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Color Image Retrieval Using Color, Texture and its Spatial Information

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ABSTRACT: This paper presents a novel, effective and efficient approach for image retrieval based on color and texture features. Instead of simply representing the color and texture information of images only, the proposed work represent the image by both color and its global as well as local spatial information, and texture and its global as well as local spatial information. For representing the color of an image, color autocorrelogram is proposed. For representing the edges and valleys, and smoothness of textures, global as well as local correlation of BDIP and BVLC is proposed. Performance of the proposed approach is analyzed using Canberra distance. Comprehensive experiments are carried out using the benchmark databases. It is concluded that the proposed combination of feature with normalized Canberra distance has good performance in terms of precision, recall and F-Score.

KEYWORDS: Color autocorrelogram, BDIP, BVLC, Canberra distance, Local spatial correlation.

I. INTRODUCTION

Increasing number of digital image databases and multimedia libraries is the main motive for developing image retrieval system. Since, the exploitation of content based image retrieval become booming in fast, there is an rising need to incorporate appropriate methods that matches the users preference in retrieving relevant images from huge database. Generally, two types of image retrieval methods are used and they are text based and content base. The major limitation with text based method are vast amount of task is required for manual annotation of images and understanding the keyword varies with the users observation. To address these issues, image retrieval method is carried out in the direction of content based. Lot of efforts carried out by various researchers using various techniques is found in [1-3].

Low level visual features such as color, texture and shape of the image and its spatial locations plays important role in representing the image more effectively and play a vital role for retrieving relevant images from huge image databases. Color is more important feature because human visual system recognizes the color immediately. Various color features has been suggested by the various researchers in the past. In [4], color moments such as mean, variance and skewness is used for image retrieval. Swain and Ballard [5] proposed color histogram in which the global color distribution of an image is extracted. However, it results in less accuracy due to the lack of spatial information of color. In [6, 7], the spatial information based on color histogram is adopted. A binary color set is suggested by Smith and Chang [8]. It is defined as a selection of colors from the quantized color space. Pass and Zabih [9] suggested color coherence vector (CCV). The CCV partitioning the histogram bins based on the spatial coherence of the pixels. In [10], a color tuple histogram approach is presented. Huang et al. [11] proposed a color correlogram which captures local as well as spatial correlation between the colors. Subsequently, color autocorrlogram has been suggested in [11]. The Color autocorrelogram includes the spatial correlation between the identical color elements of the color correlogram, and provides better accuracy and less computational and storage cost [12, 13].

Like color, texture features also the core element of retrieval system due to the truth that it discriminate images with similar color and shape. It is very difficult to model more effective texture features. Generally there are two types of texture feature extraction methods: statistical based approach and structural based approach. The statistical based approach includes features like Tamura features, Co-occurrence matrix, multi resolution based features, local binary pattern, texton co-occurrence matrices, multi-texton histogram, motif co-occurrence matrix, block difference of inverse probabilities (BDIP) and its various representations and block variation of local correlation coefficients (BVLC) and its various representations, etc. The later approach includes Fourier domain for texture analysis, micro-structure descriptor, trous gradient structure descriptor, structure element descriptor (SED) and structure element histogram (SEH),etc. The

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various texture features discussed in the literature is found in [12, 14 - 26]. In this vein, by combining color and texture feature various image retrieval systems have been found in the literature [13].

Recently, Sathiamoorthy [27] introduced a novel feature discrimination and characterization for BDIP and BVLC and it is reported that it outperforms in accuracy then the conventional approach. Based on the aforesaid fact, this paper concentrates on improving the accuracy of image retrieval system. In this paper, the color autocorrelogram is combined with the BDIP and BVLC and its spatial information respectively.

The rest of the paper is discussed as follows. In Section 2, the image feature extraction and representation is described. In Section 3, the proposed image retrieval is reported. Section 4.1 and 4.2 discuss about similarity measure and performance assessment. Experiments and analysis of results are reported in Sections 4 and Section 5 discusses the conclusion.

II. PROPOSED FEATURES

2.1. Color Autocorrelogram

The color autocorrelogram calculates the spatial information of color and shape respectively. It is also reported that color autocorrelogram is more robust to color, appearance, contrast and brightness changes and also invariant to translation and scaling [11, 12]. Hence, in this paper, the color autocorrelogram is selected as a color descriptor.

Let I is an image of size N X N. Assume that the colors in I is quantized into m colors say c1, c2, . , . , . , cm. Let us consider the pixels p1 and p2 where p1=(x1, y1) and p2=(x2, y2). Let a distance between p1 and p2 is *d* and $d \in N$. The correlogram for image I is defined in equation (1) as in [12].

$$\varphi^{d}_{c_i c_j}(I) \overset{\Delta}{=} \Pr_{p_1 \in i_{c_i}, p_2 \in i_{c_j}} [p_2 \in I_{c_i} \mid |p_1 - p_2| = k] \tag{1}$$

where $k \in d$ and $i, j \in m$. For any pixel of color c_i in the image, $\varphi^{d}_{c_i c_j}(I)$ gives the probability that a pixel at distance k away from the given pixel is of color. c_j. The autocorrelogram of I captures spatial correlation between identical colors only and is defined in equation (2) as in [19]

$$\Phi^{k}_{c}(I) \overset{\Delta}{=} \varphi^{d}_{c_i c_j}(I) \tag{2}$$

Since smallest correlation distance offers in depth local properties of an image, the color autocorrelogram extracts the spatial correlation between the identical colors at distance *d*= 1 [12].

2.2. BDIP

BDIP is an entropy operator and is defined as the difference between the number of pixels in a block and the ratio of the sum of pixel intensities in the block to the maximum in the block, and it uses local probabilities in an image block to measure the local brightness variations. The BDIP captures the both the edges and valleys. In an image, edge pixels represent the local intensity maximum and pixels in the valley represent local intensity minima. Both the edges and valleys play a central role in human visual perception system to recognize an object. Based on the fact, BDIP is suggested in [12] and is computed as follows in equation (3).

$$BDIP^{d}(l) = \frac{\frac{1}{B^{d}_{l}} \Sigma(x,y) \in B^{d}_{l} (\max_{(x,y)\in B^{d}_{l}} f(x,y) - f(x,y))}{\max_{(x,y)\in B^{d}_{l}} f(x,y)} \tag{3}$$

where f(x,y) designates the pixel intensity at location (x,y) in the block B^{k}_{l} of size (k+l) x (k+l), l is the place index of the block in an image and k is the maximum distance of pairs of pixels in the block. Therefore, $B^{k}_{l} = (k+1)^2$.

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The maximum intensity variation in a block and the representative value in a block are expressed in the numerator and denominator of equation (1) respectively.

2. 3. BVLC

BVLC [12] is the difference between the maximum and minimum of local correlation coefficients according to four orientations $(0^{\circ},90^{\circ},45^{\circ},-45^{\circ})$ in a block. This feature measures the texture smoothness using variations of local correlation coefficients in an image blocks as follows in equation (4).

$$\rho(k,l) = \frac{\frac{1}{M^2}\sum_{(x,y)\in B} f(x,y)f(x+k,y+l) - \mu_{0,0}\mu_{k,l}}{\sigma_{0,0}\sigma_{k,l}} \quad (4)$$

Where B is a block of size M x M and $\mu_{0,0}\mu_{k,l}$ is the local mean, and $\sigma_{0,0}\sigma_{k,l}$ is the local standard deviation. The (k,l) represents a pair of horizontal shift and vertical shift associated with four orientations $(0^{\circ},90^{\circ},45^{\circ},-45^{\circ})$. After shifting the M x M windows in each of four directions, compute *p(0,1), p(1,0), p(1,1), p(1,-1)* then the BVLC is computed as shown in equation (5).

$$BVLC^{d}(l) = \max_{\Delta(k)\in O_4}[\rho^{k}(l,\Delta(k))] - \min_{\Delta(k)\in O_4}[\rho^{k}(l,\Delta(k))] \quad (5)$$

where $\Delta(k) = (\Delta_x(k), \Delta_y(k))$ stands for shift in one four directions and $O_4 = \{(-k,0),(0,-k),(0,k),(k,0)\}$

III. PROPOSED SYSTEM

3.1. Feature Extraction and Representation

In [12], the moments of BDIP and BVLC are considered for image retrieval. In [28], both low and higher order moments of BDIP and BVLC is considered for representing the texture feature of an image and Canberra distance is adopted. In [29], BDIP and BVLC features are represented using a histogram of 57 bins for each. In [27], the spatial information of BDIP and BVLC is captured. Thus, in order to increase the efficacy of the proposed image retrieval, the BDIP and BVLC features suggested in [27] and color autocorrelogram as in [12] is combined in this paper.

In the proposed system the color images in RGB color space are transformed into HSV color space [12] then the images are separated out into Hue, Saturation and Intensity component images, where Hue and Saturation component images have chromatic information and intensity component image contains achromatic information. The wavelet decomposition is performed using wavelet transform [12] on Hue, Saturation and intensity component image. The level of decomposition is set to 2 as in [12]. After that, the color autocorrelogram is extracted from the each sub bands of 2 scales of H and S component images and the BDIP and BVLC features are extracted for each sub band of 2 scales of intensity component image. Then the global distribution of local spatial correlation between the identical BDIP edges and valleys as well as the global distribution of local spatial correlation between the identical BVLC texture features are exploited. The color and texture features extracted from the corresponding sub bands of each scale are combined together to form a feature vector and is kept in the feature vector database. The combined feature vector is normalized using Z-score method. Canberra distance measure is used to measure the distance between the query and target images. The images having high similarity will be placed in the top of the retrieved image list. The proposed work suggests that the combination of new representation of BDIP and BVLC with color autocorrelogram has better performance in image retrieval.

The proposed system strongly believed that the global distribution of local spatial correlation among the identical color, the global distribution of local spatial correlation among the identical BDIP values and global distribution of local spatial correlation among the identical BVLC values play a vital in the image retrieval and experimental results evident that the proposed novel approach considerably better then the approach reported in [12]. The architecture of the proposed method is shown in Fig.1.

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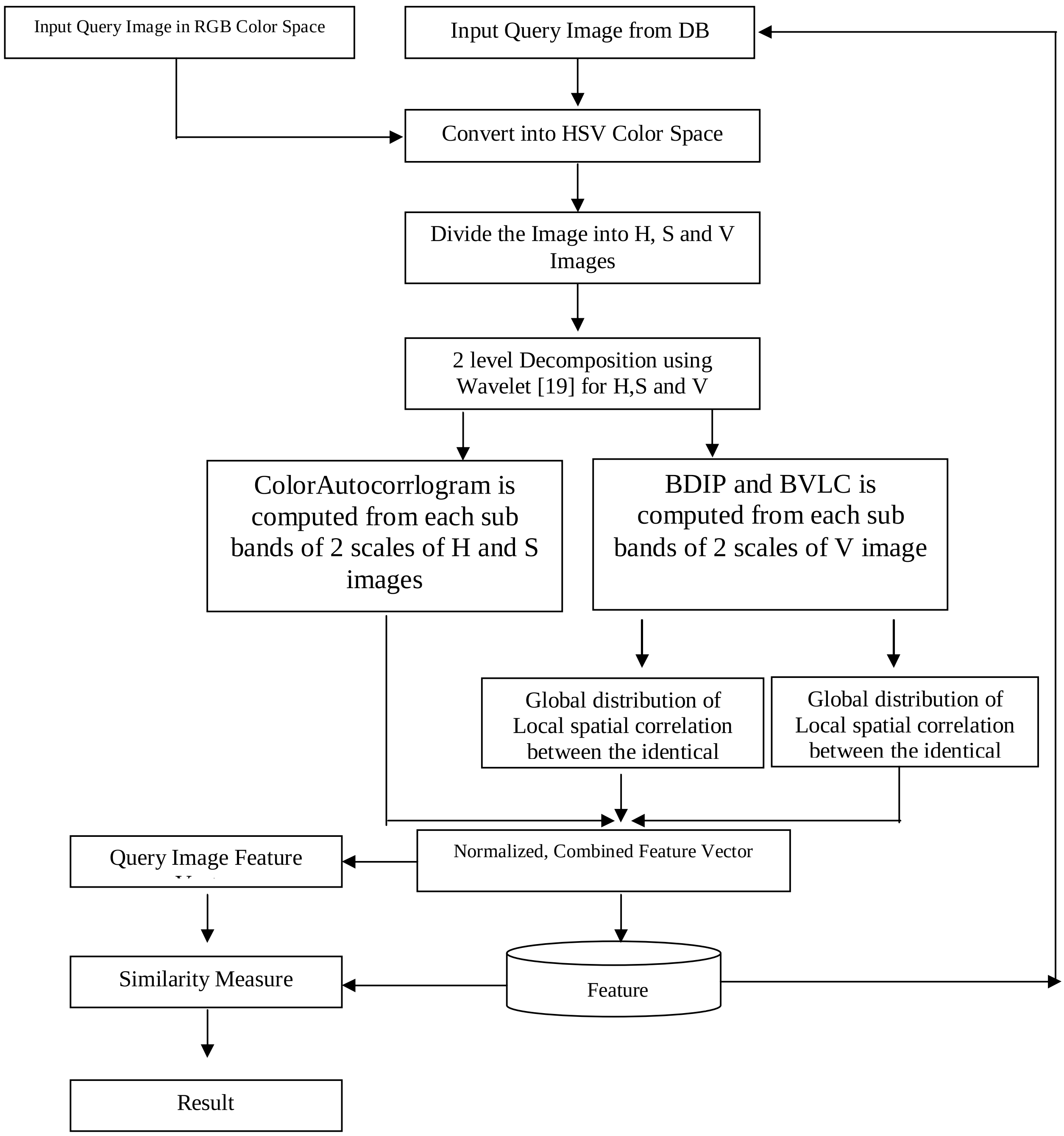

Fig.1. Architecture of proposed image retrieval system

3.2. Similarity Measure

Measuring the distance between the query and target images using the derived feature vectors is an indispensable module of any image retrieval system. Different distance measures from computational geometry, statistics and information theory are described for image retrieval systems. In the proposed work, Canberra distance [30] measure is used because of it significance performance in image retrieval. The computational cost of Canberra distance is also less. The Canberra distance is a weighted version of L1 distance and it is computed as follows in equation (6).

$$S(Q,T) = \sum_{i=1}^{n} \frac{|Q_i - T_i|}{|Q_i| + |T_i|} \tag{6}$$

Where Q and T stand for the query and target image feature vectors respectively and n is the number of features in each feature vector. The features are placed in increasing order that the value in the top most gives high similarity.

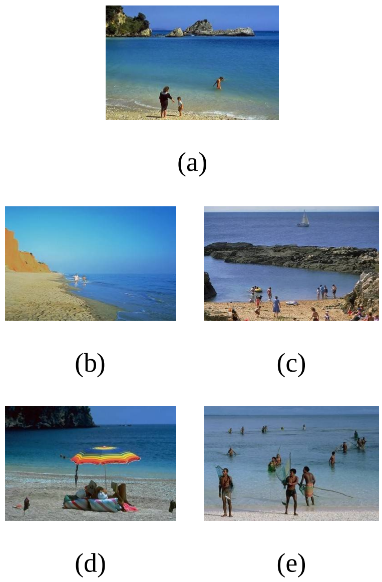

Fig. 2. (a) Query image. (b)- (e). Top most 4 akin images with query image for the proposed image retrieval

3.3. Performance Assessment

The performance of the proposed system is measured using the most widely used precision (percentage of retrieved images that are also relevant) and recall (percentage of relevant images that are retrieved) methods [31] and is defined as follows in equation (7) and (8)

$$\text{Precision} = \frac{R_i}{T_i} \tag{7}$$

$$\text{Recall} = \frac{R_i}{T} \tag{8}$$

Where Ri is the total number of relevant images retrieved, T is the total number of relevant images in the image database, and Ti is the total number of all retrieved images. The effectiveness of the proposed system is also measured in terms of average recognition rate (ARR), which is defined as the percentage of retrieved images in top matches.

The precision and recall measures cannot be considered as accuracy for the whole image retrieval systems. Thus, F-Score is incorporated in the proposed approach. F-score combines the precision and recall into a single value that defines the overall accuracy of image retrieval system. *F*-Score is defined in equation (9) as follows

$$F_{Score} = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

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IV. EXPERIMENTAL RESULTS

The proposed approach is tested by using the images in Corel database. The database is freely available for researchers [32]. The database contains 1000 images of 10 classes and each class has 100 images. The classes of images in the benchmark database are people, beaches, buildings, buses, dinosaurs, elephants, roses, horses, mountains, and food. All these classes of images are used in the experiments and all the images in the benchmark database are in the RGB color space and they are stored in the JPEG format. The images are in 256 × 384 and 384 × 256 pixels size.

The proposed approach is carried out in two stages. In the first stage, for all the images in the image database, features are extracted. The extracted features are stored in a database. In the second phase, the user is requested to input the query image to retrieve akin images from the feature database by using the proposed method. The most akin images are displayed to the user in the top as shown in Fig.2.

The effectiveness of the image retrieval is based on the performance of the feature extraction and representation and similarity measurement. The performance metrics adopted in the proposed approach are precision, recall and F-Score. Performance metrics evaluate the effectiveness of image retrieval system and also ensure the stability of the results. For example, Assume that for a given query image the CBIR system retrieves 16 relevant images out of 20 images Then the precision is 16/20 = 80% and if the total number of images in the database is 60 then recall is 14/60 = 23.33%. This shows that only recall cannot be used as a measure of CBIR system. The precision must also be computed.

The proposed method is compared with the method suggested in [12] based on precision, Recall and F-Score. In the method presented in [12], extracts the color autocorrlogram and BDIP and BVLC moments (i.e. the mean and standard deviation of BDIP and BVLC values) from all the sub bands of Wavelet Transformed [12]] image with two scales. In the proposed method, the color autocorrelogram and the global distribution of local spatial correlation of BDIP and BVLC values [27] are extracted from all the sub bands of Wavelet Transformed [12] image with two scales. Table 1 shows the average precision of 10 image classes for the proposed and existing [12] image retrieval approaches. All the images of each class are used as query images. From the results it is clear that the horses, dinosaurs, flowers and people give better results as compared to the other classes. The overall average precision of proposed method is 80.78% which is higher than the existing method and is75.87%. The Comparison of the proposed with the existing method [12] based on precision and class wise is shown in Fig.3

Table 1. Comparison of proposed with the existing method based on average precision for each class of image.

Classes	Proposed Method	Chun et al., (2008)
Dinosaurs	88.56	83.21
Horses	89.89	81.78
People	85.01	81.23
Buses	83.29	80.12
Mountains	74.34	69.20
Elephants	78.21	72.30
Buildings	73.00	70.21
Foods	78.21	72.31
Flowers	86.32	82.12
Beaches	70.99	66.24
Average	**80.78**	**75.87**

Table .2 shows the average recall in percentage of 10 image classes for the proposed and existing [12] image retrieval approach. The results evident that the performance in recall is also better for dinosaurs, roses, people and

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horses as compared to the other classes. It is evident from the results that the proposed method is more effective than the existing one. The overall average recall of proposed method is 82.95% which is higher than the existing method and is77.58%. Table.3 depicts the average *F*-Score of the proposed and existing [12] image retrieval system for various classes in the benchmark database. The overall average F-score of proposed method is 81.76% which is higher than the existing method and is76.65%. The obtained results confirm that the proposed method gives better results than the existing one [12].

Table 2. Comparison of proposed with the existing method based on average recall for each class of image.

Classes	Proposed Method	Chun et al., (2008)
Dinosaurs	90.23	85.43
Horses	92.69	83.45
People	88.22	83.78
Buses	85.01	82.82
Mountains	77.23	72.35
Elephants	78.21	72.30
Buildings	73.00	70.21
Foods	82.28	74.89
Flowers	89.08	84.32
Beaches	73.56	66.34
Average	**82.95**	**77.58**

Table 3. Average F-Score of for Proposed and Existing system

Classes	Proposed Method	Chun et al., (2008)
Dinosaurs	89.39	84.31
Horses	89.39	82.78
People	89.05	82.77
Buses	85.01	82.02
Mountains	80.15	76.04
Elephants	76.23	70.72
Buildings	75.52	71.24
Foods	77.36	72.47
Flowers	83.29	77.85
Beaches	72.25	66.29
Average	**81.76**	**76.65**

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IV. CONCLUSION

The proposed work suggested the combination of global distribution of local spatial correlations between the identical color, global distribution of local spatial correlations between the identical BDIP values and global distribution of local spatial correlations between the identical BVLC values for image retrieval. The Canberra distance measure is employed to find the similarity. The images in the Corel database are used for experiments. The proposed system is considerably superior to existing method in terms accuracy.

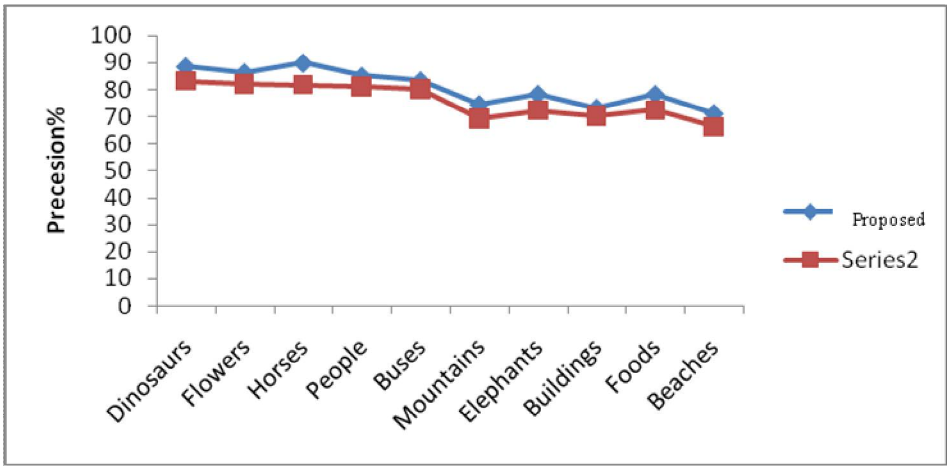

Fig. 3. Comparison of the proposed with the existing method [12] based on precision and class wise.

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