

Content Based Image Retrieval Using the Low and Higher Order Moments of BDIP and BVLC

S.Sathiamoorthy¹, M.Kamarasan^{2*}Computer Science and Engineering Wing, DDE, Annamalai University, Annamalainagar, Tamilnadu, India¹Department of Computer Science and Engineering, Annamalai University, Annamalainagar, Tamilnadu, India²

* Corresponding Author

ABSTRACT: This paper deals with efficient retrieval of images from massive databases based on texture, edges and valley contents in images. With the increasing necessity of the use of massive image databases in different applications, it becomes very essential to construct an automatic and efficient image retrieval system to search through the whole database. The proposed approach relies on the low order and higher order moments of visual cues that exploits edges and valleys, and textures using the BDIP (block difference of inverse probabilities) and BVLC (block variation of local correlation coefficients) respectively. Unlike the previous approach which concentrates only on extracting low order moments, the proposed work combines the both low order and higher order moments to characterize the BDIP and BVLC. Experimental results on a database of 1000 trademark images show that an integration of both low and higher order moments of BDIP and BVLC feature representation results in better accuracy. To access the performance of the proposed work precision, recall and average retrieval rate is incorporated.

KEYWORDS: BDIP, BVLC, mean, standard deviation, skewness, kurtosis, Euclidean Distance.

I. INTRODUCTION

Owing to the low cost of digital devices, digital images are playing significant role in depicting and disseminating picture information. As a result, vast amount of images are generated and used in number of applications including geographic information system, remote sensing, law enforcement, medical imaging archives, etc. The huge volume of images makes it very hard to browse through the whole database. Thus, an efficient and automatic procedure is required for retrieving images from databases.

In earlier days, textual features like keywords, filenames, titles, etc have been used to manually annotate and retrieve the image. But, the keywords are subjective and not unique. When the size of the image database becomes huge, the use of keywords becomes more complex and also inadequate to represent the content of an image. Since the conventional textual based approach is less proficient with massive collection of data, the image retrieval based on low level visual features is much more advantageous in number of domains. As a result, there is a need for extracting the low level visual features such as color, texture and shape from the image automatically and in turn it is used to search the image from the huge databases.

Texture feature is an eminent and imperative feature for content based image retrieval (CBIR) than the color and shape [1]. Over the last decades, texture based CBIR has been presented broadly for the images of various domains. In [2], Query by image content (QBIC) is suggested, it uses improved version of the Tamura texture with the average of (R,G,B), (Y,I,Q), (L*,a*,b*), mathematical transform to Munsell coordinates, k -element color histogram, area, circularity, eccentricity, major axis orientation and a set of algebraic moment invariants for image retrieval. Consequently, next version of QBIC is introduced in which the text-based and content-based methods have been combined. The wavelet transform based texture feature and color set with spatial relationships is reported in the VisualSEEk [3]. The Virage is a image search engine [4] based on color, color layout, texture and structure. In Virage, users can adjust the weights associated with the features based on their own interest. The color, texture, shapes and spatial location information in the segmented image regions is suggested in Netra [5]. The WebSEEk [6] is a text/image

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search engine based on both keywords and visual content. In [7], motif co-occurrence matrix (MCM) is reported for image retrieval. The MCM combines the information related to both color and texture features. Though the MCM is quite similar to the color co-occurrence matrix (CCM), it is reported that the retrieval using the MCM is significantly better than the CCM. Because, the third order moments is calculated in MCM from the local neighbourhood. In [8], local uni-color and bi-color distributions and local directional distribution of intensity gradient are employed for image indexing and retrieval. Texture distribution based approach is introduced in [9]. Chun et al [10] suggested an image retrieval using color autocorrelogram, block difference of inverse probabilities (BDIP) and block variation of local correlation coefficients (BVLC) moments in wavelet domain. In the same direction, a number of CBIR systems have been proposed in the past.

The BDIP and BVLC moments suggested in [10] captures the edges and valley information and smoothness of texture surface in the image respectively. It is reported that BDIP and BVLC moments outperforms in terms of accuracy and storage cost than the stat-of art systems. In [10], low order moments i.e. mean and standard deviation of BDIP and BVLC features are computed and it is used for image indexing and retrieval. I believe strongly that the low order moments alone is not sufficient to discriminate the efficiency of BDIP and BVLC features. Though the color autocorrelogram is also used with BDIP and BVLC features to improve the efficacy of image indexing and retrieval, texture feature must be prominent because it play a central role in identifying the images [1]. Thus, the objective of this paper is improving the efficacy of conventional BDIP and BVLC features.

It is reported in the literature that higher-order moments (HOS) have shown promising results in a number of signal processing applications [11] and including the third order moments will improve efficiency of the MCM when compare to CCM is reported in [7]. In line with this fact, the conventional BDIP and BVLC feature representation is also characterized and discriminated using the higher order moments like skewness and kurtosis. That is, the proposed method demonstrates the effectiveness of BDIP and BVLC texture features by characterizing them using the both low and higher order statistics. Retrieval on the basis of proposed low and higher order moments of BDIP and BVLC has been shown to outperform in terms of accuracy.

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

$$BDIP^d(l) = \frac{\frac{1}{B_1^d} \sum_{(x,y) \in B_1^d} (\max_{(x,y) \in B_1^d} f(x,y) - f(x,y))}{\max_{(x,y) \in B_1^d} f(x,y)} \quad (1)$$

Where $f(x,y)$ designates the pixel intensity at location (x,y) in the block B_1^k of size $(k+1) \times (k+1)$, 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, $B_1^k = (k+1)^2$. 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.

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2. BVLC

BVLC [10] 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).

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

Where B is a block of size $M \times M$ 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 $M \times M$ 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).

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

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. Proposed Feature Extraction and Representation

In [10], first the images in RGB color space is transformed into HSV color space then the image in HSV color space is divided into hue, saturation and intensity component images. Where hue and saturation components belong to color information and V component consists of texture information. Since the discussion in this paper is limited with texture feature of an image, the proposed work considers the intensity component of image only from which texture features are extracted. In [10], the intensity component image is decomposed into 2 levels using the wavelet transform [10] then from each sub-band i.e. from LL, LH, HL and HH of each level of decomposition, the BDIP and BVLC features are computed separately. Later, the low order moments i.e. mean and standard deviation is calculated for both BDIP and BVLC features and the low order statistics of BDIP and BVLC discriminate the texture feature in [10].

As reported in [7, 11], higher order moments also play a imperative role in characterization of texture features, this paper characterize and discriminate the computed BDIP and BVLC texture features using the higher order moments namely skewness and kurtosis.

3.1.1. Skewness

The skewness is defined as a measure of dataset's symmetry or lack of symmetry. If the skewness of texture data is 0, the texture values are perfectly symmetrical. If the skewness of texture data is in between -0.5 and 0.5, it is fairly symmetrical. If the skewness of texture data is in between -1 and -0.5 or between 0.5 and 1, it is moderately skewed and if the skewness of texture data is less than -1 or greater than 1, then it is highly skewed. The skewness of computed BDIP and BVLC values are calculated using the equation in (4) as follows

$$\text{Skewness} = \frac{\sum (T_i - \mu)^3}{N\sigma^3} \quad (4)$$

Where T_i is the i th texture value, μ is the mean, N is the size of computed BDIP/BVLC values and σ is the standard deviation.

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3.1.2. Kurtosis

The kurtosis is used to measure the peakedness i.e. flatness of data. The kurtosis is computed as in equation (5).

$$\text{Kurtosis} = \frac{\sum (T_i - \mu)^4}{N\sigma^4} \quad (5)$$

Where T_i is the i^{th} texture value, μ is the mean, N is the size of computed BDIP / BVLC values and σ is the standard deviation.

3.2. Similarity Measure

Measuring the similarity 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, normalized Euclidean distance measure [12] is used in the proposed approach because of its significance performance in image retrieval. The normalized Euclidean distance is computed as follows in equation (6).

$$E(Q, T) = \sqrt{\sum_{i=1}^N \left(\frac{Q_i - T_i}{\sigma_i} \right)^2} \quad (6)$$

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. σ_i is the standard deviation.

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

$$\text{Precision} = \frac{R_i}{T_i} \quad (7)$$

$$\text{Recall} = \frac{R_i}{T} \quad (8)$$

Where R_i is the total number of relevant images retrieved, T is the total number of relevant images in the image database, and T_i 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.

IV. EXPERIMENTAL RESULTS

The low and higher order moments of BDIP and BVLC based texture image retrieval is experimented with standard images taken from Wang's benchmark database [13]. The size of the images in the database is different. The database consists of 1000 images including flowers, horses, elephants, sea shores, mountains, buildings. Some of the sample images from the benchmark database are shown in Fig.1.

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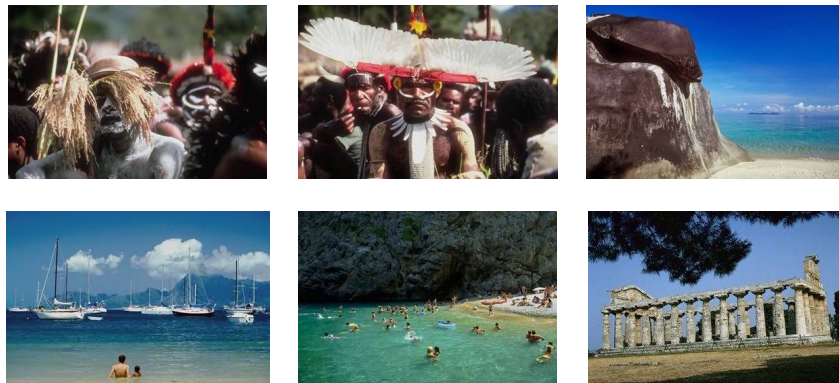


Fig.1. Sample images from benchmark database

During the experimentation, the proposed approach decomposes the intensity component image into 2 levels using the wavelet transform [10] then the BDIP and BVLC is computed for each sub bands at each level. From the computed BDIP and BVLC values low and higher order statistics are computed which in turn used to represent the images uniquely.

Few images in the benchmark 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.



(a)



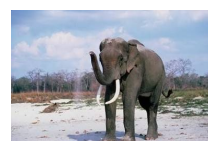
(b)



(c)



(d)



(e)

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

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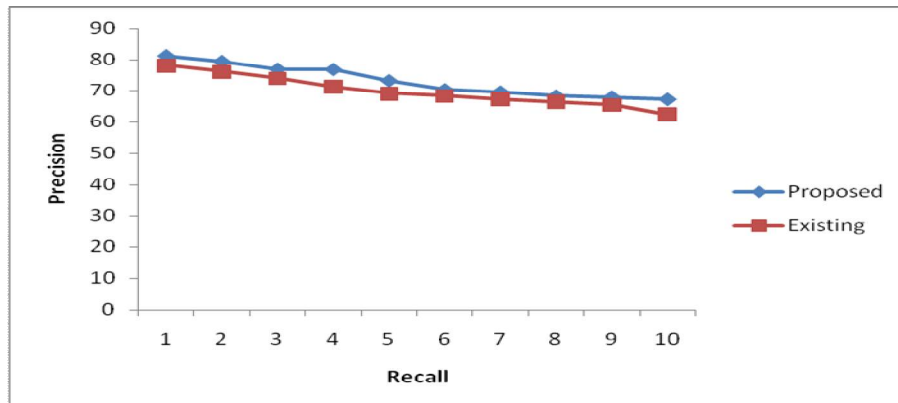


Fig.4. The precision Vs recall of the proposed low and higher moments of BDIP and BVLC features and existing low order moments of BDIP and BVLC.

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 normalized Euclidean distance. 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 is reported in Fig.2. The precision versus recall of the proposed low and higher order moments of BDIP and BVLC and existing [10] one is depicted in Fig.4. The average retrieval rates of proposed and existing system are 73.26% and 69.14. The obtained results confirm that the proposed method is superior then the existing one. It is believed that the high accuracy of the proposed system is attained because of including the both low and higher order moments of BDIP and BVLC.

IV. CONCLUSION

The proposed system presents a low and higher moments of BDIP and BVLC values instead of considering the low order moments only. The normalized Euclidean distance measure is used to measure the performance of the proposed system. The result of the proposed system is superior to existing one because of capturing the higher order moments of texture information. In future, the proposed system may be improved further to increase the accuracy. The proposed system is very useful in various domains like medicine, engineering, agriculture, etc.

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