International Journal of Advanced Computer Research (ISSN (print): 2249-7277 ISSN (online): 2277-7970)
Volume-4 Number-1 Issue-14 March-2014

Retrieval of Images Using Weighted Features

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Abstract

Color and texture are the important features used in Content-based image retrieval (CBIR) systems. CBIR is a process that searches and retrieves images from large image databases. To perform this operation, CBIR requires color, texture and shape features of images. In this paper, color and texture features of images are considered. First order statistics and run-length characteristics of images corresponding to color and texture features are extracted. Then, different weights are assigned to each feature which is represented as weighted features. The primary goal is to determine which feature dominates in image retrieval. Similarity measurement between query image and database images are done using sum of absolute difference (SAD), Sum of squared absolute difference (SSAD) and Euclidean distance(ED). It is found experimentally that the weighted features using Euclidean distance gives better performance.

Keywords

Color feature, Run-length features, Sum of absolute difference, Sum of squared absolute difference, Euclidean distance.

1. Introduction

In recent times, due to the advent of computers and Internet technologies, image databases have an important role. In these databases, the need of searching similar images for the given query image is a tedious and time consuming task. Content Based Image Retrieval technique is the panacea for these problems [1][2]. The first CBIR was QBIC [3]. A number of general purposes CBIR have been developed since then. They used different algorithms for their software's [4, 5, 6]. In this paper [7], localized content-based image retrieval using interest point is presented. The image is divided into a series of sector sub-region with different area according to the distribution of interest points and local features. Interest points are extracted and considered as features. In [8], the color and texture features are extracted using color histograms and grey level co-occurrence matrix (GLCM) respectively. In this paper [9], a technique for content based image retrieval is proposed in which motif co-occurrence matrix (MCM) is used. The MCM is a 3D matrix whose (i,j,k) entry denotes the probability of finding a motif i at a distance k from the motif j in the transformed image. It is found that this feature gives better results than color occurrence matrix (CCM). In this paper [10], the color feature is extracted using joint histogram in HSV color space. The texture feature is extracted using Gray level co-occurrence matrix (GLCM). In [11] first order and second order features of Anal intraepithelial neoplasia(AIN) images are used. They used different classifiers to classify the diseases. In [12] Five dominant colors are used for color features. Edge histogram is used for texture features and moment invariant is used for shape features. In this paper [13], both statistical and structural texture features are analysed and compared. It is found that the combinations of texture features give better results. This paper [14] deals with the texture features of images in DCT domain using median and laplacian filters. It is observed that the laplacian filters with sharpened images give better performance in retrieval of JPEG images as compared to the median filter in the DCT frequency domain. The performance of content based image retrieval using HSV color space is evaluated and then RGB and HSV is compared in [15]. It is observed experimentally that CBIR using HSV color scheme transfers each pixel of image to a quantized color code and using the quantized color code to compare the images of database. In this paper [16], a new image representation called extended Histogram is presented in conjunction with a well-defined distance function on CX-Histogram. The CXSim() is a new image-to-image similarity measure to compute the partial similarity between images. It achieves up to 5.9-fold speed-up in search over R* true search followed by sequential scanning. In this paper [17], structural elements descriptor (SED), is proposed. SED can effectively describe images and represent image local features. SED can extract and describe color and texture features. They demonstrated that the method has a better performance than other image

Manuscript received January 10, 2014.
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retrieval methods. It is found that in the above literature, weighted features of first order statistical (F1) properties and run-length features (RLF) are not considered. It is very important to find the dominant feature among the color and texture features. To determine the dominance among features, various similarity measurements are considered. As it is very much necessity for image retrieval from the large image databases. The following CBIR system is proposed.

2. Proposed work

In this research work, after the process of noise removal, first order statistical features of image which signifies the color features and run-length features which represent the texture features of query and database images are considered. It is proposed that the weights are assigned to each feature. The optimal weight is found experimentally to find the dominant features of an image. Then, the similarity measurement between query image and database images are calculated using different distances like sum of absolute difference (SAD), Sum of squared absolute difference(SSAD) and Euclidean distance(ED). The block diagram of proposed CBIR system is shown in Figure 1.

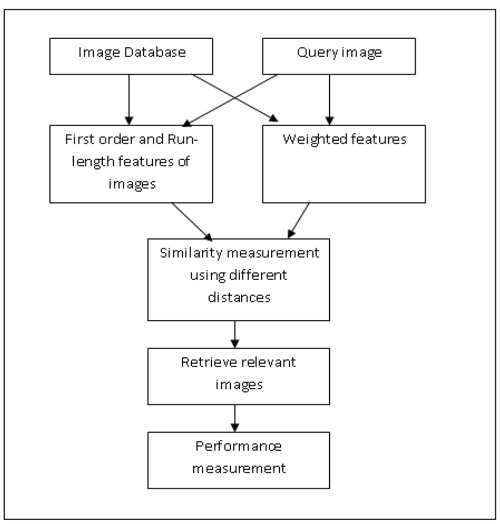

Figure 1: Block diagram of proposed CBIR System

2.1Algorithm

The step by step procedure for the proposed work is as follows.

1. Select the query image and preprocess it to remove the noise.
2. Extract the six first order statistical features.
3. Extract the seven run-length features.
4. Combine the above thirteen features and forms the combined feature vector.
5. Assign the weight α and β for the first order statistical features and run-length features respectively and the add them.
6. Repeat the steps 1 to 5 and store the combined feature vectors and weighted feature vectors separately for all images in the database.
7. Similarity measurement is calculated using different distance measures like SAD, SSAD and ED for combined and weighted feature vectors.
8. Retrieve the minimal distance top ranked relevant images.
9. Compute the performance measures and compare the results.

2.2 Preprocessing

In this work, the images are preprocessed to remove the noise. In the process of noise removal by median filtering, the value of an output pixel is determined by the median of the neighborhood pixels. The median is much less sensitive than the mean to extreme values, called outliers. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

3. Methods and Materials

3.1 The statistics of images

Images in the database have definite statistics. Such images fit a description of randomly generated pixels. The different features of images are described by the n^{th} order statistics. For example, the first order statistics refers to the probability distribution of the values of each pixel. i.e intensity of pixel at different points. First order statistics refers to the color features of the images. Run-length matrices refer to gray pixels of texture features.

3.2 First order statistics

First-order features (F1) are calculated from the original image values. They do not consider the relationships with neighbor pixels. Features derived from this approach include moments such as mean, standard deviation, energy, entropy, skewness and kurtosis of an image. These statistics are represented as

$$mean(\mu) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)}{M*N} \quad (1)$$

$$standard\ deviation(\sigma) = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y) - \mu}{M*N}} \quad (2)$$

$$Energy(e) = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i^2\,(x,y) \quad (3)$$

$$Entropy = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)(-\ln I_i\,(x,y)) \quad (4)$$

$$skewness = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y) - \mu^3}{M*N*\sigma^2} \quad (5)$$

$$Kurtosis = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y) - \mu^4}{M*N*\sigma^4} \quad (6)$$

Where M and N are the number of rows and columns of the image.

3.3 Run-length Features

Run length matrices characterize texture features of images. Galloway [18], Chu et. al. [19] and Dasarathy and Holder [20] introduced different run-length matrices as feature representatives. For a given image, a run-length matrix p(i, j) is defined as the number of runs with pixels of gray level i and run-length j. Let M be the number of gray levels and N be the maximum run- length .Galloway [18] introduced five original run-length features(RLF). They are defined as follows.

Short Run Emphasis(SRE)

$$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{j^2} \quad (7)$$

SRE measures the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and it is expected large for fine textures.

Long Run Emphasis(LRE)

$$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j)\,.\,j^2 = \frac{1}{n_r}\sum_{j=1}^{N} p_r\,(j).\,j^2 \quad (8)$$

LRE measures distribution of long runs. The LRE is highly dependent on the occurrence of long runs and is expected large for coarse structural textures.

Gray-Level Non-uniformity(GLN)

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N} p(i,j)\right)^2 = \frac{1}{n_r}\sum_{i=1}^{M} p_g\,(i)^2 \quad (9)$$

GLN measures the similarity of gray level values throughout the image. The GLN is expected small if the gray level values are alike throughout the image.

Run Length Non-uniformity(RLN)

$$RLN = \frac{1}{n_r}\sum_{j=1}^{N}\left(\sum_{i=1}^{M} p(i,j)\right)^2 = \frac{1}{n_r}\sum_{i=1}^{M} p_g\,(i)^2 \quad (10)$$

RLN measures the similarity of the length of runs throughout the image. It is expected small if the run lengths are alike throughout the image.

Run Percentage(RP)

$$RP = \frac{n_r}{n_p} \quad (11)$$

RP measures the homogeneity and the distribution of runs of an image in a specific direction. The RP is the largest when the length of runs is 1 for all gray levels in specific direction. Where n_r is the total number of runs and n_p is the number of pixels in the image. Chu.et.al [19] proposed the following two features:

Low Gray-Level Run Emphasis(LGRE)

$$LGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2} = \frac{1}{n_r}\sum_{i=1}^{M}\frac{p_g(i)}{i^2} \quad (12)$$

LRGE measures the distribution of low gray level values. It is expected large for the image with low gray level values.

High Gray-Level Run Emphasis (HGRE)

$$HGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j)\,.\,i^2 = \frac{1}{n_r}\sum_{j=1}^{N} p_r\,(j).\,i^2 \quad (13)$$

HRGE measures the distribution of high gray level values. It is expected large for the image with high gray level values.

4. Weighted Features

In this paper, it is proposed to include weighted factor to statistical features of images. It is as follows.

$$F = \alpha * F1 + \beta * RLF \quad (14)$$

where F is the feature vector of images. F1 is the first order statistical features and RLF is the run length features. In this work, six first order statistical features that signify the color features of images and seven run-length features which signify the texture features of images are considered. Then, the combinations of F1 and RLF features (i.e) thirteen features are used. Experiment is done for different weights of α and β. (i.e) α = 0.30, 0.40, and 0.60 and β= 0.70, 0.60 and 0.40 respectively.

The precision and recall values of the CBIR system are calculated.

5. Similarity Measurements

5.1 Sum of absolute difference (SAD)

$$\delta d = \sum_{i=1}^{n}(|Q_i| - |D_i|) \quad (15)$$

where n is the number of features, i = 1,2,3,....n.

5.2 Sum of squared absolute difference (SSAD)

$$\delta d = \sum_{i=1}^{n}(|Q_i| - |D_i|)^2 \quad (16)$$

The squaring always gives a positive value and highlights its big difference.

5.3 Euclidean distance

This distance matrix is mostly used for similarity measurement in image retrieval because of its efficiency and effectiveness. It measures the distance between two vectors of images by calculating the square root of the sum of the squared absolute differences and it is defined as

$$\delta d = \sqrt{\sum_{i=1}^{n}(|Q_i| - |D_i|)^2} \quad (17)$$

where Q and D are the query feature vectors and database feature vectors respectively.

6. Experimental Results

In this work, corel database of 1000 images are used. It consists of 10 classes like Dinosaurs, Elephants, Buses, Roses, etc., each class contains 100 images. After finding the similarity measurement, the minimal distance images are ranked [Ti] where i = 1 to 100. Then, the top ranked images are displayed. After precision and recall values are calculated for retrieved and relevant images. If there are C_i classes in the total image database where i =1 to 10, then the query image in particular class C_j is given. After CBIR process, the relevant images of C_j and images from other C_i classes are retrieved. If top T_i belongs to C_j then all retrieved images are relevant images. Experiment is done for different retrieved images and their corresponding relevant images are found.

$$Precision = \frac{No.of\ retrieved\ relevant\ images\ of\ class\ C_j}{No.of\ retrieved\ images\ of\ class\ C_i} \quad (18)$$

$$Recall = \frac{No.of\ retrieved\ relevant\ images\ of\ class\ C_j}{No.of\ relevant\ images\ of\ class\ C_i} \quad (19)$$

$$Accuracy = \frac{Precision + Recall}{2} \quad (20)$$

$$F - Score = 2 * \frac{precision * recall}{precision + recall} \quad (21)$$

Figure 2 gives the Graphical user interface (GUI) of the proposed CBIR system developed for the optimized weighted features to retrieve the images.

Figure 2: GUI of proposed CBIR system

Table 1 shows the average precision and recall values of all image categories using both combination of First order statistical feature (F1) and run-length features(F1+RLF) and optimized weighted features for α= 0.60 and β= 0.40. The similarity measurement used is Sum of absolute difference. Table 2 shows the average precision and recall values of all image categories using combined F1+RLF features and optimized weighted features for α= 0.60, β = 0.40. The similarity measurement used is Sum of squared absolute difference. Table 3 shows the average precision and recall values of all image categories using combined F1+RLF features and optimized weighted features for α= 0.60, β= 0.40 using Euclidean distance. Figure 3 shows the results of images retrieved without weighted features. Figure 4 shows the images retrieved using weighted features. It is observed that more relevant images are retrieved only using weighted features.

Table 1: Average Precision, Recall of all image categories using SAD

	F1+ RLF		Weighted F1+RLF	
Type of Images	**Precision**	**Recall**	**Precision**	**Recall**
African	0.66	0.26	0.68	0.17
Beaches	0.55	0.36	0.58	0.32
Buildings	0.63	0.29	0.65	0.27
Buses	0.70	0.13	0.71	0.12
Dinosaurs	0.70	0.13	0.75	0.11
Elephants	0.65	0.27	0.67	0.26
Roses	0.69	0.15	0.73	0.13
Horses	0.68	0.17	0.71	0.18
Mountains	0.56	0.35	0.62	0.33
Food	0.58	0.32	0.60	0.31

Table 2: Average Precision, recall of all images categories using SSAD

	F1+ RLF		Weighted F1+RLF	
Type of Images	**Precision**	**Recall**	**Precision**	**Recall**
African	0.68	0.17	0.69	0.15
Beaches	0.58	0.32	0.60	0.31
Buildings	0.65	0.27	0.68	0.17
Buses	0.73	0.13	0.76	0.10
Dinosaurs	0.71	0.12	0.76	0.10
Elephants	0.68	0.17	0.71	0.12
Roses	0.70	0.13	0.72	0.12
Horses	0.69	0.15	0.70	0.13
Mountains	0.60	0.31	0.61	0.30
Food	0.65	0.27	0.63	0.29

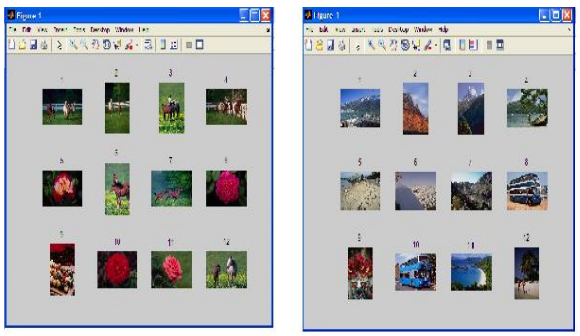

Figure 3: Results of images retrieved using F1+RLF features.

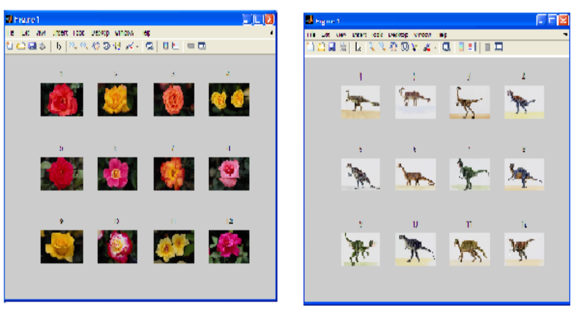

Figure 4: Results of images retrieved using weighted F1+RLF features.

Figure 5 and Figure 6 show the accuracy and F-score values of the CBIR using without weighted features and with weighted features respectively. The similarity measurement used is Euclidean distance. It is found that the best results are obtained only for α= 0.60, β= 0.40 i.e. color features dominate 60% whereas texture features contributes 40% among the image features

Table 3: Average Precision, recall of all images categories using Euclidean distance

	F1+ RLF		Weighted F1+RLF	
Type of Images	**Precision**	**Recall**	**Precision**	**Recall**
African	0.72	0.12	0.74	0.12
Beaches	0.55	0.36	0.56	0.35
Buildings	0.68	0.17	0.69	0.15
Buses	0.74	0.12	0.75	0.11
Dinosaurs	0.78	0.09	0.80	0.05
Elephants	0.70	0.13	0.71	0.18
Roses	0.77	0.09	0.79	0.04
Horses	0.75	0.11	0.75	0.11
Mountains	0.57	0.33	0.58	0.32
Food	0.58	0.32	0.58	0.32

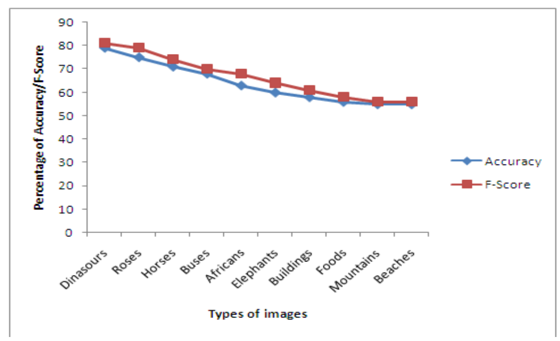

Figure 5: Accuracy and F-Score of F1+RLF using Euclidean distance

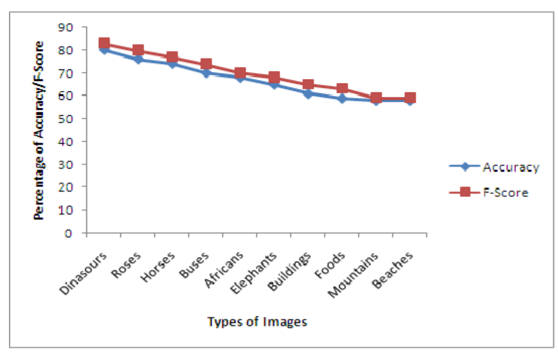

Figure 6: Accuracy and F-Score of weighted F1+RLF using Euclidean distance

7. Conclusion

In this paper, the first order statistical features which signify the color features of images are used. Then, run-length features which show the texture features are considered. Six F1 features and seven RLF features, totally thirteen features are used. Weighted features concept is introduced in this research work. Experiments are done for different weights of F1 and RLF using different similarity measurements like SAD, SSAD, ED., It is found that the weighted features give better results with Euclidean distance method. Further, it is observed that the best results are obtained only for $\alpha = 0.60$ and $\beta = 0.40$ (i.e). Color features dominate 60% whereas texture features contributes 40% among image features.

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