ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 9, September 2014

A Novel Approach for Image Retrieval using BDIP and BVLC

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ABSTRACT: This paper introduces a simple and efficient image retrieval method by proposing a novel representation for effective texture features namely BDIP (block difference of inverse probabilities) and BVLC (block variation of local correlation coefficients). The BDIP and BVLC capture edges and valleys, and smoothness in texture respectively. Instead of computing the low and higher order moments of BDIP and BVLC, in this paper, histogram of BDIP and BVLC is constructed, which captures rich edges and valleys, and texture information respectively. Thus, it produces high accuracy. The proposed method of feature representation for BDIP and BVLC is tested extensively on benchmark database. The Canberra distance is incorporated for measuring the similarity between the query and target images. The results reveal that the proposed approach is much more efficient then the existing one in terms of precision and recall.

KEYWORDS: BDIP, BVLC, Canberra distance, Precision, Recall.

I. INTRODUCTION

Nowadays, image retrieval is much more important in domains like media, medicine, remote sensing, etc. In earlier days, image retrieval is based on file name, keyword, caption, etc. While using them in huge databases, it leads to time consuming, tedious and subjectiveness and also the image description is not adequate one. Thus, lots of image retrieval system has been presented based on the low level visual content of an image like color, spatial and temporal constructs, shape, texture, etc. The low level visual features are computed without the human involvement and it should have perceptual similarity, efficiency and effectiveness, and it is classified into global, local and relational low-level features. [1] Suggested that local level features are much more efficient than the global one.

It is revealed that texture plays a central role in understanding the characteristics of image surface like roughness, directionality, smoothness, coarseness, regularity, etc. For image analysis, image classification and retrieval, texture features are so important and are most widely used in many content based image retrieval systems. For example, the gray-level co-occurrence matrix (GLCM) is suggested [2], the local contextual information in an image is captured by the Markov random field (MRF) model is described in [3] and it assumes that each pixel's intensity depends on the intensities of the neighbouring pixels, the measure of roughness of a surface is given by fractal dimension [4], the local binary pattern (LBP) is reported in [5], Scale Invariant Feature Transform descriptor is described in [6], Fourier domain for texture analysis is reported in [7], shift sensitivity and complex wavelet methods have been proposed in [8]. The Color edge co-occurrence histogram is described in [9], texton co-occurrence matrices is introduced by Liu and Yang [10] and it describes the spatial correlation of textons for image retrieval. In [11] the multi-texton histogram is proposed for analysing natural images. It represents the attributes of co-occurrence matrix using histogram. For biomedical image retrieval local ternary co-occurrence patterns is presented in [12] and it encodes the co-occurrence of similar ternary edges.

In [13], image retrieval system using color autocorrelogem, BDIP and BVLC moments have been presented. The BDIP captures the edges and valleys and BVLC extracts the smoothness in texture surface of an image. It is reported that the combination of color autocorreloagram, BDIP and BVLC significantly outperforms the existing systems. The BDIP and BVLC features are extracted after decomposing an image using the wavelet transform [13]. In [13], they defined the level of decomposition to 2. From the computed BDIP and BVLC values of each sub band of an image, first order moments i.e. mean and standard deviation is computed. The computed BDIP and BVLC moments are combined

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 2, Issue 9, September 2014

together with the color autocorrelogram computed for each corresponding sub bands of H and S images to form a single feature vector and it is used for retrieving the images from the database. Minkowski distance is employed in [13] for measuring the similarity between the input and target images. In [14], Sathiamoorthy suggested a image retrieval system based on the low and higher order moments of BDIP and BVLC features and they reported that it outperforms the existing method in [13].

Being enthused by the aforesaid effectiveness of BDIP and BVLC, in this paper, a novel feature representation is suggested for the computed BDIP and BVLC values i.e. instead of extracting the first and second order statistics, extracted BDIP and BVLC features are represented using histograms. Before constructing a histogram the computed BDIP and BVLC values are normalized separately. The level of normalization is decided empirically and in my case, it is set to 57. Then the BDIP and BVLC histograms are constructed and each of them having 57 bins and the constructed histograms of BDIP and BVLC is used for image indexing and retrieval. Our experimental results confirm that the proposed method of representing BDIP and BVLC significantly better then the BDIP and BVLC moments in [14].

This paper is designed as follow: Introduction about the image retrieval system and review of literature is discussed in Section1. The BDIP and BVLC features are explained in section 2. The Proposed feature extraction and representation is suggested in Section 3. The section 3.2 and 3.3 discussing about the distance measure and performance assessment methods incorporated in this paper. Experimental results and conclusion is revealed in Sections 4. In Section 5, conclusion is discussed.

II. PROPOSED TEXTURE FEATURES

2.1. 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 [13] and is computed as follows in equation (1).

$$\mathrm{BDIP}^{d}(l) = \frac{\frac{1}{B_l^d}\,\Sigma(x,y)\in B_l^d\left(\max_{(x,y)\in B_l^d} f(x,y) - f(x,y)\right)}{\max_{(x,y)\in B_l^d} f(x,y)} \tag{1}$$

Where f(x,y) designates the pixel intensity at location (x,y) in the block B_l^k 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, $B_l^k = (k+1)^2$. 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. BVLC

BVLC [13] 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 (2).

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

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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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 (3).

$$BVLC^{d}(l) = \max_{\Delta(k)\in O_4} [\rho^{k}(l, \Delta(k))] - \min_{\Delta(k)\in O_4} [\rho^{k}(l, \Delta(k))] \quad (3)$$

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

The architecture of the proposed image retrieval system is shown in Figure 1. In the proposed system the color images in RGB color space are transformed into HSV color space [13] then the images are separate out into Hue, Saturation and Intensity component images, where Hue and Saturation component images have chromatic information and intensity component image contains achromatic information. In the proposed work, the discussion is limited to texture feature only. Hence, we consider intensity component image only. Wavelet decomposition is performed using wavelet transform [13] on intensity component image. The level of decomposition is set to 2 as in [13]. After that, the BDIP and BVLC features are extracted for each sub band of intensity image. In [14], the low and higher order moments of BDIP and BVLC is considered for representing the texture feature of an image. However, the low and higher order statistics alone will not give an efficient discriminative power for an image even though it is computed for each sub bands (LL, LH, HL, HH) of intensity image in all the level of decomposition. Thus, in order to increase the efficacy of BDIP and BVLC features, in this paper, a histogram is constructed separately for the BDIP and BVLC values of each sub bands in all the level of decomposition.

It is reported [15] that the histogram based feature representation is robustness to noise and compactness. Moreover, histogram representation of BDIP and BVLC captures rich information then the approach reported in [14]. In line with this, the BDIP and BVLC are represented using the histogram and it captures rich edge and valleys and texture information respectively then the existing method of BDIP and BVLC moments.

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 [16] 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 (4).

$$S(Q,T) = \sum_{i=1}^{n} \frac{|Q_i - T_i|}{|Q_i| + |T_i|} \quad (4)$$

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.

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 [17] and is defined as follows in equation (5) and (6)

$$Precision = \frac{R_i}{T_i} \quad (5)$$

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 2, Issue 9, September 2014

$$\mathrm{Recall} = \frac{R_i}{T} \tag{6}$$

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.

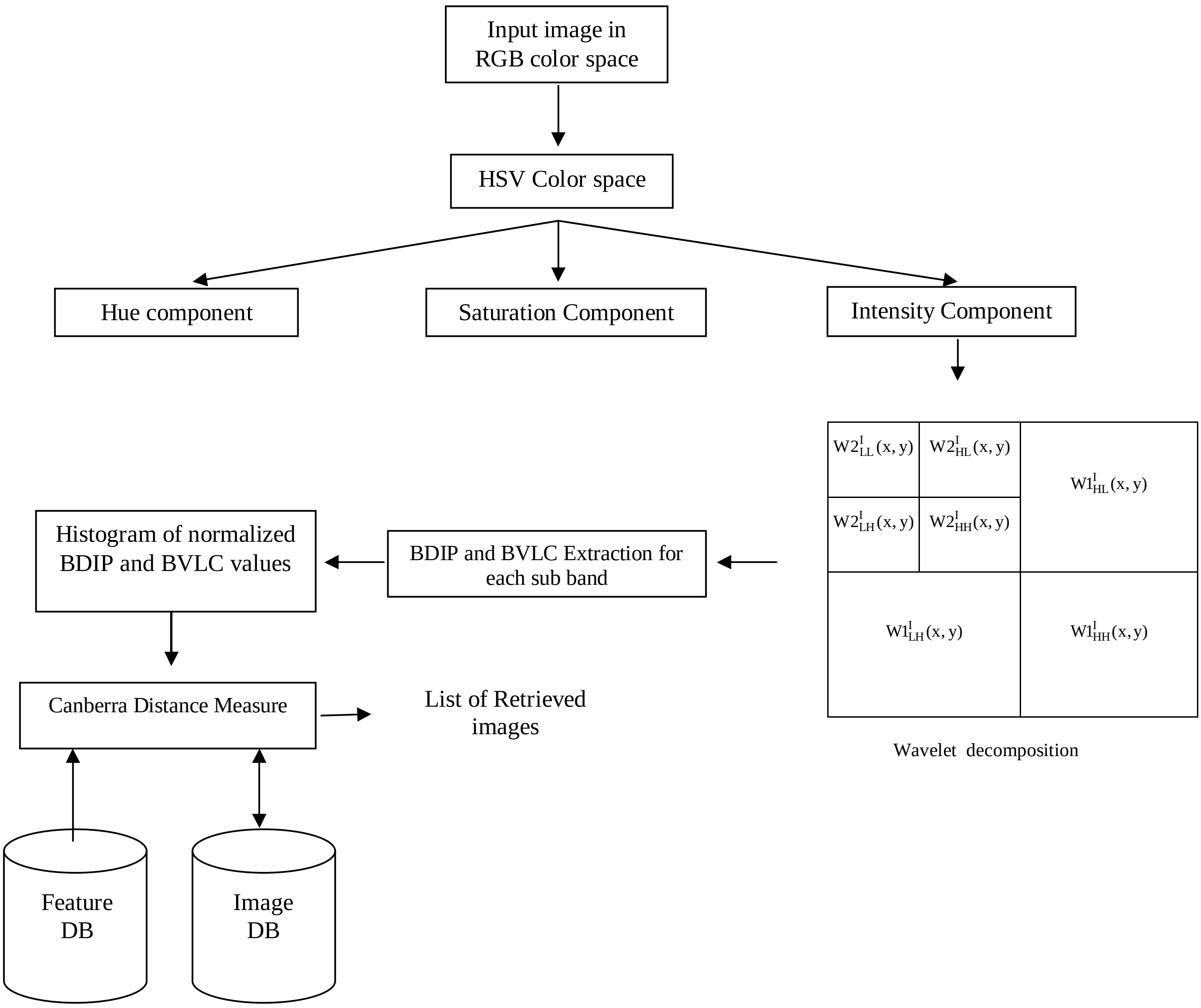

Fig.1. Architecture of proposed image retrieval system

IV. EXPERIMENTAL RESULTS

The proposed system is implemented using the Wang's benchmark database [18] which consists of 1000 images. Some of the images from the benchmark database are shown in Fig.2. Some self-photographed images are considered for the experimental study. The images are in JPEG format, and vary in size-wise. Few images in the benchmark

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

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database are duplicated and few of them are rotated through different angle and few of them are scaled up and scaled down to different sizes in order to measure the robustness of the proposed system against rotation and scaling.

More than 100 Query images are chosen randomly from the image database for assessing the retrieval performance of the proposed system. The extracted feature vector of query is compared with all the feature vectors kept in the feature vector database using the Canberra distance. The result of the distance measure is less when the target image is relevant otherwise not relevant to query image. The result of distance measure between the query and all the feature vectors in the feature vector database are sorted in ascending manner as the top most relevant images are in the top. The query and 4 top most images retrieved by the proposed system are shown in Fig.3. The precision versus recall of the proposed representation of BDIP and BVLC and existing [14] one is depicted in Fig.4. The average retrieval rates of proposed and existing system are 76.23% and 70.23. The obtained results confirm that the proposed method is achieved better results than the existing one. It is believed that the accuracy of the proposed system is better than the existing one [14] and is because of capturing rich texture information in the form of histogram.

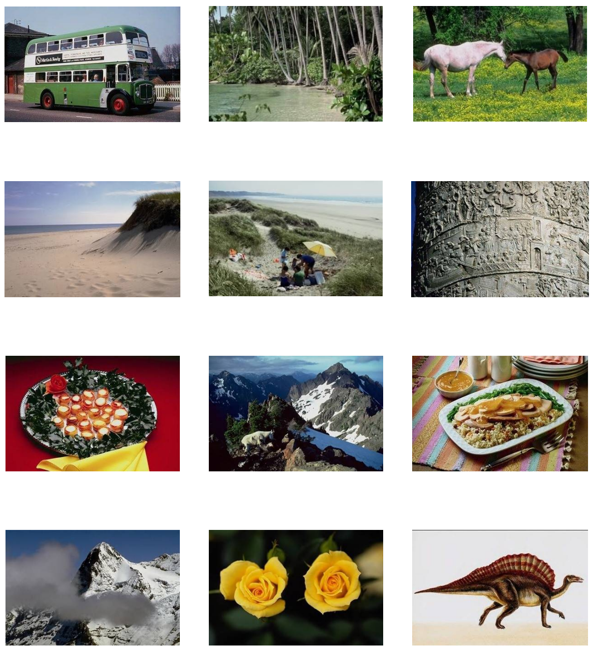

Fig.2. Sample images from benchmark database

(a)

(b)

(c)

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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(d) (e)

Fig.3.The 4 top most output (b)-(e) of the proposed system for the query image (a)

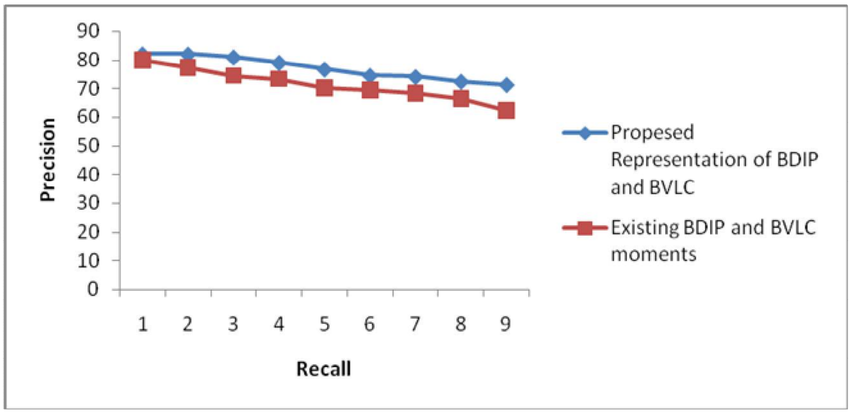

Fig.4.The precision Vs recall of the proposed BDIP and BVLC features and BDIP and BVLC moments (both low and higher order)

IV. CONCLUSION

The proposed system presents a histogram representation for the texture features BDIP and BVLC. In the existing system the low and higher order moments are computed for BDIP and BVLC and the normalized Euclidean distance is used to measure the performance whereas in this paper the more effective Canberra distance measure is incorporated to find the similarity. The result of the proposed system is superior to existing one because of the rich edge and valley and texture information captured by the histograms of BDIP and BVLC.and the proposed feature representation is also robustness to noise. The proposed system is very useful in research and education.

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ISSN(Online): 2320-9801
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International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 2, Issue 9, September 2014

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