Content-Based Image Retrieval System Based on Self Organizing Map, Fuzzy Color Histogram and Subtractive Fuzzy Clustering

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Abstract: *A novel system with high level of retrieval accuracy has been presented in this paper. Color as one of the most important discriminators in Content-Based Image Retrieval (CBIR) is utilized through calculating some of the primitive color features. The indexing of image database is performed with Self-Organizing Map (SOM) which identified the BMU's best matching units. Subsequently, Fuzzy Color Histogram (FCH) and subtractive fuzzy clustering algorithms have been utilized to identify the cluster for which the query image is belonging. Furthermore, the paper presents an enhanced edge detection algorithm to remove unwanted pixels and to solidify objects within images which ease similarity measures based on extracted shape features. The proposed approach overcomes the computational complexity of applying bin-to-bin comparison as a multi dimensional feature vectors in the original color histogram approach and improves the retrieval accuracy based on shape as compared with the most dominant approaches in this filed of study.*

Keywords: *CBIR, FCH, SOM, subtractive fuzzy clustering.*

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1. Introduction

In Content-Based Image Retrieval (CBIR), researchers seek for efficient and robust methods to retrieve relevant images from huge images database utilizing automatic derivation of local and global features from image query as well as images database. Features as shape, color, and texture are the most dominant features to be considered. There are many similarity or dissimilarity measures to rank the retrieved images based on its relevancy to the query image.

1.1. Previous Work

In [2], they propose probabilistic framework to process multiple image queries. The proposed framework is independent from similarity measures and gives rise to a relevance feedback mechanism. In [26], CBIR method to diagnose aid in medical images is proposed. Images are indexed without extracting domain-specific features; a signature is built for each image via wavelet transform. In [10], they propose two CBIR frameworks based on genetic programming. The first framework is concerned with user indication of relevant images, while the second one considers the relevant and non-relevant indicated images. In [27], new multi-resolution fusion algorithm for spatially registered multi-sensor fusion is proposed. They modified watershed algorithm for the purpose of producing a region map to source images. The region-based decision tree is obtained based on local texture features in dual-tree discrete wavelet transform. In [14], the KFCM (Fuzzy Kernel Clustering and Invariant Moments) is utilized in CBIR. The proposed method relies on extracting features of images, clustering using fuzzy kernel clustering, detecting edges using Canny operator, and finally edge invariant moments are calculated. CBIR differs from many of other disciplines in computer vision because of its evaluation difficulty, due to the fact that human subjectivity cannot totally be isolated from that evaluation [5, 18]. New visual feature representations for image that provide an efficient discriminator for similarity queries have been the main interest for most of researchers in CBIR [1, 11, 16, 21, 23, 24, 29]. Furthermore, multi-dimensional indexing techniques to speed up the retrieval process from large image database with complex feature representation were discussed in [13, 28]. In [6], they propose a new region based fuzzy feature matching approach based on segmenting the image into blocks with 4×4 pixels each. The size of images was limited to 256×384 or 384×256. Since they used 6 features to represent each block, the number of feature vectors for each image is 6,144. Three features represent the average color components using LUV color space while the remaining features represent energy in the high bands of wavelet transform. The results of the proposed system were promising. In CBIR there is a need for simple and efficient approaches to handle the color and shape-based retrieval. Any attempt at this direction should consider the speed of performance, the varying size of images database, the accuracy of retrieval, and the ability to achieve an accurate ranking for the retrieved images. Color and shape are considered as the most important visual features, while texture has no value if not associated with color. Color Histogram (CH) is one of the standard approaches for color-based retrieval. There are many attempts to enhance this approach and to overcome some of the associated problems. CH approach relies on multi-dimensional feature vectors in which a bin-to-bin comparison is conducted. The computational complexity problem is obvious. Furthermore, incorporating color similarities into the distance function does not yield to a robust distance function that corresponds to the perceptual similarity of a color histogram.

1.2. Paper Outline

In this paper, a new approach for color and shape-based image retrieval based on SOM and subtractive fuzzy clustering algorithm is presented. The rest of the paper is organized as follows. Section 2 is an overview of the proposed approach. Shape features extraction and algorithms are presented in section 3. Section 4 illustrates similarity measures and performance evaluation. Section 5 presents the experimental results. Finally, the conclusion is drawn in section 6.

2. Proposed Approach

The major components of the proposed CBIR system are shown in Figure 1.

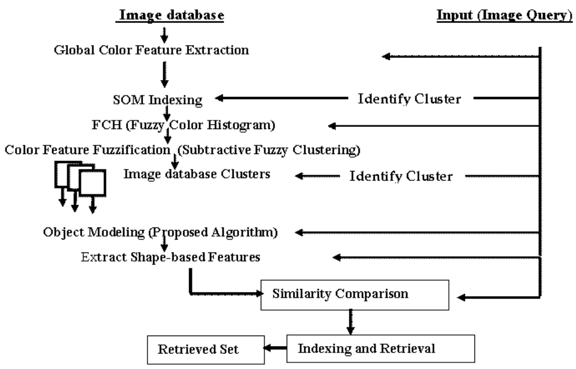


Figure 1. System block diagram.

2.1. SOM Indexing

Self-Organizing Map (SOM) [17] is used as an indexing technique to organize the feature vectors due to its efficiency in organizing unsupervised statistical data. A SOM consists of a regular grid of map units. A model vector is $m_v \in \Re^d$ associated with each map unit v. The map tries to represent all available observation $x \in \Re^d$ with optimal accuracy. The fitting of the model vectors is a sequential regression process, where t=0, 1, 2,…, $^{t}max^{-1}$ is the step index. For each input sample *x(t)*, first the index *c(x)* of the Best Matching Unit (BMU) or winner model $m_{c(x)}(t)$ is define the condition:

$$\forall v : \|x(t) - m_{c(x)}(t)\| \le \|x(t) - m_v(t)\| \quad (1)$$

After identifying the BMU, a subset of the model vectors constituting a neighborhood centered at the BMU (node *c(x)*) are updated as:

$$m_v(t+1)=m_v(t)+d(t;c(x),v)(x(t)-m_v(t)) \quad (2)$$

Where *d(t;c(x),v)* is a decreasing neighborhood function of the distance between v^{th} and $c(x)^{th}$ units on the map grid. After the training phase, the BMU's partition the feature space into a set of Voronoi regions. The interior of each region consists of all points in the feature space that are closer to the respective BMU than to any other. Four major global features are used in this research to index the image database. These features are as follows:

- *Mean:* The value of the Mean shows the general brightness of the image. As a general rule bright images has high mean, while dark image has low mean.
- *Standard Deviation:* The standard deviation gives a clear idea about the image contrast. As a general rule high standard deviation means high image contrast, while small standard deviation means low image contrast.
- *Energy:* Energy shows how the grey level is distributed. The maximum value of energy is 1 and it gets smaller as the pixel value distributed among the grey level.
- *Skew:* Measures the asymmetry about the mean in the grey level distribution.

Based on these features the BMU is identified with respect to the image query. This technique filters the image database and reduces the candidate images for the next stage. For each image the feature vector consists of 4 features. Feature vectors are merged and normalized. The normalized vectors of all images are fed into the map calculation algorithm which produces a map with hexagonal layout. Each cluster is represented by a feature vector pointing to its centre and the BMU of the query image is identified. The distance between the search image cluster and the neighboring clusters is identified through weight calculation to all features based on the reciprocal value of the sum of distances. For this purpose Euclidean distance function is used. At the end of this phase, the images database is filtered based on the cluster and neighboring clusters for which the search image is belongs.

2.2. Image Segmentation and Fuzzy Color Histogram

Traditional color histogram approach does not take into consideration the color similarity across different bins shades or the color dissimilarity in the same bin. Fuzzy Color Histogram (FCH) approach [31] has many advantages over the conventional color histogram approach. FCH considers the color similarity of each pixel's color associated to all the histogram bins through fuzzy set membership function such as the degree of “belongingness”. As compared to the traditional color histogram approach which assigns each pixel into one of the bins only, FCH spreads each pixel's total membership value to all histogram bins. Color histogram of image I containing N pixels represented as: $H(I)=[h_1, h_2, ..., h_n]$, where $h_i=N_i/N$ is the probability of a pixel in the image belong to the i^{th} color bin, and N_i is the total number of pixels in the i^{th} color bin. Based on the conditional probability h_i may define as follows:

$$h_i = \sum P_{i|j} P_j = 1/N \sum P_{i|j} \tag{3}$$

Where $P_{i|j}$ is the conditional probability of the chosen j^{th} pixel belonging to the i^{th} color bin and P_j is the probability of the j^{th} pixel chosen from the image.

Since FCH considers each of the N pixels in image I, related to all the n color bins via Fuzzy set membership function which is the degree of belongingness of the j^{th} pixel to the i^{th} color bin. This may be achieved by distributing the membership value of the j^{th} pixel, x_{ij} to the i^{th} color bin. Fuzzy color histogram of image I can be represented as:

$$F(I) = [f_1, f_2, ..., f_n] \tag{4}$$

Where $f_i = (1/N) \sum \chi_{ij}$. To compute the membership values, Fuzzy C means [30] was performed on the color component using CIELAB color space. The major problem with Fuzzy C mean is that the number of clusters needs to be identified by the user, which means that a pre-knowledge in the image domain is necessary to identify the exact number of clusters for any given set of data. It is well known that smaller block size may preserve texture details but at the same time increases the computational time. In this study images are segmented into 4×4 non overlapping blocks. Each image is represented by 16 feature vector, $\vec{f_i}$ each of which consists of 256 features.

The subtractive Fuzzy clustering algorithm [7] is used to cluster feature vectors into several classes with every class corresponding to one region in the segmented image. Subtractive is a fast, one-pass algorithm for estimating the number of clusters and centers of clusters in a set of data without any interference from users. This advantage eliminates the need to a pre-knowledge in the image domain.

2.3. Subtractive Fuzzy Clustering

In subtractive clustering each data point is a candidate to be a cluster center. A density measure at data point p_i is defined as:

$$D_i = \sum_{k=1}^{n} \exp\left[- \frac{\left\| p_i - p_k \right\|^2}{\left(\frac{c_a}{2} \right)^2} \right] \tag{5}$$

Where c_a is a positive constant which represent neighborhood radius. The initial cluster center P_{c1} is selected as the point with the largest density value D_{c1}. Then the density measure of each data point P_i is revised based on the following equation:

$$D_i = D_i - D_{c1} \sum_{k=1}^{n} \exp\left[- \frac{\left\| p_i - p_{c1} \right\|^2}{\left(\frac{c_b}{2} \right)^2} \right] \tag{6}$$

Where c_b is a positive constant that defines a neighborhood, having a measurable reduction in density measure. After revising the density function, the next cluster center is selected based on the greatest density value. Subtractive clustering algorithm allows partitioning the feature vectors F to k groups $F=\{F_1,F_2,...,F_k\}$ and, consequently, the image is segmented into k regions $R=\{R_1,R_2,...,R_k\}$.

2.4. Image Representation Based on Fuzzy Features

An image may be viewed as a collection of regions $\{R_1,...,R_k\}$ and feature sets, $F=\{F_1,..., F_k\}$. Direct region comparison based on related feature set is not preferable due to the uncertainties related to sensitivity of segmentation. In [6], an improved region representation is presented in which each region R_i is represented by the center $(\hat{\vec{f_i}})$ of the corresponding feature set F_i. The center $(\hat{\vec{f_i}})$ may define as:

$$\hat{\vec{f_i}} = \frac{\sum_{\vec{f} \in F_i} \vec{f}}{\vee (F_i)} \tag{7}$$

Which represent the mean of elements of F_i and not necessarily be an element of F_i. To identify the degree of membership of the feature vector $(\hat{\vec{f_i}})$ to the corresponding Fuzzy feature F_i a proper membership function is used. Cone and Cauchy [15] are the most common examples of membership function. In this research Cauchy is selected due to its retrieval accuracy. Cauchy function may define as:

$$\varsigma(\bar{f}) = \frac{1}{1 + \left(\frac{\left\| \bar{f} - \hat{\hat{f}} \right\|}{d_f} \right)^{\theta}} \tag{8}$$

Where d represents the width of the function $\hat{\hat{f}}$ represents the center location of the fuzzy set and θ represents the smoothness of the function.

3. Shape Features Extraction and Algorithms

3.1. Edge Detection Enhancement

Many of edge detectors are available to researchers [19]. Marr and Hildreth [20] convolve a mask over the image and label zero-crossings of the convolution output as edge points. In [12], an approach combining contrast threshold and analysis of direction dispersion to find edges is presented. In [3], they label peaks in the magnitude of the first derivative of the intensity profile along a scan-line as feature points for matching. Other popular gradient edge detectors are the Canny, Roberts, Sobel and Prewitt operators [4]. Comparing objects based on edge operators only does not yields to satisfactory results in most cases. That because if there is any variation in image brightness, then the same image looks different after applying the edge operator. Moreover, the unwanted pixels in the image affect the retrieval accuracy dramatically. In this research and in order to overcome some of these problems an algorithm to filter the images at the pre-processing stage is proposed. Many edge detectors are examined and the extensive testing shows that Prewitt operator gives a better result with a proper threshold selection. Moreover, a proposed automatic image cropping algorithm is proposed. The image cropping algorithm allows removing the image background which does not contains objects or part of objects. The proposed algorithm was applied to the images database in the pre-processing stage and in spite of its simplicity it has a tremendous effect in enhancing object modeling and comparison.

Automatic_ Cropping_ Algorithm (image I)

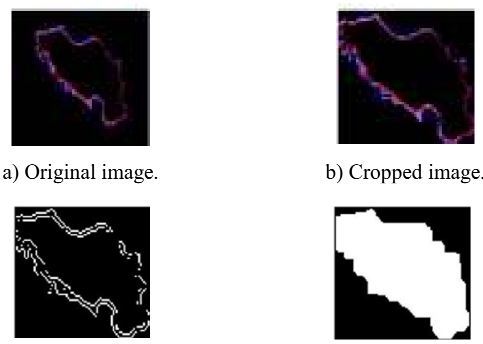
1. *Scan image row(r) by row(r)*
   If $I(x, y) == 0 \quad \forall (x, y) \in r$ *then crop the row*
2. *Scan image column(c) by column(c)*
   If $I(x, y) == 0 \quad \forall (x, y) \in c$ *then crop column*

3.2. Proposed Object Modeling Algorithm

Shape-based comparison and retrieval is problematic due to the fact that any slight variation between two similar objects may yield to unsatisfactory result. Many researches rely on edge detection to extract the shapes of objects within the image. In this research new algorithm to extract and solidify objects is proposed. The objectmodelalgorithm relies on scanning the edge detected objects horizontally and vertically and filling the intermediate pixels with 1's in order to re-build a realistic shape for these objects. After that, different shape features may be extracted and compared.

```
ObjectModelAlgorithm (Image I)
1. Read image I.
2. Convert color image to grey scale image.
3. Apply Prewitt Edge Detector.
4. Scan image row by row as follows:
        For i = 1 to Row {
          For j =1 to Column {
             If I (i, j) = = 1{
                 S1← j; Break}}
           For k = S1+1 to Column {
             If I (i, k) ==1{S2← k}
             If (S1~= 0) && (S2~= 0) {
              If (S1<S2) {
             Fill intermediate pixels in the row with 1's}}
          S2=S1}
5. Scan image column by column as follows:
         For i = 1 to Row {
           For j =1 to Column {
             If I (j, i) == 1{R1← j; Break}}
           For k = R1+1 to Column {
             If I (k, i) ==1{R2← k}}
        If (R1~= 0) && (R2~= 0) {
          If (R1<R2) {
   Fill intermediate pixels in the column with 1's}}
          R2=R1}
```

The proposed algorithm overcomes the overlapping problem of objects through updating the starting point of filling to the in between pixels. Figure 2 shows an example of applying the proposed algorithm.



a) Original image. b) Cropped image.

c) Edge detected image (Prewitt). d) Result image after applying the proposed algorithm.

Figure 2. Applying the proposed algorithm.

3.3. Shape-Based Descriptors

Shape descriptors consist of some values that are used to describe a given shape. In general, the descriptors for different shapes should be different enough in order to discriminate between shapes. The good descriptor is classified as the descriptor that shows greater differences of significantly different shapes and lesser differences for similar shapes. In this study, region-based properties are considered. The shape feature descriptors that have been extracted within this research work are shown in Table 1.

Table 1. Shape features descriptors.

Shape Feature	Description
Area	Scalar value representing the actual number of pixels in the region.
Centroid	The center of mass of the region. Note that the first element of Centroid is the horizontal coordinate (or x-coordinate) of the center of mass, and the second element is the vertical coordinate (or y-coordinate)
Major Axis Length	The length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region.
Minor Axis Length	The length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region.
Eccentricity	The ratio of the length of the longest chord to the longest chord perpendicular to it. The value is between 0 and 1.
Orientation	The angle (in degrees) between the x-axis and the major axis of the ellipse that has the same second-moments as the region.

The centroid of a non-overlapping closed polygon defined by n vertices (x_i, y_i) can be calculated as follows:

$$C_x = \frac{1}{6 * Area} \sum_{i=0}^{n-1} (x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \quad (9)$$

$$C_y = \frac{1}{6 * Area} \sum_{i=0}^{n-1} (y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \quad (10)$$

4. Similarity Measures and Performance Evaluation

The image comparison in the proposed CBIR module is based on query by example [25]. The example image is analyzed and the necessary features are extracted in each phase then compared with other database images. There are different metric functions (e.g., City block and Euclidean) which may be utilized to make measurement in each feature space. As shown in [9], these metrics have been defined to calculate the similarity between two probability distributions. Prior to decide on evaluation of any CBIR approach a trade off decision should be taken. For instant, if the number of retrieved images is important then retrieval accuracy may be seriously affected. The following formula is developed to represent the relationship between the different retrieval variables features and their weights.

$$Q(R_{CBIR}) = \begin{cases} P(i) & i = 1 \\ \sum_{i=2}^{n} P(i) \times W_i & 2 \le i \le n \end{cases} \quad (11)$$

Where i is the variable (feature) which considered in the retrieving process and W_i is the weight of that feature. Considering that $\sum_{i=2}^{n} W_i = 1$ this implies that $0 \le W_i \le 1$. CBIR system like any other Information Retrieval (IR) system resolves queries in an approximate way, because the users are not specific about the precise results that should be delivered [32]. It is believed that what is important is the image retrieval module. Even so, it is good to evaluate the performance of that module. To measure the performance of any retrieval system, precision and recall are still the most prominent techniques to use. In [22], they present a framework to evaluate CBIR based on recall and precision:

$$\text{Precision} = \frac{Number\ of\ relevant\ retrieved\ images}{Number\ of\ all\ retrieved\ images} \quad (12)$$

$$\text{Recall} = \frac{Number\ of\ relevant\ retrieved\ images}{Number\ of\ all\ relevant\ images\ in\ the\ category} \quad (13)$$

For several queries average precision is preferable, which may define as:

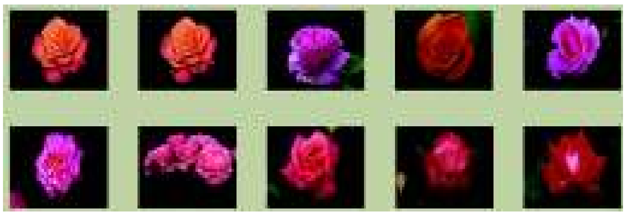
$$\overline{P}(r) = \frac{\sum_{i=1}^{N_q} P_i(r)}{N_q} \quad (14)$$

Where $\overline{P}(r)$ is the average precision at recall level r, N_q is the number of queries, and $P_i(r)$ is the precision at recall level r for the i^{th} query.

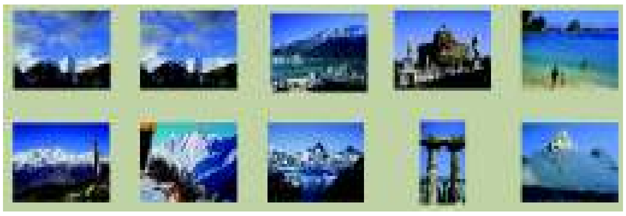
5. Experimental Results

The proposed approach is tested on a general purpose image database with 1000 images from COREL. The 1000 images are classified to 10 categories with 100 images each. Five images are randomly selected from each category (e.g., Dinosaur, Beach, and Vehicles). A retrieved image represents a correct match if and only if it belongs to the same category as the query image. The average precision is calculated through evaluating the top 20 returned results. Due to space limitations, only the top 9 matches to query images are shown in Figure 3.

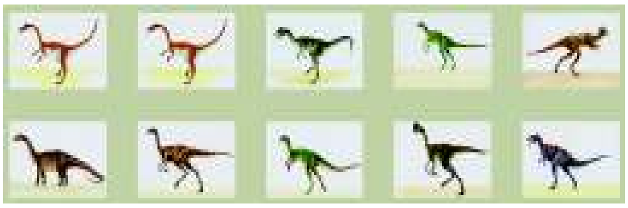
Moreover, and to ensure consistency and rational comparison with other methods, the proposed method is compared with global Histogram method with 32 Color bins (HisC), non-fuzzified Efficient Color Representation (ECR) method [8], and UFM method [6] using the same set of images categories from the same images database (COREL). Table 2 shows that the proposed method outperforms the HisC in all image categories and improves the overall average retrieval accuracy by 85%. As compared with ECR method it improves the average retrieval accuracy in all image categories except horses and the overall improvement in average accuracy is 50%. The proposed method has better retrieval accuracy as compared with UFM method in 5 categories and worse accuracy in 3 and the overall improvement in average accuracy is 6%.



a) Flower, 9 matches out of 9, 18 matches out of 20.



b) Mountain, 7 matches out of 9, 16 matches out of 20.



c) Dinosaur, 9 matches out of 9, 20 matches out of 20.

d) Horses, 8 matches out of 9, 17 matches out of 20.

e) Vehicle, 8 matches out of 9, 17 matches out of 20.

Figure 3. Sample of retrieved results. The query image is in the upper left corner.

Table 2. Average retrieval precision comparison.

Category	Proposed Method	HisC	ECR	UFM
Elephant	0.50	0.33	0.44	0.42
Beach	0.68	0.16	0.37	0.55
Vehicles	0.84	0.17	0.22	0.78
Dinosaur	1.00	1.00	0.90	1.00
Building	0.70	0.22	0.15	0.71
Horses	0.85	0.61	0.89	0.89
Flower	0.97	0.40	0.46	0.95
Food	0.63	0.36	0.27	0.65
Mountain	0.32	0.16	0.42	0.33
Africa	0.87	0.60	0.81	0.70
Average	0.742	0.401	0.493	0.698

6. Conclusions

Region based segmentation and image clustering combined with edge detection enhancement is promising approach in CBIR. In this research the integration of different methods in CBIR succeeds to achieve robust, reliable, and a high level of retrieval accuracy system. The experimental results on 1000 images from COREL database show that the proposed approach achieves high retrieval accuracy with valuable reduction to the number of extracted features. Moreover, the comparisons with traditional color histogram, ECR, and UFM methods prove that the proposed approach is able to improve the accuracy of retrieval dramatically.

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