International Journal of Advanced Research in Engineering Technology & Sciences

ISSN: 2349-2819

Email: editor@ijarets.org Volume-7, Issue-1 January- 2020 www.ijarets.org

A NOVEL APPROACH FOR CBIR USING STRUCTURAL CONNECTIONS AND LOCAL BINARY PATTERN

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ABSTRACT:

Content Based image retrieval (CBIR) also known as the query by the image content i.e QBIC. Content Based image retrieval basically a system in which we input a query image and after the some preprocessing work we retrieved the matching images. Content-based means that the search analysis the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image. The term content in this context refers to colors shapes, textures, or any other information that can be derived from the image itself. The quality of response is heavily dependent on the choice of the approach used to generate vectors and similarity measure for comparison of features. In this paper we proposed an algorithm which incorporates the advantages of various other algorithms to improve the accuracy and performance of retrieval. Color Histogram based matching accuracy can be improved by using CCV (Color Coherence Vector). The speed of retrieval is improved by considering approximate shape rather than the exact shape. Inaddition to this a combination of color and shape-based retrieval is also included to improve the accuracy of result.

The primitive features required to compute an image feature vector are color and holistic structure features. If spatial distribution is considered when extracting color features of an image along with the LBP, then the resultant features vector is considered to be high retrieval accuracy. Thus we used an approach, based on feature extraction by integrating the CH in the HSV space, The CCV and the LBP histogram, for CBIR.

Keywords: CBIR, CCV, HSV, LBP.

INTRODUCTION

Image Processing is one of the most explored research areas that is been defined under the specification of various associated processes. Image processing is having its importance and requirements in many application areas. These application areas include medical image processing, agricultural image processing, etc. The associated fields to the image processing further divided into several subareas so that the information processing is defined as the framework so that the image information processing will be done. The work is here defined to apply various information stages to process on data values and relative results will be obtained from the work.

The image processing is here defined under the specification of image level analysis applied on the information process also described with associated process stages and each process stage itself defines an application area. This process stages includes the recognition system, feature generation, segmentation, classification etc. In recent years, image processing comes up with better functionality and with its integration to many other sub domains such as video system processing, animated image processing will be done in effective and relative way.

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This broad process area is defined along with the specification of various sub stages or the sub processes. Some of these sub processes associated to the system are described under

- Image Information Classification
- Object Detection
- Feature Extraction
- Image Enhancement

The representation of image is described with data processing form of image processing along with various data processing toolkits. These integrated toolkits includes neural network, genetics, differential equation based processing, Self-Organizing Map etc.

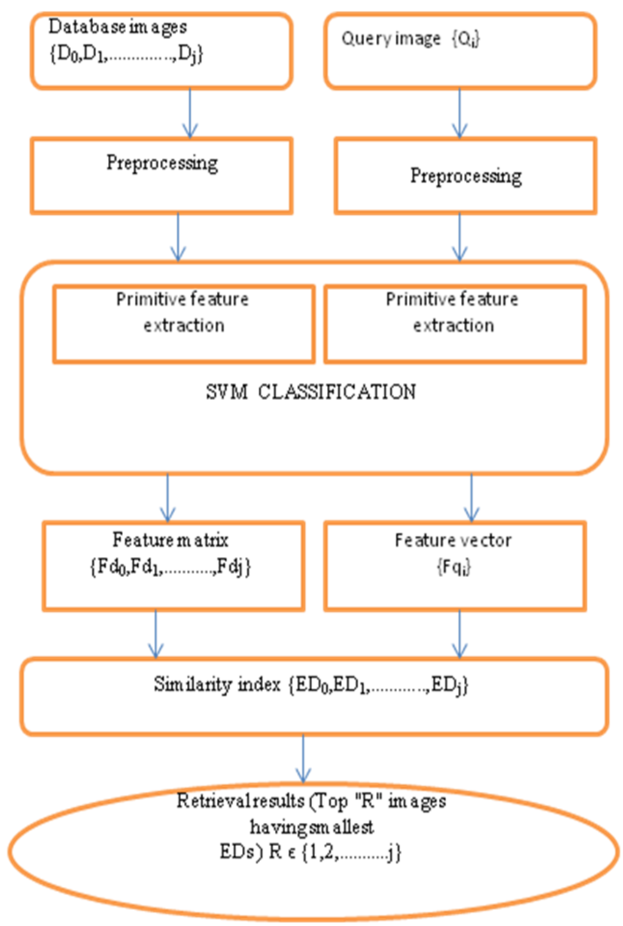


Fig.1.Architecture of CBIR

The main concern in CBIR is the need for an effective and efficient feature extraction method for image representation, which conforms to the subjective human perception. This subjectivity transpires at all semantic levels while analyzing images because different users in the same situation or the same user in different circumstances may investigate or classify the same image differently. This inconsistency between image retrieval, by using low-level image features and high-level human semantics, is termed as the “semantic gap” [1-3].

LITERATURE REVIEW

Zhang et al. [4] extracted low-level features by using a 3-dimensional dominant color vector (H, S. and V) and a 24-dimensional Gabor feature vector. This paper proposed a new approach for digital image retrieval by using intermediate semantic features and multi-step search. This approach suggests a new direction from the existing image retrieval approaches, which works with high- or low-level semantic features. Unlike the existing systems in literature, the proposed system was capable of capturing regional and global features using semantic and low-level features. The results suggested that this system had notable advantages and is more promising compared with the existing techniques. In addition, it has a powerful SQL-based retrieval interface to support semantic and low-level retrieval.

Li et al. [5] represented the image by computing the HSV histogram as a color feature, pyramid wavelet transforms (PWT) by using the Haar wavelet as a texture feature (in YCbCr color space), and an edge histogram as a shape feature (in YCbCr color space). This study focused on solving the small sample size problem and improving the capability of a kernel machine compared to traditional SVM-based RFs.

Hong et al. [6] used visual features, such as CM and wavelet moments, for computing feature vectors and comparing the query image and database images by using Mahala Nobis distance.
Gosselin and Cord [7] exploited the color and texture information using the L*a*b* space and Gabor filters, respectively. Tests were conducted on the generalist COREL photo database containing 50,000 pictures. This method merged all the semantic information based on binary annotations provided by users during retrieval sessions. Therefore, the kernel matrix framework, which offers acceptable properties of matrices and efficient combinations with kernel-based techniques for image retrieval classifiers, was adopted.

Rui et al. [8] used the CH and CM and co-occurrence matrix for the COREL test set in an interactive approach using relevance feedback. Similarity matrix used for CH vectors was CH intersection and that for CM was Euclidean distance (ED). The authors also used the MESL test set for which the visual features used are the CH, CM, Tamura, co-occurrence matrix, Fourier descriptors, and Chamfer shape descriptors. Chamfer matching was used for Chamfer shape representation, whereas weighted ED was used for the remaining features.

Broilo and Natale [9] presented the feature vector comprising of 32 CH bins, 9 CMs, 16 edge histograms and wavelet texture energy values. The HVS color space was used to extract the CM, and the RB space was used for the CH. Weighted ED was used for similarity matching. The image retrieval problem was formulated as an optimization problem and was solved by using particle swarm optimization.

Bian and Tao [10] used the CH in the HSV color space, a 128-dimensional CCV in the L*a*b* space, and a 9dimensional CM feature in the LUV color space. The texture and shape features were extracted using a wavelet transform and the edge directional histogram, respectively.

PROPOSED WORK

The primitive features required to compute an image feature vector are color and holistic structure features. If spatial distribution is considered when extracting color features of an image along with the LBP, then the resultant feature vector is considered to give high retrieval accuracy. Thus, we used an approach, based on feature extraction by integrating the CH in the HSV space, the CCV, and the LBP histogram, for CBIR.

A. Primitive Features

In case of huge image data sets, CHs proved to be efficient and robust features for image indexing if the color pattern was unique compared with the remaining data sets. The CH [8,11,12] of an image portrays the frequency of each color level present in the image in the pixel domain. An image is quantized into sets of colors called bins to extract a CH. The CH is then computed by counting the frequency or the number of times each quantized color level is present in the image. The CH is robust for translation and rotation, and tolerant to changes in the viewing angle, scale, and occlusion.

The CCV includes the information about the spatial location of colors in an image [13]. The CCV is constructed by first blurring the image and then quantizing the color space such that it only contains n distinct colors. The CH of the image is then computed. Each histogram bin is then classified into two categories: coherent and incoherent. The pixel value is considered coherent when it belongs to a large, uniformly colored region, or it is considered to be incoherent. All the coherent and incoherent pixels of each bin are then counted and stored together in a vector. Thus, this forms a histogram-based CCV feature vector consisting counts of coherent and incoherent pixels of all the bins. The CCV corresponds to this classification for each color in the image. The dimensions of the CCV feature vector depend on the number of bins chosen when creating the histogram.color level of the centre-most pixel is represented byb . For each block in the image, the center-most pixel level is compared with every neighboring pixel value. When the color level of the neighboring pixel is greater than or equal to the center-most pixel value, it is coded as 1; otherwise it is coded as 0.

The LBP value of the block is calculated as shown in Equation (1).

$$V_{LBP} = \sum_{x=0}^{7} fn(\, b_x - b) * 2^x \qquad (1)$$

Where, the function “f(n)”for the comparison is expressed as shown in Equation (2)

$$f(n) = \begin{cases} 1, & y \geq 0 \\ 0, & x < 0 \end{cases} \qquad (2)$$

b0	b1	b2
b7	b	b3
b6	b5	b4

Fig.2. Pixel Block of size 3 × 3.

The LBP levels fall between 0 and 255. The LBP histogram is computed as shown in Equation (3).

$H_{LBP} = \{h_0, h_1, \ldots\ldots, h_{255}\}$ (3)

Here hi, ($0 \leq i \leq 255$) represents the frequency of an LBP level " i " extracted from the complete image pixels

Proposed Algorithm

- Load the database image *DnDn*={*Di*| i=1,2,.....1000}
- Transform an RGB image into the HSV color space.
- Compute the feature vector *Fi*={*fh*,*fl*,*fc*} where, *fh* is the HSV histogram, *fl* is the LBP histogram, and *fc* is theCCV of the databaseimage.
- Compute the feature matrix*FD* of all database images where *FD* ={*F*1,*F*2,..........,*F*1000}.
- Save FD.
- Classification using SVM.
- Input a query image Qi.
- Compute the feature vector *Fi*={*fh*,*fl*,*fc*} where, *fh* is the HSV histogram, *fl* is the LBP histogram, and *fc* is the CCV of the query image.
- Calculate ED.
- Where, xp and yp are the l-dimensional feature vectors of the database and query images, respectively.
- Compute ED for all the database images and retrieve the similar top 20 images having least ED

We implemented the retrieval system using different feature extraction methods (Table 1) and compared the results to evaluate the performance of our proposed algorithm represented by proposed method (PM)

Table 1. Details of the Methods Implemented (Numbers in Curly Braces Show Feature Length).

Name of the Method	Color features	Texture features	Shape Features	Structure Features
M-1	HSV {24}	LBP{16}		CCV{48}
PM	HSV {16}	LBP{8}		CCV{24}

We developed a new approach (PM) to improve the retrieval performance, which integrates the global basic color feature (CH) and the features exploring spatial relationships (LBP and CCV). This approach amalgamates many orientations and maintains comparatively low feature size.

EXPERIMENTATION

Experiments were conducted using a standard database [14] of 1000 images. This database is a collection of colored images from 10 different categories such as African people, buildings, beaches, buses, dinosaurs, elephants, roses, horses, snowy mountains, and food plates. The image features were extracted using different primitive feature extraction methods, as shown in Table 1. In addition, similar features were extracted from the query and stored images. The distance between the query image and database images was computed, by calculating the ED or L-2 distance, and arranged in an ascending order array. The top 20 similar images were displayed and evaluated. The performance parameter i.e. precision is evaluated using Equation (3)

Precision=R/T (3)

Where, R is the number of relevant images retrieved and T is the total number of images retrieved.

RESULTS

It was observed that M-1 (the combination of color structure descriptor [CSD] and edge histogram descriptor [EHD] for feature extraction) proves to be useful for the retrieval of more semantically significant images.

The retrieval results vary according to the method used and the image type. For example, EHD and the integrated method show prominent results in the presence of a distinct object in the background, such as buses or flowers. CSD method is outperformed when an image comprises principal colors. The combined approach was found to be better for images with principal colors and distinct objects. Furthermore, the approach proved to work best when the database contained images, such as dinosaurs, which have similar texture, color, and background. The CSD and integrated method of color and texture work better in "multiple object images," which contain many objects such as horse, pony, fencing, and green field. However, the three approaches perform poorly when retrieving images from the food category.

Table 2 Comparision of Methods

	Precision (%)	
Image category	Methods Implemented	
	M	PM
Building	63	61
Bus	68	95
Food plates	70	61
African People	90	92
Beach	47	63
Dinosaurs	95	98
Elephants	64	57
Flowers	88	95
Snowy mountains	56	58
Horses	85	93
Average Performance	**72.6**	**77.3**

Our approach (PM), which integrates the global basic color feature (CH) and features exploring the spatial relationship (LBP and CCV), delivered improved results. This approach outperforms the existing methodsof CBIR because of a significant improvement in the image retrieval of snowy mountains (56%), buildings (63%), African people (68%), food plates (70%), and dinosaurs (100%). Our approach demonstrated comparable retrieval accuracy for other image categories as well. The retrieval results for a query image from the African category are shown in Fig. 3 and Fig.4. It is marked that along with good retrieval accuracy, the positive images were obtained at a lower rank, i.e. fast retrieval is achieved by using our proposed approach.

In the method M, we have used 88 features which were less when contrasted with PM (48 features). By this experimentation it is also observed that less computational time and better accuracy can be obtained by using optimum number of features as shown in Table 2.

Fig.3. Retrieval Results for the Images of the 'Africans' by using the Proposed Method-1(Rank 1 to 20)

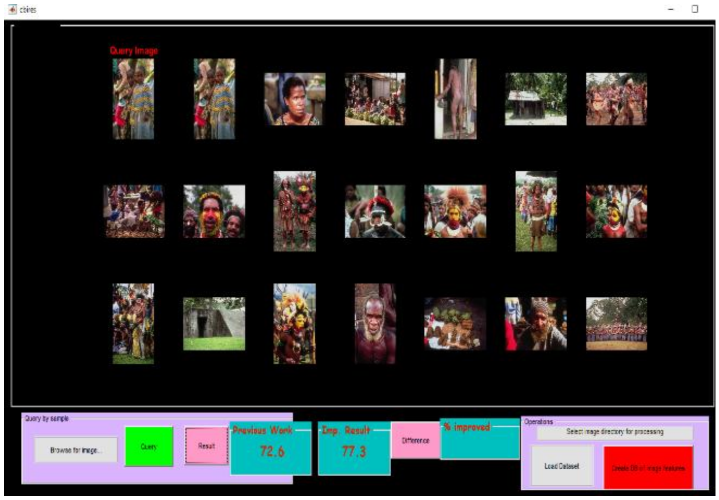


Fig.4. Category wise result using Bar Graph total 10 Categories.

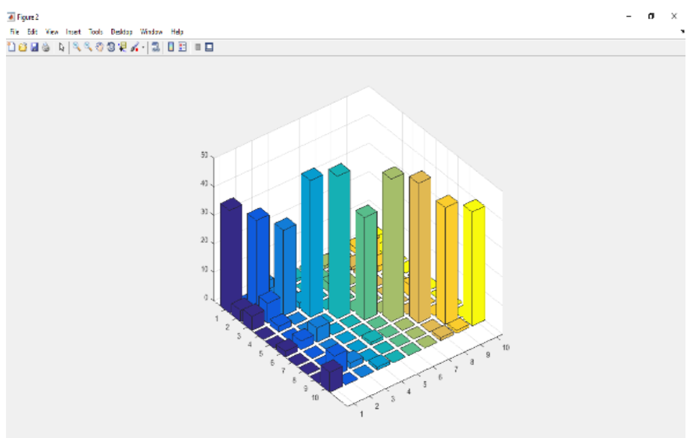
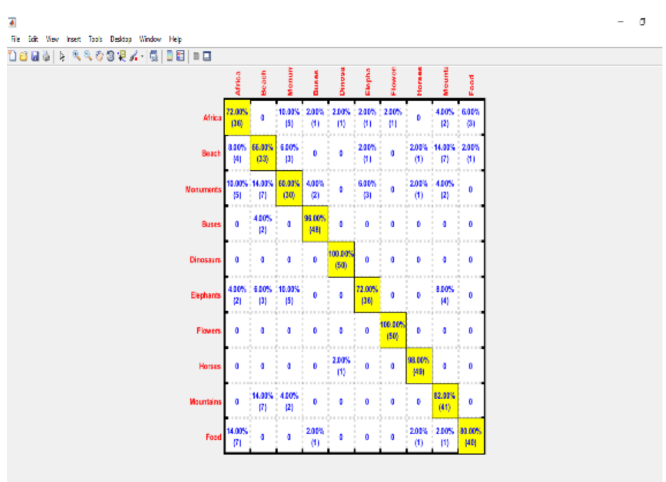


Fig.4. Confusion Matrix for the Result Retrieved from Different categories.



CONCLUSION & FUTURE SCOPE

The main contribution of this work is the use of global color features and the features exploring the spatial relationship to amalgamate many orientations, textures, and color distributions among the images. Other improvements, such as minimizing the feature vector size and quickening the process using SVM classifier is proposed and discussed. Using a large number of bins was not necessary when extracting the histograms; rather it was observed that a better retrieval accuracy was obtained using 24 bins for HSV histogram and 8 bins for the LBP histogram. In Future we can work on Low contrast images Dataset and improve results according to the Dataset.

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