Color Image Retrieval Based on Content by Using Linear and Nonlinear Combiner

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ABSTRACT

Color has been widely used in content based image retrieval applications. In such applications, the color properties of an image are usually characterized by the probability distribution of the colors in the image. A distance measure is then used to measure the dissimilarity between images based on the descriptions of their color distributions in order to quickly find relevant images. The methods for color are the Color Histogram, Color Moment and Color Correlogram. All of these color features are combined to produce an efficient Combined Method. The system is also developed by using K-means clustering algorithm to group the images in the database into clusters of images with similar color content. Thus, at the retrieval time, the query image is not compared with all the images in the database, but only with a small subset. and also used M1k-means that used a better similarity distance, and M2k-means this algorithm is an efficient algorithm and produce efficient retrieval. Moreover, we present a new human computer interaction system model of content based image retrieval with nonlinear combination of features of the images. 'Neural Network Based Image Retrieval' is an approach based on Back propagation Neural Network and Radial Basis Function Network that is improved by using sigmoid function to calculate the actual output of output layer nodes, and by adding bias node to the input layer nodes. This approach is very efficient; and it produces 100% retrieval of images.

Keyword: Color Image, image retrieval, feature extraction, color histogram, color moments, color Correlogram, clustering algorithm, back propagation network, radial basis function network.

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1- INTRODUCTION

The fundamental idea of Content-based image retrieval CBIR is to generate automatically image descriptions directly from the image content by analyzing the content of the images. Given a query image, a CBIR system retrieves images from the image database which are similar to the query image. In a typical situation, all the images in the database are processed to extract the selected features that represent the contents of the images. This is usually done automatically once when the images are entered into database. This process assigns to each image a set of identifying descriptors which will be used by the system later in the matching phase to retrieve relevant images. The descriptors are stored in the database, ideally in a data structure that allows efficient retrieval in the later phase[1].Color is a simple and straightforward feature for all kinds of color images. The human eye is much more sensitive to color shades than gray-level intensities in an image. The colors of different objects are also largely resolution and view invariant. Selecting an appropriate color space and the used color quantization are key issues for color feature extraction. Color quantization is used to reduce the number of distinct colors in an image. It is used to reduce both computational complexity of color feature extraction and the dimensionality of the resulting feature vectors[2].

2-COLOR FEATURES

Color has been the most commonly-used feature type in Content Based Image Retrieval CBIR. Basic color features are easy to implement and usually yield reasonable and predictable results which can then be improved by including other types of features. The standard representation for color information in CBIR has been the color histogram. The color histogram describes the distribution of different colors in an image in a simple and computationally efficient manner. Other commonly used color features include color moments and the color correlogram [2].

2.1-Color Histogram

One of the widely used methods for querying and retrieval by color content is color histograms. The color histograms are used to represent the color distribution in an image. Mainly, the color histogram approach counts the number of occurrences of each unique color on a sample image. Since an image is composed of pixels and each pixel has a color, the color histogram of an image can be computed easily by visiting every pixel once. By examining the color histogram of an image, the colors existing on the image can be identified with their corresponding areas as the number of pixels [3]. The histogram approach is commonly used in most of the existing systems supporting query-by-color content. The retrieval of similar images is based on the similarity between their respective color histogram. A common similarity metric is based on the Euclidean distance between the abstracted feature vectors that represent two images, and it is defined as: $d(Q,I) = \sqrt{\sum_{j=1}^{n} \left(h_j^Q - h_j^I\right)^2}$ Where *Q* and *I* represent the query image and one of the images in the image set, and h_j^Q and h_j^I represent the values of the feature vectors of these images respectively, i.e. color histogram feature. While the distance between intensity histogram features is calculated as follows: $d(Q,I) = \sqrt{\sum_R \sum_G \sum_B \left(h_{rgb}^Q - h_{rgb}^I\right)^2}$ Where h_{rgb}^Q , h_{rgb}^I represent the histogram of query image and one of the images in the image set. Note that a smaller distance reflects a closer similarity match [4].

Even though color histogram based techniques have been quite successful in given settings, they have some notable shortcomings. Firstly, the color histogram is too finely quantized in color space, and hence, does not take into consideration the fact that the human visual system can only perceive a few colors at a time. The large number of feature vectors is often difficult to index and raises the retrieval cost. Another shortcoming of color histogram is that it does not incorporate any spatial information[5].

2.2-Color Moment

Color moments have been successfully used in many retrieval systems, especially when the image contains just the object. The first order mean, the second variance or standard deviation and the third order skewness color moments have been proved to be efficient and effective in representing color distributions of images. Mathematically, the first three moments are defined as:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \qquad \sigma_i = \left[\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^2\right]^{1/2} \qquad S_i = \left[\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^3\right]^{1/3}$$

Where f_{ij} is the value of the i^{th} color component of the image pixel j, *N*is the number of pixels in the image, and μ , σ , s represent mean, standard deviation , and skewness respectively [6].Since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image, color moments are a very compact representation compared to other color features. Usually, color moments can be used as the first pass to narrow down the search space before other sophisticated color features are used for retrieval. The distance measure d_{CM} between query image Q and target image T is calculated by[7]:

$$d_{CM}(Q,T) = \sqrt{\sum_{i\in(R,G,B)} [\mu_i(Q) - \mu_i(T)]^2 + [\sigma_i(Q) - \sigma_i(T)]^2 + [S_i(Q) - S_i(T)]^2}$$

2.3-Color Correlogram

A color correlogram expresses how the spatial correlation of color changes with distance. A color histogram captures only the color distribution in an image and does not include any spatial information. Thus, the correlogram is one kind of spatial extension of the histogram[8].The Correlogram represents the distribution of the Co-occurrence matrix, but it is calculated using several different distances (*d*) instead of using a single distance; and it uses eight directions (angles).Let [*D*] denote a set of *D* fixed distances $\{d_1,..., d_D\}$, and *f* be an image consisting of *M* different colors $c_1, c_2,..., c_M$. For a pixel $p(x,y) \in f$, let*f(p)*expresses the pixel color and $f_c = \{p \mid f_{(p)} = c\}$. Therefore, $p \in f_c$ is equivalent to $p \in f, f_{(p)} = c$. For simplicity, $L_\infty - Norm$ is used to measure the distance between pixels. This measure is computed for two pixels $p_1(x_1,y_1)$, $p_2(x_2,y_2)$ as follows: $|p_1 - p_2| = \max\{|x_1 - x_2|, |y_1 - y_2|\}$

Assume that k is a specified distance and $i, j \in \{1,..., M\}$. The correlogram of f is defined by: $\gamma(i,j,k) = \underset{p_1 p_2 \in f}{pr}\{p_2 \in f_{cj} \,|\, p_1 \in f_{ci}, |p_1 - p_2| = k\}$ where $\gamma(i,j,k)$ denotes the probability of finding pixels with color c_j at the distance k of the pixel with color c_i[9]. In this research we calculate five features from the correlogram that is :

$$Energy = \sum_{ci}\sum_{cj}\sum_{k}\left(\gamma_{cicj}^{k}\right)^2 \qquad Entropy = \sum_{ci}\sum_{cj}\sum_{k}\gamma_{cicj}^{k}\log\left(\gamma_{cicj}^{k}\right) \qquad Contrast = \sum_{ci}\sum_{cj}\sum_{k}(ci - cj)^2\gamma_{cicj}^{k}$$

$$Inverse - Difference - Moment = \sum_{ci}\sum_{cj}\sum_{k}\frac{\gamma_{cicj}^{k}}{|ci - cj|^2}, ci \neq cj \qquad Correlation = \frac{\sum_{ci}\sum_{cj}(cicj)\gamma_{cicj} - \mu_x\mu_y}{\sigma_x\sigma_y}$$

where means and standard deviations are defined as:

$$\mu_x = \sum_{ci} ci \sum_{cj}\gamma_{cicj} \qquad \mu_y = \sum_{cj} cj \sum_{ci}\gamma_{cicj} \qquad \sigma_x = \sum_{ci}(ci - \mu_x)^2\sum_{cj}\gamma_{cicj} \qquad \sigma_y = \sum_{cj}(ci - \mu_y)^2\sum_{ci}\gamma_{cicj}$$

Using this method, we achieve two important benefits: 1) Decreasing the computational cost and 2) Quantization of the image into sets of similar levels generalizes the image content, which improves the retrieval results.The main advantages of using color correlogram are: ***i)*** taking into consideration the spatial correlation of colors, ***ii)*** describing the global distribution of local spatial correlation of colors, ***iii)*** being easy to implement, and ***iv)*** producing fairly small size index.

2.3-The Combined Method

To obtain effective retrieval of an image, we combined the three image features: color histogram, color moment, and color correlogram. In order to obtain best retrieval, figure (1) explains the outline of the combined method. Since different features can generate different ranges of values of similarity, a normalization method should be applied to each similarity computation. We normalize each similarity by min/max normalization (linear scaling) method according to equation as follows:

$$N(I, I') = \frac{D(I, I') - \min(D(I, I'))}{\max(D(I, I')) - \min(D(I, I'))}$$

After normalizing similarity, the total similarity between the query and the image in the data collection is calculated via a weighted sum of the similarities provided by each of the features. The equation for combining the similarities of three image features is defined as follows:

$$D_{combine}(I, I') = W_1 N_{color}(I, I') + W_2 N_{moment}(I, I') + W_3 N_{correlogram}(I, I')$$

where $D_{combine}(I, I')$ is the weighted sum of similarities; $N_{color}(I, I')$ is the normalized similarity of color histogram; $N_{moment}(I, I')$ represents the color moment features; and $N_{correlogram}(I, I')$ represents the color correlogram features. W_1, W_2, and W_3 are weighting factors to adjust the relative importance of image features. We choose W_1 =1.0, W_2 =0.5, and W_3 =0.02 for our experiments in this research. The application of the combined algorithm in this work is very efficient compared with the previous techniques with precision and recall metrics and also with average precision.

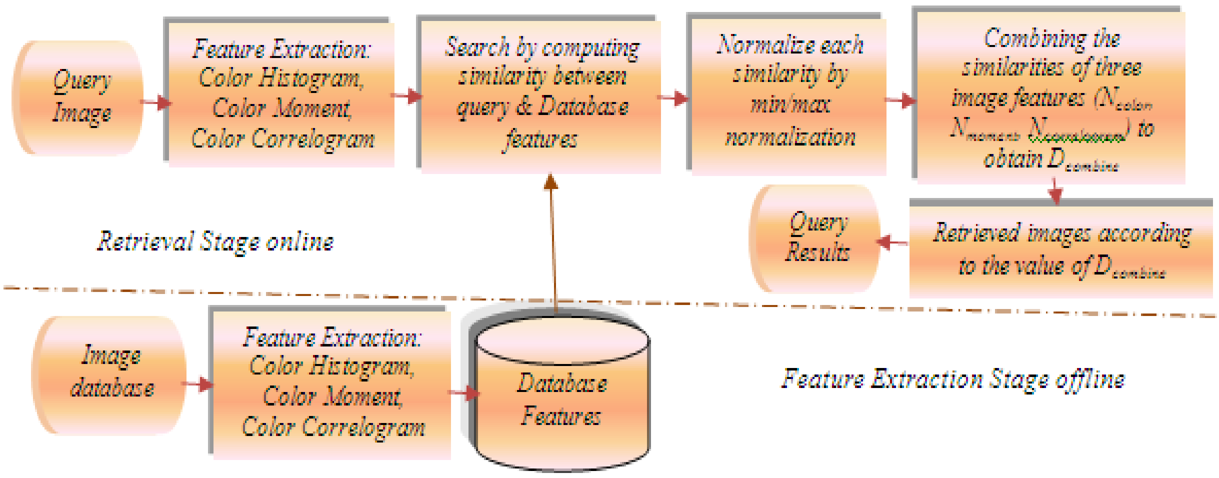

Figure 1: The Outline of Combined Method

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3-CLUSTERING

Clustering is an unsupervised learning problem, which tries to group a set of points into clusters such that points in the same cluster are more similar to each other than points in differents clusters, under a particular similarity metric [10].Clustering can be used to produce an effective image index as follows: After clustering, each cluster is represented by its centroid or sometimes a single representative data item (i.e. the image lable for that cluster) and, instead of the original data items, the query point is compared to the centroids or the cluster representatives. The best cluster or clusters, according to the used similarity measure, are then selected and the data items belonging to those clusters are retrieved also according to the used similarity measure [11].

3.1-K-Means Clustering Algorithm

The k-mean algorithm is the most frequently used clustering algorithm due to its simplicity and efficiency. K-means is a partitional clustering algorithm. It performs iterative relocation to partition a dataset into k cluster [6]; and it is based on the minimization of a performance index which is defined as the sum of the squared distances from all points in a cluster domain to the cluster center [6,50]. using the relation to distributing the samples $\{ x \}$ at the K^{th} iterative step among the K cluster domains: $x \in S_j(k) \quad if \quad \| x - z_j(k) \| < \| x - z_i(k) \|$ for all $i = 1,2,..., K, i \neq j$, where $S_i(k)$denotes the set of samples whose cluster is $z_j(k)$.And the new cluster center is given by: $z_j(k+1) = \frac{1}{N_j} \sum_{x \in S_j(k)} x \quad , i = 1,2,..., K$ where $N_j$is the number of samples in $S_i(k)$.The behavior of the k-means algorithm is influenced by the number of cluster centers specified, the choice of initial cluster centers, the order in which the samples are taken, and, of course, the geometrical properties of the data. Although no general proof of convergence exists for this algorithm, it can be expected to yield acceptable results when the data exhibit characteristic pockets which are relatively far from each other. In most practical cases the application of this algorithm will require experimenting with various values of$K$as well as different choices of starting configurations [12].

3.2-Modified$_1$k-Means Clustering Algorithm

The performance of k-means algorithm is not only dependent on the type of data being analyzed, but is also strongly influenced by the chosen measure of pattern similarity i.e. the measure used for identifying clusters in the data. In the preceding algorithm (i.e. k-means clustering algorithm) we considered the Euclidean distance for comparing two feature vectors. Here we use the k-means by using L_1 norm distance metrics instead of Euclidean distance; in practice, L_1 norm performs better than Euclidean distance since it is more robust and computationally efficient, and this algorithm is called M_1k-means. Classifying each feature f to the cluster p_s with the smallest distance: $p_s = \arg_{1 \le j \le k} \min \quad D(f, \mu_j)$ this D is a function to measure the distance between two feature vectors and defined as:

$D(f, f') = \frac{1}{z(f, f')} \left[\sum_{i=1}^{n} | f(i) - f'(i) | \right]$ where $z(f, f') = \sum_{i=1}^{n} f(i) + \sum_{i=1}^{n} f'(i)$ which is a normalizing function, and n represents number of features in feature vector, where f' is cluster center. To update cluster centroids as: $\mu_j = \frac{1}{n_j} \sum_{i=1}^{n_j} f_i^{(j)}$ where$nj$is the number of images in cluster$j$, and $f_i^{(j)}$ is theith feature vector in cluster$j$ [13].

3.3- Modified$_2$k-Means Clustering Algorithm

In the k-means, the initial cluster assignment is random; different runs of the k-means clustering algorithm may not give the same final clustering solution; or when selected as the first k samples of the sample set the same as modified$_1$ k-means, these two states may not give the good solution. To deal with this, we need to get good starting points for the initial cluster assignment. This leads to develop a modified$_1$ k-means clustering algorithm where an additional step is used to provide the initial cluster centers and L_1 norm distance metric when computing the distance between two feature vectors.The initial centroids are selected in the following way:***1)***Given v d -dimensional feature vectors, divide the d dimensions to $p = \frac{d}{K}$. these subspaces are indexed by:

$[1,2,3,..., p], [p+1, p+2,..., 2p],..., [(k-1)p+1, (k-1)p+2, (k-1)p+3,..., kp]$. ***2)*** In each subspace j f $[(j-1)p+1,..., jp]$, associate a value f_i^j for each feature vector$f_i$by : $f_i^j = \sum_{d=(j-1)p}^{jp} f_i(d)$. ***3)***Choose the initial cluster centroids $\mu_1, \mu_2,..., \mu_K$ by $\mu_j = \arg_{f_i} \min_{1<i<v} f_i^j$ [13]. In this research, we based on M_2K-means algorithm to cluster all the images in the database into classes.

4-THE NEURAL NETWORK BASED IMAGE RETRIEVAL

In CBIR, content of an image can be expressed in terms of different features such as color, color moment or correlogram. Retrieval based on these features can be various by the way how to combine the feature values. All the preceeding approaches assume a linear relationship between different features. In this research, we work human-computer interaction system model of contentbased image retrieval with nonlinear combination of features of the images. The approach Neural Networkbased image retrieval NNBIR is based on Backpropagation neural network BPNN, and Radial Basis Function Network Model RBFN. NNBIR can be used to determine nonlinear relationship between different features in images. The input to the neural network is the set of metric values of each pair of images and the output is a number between 0 and 1 signifying similarity of images based on various input features.NNBIR offers a new method of combining image features. Using combined rather than individual features is especially efficient for generic image databases, for which no single feature is outstanding. An experimental evaluation will demonstrate that the NNBIR model can achieve both efficiency and flexibility on CBIR combined features of images.

5-THENNBIR SYSTEM

We first describe the structure of the NNBIR system. Figure(2) shows the main components of the NNBIR system and the control flows among them.Given a query image, the content of query image in terms of different feature classes is extracted. The same type of features are already extracted and stored for the database images. The system then compares the features of query image to those of database images, resulting in a group of metric value vectors based on individual feature classes. And then, the system combines the metric value vectors obtained from individual feature classes based on their importance, to form the final set of retrieved image. We specify the NNBIR model as two stage: pre-processing stage & retrieval stage.

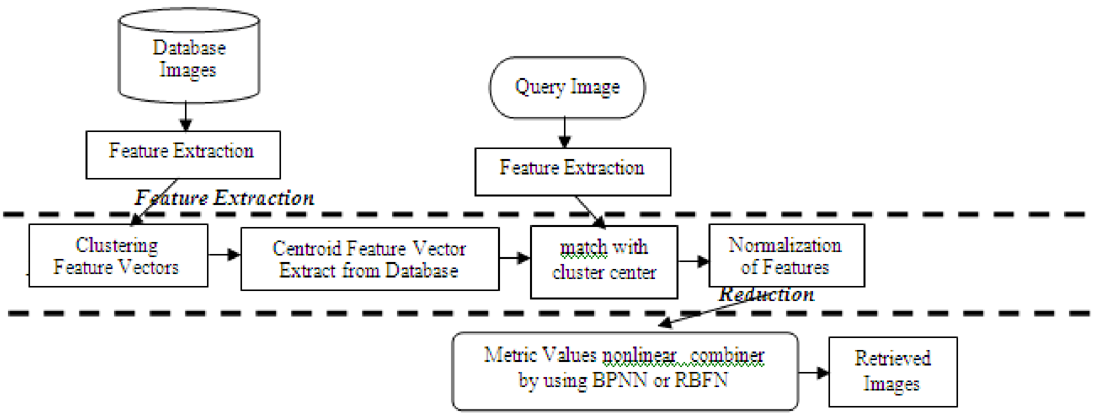

Figure 2: NNBIR System

5.1-Pre-Processing Stage

The offline pre-processing required for NNBIR system has three steps: Feature extractor, Dimensionality reduction, and Combiner using neural network.

Step1. Feature Extractor: extracting suitable features to describe the images; here, we use RGB image and extract color histogram, color moment, and color correlogram of all images in database.

Step2. Dimensionality Reduction: the features represented at the feature space spanned by the dimensions are often highly correlated. This property makes it feasible to approximate the original space by projecting it into a new space with a lower dimensionality and thus reduce computational requirements. This is done by clustering the database images by using k-means, M_1k-means, and M_2K-means.Then we obtaine centroid feature vectors, and compare each query feature vector with the corresponding features of centroids and returns the compared metric values. These metric values are normalized by using linear scaling equation. The dimensionality reduction reduces the complexity of measuring similarity between data items, its efficiency and effectiveness in retrieval.

Step3. Combiner Using Neural Network: combines the compared metric values $v_k$using BPNN and RBFN, and yields the list of retrieved images. Here, in this step, we describe the BPNN& RBFN to combine the metric values. The input to the BPNN & RBFN is the set of measurements v_k between images$I_1$and I_2 for all the feature classes, which represent three metric values (i.e. the number of nodes in input layer is equal to three nodes). If all the features of images I_1 and I_2 are similar, the output of the BPNN & RBFN shall be close to 1. However, if I_1 and I_2 are not similar, the output should be close to 0 (i.e. the output layer is contained of one node). To train the BPNN or RBFN and find the weights, a set of images that are visually similar (positive examples) and a set of images that are not similar (negative examples) are provided. The system then finds the similarity (or dissimilarity) between images based on different feature classes and feeds these measurements to the BPNN or RBFN. Once the network is trained, the feature classes have the proper weights; so they can be used in combining features. Here the BPNN & RBFN are used with bais node and without. But the experimental results prove that the use of bais node is the best.

5.2-Retrieval Stage

Given a query image with the features and the set of metric value vector v_k, our goal is to find the most relevant images in database with respect to all the features. Using the trained BPNN or RBFN, we find the similarity between the query image q and each image in clustered database based on the metric value vectors. In each step, the similarity measurements of feature classes of the query image and an image in clustered database are fed into the BPNN or RBFN. The output value of the network is the similarity between the two images.

6-EXPERIMENTAL AND RESULTS

Color is a simple and straightforward feature for all kinds of color images. Color features are easy to implement and usually yield reasonable and predictable results which can then be improved by including other types of features. The standard representation for color has been the color histogram. Other color features include color moments and color correlogram. These three features extraction are applied on color image in this research, and combined all these features in one method called “Combined Method”; Moreover, the three clustering algorithms are also applied to all these methods.

6.1-Color Histogram Method

A single color histogram for all of the color channels are used in this research, and the three clustering algorithms are also applied. The M_2k-means is the best of all the algorithms. This can be noticed in table (1), the abbreviation Hist is mean color Histogram method.

Table 1: The Effectiveness of M_2K-means in Color Histogram Method

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	17	25	32	0.680000	0.531250	Hist
	19	25	19	0.760000	1.000000	Hist-kmeans
	21	25	21	0.840000	1.000000	Hist- M_1K-means
	21	25	21	0.840000	1.000000	Hist- M_2K-means
	8	11	16	0.727273	0.500000	Hist
	8	11	8	0.727273	1.000000	Hist-kmeans
	9	11	11	0.818182	0.818182	Hist- M_1K-means
	9	11	9	0.818182	1.000000	Hist- M_2K-means
	5	11	13	0.454545	0.384615	Hist
	7	11	7	0.636364	1.000000	Hist-kmeans
	8	11	12	0.727273	0.666667	Hist- M_1K-means
	8	11	8	0.727273	1.000000	Hist- M_2K-means
	24	25	39	0.960000	0.615385	Hist
	18	25	21	0.720000	0.857143	Hist-kmeans
	18	25	18	0.720000	1.000000	Hist- M_1K-means
	24	25	30	0.960000	0.800000	Hist- M_2K-means

6.2-Color Moment Method

Color moments are used to represent the color content of each image. Three moments for each of the three color components are extracted; these are Mean, Standard deviation and Skewness. M_2K-means is better than other clustering algorithms when applied in this method as illustrated in table (2), Mom means Color Moment method.

Table 2: The Effectiveness of M_2K-means in Color Moment Method

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	6	25	22	0.240000	0.272727	Mom
	1	25	15	0.040000	0.066667	Mom-kmeans
	3	25	18	0.120000	0.166667	Mom- M_1K-means
	6	25	18	0.240000	0.333333	Mom- M_2K-means
	21	21	63	1.000000	0.333333	Mom
	14	21	14	0.666667	1.000000	Mom-kmeans
	16	21	16	0.761905	1.000000	Mom- M_1K-means
	18	21	18	0.857143	1.000000	Mom- M_2K-means
	14	15	78	0.933333	0.179487	Mom
	6	15	18	0.400000	0.333333	Mom-kmeans
	3	15	11	0.200000	0.272727	Mom- M_1K-means
	5	15	10	0.333333	0.500000	Mom- M_2K-means
	14	14	59	1.000000	0.237288	Mom
	11	14	16	0.785714	0.687500	Mom-kmeans
	10	14	11	0.714286	0.909091	Mom- M_1K-means
	11	14	12	0.785714	0.916667	Mom- M_2K-means

6.3-Color Correlogram Method

We calculate five features from the correlogram: Energy, Entropy, Contrast, Inverse-difference-moment, and Correlation. This method also prove that M_2k-means is better than other methods, see table (3), the abbreviation Corr mean Color Correlogram.

Table 3: The Effectiveness of M_2K-means in Color Correlogram Method

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	21	21	85	1.000000	0.247059	Corr
	10	21	11	0.476190	0.909091	Corr-kmeans
	20	21	33	0.952381	0.606061	Corr- M_1K-means
	19	21	24	0.904762	0.791667	Corr- M_2K-means
	12	15	27	0.800000	0.444444	Corr
	3	15	7	0.200000	0.428571	Corr-kmeans
	5	15	11	0.333333	0.454545	Corr- M_1K-means
	11	15	21	0.733333	0.523810	Corr- M_2K-means
	10	11	91	0.909091	0.109890	Corr
	3	11	15	0.272727	0.200000	Corr-kmeans
	3	11	13	0.272727	0.230762	Corr- M_1K-means
	3	11	7	0.272727	0.428571	Corr- M_2K-means

6.4-The Combined Method

In this work, we present a new method called combined method. In this method, we combine the three image features: color histogram, color moment and color correlogram to obtain efficient retrieval of image; it is more effective than using each feature alone. The M_2k-means proved that it is the best clustering algorithm. This can be shown in table (4). Table (5) shows us that the combined method is the best. Also table (6) lists some results of combiner method that used external example image in two types: relevant and non-relevant images. We noticed that the retrieval of an external image (relevant) does not satisfy 100% retrieval. To improve the relevant image retrieval we used nonlinear combiner by using BPNN and RBFN. Here, we obtained 100% retrieval image for external example with relevant and non-relevant image, the abbreviation Com mean Combined method.

Table 4: The Effectiveness of M_2K-means in the Combined Method

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	24	25	50	0.960000	0.480000	Com
	23	25	23	0.920000	1.000000	Com-kmeans
	25	25	25	1.000000	1.000000	Com- M_1K-means
	25	25	25	1.000000	1.000000	Com- M_2K-means
	22	25	46	0.880000	0.478261	Com
	23	25	23	0.920000	1.000000	Com-kmeans
	25	25	25	1.000000	1.000000	Com- M_1K-means
	25	25	25	1.000000	1.000000	Com- M_2K-means
	15	15	75	1.000000	0.200000	Com
	6	15	6	0.400000	1.000000	Com-kmeans
	15	15	26	1.000000	0.576923	Com- M_1K-means
	14	15	17	0.933333	0.823529	Com- M_2K-means
	25	25	77	1.000000	0.324675	Com
	13	25	17	0.520000	0.764706	Com-kmeans
	13	25	13	0.520000	1.000000	Com- M_1K-means
	19	25	20	0.760000	0.950000	Com- M_2K-means
	25	25	83	1.000000	0.301205	Com
	16	25	20	0.640000	0.800000	Com-kmeans
	16	25	16	0.640000	1.000000	Com- M_1K-means
	18	25	20	0.720000	0.900000	Com- M_2K-means

Table 5: Comparison between Color Histogram, Color Moment, Color Correlogram, and Combined Method with M_2K-means

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	21	25	21	0.840000	1.000000	Hist
	20	25	27	0.800000	0.740741	Mom
	16	25	33	0.640000	0.484848	Corr
	25	25	25	1.000000	1.000000	Com
	17	21	17	0.809524	1.000000	Hist
	18	21	20	0.857143	0.900000	Mom
	19	21	29	0.904762	0.655172	Corr
	21	21	21	1.000000	1.000000	Com
	15	15	22	1.000000	0.681818	Hist
	3	15	10	0.200000	0.300000	Mom
	12	15	39	0.800000	0.307692	Corr
	14	15	14	0.933333	1.000000	Com
	7	11	7	0.636364	1.000000	Hist
	8	11	20	0.727273	0.400000	Mom
	3	11	13	0.272727	0.230769	Corr
	11	11	11	1.000000	1.000000	Com
	12	14	12	0.857143	1.000000	Hist
	12	14	16	0.857143	0.750000	Mom
	13	14	21	0.928571	0.619048	Corr
	14	14	14	1.000000	1.000000	Com
	25	25	29	1.000000	0.862069	Hist
	10	25	10	0.400000	1.000000	Mom
	3	25	29	0.120000	0.103448	Corr
	24	25	25	0.960000	0.960000	Com

Table 6: External Images Relevant & Non-relevant Retrieval of Combined Method with M_2K-means

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
Balloon	25	25	25	1.000000	1.000000	Relevant
Lion	21	21	21	1.000000	1.000000	Relevant
Monkey	9	15	9	0.600000	1.000000	Relevant
Monkey	14	15	14	0.933333	1.000000	Relevant
Rabit	11	11	11	1.000000	1.000000	Relevant
Wild goats	14	14	14	1.000000	1.000000	Relevant
Tiger	24	25	25	0.960000	0.960000	Relevant
Tiger	25	25	27	1.000000	0.925926	Relevant
Cats	0	10	0	0.000000	0.000000	Non-relevant
a horse	0	12	0	0.000000	0.000000	Non-relevant
Natural view	0	8	0	0.000000	0.000000	Non-relevant
Flowers	0	10	0	0.000000	0.000000	Non-relevant
Plane	0	14	0	0.000000	0.000000	Non-relevant
car	0	5	0	0.000000	0.000000	Non-relevant

6.5-The Nonlinear Combiner Method

In this research, we present a new combiner method called nonlinear combiner method. In this method, we combined the three image features color histogram, color moment and color correlogram with a nonlinear combiner by using BPNN and RBFN. The input to the BPNN and RBFN is the set of compared metric values v_k between images I_1 and I_2 for all the feature classes. The BPNN and RBFN are used with bias node and without bias, and also with both training type: online training and batch training. Three clustering algorithms (k-means, M_1K-means, M_2K-means) are used in both BPNN and RBFN with bias node and without. The M_2K-means proved that it is the best clustering algorithms in both online and batch training algorithm; this can be shown in table (7). Although M_1K-means is efficient but sometimes does not give us efficient results compared with M_2K-means which gives us efficient results in all times and of all images. Therefore, the M_2K-means is considered as the best algorithm.

Table 7: The Effectiveness of M_2K-means in the Nonlinear Combiner method with BPNN & RBFN with Bias Node and without in Online Training & Batch Training

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	5	15	5	0.333333	1.000000	BP-bias-online
	13	15	13	0.866667	1.000000	BP-bias-online-kmeans
	14	15	16	0.933333	0.875000	BP-bias-online- M_1K-means
	15	15	15	1.000000	1.000000	BP-bias-online- M_2K-means
	0	11	6	0.000000	0.000000	BP-online
	10	11	10	0.909091	1.000000	BP-online-kmeans
	10	11	10	0.909091	1.000000	BP-online- M_1K-means
	11	11	11	1.000000	1.000000	BP-online- M_2K-means
	6	15	6	0.400000	1.000000	RBF –bias-online
	13	15	13	0.866667	1.000000	RBF-bias-online-kmeans
	15	15	15	1.000000	1.000000	RBF-bias-online- M_1K-means
	15	15	15	1.000000	1.000000	RBF-bias-online- M_2K-means
	20	25	44	0.800000	0.454545	RBF-online
	23	25	23	0.920000	1.000000	RBF-online-kmeans
	25	25	25	1.000000	1.000000	RBF-online- M_1K-means
	25	25	25	1.000000	1.000000	RBF-online- M_2K-means
	0	25	0	0.000000	0.000000	BP-bias-batch
	25	25	28	1.000000	0.892857	BP-bias- batch –kmeans
	25	25	25	1.000000	1.000000	BP-bias- batch - M_1K-means
	25	25	25	1.000000	1.000000	BP-bias- batch – M_2K-means
	5	11	105	0.454545	0.047619	BP-batch
	10	11	10	0.909091	1.000000	BP-batch –kmeans
	11	11	11	1.000000	1.000000	BP-batch - M_1K-means
	11	11	11	1.000000	1.000000	BP-batch– M_2K-means

Finally, it is noted that the M_2K-means is the best clustering algorithm in both BPNN and RBFN by using bias node and without using it. It is also the best algorithm with online training and batch training for both networks BPNN & RBFN. The batch training is better than online training as illustrated in table (8).

Table 8: The Effectiveness of Batch Training in both BPNN & RBFN with M_2K-means

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Error	Iter	Method
	14	15	14	0.933333	1.000000	0.000001	14296	BP-bias-online
	15	15	15	1.000000	1.000000	0.003194	30000	BP-bias-batch
	8	15	8	0.533333	1.000000	0.000001	24931	BP-online
	15	15	15	1.000000	1.000000	0.007046	30000	BP-batch
	15	15	15	1.000000	1.000000	0.000002	30000	RBF-bias-online
	15	15	15	1.000000	1.000000	0.004012	30000	RBF-bias-batch
	14	15	14	0.933333	1.000000	0.000002	30000	RBF-online
	15	15	15	1.000000	1.000000	0.002326	30000	RBF-batch
	17	25	17	0.680000	1.000000	0.000001	30000	BP-bias-online
	25	25	25	1.000000	1.000000	0.003194	30000	BP-bias-batch
	20	25	20	0.800000	1.000000	0.000001	30000	BP-online
	25	25	25	1.000000	1.000000	0.007046	30000	BP-batch
	24	25	24	0.960000	1.000000	0.000002	30000	RBF-bias-online
	25	25	25	1.000000	1.000000	0.004012	30000	RBF-bias-batch
	24	25	24	0.960000	1.000000	0.000002	30000	RBF-online
	24	25	24	0.960000	1.000000	0.002326	30000	RBF-batch

In external images, the M_2k-means is also the best clustering algorithm. Batch training is better than online training, the images that are trained with batch, the accuracy of the retrieved image internal, external relevant & non-relevant is 100% retrieval. Table (9) show that.

Table 9: The Effectiveness of Batch Training in External Image Example for BPNN & RBFN with Bias Node and without (Relevant Image & Nonrelevant)

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method	External Type
Balloon	23	25	23	0.920000	1.000000	BP-bias-online	Relevant
	25	25	25	1.000000	1.000000	BP-bias-batch	Relevant
	23	25	23	0.920000	1.000000	BP-online	Relevant
	25	25	25	1.000000	1.000000	BP-batch	Relevant
	23	25	23	0.920000	1.000000	RBF-bias-online	Relevant
	25	25	25	1.000000	1.000000	RBF-bias-batch	Relevant
	23	25	23	0.920000	1.000000	RBF-online	Relevant
	25	25	25	1.000000	1.000000	RBF-batch	Relevant
Tiger	21	25	21	0.840000	1.000000	BP-bias-online	Relevant
	25	25	25	1.000000	1.000000	BP-bias-batch	Relevant
	13	25	13	0.520000	1.000000	BP-online	Relevant
	24	25	24	0.960000	1.000000	BP-batch	Relevant
	18	25	18	0.720000	1.000000	RBF-bias-online	Relevant
	25	25	25	1.000000	1.000000	RBF-bias-batch	Relevant
	18	25	18	0.720000	1.000000	RBF-online	Relevant
	24	25	24	0.960000	1.000000	RBF-batch	Relevant
Cat	0	10	0	0.000000	0.000000	BP-bias-online	Non-relevant
	0	10	0	0.000000	0.000000	BP-bias-batch	Non-relevant
	0	10	0	0.000000	0.000000	BP-online	Non-relevant
	0	10	0	0.000000	0.000000	BP-batch	Non-relevant
	0	10	0	0.000000	0.000000	RBF-bias-online	Non-relevant
	0	10	0	0.000000	0.000000	RBF-bias-batch	Non-relevant
	0	10	0	0.000000	0.000000	RBF-online	Non-relevant
	0	10	0	0.000000	0.000000	RBF-batch	Non-relevant
a horse	0	12	0	0.000000	0.000000	BP-bias-online	Non-relevant
	0	12	0	0.000000	0.000000	BP-bias-batch	Non-relevant
	0	12	0	0.000000	0.000000	BP-online	Non-relevant
	0	12	0	0.000000	0.000000	BP-batch	Non-relevant
	0	12	0	0.000000	0.000000	RBF-bias-online	Non-relevant
	0	12	0	0.000000	0.000000	RBF-bias-batch	Non-relevant
	0	12	0	0.000000	0.000000	RBF-online	Non-relevant
	0	12	0	0.000000	0.000000	RBF-batch	Non-relevant

6.6-The Comparison between Linear and Nonlinear Combiner

As we have seen in section 8.3.4, the combined method with k-meansnormL_1min is very efficient when query image internal is used with database, when the external images (relevant images) are used, the combined method with k-meansnormL_1min is not very efficient (i.e the accuracy of retrieval is not 100%). However, when the nonlinear combiner is used by BPNN & RBFN, the accuracy of retrieval of internal & external images with two types relevant & non-relevant is 100% as illustrated in table (10).

Table10: Comparison between Linear & Nonlinear Combiner withM_2K-means of External Image (Relevant Image)

Images	Rel-Ret	Rel-Num	Ret-Num	Recall	Precision	Method
	9	15	9	0.600000	1.000000	Com- M_2K-means
	15	15	15	1.000000	1.000000	Bp-bias- M_2K-means
	15	15	15	1.000000	1.000000	RBF-bias- M_2K-means
	20	25	26	0.800000	0.769231	Com- M_2K-means
	25	25	25	1.000000	1.000000	Bp-bias- M_2K-means
	25	25	25	1.000000	1.000000	RBF-bias- M_2K-means

CONCLUSIONS

We have designed and implemented a content based image retrieval system that evaluates the similarity of each image in its data store to a query image in terms of color and textural characteristics, and returns the images within a desired range of similarity. Here, the color content extraction, a well-known and powerful techniques, Color Histogram, Color Moment and Color Correlogram are used in one method by combining all these features to produce efficient method called “Combined Method”. We used the Combined Method is more effective than using each feature alone.This research introduces a cluster based retrieval of image, a novel image retrieval scheme, based on a rather simple assumption: semantically similar images tend to be clustered in some feature space. Clusterbased retrieval of an image attempts to retrieve semantically coherent image clusters from unsupervised learning of how images of the same semantics are alike. At search time, the query image is not compared with all the images in the database, but only with a small subset. Here we used k-means clustering algorithm and also M_1k-means thatused a better similarity distance,and M_2k-means this algorithm is an efficient algorithm and produce efficient retrieval.

Beside the above, a new human interaction system model of CBIR with nonlinear combination of features of the images is presented. This approach is Neural NetworkBased Images Retrieval and is based on BPNN and RBFN. It is very efficient and produces 100% retrieval of images.

We conclude that color methods are useful in content based image retrieval. Combining color information usually improves the performance of the method; and it further improves the performance if the M_2k-means clustering algorithm and nonlinear combiner (BPNN & RBFN) are used. These methods proved an efficient performance when used in contentbased image retrieval.

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