Image Retrieval System with Self Organizing Map and Subtractive Fuzzy Clustering

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***Abstract*—A system with high level of retrieval accuracy is presented in this paper. Color as one of the most important feature in CBIR (content-based image retrieval) is strongly considered through calculating some of the primitive color features and fuzzy color histogram. Indexing of image database is performed with SOM (self-organizing map) which identified the BMU's (best matching units). Subsequently, fuzzy color histograms (FCM) and subtractive fuzzy clustering algorithm are used to identify the cluster for which the query image is belonged. Furthermore, the paper presents an enhanced edge detection algorithm to remove the unwanted pixels and to solidify objects within images which ease similarity measure based on shape feature. 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 accuracy of retrieval based on shape**

***Index Terms*— CBIR, FCM, SOM, subtractive fuzzy clustering.**

I. Introduction

IN content-based image retrieval (CBIR), researchers seek for an efficient and robust methods to retrieve relevant images from huge image databases utilizing automatic derivation of local and global features from image query as well as image databases. 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.

A. *Previous Work*

Many popular CBIR systems include IBM'S QBIC project[1], VisualSeek [2], PicSOM [3], PicHunter[4], and MIRROR [5] are available. CBIR differs than many of other disciplines in computer vision because of the difficulty of its evaluation due to the fact that human subjectivity cannot totally be isolated from that evaluation [6], [7], [8]. New visual feature representations for image that provide an efficient discriminator for similarity queries has been the main interest for most of researchers in CBIR [9], [10], [11], [12], [13], [14]. Furthermore, multi-dimensional indexing techniques to speed up the retrieval process from large image database with complex feature representation were discussed in [15], [16]. In [29], they propose a new region based fuzzy feature matching approach. They segmented the image into blocks with 4 x 4 pixels each. The size of images was limited to 256 x 384 or 384 x 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 main component of the visual features which may consider in the retrieving process, while texture has no value if not associated with color. Color histogram (HC) is one of the standard approaches for color-based retrieval. There are many attempts to enhance this approach and to overcome some of the problems associated with the original color histogram approach. Color histogram 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.

B. *Paper Outline*

In this paper, 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 is 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.

II. PROPOSED APPROACH

The main components of the proposed CBIR system are shown in Fig.1.

A. *SOM Indexing*

SOM (Self-organizing map) [22] is an indexing technique to organize the feature vectors that due to the efficiency of SOM in organizing unsupervised statistical data.

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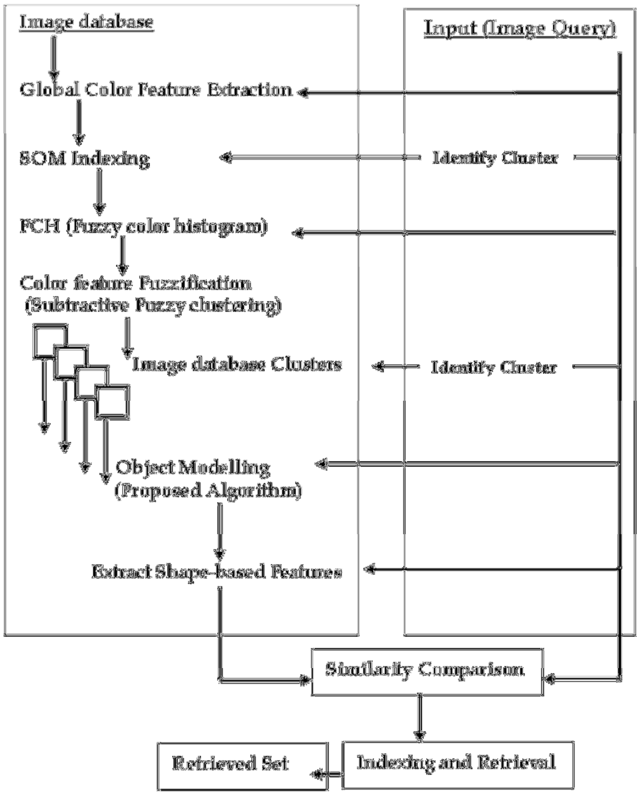

Fig. 1. System block diagram

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:

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

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

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

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 order to index the image database. These features 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 become 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. Then the BMU of the query image is identified. The distance between the search image cluster and the neighboring clusters is identified through the calculation of the weight for 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 database images are filtered based on the cluster for which the search image and some of the neighboring clusters are belongs.

B. *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 approach [27] has many advantages over the conventional color histogram approach. Fuzzy color histogram (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:

$$h_i = \sum P_{i|j} P_j = 1/N \sum P_{i|j} , \qquad (1)$$

where $P_{i|j}$ is the conditional probability of the chosen *jth* pixel belonging to the *i*th color bin and P_j is the probability of the *jth* 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, χ_{ij}, to the *i*th color bin. Fuzzy color histogram of image I can be represented as F(I) $=[f_1, f_2, ..., f_n]$, where $f_i = (1/N)\sum \chi_{ij}$. For computing the membership values, Fuzzy C means [28] was performed on the color component using CIELAB color space. The problem with the Fuzzy C mean is that the number of clusters needs to be identified and since we don't have clear and precise idea about 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 we segment the image into 4 x 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 [30] 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 the cluster centers in a set of data without any interference from users. This advantage eliminates the need for a pre-knowledge in the image domain.

C. 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:

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

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.

$$D_i = D_i - D_{c1} \sum_{k=1}^{n} \exp\left[-\frac{\|p_i - p_{c1}\|^2}{\left(c_b/2\right)^2} \right], \qquad (3)$$

where c_b is positive constant that defines a neighborhood that has 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 $\mathbf{F} = \{\mathbf{F}_1, \mathbf{F}_2, ..., \mathbf{F}_k\}$ and, consequently, the image is segmented into k regions $\mathbf{R} = \{\mathbf{R}_1, \mathbf{R}_2, ..., \mathbf{R}_k\}$.

D. 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 [29] an improved region representation is presented in which each region $\mathbf{R}_i$ is represented by the center $(\hat{\vec{f}}_i)$ of the corresponding feature set $\mathbf{F}_i$. The center $(\hat{\vec{f}}_i)$ may define as:

$$\hat{\vec{f}}_i = \frac{\sum_{\vec{f} \in \mathbf{F}_i} \vec{f}}{\vee(\mathbf{F}_i)} \qquad (4)$$

which represent the mean of elements of $\mathbf{F}_i$ and not necessarily be an element of $\mathbf{F}_i$.

To identify the degree of membership of the feature vector $(\hat{\vec{f}}_i)$ to the corresponding Fuzzy feature $\mathbf{F}_i$ a proper membership function is used. Cone and Cauchy [31] are the most common examples of membership function. Due to retrieval accuracy and computational intensity Cauchy is selected. Cauchy function, defined as:

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

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

III. SHAPE FEATURES EXTRACTION AND ALGORITHMS

A. Edge Detection Enhancement

Many of edge detectors are available to researchers [17]. Marr and Hildreth convolve a mask over the image and label zero-crossings of the convolution output as edge points [18]. In [19], a combination of contrast thresholding and an analysis of direction dispersion approach to find edges is presented. In [20], 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 Canney, Roberts, Sobel and Prewitt operators [21]. Comparing objects based on edge operators only does not yields to satisfactory results in most cases. That due to the fact, if any variation of the image brightness is exist then the same image looks different after applying the edge operator. Moreover, the unwanted pixels in the image affect the retrieval accuracy too. 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. In this study, many of edge detectors are examined the extensive testing shows that Prewitt operator gives a better result with a proper threshold. Moreover, a proposed automatic image cropping algorithm is used. The image cropping algorithm allows removing part of the image background which does not contains objects or part of objects. The proposed algorithm was applied to the image 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 by row

If $I(x, y) == 0 \quad \forall (x, y) \in r$ *then crop the row*

2. Scan image column by column

If $I(x, y) == 0 \quad \forall (x, y) \in c$ *then crop column*

B. An algorithm View of Object Modeling

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 extracted and compared

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ObjectModelAlgorithm (Image I)
1.  Read image I.
2.  Convert color image to gray 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 the objects through updating the starting point of filling the in between pixels. Fig.2 shows an example of applying the proposed algorithm.

C. Shape-based Descriptors

Shape descriptors are some numbers 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 paper region-based properties are considered. The shape feature descriptors that have been extracted within this research work are shown in Table 1.

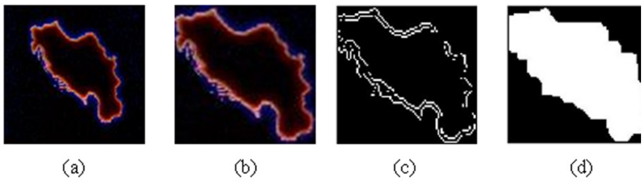

Fig. 2. (a) Original image. (b) Cropped image. (c) Edge detected image (Prewitt). (d) Result image after applying the proposed algorithm

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

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

TABLE I
SHAPE FEATURES DESCRIPTION

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. An ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment.
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

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

IV. SIMILARITY MEASURES AND PERFORMANCE EVALUATION

The image comparison in the proposed CBIR module is based on query by example [23]. The example image is analyzed and the necessary features are extracted in each phase then the compared with other database images. There are different metric functions (e.g. City block and Euclidean) which may use to make measurement in each feature space. As shown in [24], these metrics have been defined to calculate the similarity between two probability distributions. Prior to decide on evaluation of any CBIR system (approach) a decision should be considered which we may call it as a **trade off decision.** For instant, if the number of retrieved images is important then some sacrificing of quality should be considered with serious attempts to improve this quality.

The following formula is developed within this study to represent the relationship between the different retrieval variables (features) and their weights.

$$Q(R_{CBIR}) = \begin{cases} P(i) & i = 1 \\ \sum_{i=2}^{n} P(i) \times W_i & 2 \le i \le n \end{cases} \qquad (5)$$

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 IR (information retrieval system) resolves queries in an approximate way, because the users are not specific about the precise results that should be delivered [25]. 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. Muller *et al.* [26] presents a framework to evaluate CBIR based on recall and precision:

$$Precision = \frac{Number\ of\ relevant\ retrieved\ images}{Number\ of\ all\ retrieved\ images}$$

$$Recall = \frac{Number\ of\ relevant\ retrieved\ images}{Number\ of\ all\ relevant\ images\ in\ the\ category}$$

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

$$\overline{P}(r) = \frac{\sum_{i=1}^{N_q} P_i(r)}{N_q} \qquad (6)$$

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.

V. 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 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 calculating by evaluating the top 20 returned results. Due to space limitations, only the top 9 matches to some of the query images are shown in Fig.3.

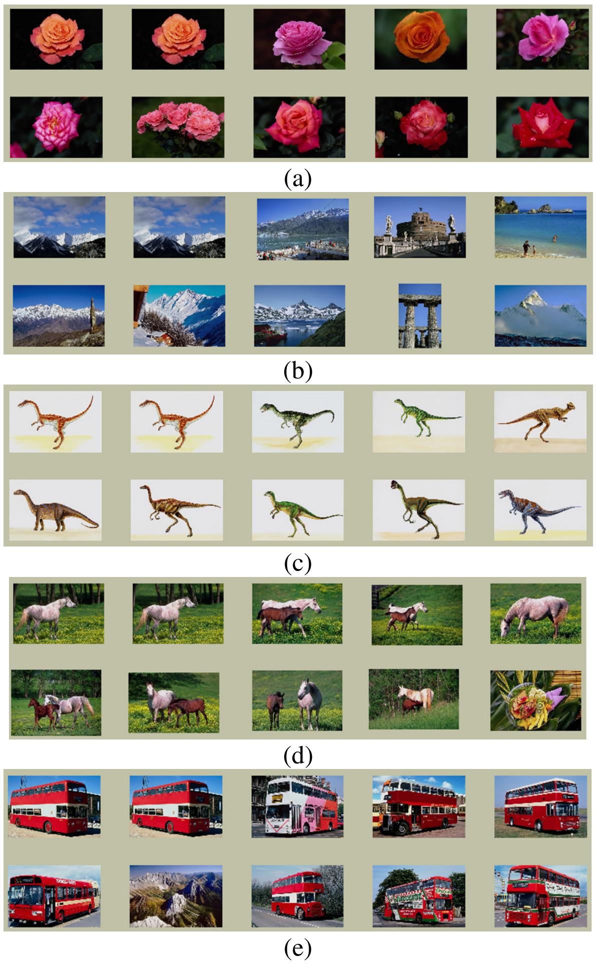

Fig. 3. Sample of retrieved results. The query image is in the upper left corner. (a) Flower; 9 matches out of 9; 18 matches out of 20. (b) Mountain; 7 matches out of 9; 16 matches out of 20. (c) Dinosaur; 9 matches out of 9; 20 matches out of 20. (d) Horses; 8 matches out of 9; 17 matches out of 20. (d) Vehicle; 8 matches out of 9; 17 matches out of

Furthermore, and to ensure consistency and fair 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 [32], and with UFM method [29].

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%.

TABLE II
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

VI. CONCLUSION

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 high accurate 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 features extracted. 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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