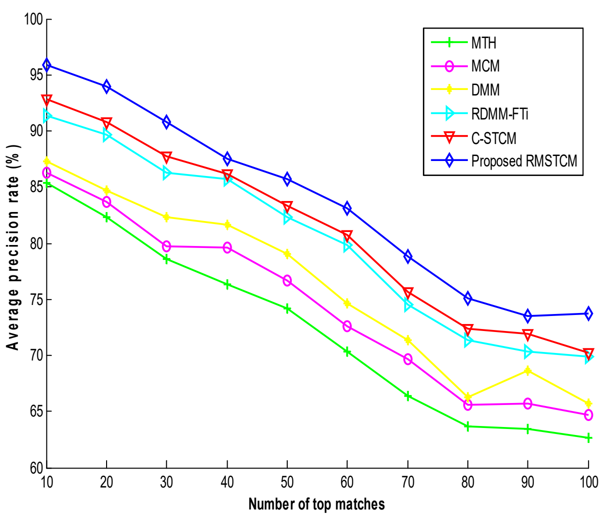

Fig: 14 performances graph on Corel-1K: APR.

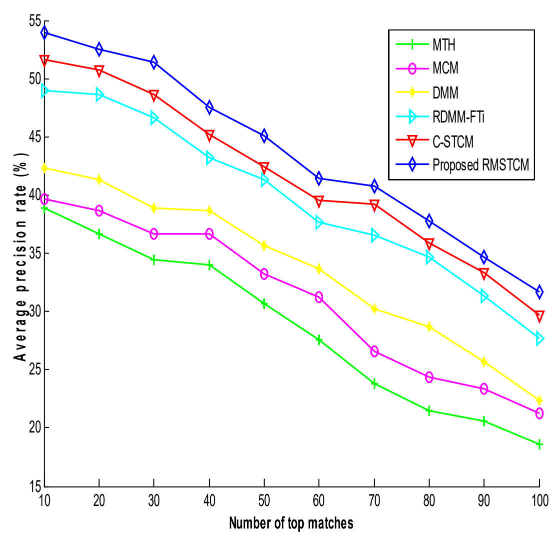

Fig. 16 Performance Graph on Corel-10K using APR.

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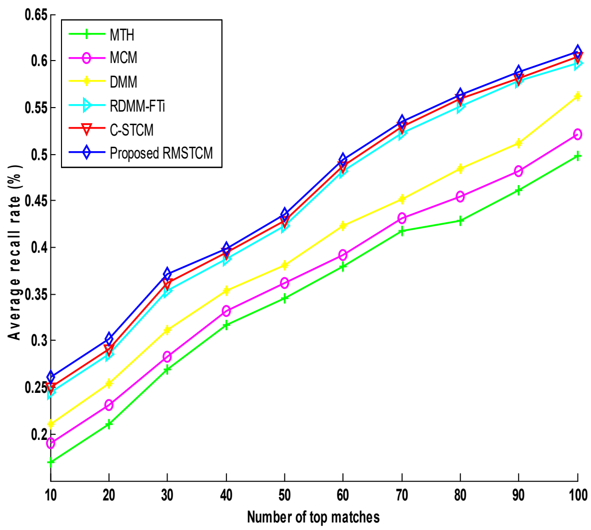

Fig.17 Performance Graph on Corel-10K using ARR.

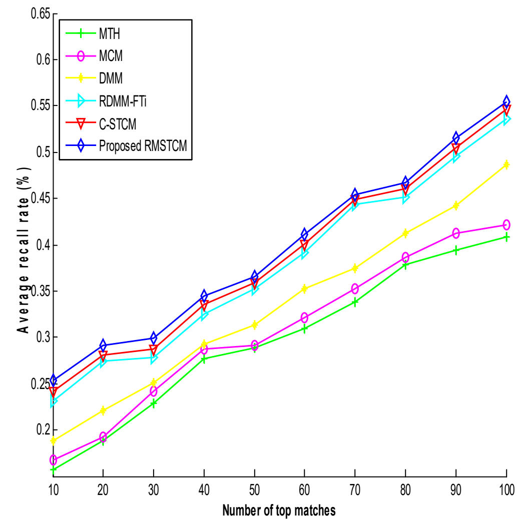

Fig 19 . Performance Graph using ARR on Brodatz database.

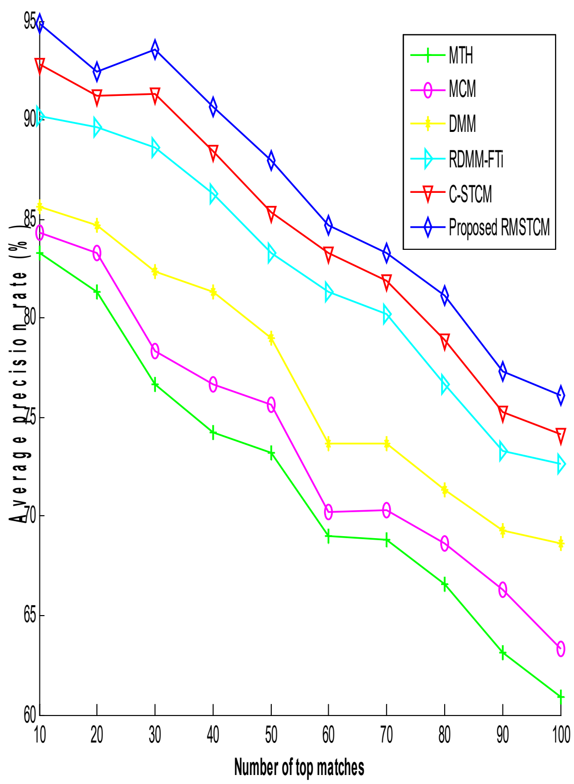

Fig. 18 Performance Graph on Brodatz using APR.

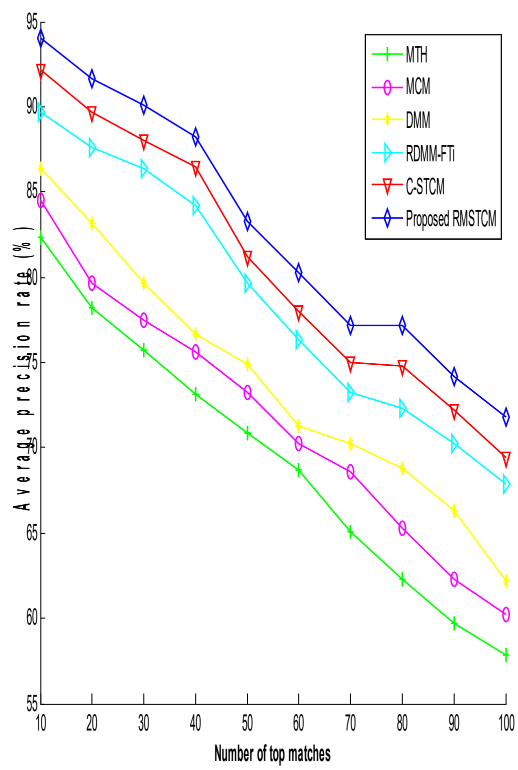

Fig. 20 Performance Graph on Color Brodatz database using APR.

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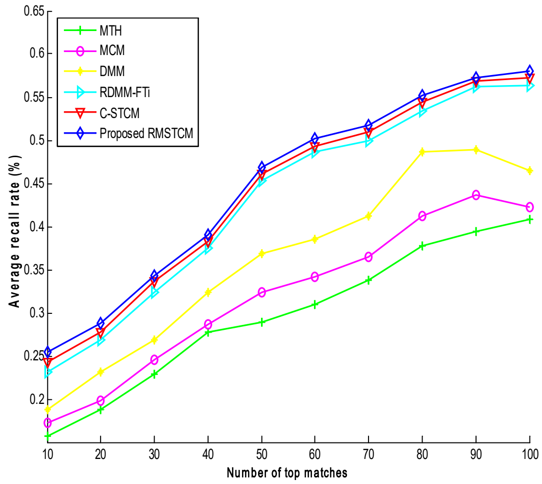

Fig. 21 Performance on Color Brodatz database using ARR.

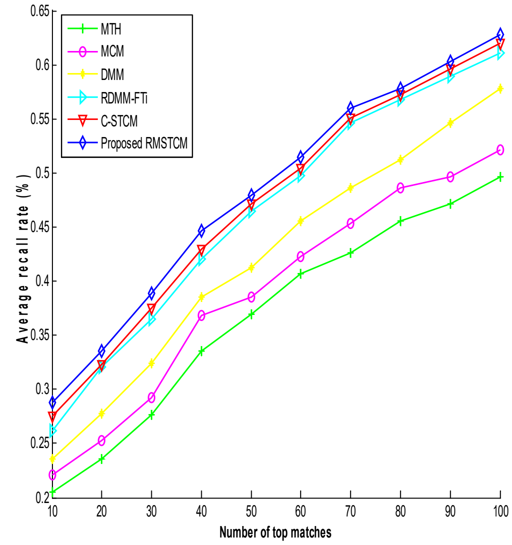

Fig.23 Performance Graph on MIT-VisTex database using ARR.

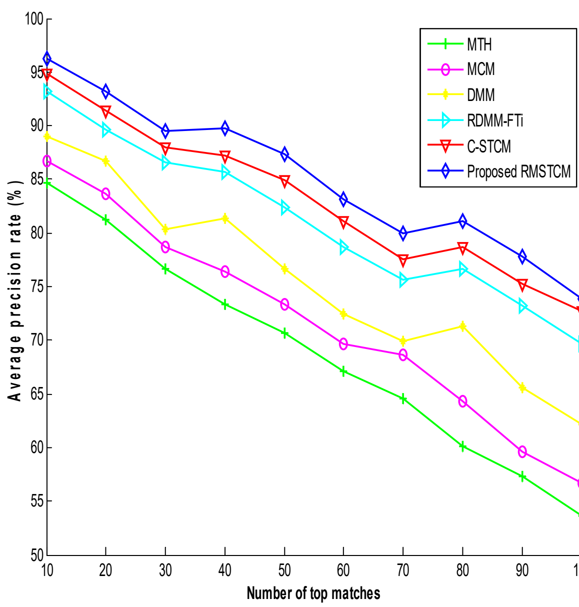

Fig. 22 Performance Graph on MIT-VisTex database using APR.

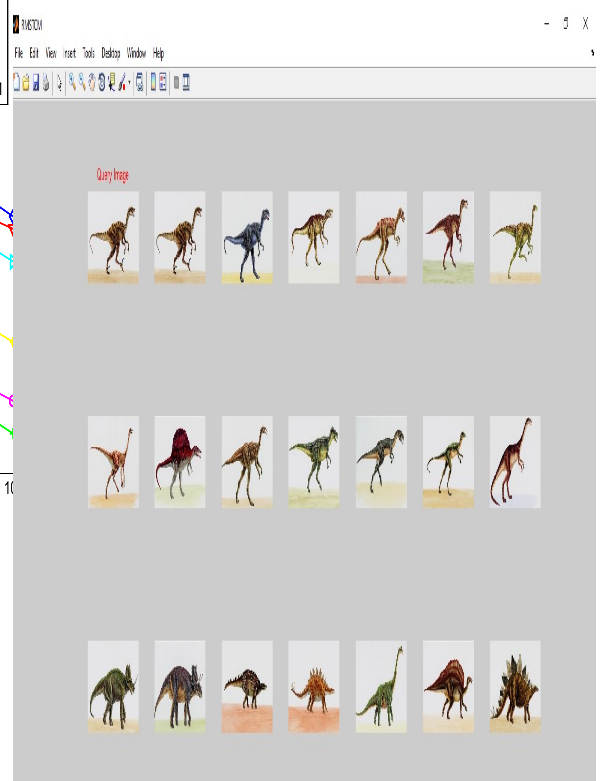

Figure.24 Twenty top retrieved images of Corel-1k : RMSTCM

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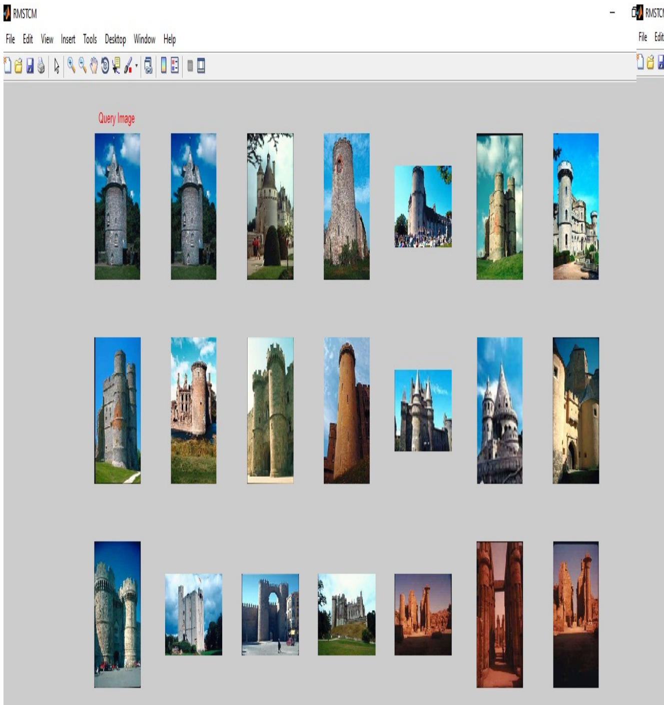

Figure.25 RMSTCM : Twenty Top images recovered on Corel-10k database

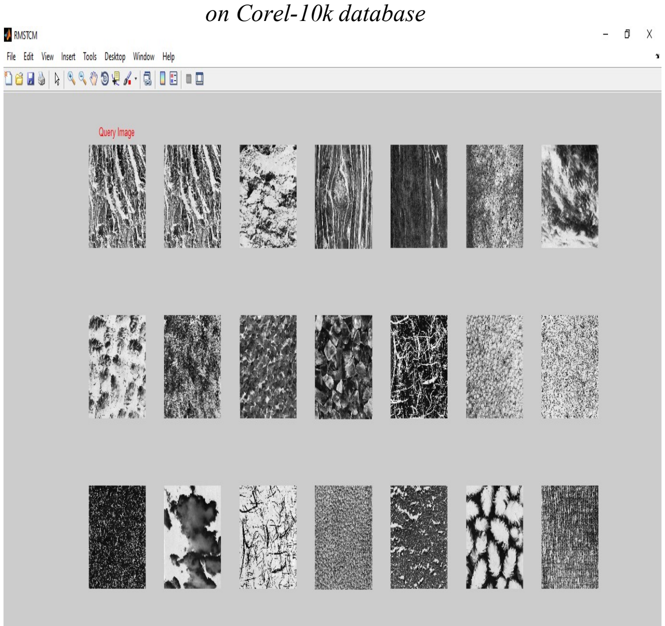

Figure 26. Brodatz database : Twenty Top images: RMSTCM framework

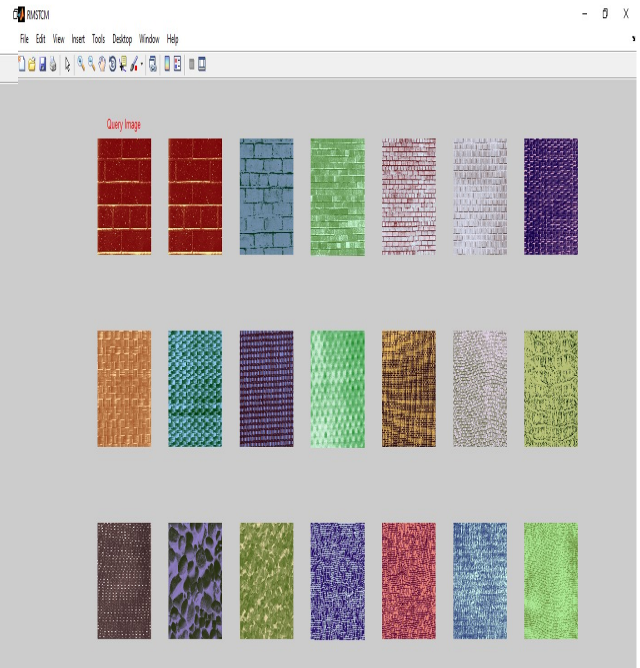

Figure.27 Color Brodatz database: Top Twenty images: RMSTCM framework

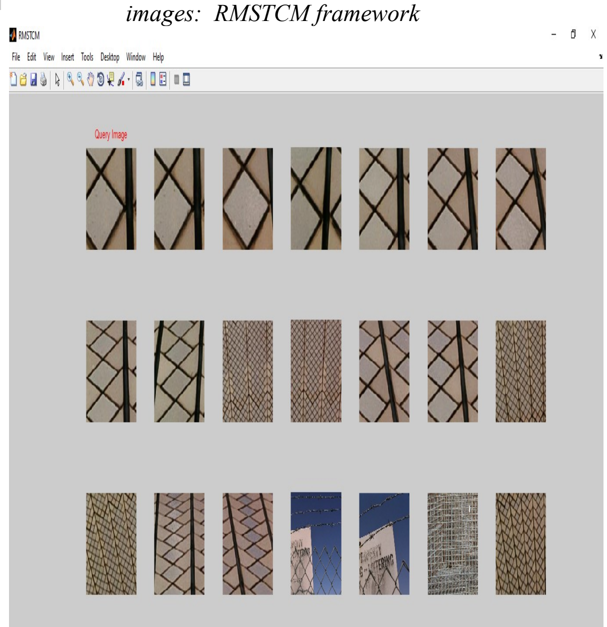

Figure.28 MIT-Vistex : Top Twenty images: proposed RMSTCM

On APR and ARR, the RMSTCM is compared to that of existing descriptors and performance factor is displayed on each of the considered databases in Figs. 15 to 23. (ARR). In Fig. 24 to 28, the top 20 images returned for the specified query image using the RMSTCM are shown.

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4. CONCLUSION

This paper derived a novel RMSTCM framework that is entirely different from earlier integrated methods of texons, motifs, and Co-occurrence matrix. This paper derived local motif features by eliminating all kinds of ambiguities by employing a rule-based dynamic motif on a 2x2 grid. This has derived local structural patterns based on dynamic piano scan direction. The ST indexes are derived on the four RM indexes. The ST index derives the magnitude-based texton on a law-based dynamic motif structure. This process transforms the a 3x3 widow in to a strong structural pattern, that holds both local textual, structural information. The exploration of statistical features from the above significant local structural pattern derived the strong integrated statistical features. Final feature vector is derived by fusing of color component in the form of histograms with RMSTCM features. There are few integrated methods of motifs and texton in the literature, however, they have failed in capturing the strong structural patterns, and also, they created ambiguous patterns, which are eliminated in this paper. The use of magnitude-based textons derived the structural features by considering the micro-levels of a 2x2 grid, which is missing in the previous studies. The suggested method justifies its superiority over current approaches in terms of recall and precision.

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