Quadrant Motif Approach for Image Retrieval

Tsong-Wuu Lin and Chung-Shen Hung
Department of Computer and Information Science, Soochow University
56 Sec. 1 Kui-Yang St.
Taipei 100, Taiwan, R.O.C.
twlin@cis.scu.edu.tw, ms9315@cis.scu.edu.tw

ABSTRACT

In this paper, we propose an image retrieval approach based on *Quadrant Motif Scan* (QMS). Motif scans from segmented blocks inside an image are the primary notion to extract image features. We exploit recursive quadrant segmentation in images and stratify hierarchical regions for matching comparison. Regions in the same stratum hold an identical credit, which is used for similarity metric. For the sake of matching flexibility, a dynamic adjustment scheme of credit setting is offered. In this sense, a user can arbitrarily adjust the credit parameters to pursue better retrieval results. Besides, a peak inspection technique is also added in the QMS matching metric to enhance performance. This means can helpfully refine retrieval performance with trivial computational cost. Experimental results reveal that effectiveness and efficiency of QMS are comparable to the Motif Cooccurrence Matrix (MCM) method while QMS is competent to deal with image scaling.

Keywords

Content-based image retrieval, motif scan, quadrant segmentation

1. INTRODUCTION

Visual information has proliferated for multiple purposes in recent years. With the Internet burst, a number of multimedia applications are evolving pervasively for intuitive information expression. Over the decades, many brilliant researches have produced a variety of outstanding techniques in image-related fields, and some of those became the de facto standards, such as JPEG [Pen93]. However, those mature studies largely reside in image encoding and storage format. By contrast, a wide range of approaches [Mah03, Pou04, Swa91, Pas96] using color, shape, or other factors for *Content-based image retrieval (CBIR)* is still under sprightly development. They retrieve images on particular occasions while some existent CBIR systems provide users with versatile querying ability [Nil93].

There are a plenty of works in the image retrieval area. Some of the renowned approaches are recognized as introductory examples for later works. For instance, color histogram [Swa91] is one of those precedents. It utilizes the statistics of global color distribution to calculate the similarity between two images. Afterwards, other advanced techniques were devised to remedy color histogram afterwards. Color Coherence Vectors (CCV) [Pas96] adds the information of pixels coherence of one particular color and generates coherent regions. This enhances distinction of pixels with same colors but not distributed in the same regions. Moreover, another attractive technique, Color Correlogram (CC) [Hua97], highlights the spatial correlations of colors. It takes on the probability of joint occurrence from any two pixels in separate colors or an identical color for autocorrelogram [Hua97]. Both of the two methods appear to perform much better than traditional color histogram. In a word, they presented the significance of spatial information in image retrieval. Not only the mentioned methods but more related studies have shown spatial property feasible and useful to retrieval refinement. From this point of view, we adopt the spatial factor into our work to reduce fidelity loss. Other schemes like Blobworld [Car02] and SIMPLIcity [Wan01], region-based techniques for image retrieval flourish in an alternate way.

Jhanwar et al. [Jha04] use motif notion to capture the low level semantics of space filling curves. Their *Motif Cooccurrence Matrix* (MCM) is the container

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of motif features literally scanned from image pixels. Each 2×2 pixel grid is replaced by one from a set of six Peano scan motifs [Pea90, See97]. This particular version of motifs is shown in Fig. 1. For each cooccurrence, it accumulates times of finding a motif i at a distance k from a motif j in the matrix. Efficiently, it merely includes individual 6×6 motif matrices for every color plane irrespective of the image size. Apparently, the MCM scheme is especially suitable for retrieving images in equal size. Variations in image size can inevitably induce inconsistent motif amount so it may lead to a meaningless matching process. Meanwhile, because the granularity of motif san is so minute, this is beneficial for textured images. Once the query scenario is in images from outdoor scene, the performance might drop down unexpectedly.

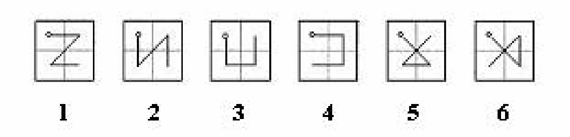

Figure 1. Codes for each type of motifs

In this paper, we propose another image retrieval approach based on motif symbols, called *Quadrant Motif Scan* (QMS). Consecutive quadrant segmentation on images is the main strategy in our scheme. With a motif extraction for each region, we collect all motif data for matching. By the hierarchical structure of motif information inside an image, we devise a matching algorithm for similarity comparison with ranked results. Our experiments show that QMS has the merits comparable or even superior to the MCM method.

This paper is organized as follows. In section 2, the proposed QMS is explored. Section 3 describes the matching metrics used in QMS. In section 4, the experimental results are presented with a related discussion. The final section gives the conclusion and prompts the relevant errands for future work.

2. QUADRANT MOTIF SCAN

Motif is an important feature to express the chromatic trend lying in a bounded region. In the QMS scheme, we use an entire image as the initial region, as shown in Fig. 2a. An image is first subdivided into four non-overlapping parts in Fig. 2b. The four segmented quads form the source generating a motif for the first region which also belongs to the 1st stratum. In Fig. 3, QMS then calculates separate mean values of all pixels for each quad and uses them to derive a motif. Here, the RGB colorspace is applied and the 3 colors are synthesized by averaging them, ranging from 0 to 255.

Figure 2. The recursive segmentation processes in Quadrant Motif Scan. (a) The original image. (b) 4 quads for the region in the 1st stratum. (c) 4 quads for successive sub-region.

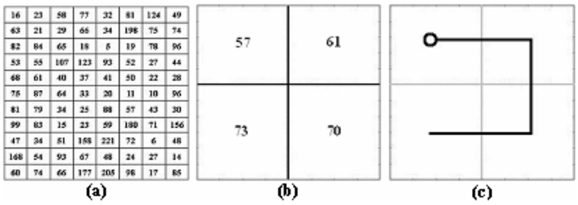

Figure 3. Formation of a motif from a region. From left to right are (a) image pixel values, (b) means of four quads, and (c) a resulting motif.

Likewise, successive subdivision operations (see Fig. 2c) from the current region continue until a pre-defined stratum threshold is reached. Continually, the same manipulation to evaluate mean values is carried out for every child region, and separate motifs are eventually derived as shown in Fig. 4. In particular, the four motif blocks belong to the same stratum (2nd) so they share a common credit for the matching metrics. In short, a parent's quad, used as an element for its motif derivation, is regarded as a child's intrinsic region.

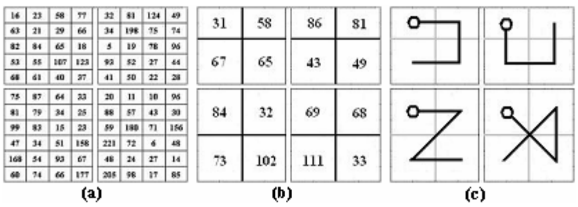

Figure 4. Successive subdivisions into four child regions.

To avoid ambiguity of motif scan, we introduce the suggestion used in the MCM study [Jha04]. Our QMS follows the breadth-first strategy to regulate the motif recognition. For instance, Z-type motif is recognized rather than N-type in Fig. 5. Note that any kind of motif traverse starts from the upper-left quad regardless of its actual value. Besides, supplementary uniformity detection is taken into account simultaneously. During a motif extraction, the highest and lowest mean values from four quads are recorded. A simple subtraction operation is performed to retain the information whether the region is uniform or not. Finally, both of the motif and uniformity information for a region is collected and assembled together into a single data structure. The uniformity threshold in our scheme is set to 35 in default; the difference less than the threshold will lead a region to be uniform.

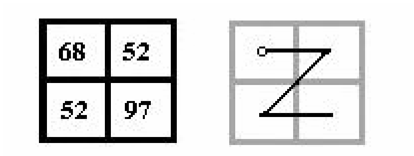

Figure 5. Example of motif traverse.

This architecture of stratified motif scan is to find out local motif information throughout an image. Due to different significance of separate strata, varied credits, or so-called weights, are granted to reflect their power. In the QMS scheme, we designed an algorithm using these credits to match images. On the other hand, what the exact stratum threshold is supposed to be becomes another issue. If a higher stratum threshold is designated, more blocks of motif are then received and can depict an image more precisely. From this viewpoint, the retrieval performance can explicitly rise via adding more strata at the expense of computational costs. In practice, an adjustable stratum threshold may be needed according to the user's demand. As a general rule, performance choice is recommended to come to a compromise between speed and effectiveness. Table 1 shows a cross mapping among strata, regions, and motif blocks.

Stratum No.	1	2	3	4	5	6	7
Regions	1	4	16	64	256	1024	4096
Accumulated motif blocks (A)	1	5	21	85	341	1365	5461

Table 1. Variations in corresponding numbers of strata, regions, and motif blocks

3. MATCHING METRICS

Before matching two images, there are some prerequisite preparations to launch image comparison.

System Settings

Stratum Threshold - A pre-defined stratum threshold is set for the motif scan process. All images are manipulated by this rule so that they have the consistent number of motif blocks stored in the database for the matching functionality.

Uniformity Criterion - The method requires a criterion for uniformity detection. This is used as a value range to recognize whether a region/motif block is uniform or not. The same as stratum threshold, this must be decided at the very beginning.

Credit Setting - Varied credits (weights) are specified for each stratum. These variables are in relation to retrieval results.

The first two items are the most important parameters for QMS implementation. Both of them can also be critical to retrieval performance. In turn, the third setting is about scoring schemes and is independent of the two previous settings. This can be dynamically adjusted at run-time to evaluate and rectify the retrieval results.

Distance

Assumed that the required parameters are verified and the QMS database is then constructed, the matching process can launch on the final comparison stage. Motif blocks of two images, the query and target, are matched on the blockwise basis. If a pair of corresponding blocks/regions is exactly the same, which have equal motif type and uniformity property, the target scores the specified credit. Otherwise, the target fails in this block and goes on next until all motif blocks are through. When the process is finished, a total score will be attached to that target. The higher the score is, the more similar the query and target images are. In effect, it will receive a perfect score when the query and target are exactly the identical image. After all images in the database are thoroughly matched with the query, a score list is made in a descending manner.

Given a mapping function, it can find out the *j*th stratum to which the *i*th block belongs and hence the corresponding credit $\boldsymbol{C_j}$. Each pair of motif blocks, M_i^q and M_i^t, for the query and target respectively, is compared to get a similarity status $\boldsymbol{S_i}$. If two blocks are equal, it leads to $\boldsymbol{S_i} = 1$, or 0 otherwise. The overall matching expression is as follows:

$$D(I_q, I_t) = \sum_{i=1}^{K} S_i C_j \quad \forall j \in [1 \ldots N],\ j = map(i)$$

$$with\ S_i = \begin{cases} 1, if\ M_i^q = M_i^t \\ 0, if\ M_i^q \neq M_i^t \end{cases},\ \mathrm{A}[j-1] < i \leq \mathrm{A}[j], \qquad (1)$$

where I_q and I_t are the query and target images and K means the maximum of motif blocks assigned by the number of strata N specified for motif scan process. Array A gives the information the ith block is subsidiary to the jth stratum. This distance metrics will result in a score sum for ranking.

Besides the parameters in motif construction, we add a peak inspection function for retrieval supplement. This function uses a peak number to set how many global peaks of pixel values in an image are selected. These peaks are traversed from the highest with proximal peaks omission. To enhance the proposed QMS method, the inspection will result in a percentage of matched peaks between images and use it to weight original matching score. The computational cost is trivial to this additional enhancement in exchange for advancement of precision.

Scheme	Strata	Motif Blocks	Uniformity	Peaks
A	5	341	35	10
B	6	1365		

(a)

Stratum No.	1	2	3	4	5	6
Credit	4	4	4	4	4	4

(b)

Table 2. (a) QMS system parameters and (b) Credit settings for scoring

4. EXPERIMENT RESULTS

Query-By-Example is a common technique used in many image retrieval systems. For instance, IBM QBIC [Fli95] is one of the best-known systems. The QMS system also applies such a skill in the system design. On the side, we chose the MCM method to serve as the opposite to show the comparison of motif-based approaches.

Experimental Setup

For a variety of queries, we collected a huge amount of images to test the retrieval performances in different query scenarios. These resources includes: nearly 10,000 images used in the WBIIS system [Wan98], 25 images from the Aridi art collection, and the MIT Media Lab's Vistex collection. Textured and non-textured images are existent in our experiments for specific comparison purposes. Scaling manipulation for some samples is also done to emphasize that QMS is invariant to image scaling. About the stratum threshold, it is adequately set to 5 in default with 341 motif blocks as a good start point. This setting is, however, still subject to variations of image size. Table 2 shows the related parameters used in our experiments.

With different setups, two typical schemes (see Table 2a) are presented for performance analysis. Scheme B is used to seek if there is a better solution after scheme A is tried out. In most cases, one more stratum (adding more motif blocks) could bring out substantial retrieval effectiveness. However, some other factors more or less give rise to direct or indirect influences on our multi-stratum comparison.

Again, the credit settings in Table 2b are for examples and could be dynamically adjusted in our experiments. Since there may be many diverse images in the database, a universal credit setting for all sorts of queries is really hard to define. We therefore design this flexible facility to meet needs in possible demands. This feature is also very helpful when we want to clarify an empirical credit setting toward a specific content in a query image.

Results

4.2.1 Database from MIT Vistex

We have performed voluminous queries in order to identify which type of images is more favorable for the QMS scheme. The 128 × 128 set of images in the MIT Vistex database was the first case in our comparison with the MCM method. Information for the classification and corresponding quantities in the database is shown in Table 3.

Fig. 6a shows the query image, and the retrieval results in Fig. 6b expose the effectiveness of the MCM method, retrieving 10 out of 11 in the series of buildings. Although the results may cause different

Class	Bark	Brick	Buildings	Fabric	Flower	Food	Grass	Leaves	Metal
Pieces	13	9	11	20	8	12	3	17	6

Class	Misc.	Paintings	Sand	Stone	Terrain	Tile	Water	Wood	Total
Pieces	4	13	7	6	11	11	8	3	162

Table 3. Image classification in the 128 × 128 set from the MIT Vistex database

evaluations from individual perceptions, some characteristics are apparent to realize. For example, the intricate grids, which form the appearance of the buildings, are the most salient features in this query image. On these grids, two colors black and yellowish gray are alternate regularly throughout the surface of the buildings. The extent of buildings also occupies most of the image. Hence, we can intuitively infer that a great deal of some repeated motifs will be extracted and stored in the MCMs. Because of the subtle granularity to form a motif, any massive prominent patterns are crucial to retrieval. Despite the fact that there are a few deficiencies in this retrieval sample, the performance is brilliant. However, queries in other categories in Table 3 do not necessarily give the same performance as well.

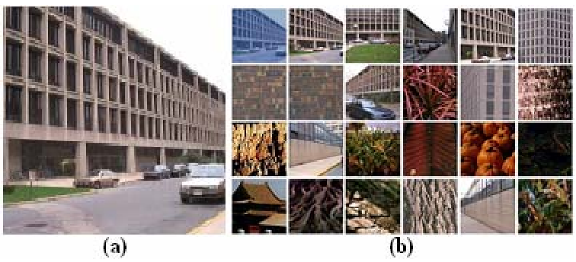

Figure 6. (a) The query image and (b) retrieval results using the MCM method. The retrieved images are ordered from left to right and top to bottom by their similarity to the query image.

Referring to the performance measure in Guoping Qiu's study [Qiu03], we made a slight modification of it and only the first 24 retrieved images in the first page in our system are shown for discussion. Other images are still ranked and remained below the retrieval manifest.

The same query sample is conducted in QMS as shown in Fig. 7. We use two schemes, A for 5 strata with the credit setting 4-4-4-4-4 and B for 6 strata with 4-4-4-4-4-1, to demonstrate performance. In scheme A, the results in the first row seem better than MCM, but, in terms of quantity, A merely retrieves 5 images of the same category (buildings). In turn, B improves both retrieval quality and quantity from A. Obviously, scheme B outperform MCM in retrieval quality, i.e. the ranking order, with a little inferior quantity of 8. At least, from synthesizing both criteria, our QMS remains quite comparable.

Furthermore, we made an interesting experiment to evaluate retrieval ability when the database only consists of images in the buildings category. As we can see in Fig. 8, the similarity order is much more reasonable in QMS than that of MCM. Thus, this phenomenon can explain that MCM performs considerably well while desired images in database are perceptibly distinct from others. Otherwise, ordinary queries may not give such a satisfactory performance as the previous example. Moreover, another query scenario is reported in [Lin05] when there is only one image in database perceptually similar to the query.

Figure 7. Retrieved images by QMS with different schemes. The stratum threshold is set to 5 in A and increased to 6 in B.

Figure 8. Results from querying only in the buildings category by (a) MCM and (b) QMS.

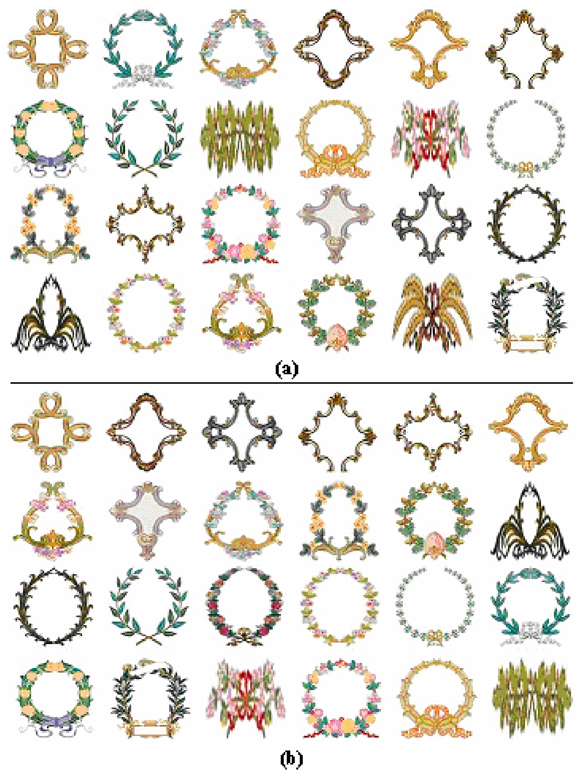

Figure 9. Retrieval results from images of unequal sizes by (a) MCM and (b) QMS. All images are displayed in thumbnail.

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4.2.2 *Querying in images of unequal sizes*

Next, the experimentation will proceed to databases containing images of unequal sizes. To account for the retrieval capability invariant to image scaling, a set of 25 color images was collected from the Aridi art collection. These images differ in size ranging from 239 × 363 to 724 × 192 in disproportional ratios. A sole entity located in the center, such as a crest or ribbon, is the common property of the images. From the query example in Fig. 9a, the performance of MCM obviously drops down due to unfixed image sizes; it can not match images on an inconsistent criterion. In effect, the match results almost lie in a disordered state. By contrast, along with the setting of scheme A in Table 2 (without peak inspection), QMS make the ranking orders in Fig. 9b much more acceptable than MCM. Ideally, images with a cross should be retrieved first before those with a circle. In this context, QMS almost fulfills this requirement. Therefore, our approach shows the capability of querying in which target images vary in size. In another trial, however, QMS is still sensitive to image rotation, whereas the MCM might be less sensitive.

4.2.3 *Performance evaluation*

As mentioned in the study of Müller et al. [Mul01], evaluation measures to retrieval performance are proposed from various viewpoints. Similarity judgments are not easily be done objectively. Thus, we resort to the notion of *recall* in this paper and modify the formula as follows:

$$\text{recall}\ (M_1) = \frac{\|\text{First}_m(M_1) \cap U\|}{m}, \qquad (2)$$

where $\text{First}_k(M)$ is the set of the first k retrieved images by the method M. $U=\text{First}_k(M_1) \cup \text{First}_k(M_2)$, $m = \|U\|$, i.e., m is the number of members in the set U while methods M_1 and M_2 are MCM and QMS in our experiment respectively. If there are many methods, M_1, M_2, ..., M_n, to be evaluated, then only the definition of U in this formula must be changed, i.e., $U = \text{First}_k(M_1) \cup \text{First}_k(M_2) \cup ... \cup \text{First}_k(M_n)$.

The first evaluation is for queries conducted from the database in Table 3. In this process, we randomly picked out 50 images (total 162) as the query and made k equal to 20 to gain the first 20 results separately from MCM and QMS. Then, an intersection (m) is made as the denominator. Besides, we repeated this process for at least 3 times to avoid biased evaluations. Table 4 shows the average times of better recall values. The schemes in use conform to the credit setting in Table 2b.

In Table 4, 5S means using 5 strata in the QMS while 5SP is with auxiliary peak inspection. TIE counts the times where the recall values of both methods are equal. From this table, increment of stratum can help raise the recall evaluation for QMS, and so does the incorporation of peak inspection. In Addition, we also apply this performance measure to the database from WBIIS (see Table 5). In this context, images are largely heterogeneous so that the accumulated times of TIE are greater than any of the other two. This situation implies that most retrieval results by MCM and QMS are not overlapped. Hence, our QMS is not arguably better than the other though the data is advantageous to QMS. From the statistical data in Table 4 and 5, however, QMS is proven superior to MCM based on this recall criterion.

	Average Times		
Schemes in QMS	MCM	TIE	QMS
5S	20	13	16
5SP	15	14	21
6S	21	7	22
6SP	15	12	23

Table 4. Average times of better recall values

	Average Times		
Queries	MCM	TIE	QMS
300	63	140	97
3000	283	2369	348

Table 5. Average times of better recall values from the database used in WBIIS

Through a plenty of experiments, QMS is very efficient to computation and economical to storage requirement. In those experiments, we use a tentative platform based on PC, a Pentium III 733MHz CPU with 512MB RAM. The time costs of motif feature construction in Table 4 are approximately 7 sec for MCM and QMS while both use less than 1 sec in matching images. For the second case in Table 5, both methods spend approx. 5 min on offline motif extraction for nearly 10,000 images while QMS merely uses less than 3 sec for matching, which is better than 11 sec of MCM. Apparently, QMS can much better fulfill the speed requirement (in linear time) of online query. Note that all time data above settles on a temporary file database system.

5. CONCLUSIONS

In this paper, we have introduced another retrieval approach, Quadrant Motif Scan, based on motif symbols. Images are segmented recursively into sub-regions, which are the sources of motif derivation. Motif scan is limited to a stratum threshold and combined with uniformity detection. With any arbitrary or empirical credit setting, the matching metrics is conducted in a simple, fast manner. Incorporating the additive of peak inspection, QMS may run at a more stable and reliable performance. Compared with the MCM method, QMS remains competitive and even better, especially when image sources are not highly textured. With the additive of peak inspection, the QMS can run at a more stable and reliable performance. Most important, the mechanism of relevance feedback is provided in the QMS system. Users can dynamically adjust the credit setting to achieve optimal results. Nevertheless, the problem of image rotation remains awkward to overcome in QMS.

Motif is a descriptor capturing features for images. Although it is not comprehensive for all features about images, it is applicable to employ with other algorithms or advanced techniques. So far, efficiency and effectiveness are demonstrated in the current method to a certain extent. In the future, we might seek to develop better algorithms to complement this motif-based method. Empirical rules of credit setting for diverse query scenarios are required analyzing in detail. In future work, we will count on other considerations like colorspaces, e.g. HSV, for further reinforcement.

6. ACKNOWLEDGEMENTS

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