A Content Based Image Retrieval Approach Based On Principal Regions Detection

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Abstract
This paper proposes a new region-based image retrieval technique called Principal Regions Image Retrieval (PRIR). This technique starts by segmenting an image to the most general principal regions and applies a fuzzy feature histogram to describe the color and texture properties of each segmented region. The proposed approach starts by generating a nearest neighbor graph for the segmented regions, and applying a greedy graph matching algorithm with a modified scoring function to determine the image rank. The proposed segmentation approach provides significant speedup toward state of the art techniques while keeping accurate precision. Moreover, the proposed approach combines local and global description to improve the retrieval results. Standard image databases are used to evaluate the performance of the proposed system. Results show that the proposed approach enhances the accuracy of retrieval compared to other approaches reported in the literature.
Keywords: *Content based Image Retrieval (CBIR), region-based segmentation, Composite descriptors, Information retrieval, Graph matching, Fuzzy color and texture histogram.*

1. Introduction

Content Based Image Retrieval (CBIR) techniques [1, 2] consider retrieving the most visually similar images to a given query image from a large collection of images. These techniques index images using their visual characteristics, such as color, texture and shape. In addition, they use similarity measures to rank the retrieved results. These measures can be categorized [2] as vector-based that treat features as vectors, region-based and global-based or a combination of both, fuzzy or deterministic similarity measures, and the use of supervised, semi-supervised, or unsupervised learning.

Recent image retrieval systems incorporate more than one feature to describe the image content more accurately. For example, the IBM QBIC [3] system used color and textures features, the VIRAGE [4] system used several features combinations, the MIRROR [5] system investigated the MPEG7 visual descriptors [6] and the Img(Rummager) [7] system extracted several features in real time. These systems traditionally used global histograms to describe image features. Global histograms are sensitive to intensity variations, color distortions, and cropping. In a previous work of ours [8], we have investigated the need for a composite image features description in searching a large image repository.

Region-based image retrieval techniques segment an image into a number of regions that work as local descriptors. These techniques either detect the most salient regions or extract a set of segmented regions. Salient regions extraction techniques [8, 9] provide a summary representation of images by choosing the most discriminant and scale invariant regions in an image. On the other hand, segmentation techniques [10, 11] segment an image into a set of homogeneous regions that may reveal the objects within an image.

This paper addresses region-based image retrieval and introduces a new generalized region-based segmentation scheme. This scheme extracts the most general principal regions of an image. A principal region is a region that results from the combination of several neighboring regions that share some criteria. In addition, the scheme provides a significant speedup over state of the art hierarchical segmentation techniques while having highly accurate results. The paper proposes the Principal Regions Image Retrieval (PRIR) technique that uses the new segmentation strategy to identify the general principal regions. This technique describes each segmented region using a fuzzy color and texture histogram. The approach is followed by applying a greedy graph matching algorithm with a modified scoring function as a similarity measure to determine the final image rank. Figure 1 shows a block diagram of the proposed approach.

The remainder of this paper is organized as follows: in section 1.1, we briefly discuss the related work. Section 2 presents the proposed region-based image retrieval technique. In Section 3, we explore the experimental results. Finally, we provide conclusions in Section 4.

1.1 Background And Related Work

Segmentation techniques partition an image into a set of homogeneous and meaningful regions, such that each partitioned region contains pixels possessing an identical set of properties or attributes. These sets of properties may include color, contrast, spectral values, or textural properties.

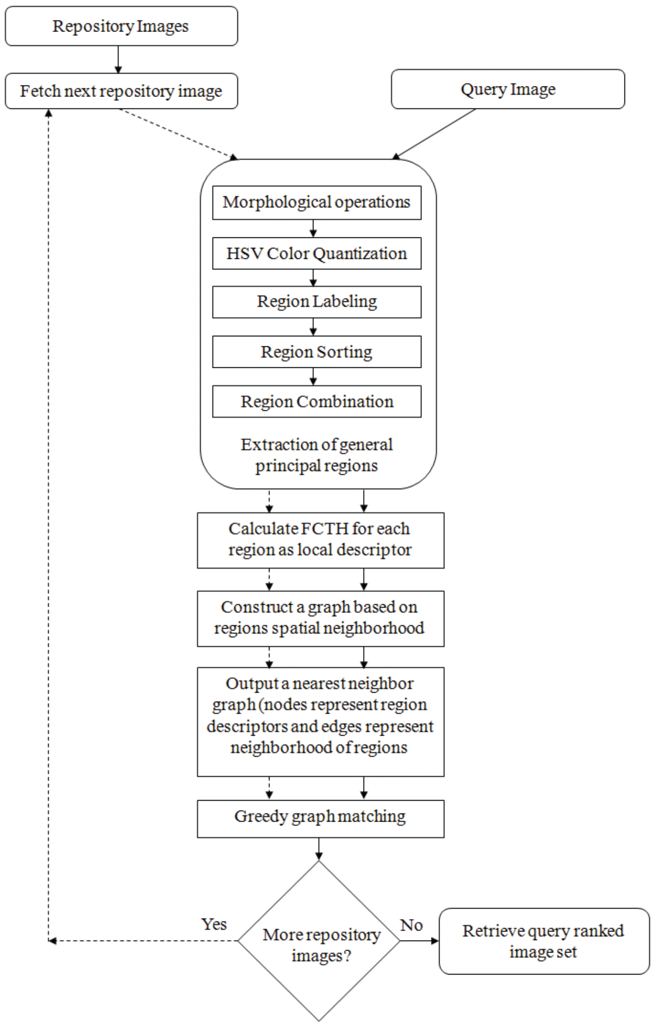

Fig. 1 A flowchart showing the proposed approach.

The watershed transform [12] is one of the popular methods used for this purpose. This approach is operated by splitting the surface of gray-level images into a set of catchment basins. The basic watershed algorithm is highly sensitive to gradient noise; it usually results in over-segmentation. The most commonly used solution is the use of a marker image [13]. The marker image reduces the number of minima of the image, hence the number of regions. The standard algorithms of detecting markers are highly domain specific and have a high computational cost. In addition, they detect markers effectively, but not automatically, when processing highly textured images.

A region based image retrieval technique [10] was proposed based on the watershed transform. This technique used two scaling parameters to overcome the over-segmentation problem. However, this technique used fixed parameter values for segmenting images, limiting its ability to provide a generalized segmentation scheme for searching large image repositories. Another technique [14] tried to solve the over-segmentation problem by applying two interactive multi-label partitioning techniques to a generated adjacency graph of the watershed regions. This technique started the segmentation by manually selecting regions of interest.

An investigation of unstable segmentations [11] highlighted the importance of the region-based features relative to other features. This investigation presented a partial region matching technique as a solution to the problem of matching regions under unstable segmentations. For each image, the technique generated a Region Adjacency Graph (RAG) to encode the extracted regions. An edge exists between two nodes if they have a common boundary. The technique ended by applying graph matching to find the image rank.

Hierarchical segmentation is a powerful tool that can provide analysis of images at various scales. The watershed transform, and the mean-shift segmentation are basic methods to provide hierarchical segmentation. In [15], a mean-shift technique started by calculating the boundary persistence between extracted neighboring regions to be used as the merging criterion in building the segmentation hierarchy. Another technique [16] tried to find similar images by indexing based on sparse image segmentation. This created a continuous scale-space of regions with coherent image content. The technique used an ordinary distance metric as the merging criterion between neighboring regions. A recent superpixel hierarchal segmentation technique [17] provided several enhancements to hierarchical segmentation. This technique used an objective function of two components. The first was the entropy rate of a random walk on a graph and resulted in compact and homogeneous clusters. The second component was a balancing term that built clusters with similar sizes. The results of this technique showed that it outperformed other state of the art techniques for hierarchical segmentation.

2. The Proposed Approach

The proposed technique (Figure 1) consists of the following six phases: morphological operations, HSV color quantization, over-segmentation handling, and description of segmented regions, spatial graph generation, and image retrieval system. Each of the six phases will be discussed in the following subsections.

2.1 Morphological Operations

Morphological operations [18] create an output image of the same size as the input image by applying a structuring element. Dilation and erosion are the most primitive morphological operations. Another two essential operations are the morphological opening and closing. These operations are built upon dilation and erosion. *Opening* is erosion followed by dilation, using the same structuring element for both operations. This operation tends to smooth the contour of an object, breaks the narrow isthmuses, and eliminates the thin protrusions. *Closing* is dilation followed by erosion with the same structuring element. The operation tends to smooth sections of contours, but as opposed to opening, it combines narrow breaks and long thin gulfs, eliminates small holes, and fills gaps in the contour. Applying *opening* followed by *closing* [19] has the effect of removing dark spots and stem marks, and attenuating bright and dark artifacts. If I is the source image and S is the structuring element; then the resulted image (R) is given by

$$R = (I \circ S) \cdot S \qquad (1)$$

Where the open dot represents opening and the solid dot represents closing. For each image, we applied an opening followed by a closing. The size of the structuring element should be the same size and shape as the objects to process. In addition, a large structuring element preserves larger details, where as a smaller element preserves finer details. Experiment results with different sizes of structuring elements show that the size of 9x9 provides the best results. This preserving the objects of size 9x9 pixels and smoothing the regions of larger objects.

Fig. 2 The effect of morphological opening followed by closing using a 9x9 structuring element of ones.

Figure 2 shows the effect of this operation on two images. It can be shown that the operation smoothed the regions and eliminated holes and breaks that could affect the segmentation result.

2.2 HSV Color Quantization

HSV is a widely adopted space in image and video retrieval. The main advantage of this color space [20] is the decoupling of the chrominance (H, S) and the luminance (V) components. The proposed approach applies HSV color quantization to eliminate the differences of color shades existing between similar regions, thus fusing the neighboring regions having the same color attribute.

An implementation of the HSV histogram was developed by [21]. This implementation divides the hue into eight regions; the saturation and the value into four each. The proposed technique uses another implementation [22] that divides the hue into sixteen regions; the saturation and the value into eight each. This division depends on the log-likelihood ratio of the foreground/background color histogram. The approach then links the three color components, creating a (16×8×8) histogram of 1024 bins. The technique generates an HSV histogram for each image and replaces each pixel color by the corresponding histogram bin color.

Fig. 3 Applying HSV color Quantization after morphological operations.

Figure 3 shows the result of applying HSV color quantization upon two morphologically processed images. It can be shown that the technique combines neighboring regions that have the same color attributes and eliminates the small differences in color shades.

2.3 Over-Segmentation Handling

The over-segmentation problem results from the existence of variations and noise in the color level values. The morphological operations and the HSV color quantization reduce the impact of over-segmentation but do not completely solve this problem. Figure 4 shows the regions generated after applying HSV color quantization on two images. The figure shows multiple overlapping regions that tend to have the same color and texture attributes.

Fig. 4 The over-segmentation problem.

In order to completely overcome this problem, the number of segmented regions has to be controlled. Firstly, the technique performs region labeling. Secondly, regions are sorted based on their size. Finally, the approach selects a number of general principal regions by combining small regions with larger ones, based on the hue criteria. The following subsections describe each step in details.

2.3.1 Region Labeling

Segmentation divides an image into a set of homogeneous regions. *Region labeling* [23] is the operation of giving a

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unique identification (ID) to these regions. This stage gives a unique ID for each region in the generated color quantization regions.

2.3.2 Region Sorting

Sorting is the process of ordering a collection of entities based on criteria. The list of segmented regions forms the collection to be sorted, and the criteria of the sort are the size (number of pixels) of each region. The approach sorts regions in descending order as shown in Figure 5.

Fig. 5 sorting segmented regions based on size.

2.3.3 Region Combination

Region combination is the process of combining neighboring regions based on some criteria. In this approach, we choose the hue criteria for region combination because the hue represents the pure color value, irrespective of its shades and saturation. The technique combines a region to one of its neighbors having the smallest difference in hue. Then, it constructs a nearest neighbor graph [24] to detect the neighborhood of regions. Two regions v_1, v_2 in the graph have an edge if they are neighbors in a fixed neighborhood threshold τ, where,

$$dist(v_1, v_2) \leq \tau \qquad (2)$$

$dist(v_1,v_2)$ is the Euclidean distance between the detected regions. The most optimal value chosen for it is one. This value models the sufficient number of edges that make the graph representation discriminative [24]. This results in a Region Adjacency Graph (RAG) [11], where a region has edges only to its direct neighbors.

The number of segmented regions can be controlled by identifying a set of large size regions and combining other small ones to them. The number of selected regions varies from smooth to complex images. The technique identifies the selected set of regions as the top size regions, in the segmented regions sorted list. Then, it combines other small regions to its neighboring regions, based on the smallest hue difference. This process continues until all small regions are combined to the identified top sized regions to produce the image general principal regions.

Figure 6 shows the segmentation results of a set of database images. The number of principal regions is chosen to be 10, 20 and 30. It shows that we can have a reasonable approximation between smoothness and complexity at 20 principal regions.

\# of regions = 10   # of regions = 20   # of regions = 30

Fig. 6 controlling the number of segmented regions by combining small regions to large regions.

2.4 Description of Segmented Regions

Local description of image general principal regions provides a summary description of image content. An appropriate descriptor must provide a local invariant description and should be robust against occlusions and geometrical transformations. This approach uses the 192 bin fuzzy color and texture histogram [25] as a local descriptor.

The fuzzy color and texture histogram is a combination of three fuzzy systems; each system output is the input to the next system. Figure 7 shows a block diagram for the generation of this histogram. Initially, the technique segments each extracted region into a number of blocks that has a minimum size of 4×4pixels. Each block passes fuzzy systems to determine its final bin in a 192-bin histogram. Then, the approach follows by describing each region by 192-bin histogram describing its color and texture information. The first fuzzy system undertakes the extraction of a quantized 10-bin histogram. The output 10-bin histogram works as input to a second fuzzy system that separates each color into 3 hues. This system shapes a 24 bins histogram as an output.

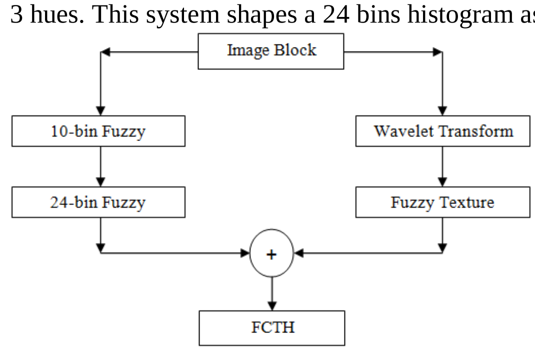


Fig. 7 a block diagram for the generation of FCTH.

For incorporating texture information, the proposed framework applies the Haar wavelet transform to the region block, and extracts the HH, LH and HL features that represent energies in high-frequency bands of wavelet transform. These features are the square root of the second-order moment of wavelet coefficients in high-frequency bands and are calculated using:

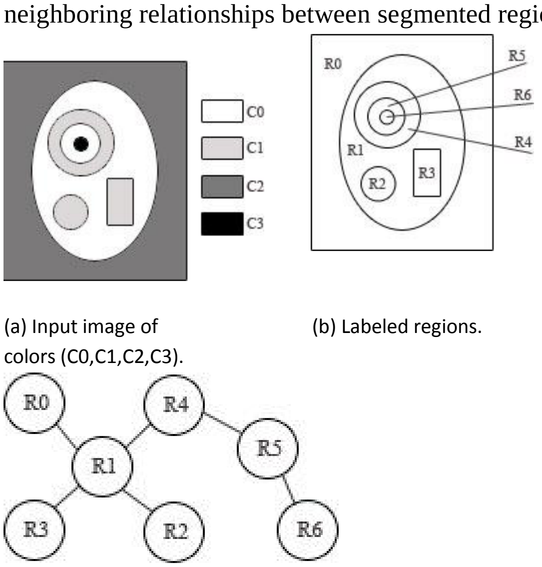
$$f = \left(\frac{1}{4} \sum_{i=0}^{1} \sum_{j=0}^{1} C_{k+i,l+j} \right)^{\frac{1}{2}} \tag{3}$$

Where k,l represents the pixel location and i, j takes the value of 0 or 1. The approach generates a 192-bin histogram for each segmented region that works as its local descriptor. It then follows by describing each image by a set of segmented regions distributed on its layout. This set of regions works as a reduced description of the entire image.

2.5 Spatial Graph Generation

Spatial graph investigates the neighboring relationships between the non-overlapping extracted segmented regions. The nearest neighbor graph [24] (NN graph) is a spatial graph constructed by connecting edges from each node to its neighborhood nodes in a fixed neighborhood threshold τ (equation 2).

The proposed approach proceeds by generating a graph for each image using the neighborhood of pixels between segmented regions (figure 8). Each pixel has 8 connected neighbors. A region is a neighbor to another, if at least one pixel from this region is 8-connected to a pixel from the other region. Each region together with its associated descriptor is a node in the graph. Edges in the spatial graph represent the neighboring relationships between segmented regions.



(a) Input image of colors (C0,C1,C2,C3). (b) Labeled regions.

(c) Spatial graph.

Fig. 8 Region adjacency graph generation, regions and their associated descriptors are nodes in the graph.

After generating the NN graph, the framework uses the greedy nearest neighbor graph matching algorithm [8] with a modified scoring function as a similarity measure. The similarity measure process works as follows, given two graphs $G_1: \{V_1, E_1\}$ and $G_2: \{V_2, E_2\}$ where V is the graph node and E is an edge connecting two nodes. For each node v_i inG_1, we attach a list of best matched nodes in 2 G according to a matching function $m\,(v_i)$. The local descriptor was chosen to be the fuzzy color and texture histogram, where the Tanimoto coefficient T [26] was used as the matching function.

$$m\,(v_i) = T_{ij} = t(x_i, x_j) = \frac{x_i^T x_j}{x_i^T x_i + x_j^T x_j - x_i^T x_j} \tag{4}$$

Where x^T is the transpose of vector x. The Tanimoto coefficient takes the value of 1 for absolute convergence and tends to zero for maximum deviation. Given the node v_i in G_1 and its associated best matched list of nodes, we need to find the best matched pair of nodes $\{v_i, v_j\}$ among matched nodes in the best matched list. The nearest neighbor graph matching technique in [24] chooses the best matched pair $\{v_i, v_j\}$ that has the lowest mean of distances between neighbors of node v_i and neighbors of each node v_j in the best matched list. This produces a non accurate rank because of neighboring nodes that may have large matching distances. We propose a different similarity function where we compare the neighborhood nodes of node vi with the neighborhood nodes of node v_j and assign the rank of pair $r(v_i, v_j)$,

$$r(v_i, v_j) = \frac{number\ of\ mateched\ neighbors\ of\ (v_i, v_j)}{total\ number\ of\ neighbors\ of\ v_i} \tag{5}$$

The chosen best matched pair is the one with the highest rank $r(v_i, v_j)$. We calculate the rank of best matched pairs $bestR(v_i)$ for each node in G_1 and assign a final similarity rank as the mean rank,

$$Similarity\ rank = \frac{\sum_i bestR(v_i)}{number\ of\ nodes\ in\ G_1} \tag{6}$$

For a given query image, the approach constructs a nearest neighbor graph for each image in the data set. The final similarity rank is determined by applying the greedy nearest neighbor graph matching algorithm.

2.6 Image Retrieval System

The proposed method combines local region description with global FCTH description. The FCTH descriptor globally represents the color and texture information from all pixels of the image. The technique uses the Tanimoto coefficient (equation 4) to measure the distance between images. This distance is used as the global score of the image. The proposed local description technique defines another local score by matching image principal regions, using the modified greedy graph matching algorithm. The final score between two images is given by,

$$final\ score = w1 \times global\ score + w2 \times local\ score \quad (7)$$

Where, $w1$ and $w2$ are the weights for the global and the local scores. The final score increases with the increase of similarity to the query image. Global image features provide an abstraction view of an image as a whole, whereas local descriptions of image extracted regions provide a summary of image content details. The use of these two views is necessary to provide accurate retrieval of images. In this framework, we use a weighted summation of the global and local image ranks, where we suggest equal importance to both ranks. So we use both weights to be 1.

3. Experimental work

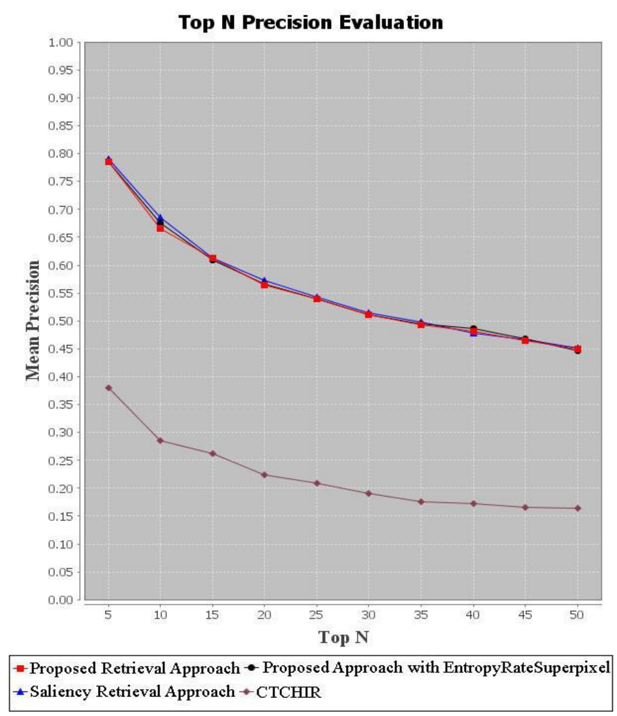
The experiments are performed on the 1000 image Wang database [27] and, the 1338 Uncompressed Color Image Database (UCID) [28]. The Wang database contains 10 categories; each category contains 100 images. The database has large variations and object dissimilarity in query relevant images. The UCID consists of 1338 uncompressed TIFF images of different topics related to indoors, outdoors and natural scenes, and man-made objects. Its query relevant images are quite similar but with little geometric and photometric variations. The top N precision and recall comparisons [29] have been used to evaluate the performance of the proposed approach toward other approaches.
These metrics define a set of relevant images called the ground truth for each test query. The precision of the retrieval is defined as the fraction of the retrieved images that are relevant to the query from the set of returned images. The recall is the fraction of the relevant images returned by the query from the ground truth. These metrics are measured only for one query. To evaluate a system for several queries, we use the mean recall and the mean precision. The top N comparison computes the mean precision and the mean recall for the top N returned results.

The MIRROR image retrieval system [5] separated the Wang database in 20 queries, each with a proposed ground truth. We extend these 20 queries to 40 queries to cover all the database categories. In addition, the evaluation uses the ground truth assigned for the UCID database [28]. This ground truth is a total of 162 query with their defined most relevant images.

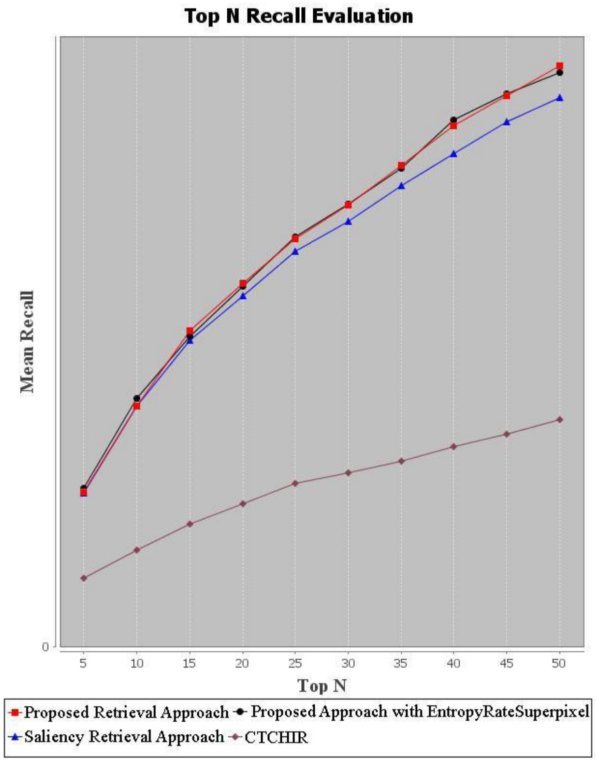
The results of the proposed retrieval approach are compared with the results of the following techniques: color–texture and color-histogram based image retrieval system (CTCHIR system) [30], the proposed approach using the regions detected by the entropy rate superpixel [17] and the saliency retrieval technique [8].

The proposed technique extracts the most general principal regions in an image that act as a local image descriptor. The experiment uses 20 (figure 6) principal regions as an approximation between smoothness and complexity. Images having segmented regions above 20 will have the small regions combined to the largest 20 regions based on the hue criteria.

Figure 9 shows the top N precision and recall comparison evaluated over the Wang database. N ranges from 5 to
50 step 5. Figure 9(a) shows that the proposed approach provides close to the saliency approach and better than other approaches. The saliency retrieval approach was efficient for images having complex spatial structure as in the Wang database; where query relevant images have large variations and object dissimilarity. Alternatively, the saliency approach has degraded accuracy for images having large smoothed regions, with less or no complexity in its structures, because a few numbers of salient regions will be extracted. Figure 9(b) shows that the proposed approach provides better recall than the other approaches.



(a) Top N precision comparison evaluated over Wang Database



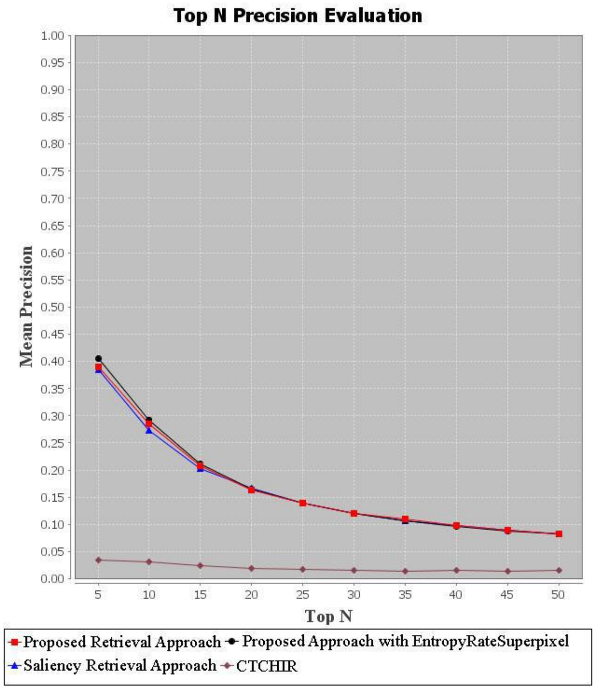
(b) Top N recall comparison evaluated over Wang database.

Fig. 9 top N recall and precision comparisons evaluated over Wang databases.

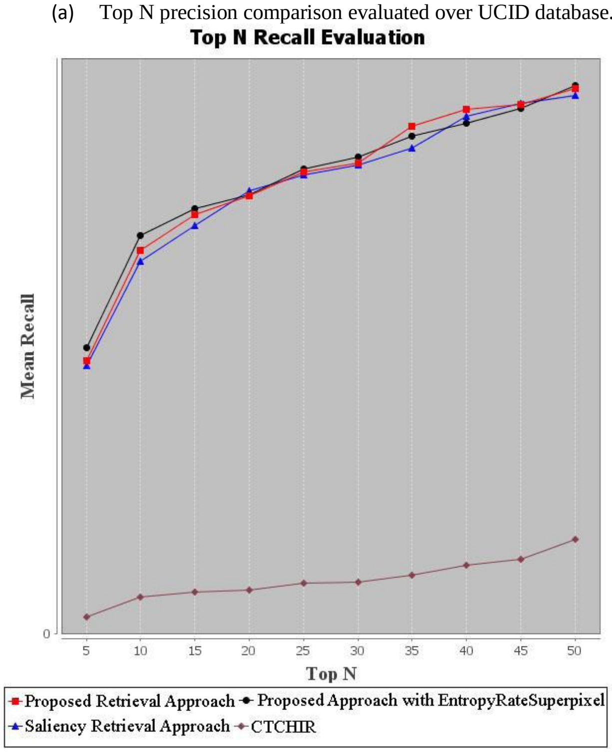
The CTCHIR system aimed to improve the precision of retrieval by combining three features: the Co-occurrence Matrix (CCM) to describe the direction of textures, the Difference between Pixels of Scan Pattern (DBPSP) to describe the complexity of textures and the Color Histogram for K-Mean (CHKM) to describe color features.

This system used fixed window sizes to determine the CCM and DBPSP features. This made it suffer from the geometric variation problems. However, the proposed technique combines globally and locally extracted color and texture features to enhance the precision of retrieval.

Figure 10 shows the top N precision and recall comparison evaluated over the UCID database. The figure shows that the proposed approach provides better precision and recall when evaluated over the UCID database. This is because the relevant images are quite similar.



(a) Top N precision comparison evaluated over UCID database.



(b) Top N recall comparison evaluated over UCID database

Fig. 10 top N recall and precision comparisons evaluated over UCID database.

The proposed retrieval approach works as an extension to the saliency approach. It enhances the precision for images having large smoothed regions and provides better recall than other approaches. In addition, the new approach captures the smooth details of images and provides an approximation between smoothness and complexity for images having large occlusion and complexity in structure. The approximation provides precision close to the saliency approach for images having large geometric variations as in the Wang database. For images with small variations, the proposed segmentation approach provides more accurate results than the saliency approach.

Table 1: Average Time of each phase measured on Wang and UCID databases.

Phase	Average Time(sec) (Wang)	Average Time (sec) (UCID)
Morphological Operations	0.00131	0.001559
HSV Color Quantization	0.0299	0.03466
Over-Segmentation Handling	0.002015	0.002236
Description of Segmented Regions	0.28514	0.3211
Total Average Time	0.3184	0.3596

Table 2: Performance evaluation of the proposed approach and the compared techniques evaluated on completely the Wang database

Method	*Local Feature vector*	*Global Feature Vector*	*Average segment. time(sec)*	*Average matching time(sec)*	*Average top N precision*	*Average top N recall*
Proposed	*20*	*1*	*0.3184*	*1.87*	*0.555*	*0.338*
Entropy rate[17]	*20*	*1*	*1.0365*	*1.83*	*0.558*	*0.388*
Saliency [8]	*252*	*1*	*0.505*	*18.47*	*0.561*	*0.324*
CTCHIR [30]	*-*	*3*	*-*	*.00125*	*.0223*	*0.133*

Table 1 shows the average time of each phase of the proposed segmentation scheme measured on the Wang and the UCID databases. This evaluation is performed on a computer that has T7500 Intel®Core™ 2 Duo 2.2 GH processor, 2GB memory and running windows 7 operating system. This table shows that the average time to segment an image using the new segmentation scheme is 0.3184Sec over the Wang database and 0.3596Sec over UCID database.

Table 2 shows a performance evaluation of the proposed retrieval approach toward other approaches. The table compares the techniques relative to the number of locally detected feature vectors, the number of globally detected feature vectors, the average segmentation time and the average matching time. The experiment used the Wang dataset. The techniques are implemented in java and operated in a single thread.

The entropy rate superpixel segmentation [17] is reported to provide more accuracy and speedup toward several state of the art segmentation techniques. We used it to evaluate the performance of the proposed technique especially regarding the segmentation time. Table 2 shows that the segmentation scheme and the entropy rate superpixel segmentation [17] perform similarly by providing equivalent average, top N precision and recall. On the contrary, the proposed segmentation scheme provides speed up by segmenting images of the Wang database in an average time of 0.318Sec where the entropy rate superpixel segmentation takes 1.036Sec. Consecutively, the proposed segmentation scheme provides a significant speedup toward state of the art techniques, while maintaining equivalent segmentation precision.

The saliency approach has no control on the number of detected salient regions. For images having large details; the number of detected salient regions may increase the size of the generated nearest neighbor graph, thus increasing the average matching time. For the matched queries, an average of 252 feature vectors are used locally with 1 global feature vector, resulting in an average matching time of 18.47sec.
The proposed retrieval approach solves the problem of the increase in the generated graph size by using a fixed number of general principal regions. For the matched queries, an average of 20 feature vectors are used locally with 1 global feature vector, resulting in an average matching time of 1.87sec. In addition, several speedups can be performed using parallel programming techniques to reduce the average matching time.

4. Conclusions

This paper proposes the Principal Regions Image Retrieval (PRIR) approach. The proposed retrieval approach works by segmenting an image into the most general principal regions that act as local descriptors. The technique follows by generating a spatial graph to detect the spatial relationships between regions. It then calculates the image score using a greedy graph matching algorithm with a modified scoring function. Moreover, the paper presents a generalized multi-resolution region-based segmentation scheme. This scheme provides significant speedup toward state of the art hierarchal segmentation techniques reported in the literature. The new segmentation scheme provides efficient segmentation and treats problems existing in previous region-based segmentation algorithms such as over segmentation. The proposed retrieval system combines the matching scores of local region description and global fuzzy color and texture histogram description to improve the retrieval results. A performance evaluation is performed between the proposed technique and others reported in the literature. It shows that the proposed approach provides better recall and precision with appropriate average queries matching time. In addition, several speedups can be performed using parallel techniques.

Results show that the proposed approach provides more accurate results than previous approaches.

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