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Content Based Image Retrieval Using Boosted Local Extrema Co-occurrence Pattern

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Abstract:
This paper presents the Boosted Local Extrema Co-occurrence Pattern (BLECoP) which focuses more on the local structures by enhancing the local extrema pattern. The proposed method can effectively combine with structural texture, GLCM and HSV color space. BLECoP tested over the standard Corel databases, which is extensively used in the Content-Based Image Retrieval(CBIR) domain. Experimental results show that BLECoP outperforms other state-of-the-art descriptors that are recently proposed in CBIR research using color and texture features. The performance of the proposed descriptor's image retrieval results is achieved best accuracy rates, that are remarkable on heterogeneous(non-flat) images. Further BLECoP can be effectively used to retrieve more accurate images in a very large scale image databases.

Keywords: *Boosted local extrema pattern, Gray level Co-occurrence matrix, HSV color space, Image retrieval, Local binary pattern.*

I. INRODUCTION

Content Based Image Retrieval (CBIR) application is majorly focused on low level features like texture, color, spatial layout and object shapes that are extracted from images to represent the feature vector. During the image retrieval stage, these low level features are matched with the database feature vector by using distance measures like Euclidean, Manhattan, Canberra, and Chi-square, etc. Depends on the requirements, either existing distance measures are used or some researchers are introduced to their own distance measure, Structure Element Histogram (SEH) [1], Color Difference Histogram (CDH) [2] and Angle Structure Descriptor (ASD) [3] to perform image retrieval task. In CBIR application, image retrieval and feature extraction time and play vital roles in the analysis of an image retrieval system. In general, the real-time system is always preferred to choose an application which takes less computation cost with best accurate image matches.

II. RELATED WORK

Haralick[4] introduced Gray Level Co-occurrence Matrix (GLCM), is the probability distribution of intensity values corresponds to the neighbor pixel in a particular direction (θ). Texton co-occurrence matrix (TCM) [5] enlighten the spatial correlation using a set of four textons represent as texture along with the color feature. Whereas Micro Structure Descriptor (MSD) [6] integrates edge orientation similarity, color layout information, and texture as

November-December 2019
ISSN: 0193-4120 Page No. 3538 - 3548

image features. Multi Texton histogram (MTH) [7] combines texture and color descriptors with co-occurrence matrix as a single histogram to represent an image feature.

The human eye perceives millions of reflected colors, but cannot recognize all those colors in the same manner. Taking this as an advantage, color quantization considers account for many image processing and computer vision applications, otherwise, the cost of computing power is too high to manipulate individual color channels in any color space. Color quantization is broadly classified into two categories i) uniform and ii) non-uniformquantization. Hue, Saturation, Value (HSV) L*a*b, and YCbCr color spaces are using uniform quantization whereas RGB color space uses non-uniform color space.

III. PROPOSED METHODOLOGY

HSV Color space and Color Quantization

HSV color space is too close to mimic human eye color perception, because of this advantage [8], [9], [10] choose uniform color space and perform color quantization instead of choosing non-uniform RGB color quantization. Nearest Neighbor Difference (NND) operator calculates an absolute difference of given 3x3 neighborhood operation with its centered pixel value for the given coordinate.

$$\text{NND}(p) = \sum_{P-0}^{P-1} |g_P - g_c| K \qquad (1)$$

Equation (1) explains NND edge map extraction from the intensity image, where p is a neighbor pixel of 3x3 local patch, g_c is the center pixel and g_p neighboring pixels and K is the constant value range from 1 to n.

Local Binary Pattern (LBP) operator widely used in an efficient texture image classification, which is introduced by Ojala [11], the spatial relationship between each center pixel and its local neighbor pixel is represented as binary form. Murala [12] introduced Local Extrema Pattern (LEP) to extract 3x3 pattern to find extrema of each center pixel (Pc) along with four directions (0°, 45°, 90°, and 135°) on the Value channel of HSV color space. LEP operator calculated by (2). Fig.1 (a) shows the example calculation of sample 3x3 window of Local Binary pattern, Fig.1 (b) shows the example calculation of sample 3x3 window of Local Extrema Pattern and in Fig.1(c) shows the example calculation of sample 3x3 window of proposed Boosted Local Extrema Pattern.

$$\text{LEP}(P_c) = \sum_{\beta} 2^{\left(\frac{\beta}{45}\right)} \times P'_c(\beta); \quad \forall \beta = 0^\circ, 45^\circ, 90^\circ, 135^\circ \qquad (2)$$

Final LEP feature has a value, ranges from 0 to 15, and applies GLCM on the LEP feature to obtain co-occurrence count of corresponding pixel pair which appeared in the intensity channel, this generates a 16x16 matrix to define the spatial relationship as introduced by [13]. Then convert 16x16 GLCM matrix into a single vector, concatenate this feature with 72 bin Hue quantization and 20 bin Saturation quantization to represent as single BLECoP feature descriptor. The proposed BLECoP image retrieval framework is shown in Fig.2

TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 3538 - 3548

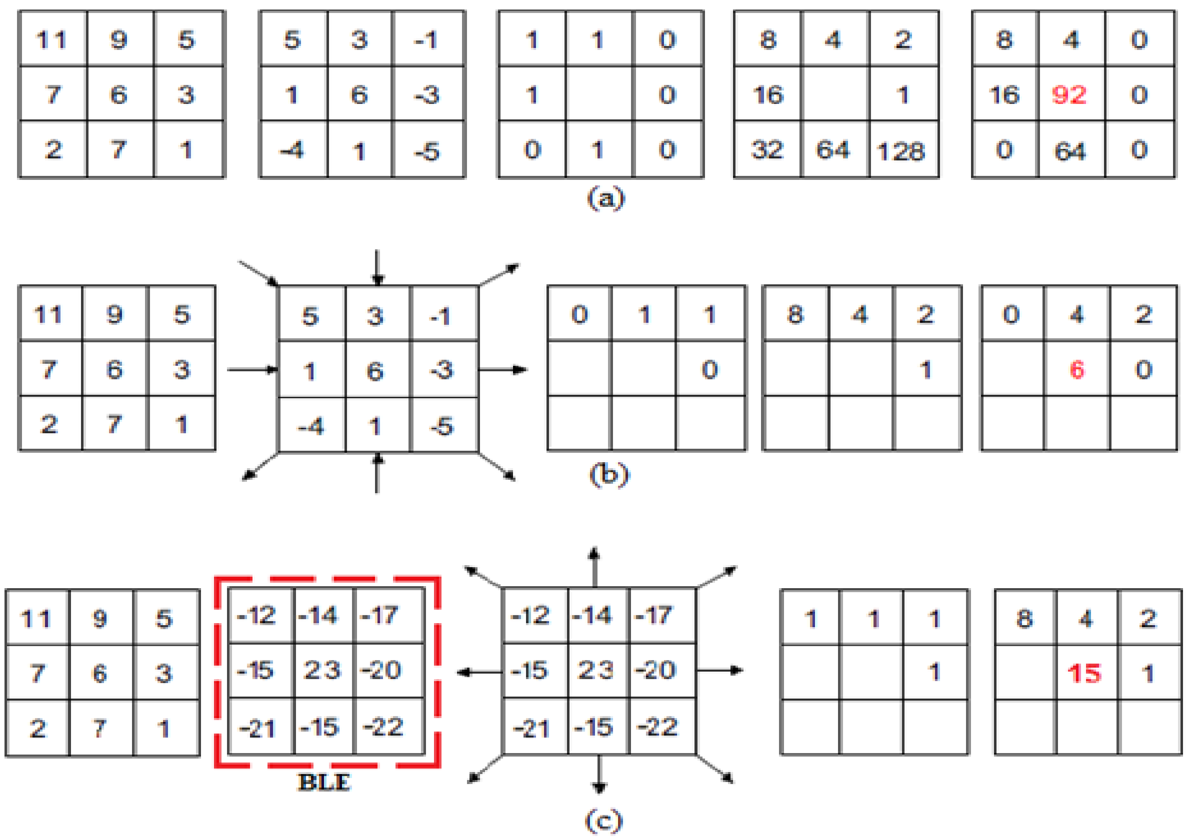

Fig.1 Example calculation of (a) LBP (b) LEP and (c) BLEP

The proposed Boosted Local Extrema Co-occurrence Pattern algorithm as follows,

.Input: HSV image(IMG)

Quantization bin(H) value for Hue cha*nnel*

Quantization bin(S) value for Saturation cha*nnel*

Output: BLECoP Descriptor

Initial: BLECoP ⟵ [ ]

begin

[height, width, Dim] ⟵size(IMG)

Q_Hue⟵ HIST (floor (reshape (H,height*width,1),Q_bin(H)))

Q_Saturation⟵ HIST (floor (reshape (S,height*width,1),Q_bin(S)))

BLE⟵ NND (V*255)

BECoP⟵ GLCM (LEP (BLE))

BLECoP⟵ [Q_Hue, Q_Saturation, BECoP]

return(BLECoP)

end

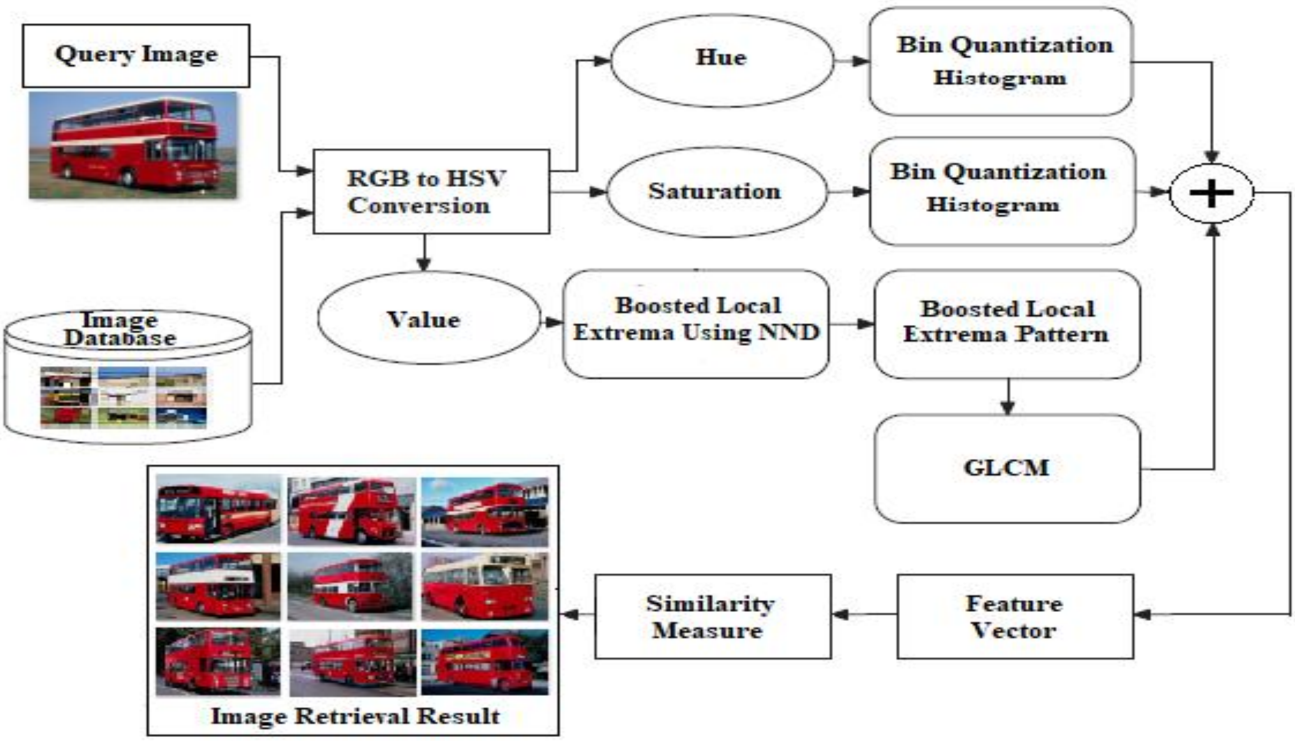

Fig.2 Proposed BLECoP image retrieval framework

.**Fig.3** Sample images from Corel 1k database

November-December 2019
ISSN: 0193-4120 Page No. 3538 - 3548

IV. RESULT AND DISCUSSION

V. COREL 1 K DATASET:

Corel 1k [3], [13] contains 10 categories of 1000 images from natural scenery such as Africans, beaches, buildings, buses, dinosaur, elephant, flower, horse, mountains, and food. Each image in the Corel 1k databaseis either 256x384 or 384x256 size, for each sample randomly chosen three images per category shown in Fig.3.

Corel 10k and Corel 5k Dataset:

Corel 10k [3], [13] dataset contains 100 categories of 100 images in each such as beach, fireworks, stained glass, bird, tiger, fox, bear, jewelry, sunset, pills, tree, wave, fish, door, etc. Each image in the Corel 10k database is either 128x192 or 192x128 size. Corel 5k [3], [13] is a subset of the Corel 10k dataset. All three datasets are used in the extensive experiment of the image retrieval task to measure the retrieval accuracy.

Distance Measure: As demonstrated in DRLBP [14] Chi-Square distance measure is used to find the similarity between the query image with the database images, less similarity value has a more similar/relevant image. To evaluate the efficiency of the BLECoP method, we used [13] precision (3), recall (4) and F-measures (4) to assess the robustness and accuracy of retrieval system.

$$\text{Precision} = \frac{\text{Relevant Image Retrieved}}{\text{Total Number of Images Retrieved}} \quad (3)$$

$$\text{Recall} = \frac{\text{Relevant Image Retrieved}}{\text{Total Number of Relevant Images in Database}} \quad (4)$$

$$\text{F Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Table-I shows the average retrieval accuracy rate for Corel 1k, Corel 5k, and Corel 10k databases. It’s seen in Table-I, the proposed BLECoP method is at the top of the list (highlighted in bold text) compared with LEPINV + Color hist, Joint LEP + Color hist, TCM, MTH, MSD, LECoP existing methods. Fig.4 shows building, bus and horse categories of top 10 images retrieved by using LECoP [13] and BLECoP descriptor. All oddrows in the image retrieval column shown the top 10 retrieved images by using the proposed method whereas all even rows shown the top 10 retrieved images using the LECoP method. Non-relevance images are highlighted in the red-colored box to understand the image retrieval task for better observation. On top of each image in Fig.4, the similarity value of the retrieved image displayed as a caption.

In the building category, we inputted "200.jpg" as a query image to test the retrieval application Fig.4 (a). The proposed method retrieved 10 images as relevant to the query image, LECoP retrieved only 6 images as relevant images. In the bus category, we inputted "307.jpg" as query image to test the retrieval system Fig.4 (b), the proposed BLECoP

November-December 2019
ISSN: 0193-4120 Page No. 3538 - 3548

descriptor retrieved 10 images as relevant images, whereas LECoP retrieved 9 images. Horse category we inputted "754.jpg" as a query image Fig.4 (c), our proposed method retrieved 10 images are related to the given query image, but the LECoP method retrieved only 7 images as relevant to the query image.

Table-I: The Average retrieval precision and recall of proposed BLECoP on Corel Databases

Method	Corel 1k		Corel 5k		Corel 10k	
	Precision	Recall	Precision	Recall	Precision	Recall
LEPINV + Color hist	72.47	38.56	50.41	20.44	41.28	15.74
Joint LEP + Color hist	75.13	37.90	53.89	22.85	44.14	16.77
TCM	58.94	26.64	36.95	18.36	26.23	14.53
MTH	69.42	32.18	49.98	20.42	40.87	17.26
MSD	72.18	31.42	55.92	23.63	45.62	19.64
LECoP	78.58	51.87	62.96	31.16	52.50	**23.29**
BLECoP(PM)	**83.34**	**53.64**	**64.79**	**33.12**	**53.75**	22.85

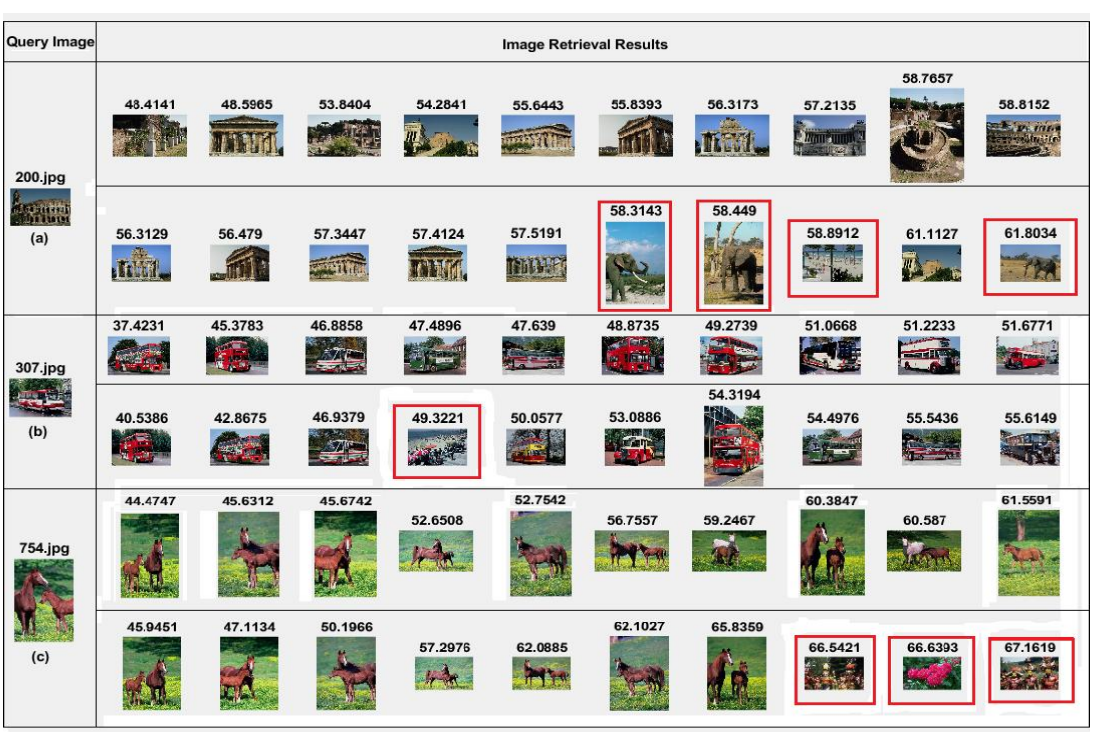

Fig.4 Top 10 image retrieval results for the query image of (a) buildings, (b) buses and (c) horse categories

TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 3538 - 3548

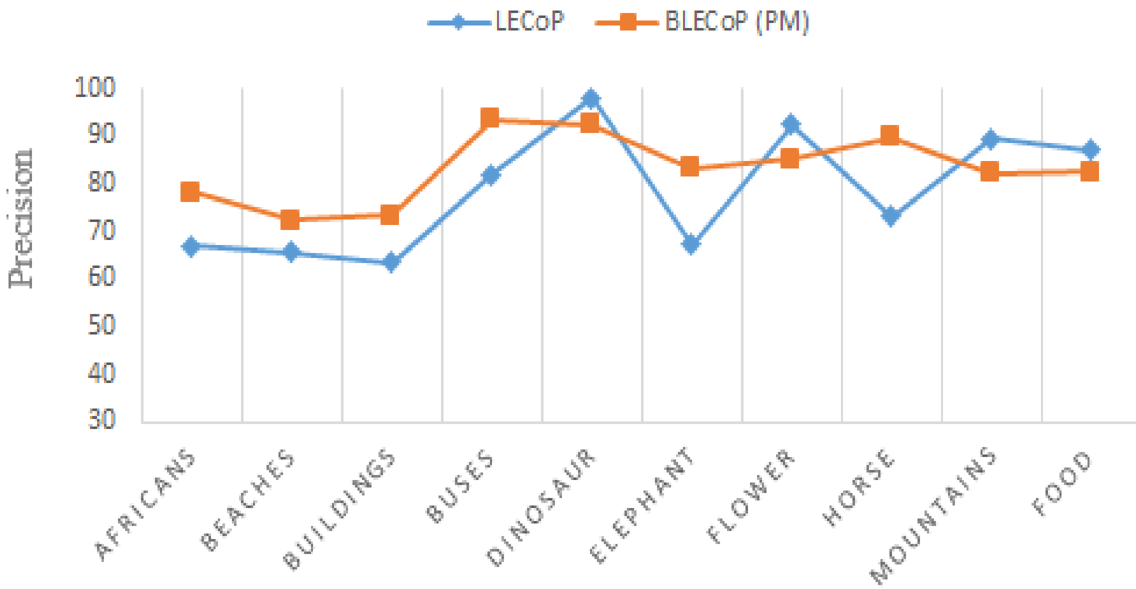

Fig.5 Precision and Corel 1K dataset image categories

V.CONCLUSION

In this work, the Boosted Local Extrema Co-occurrence Pattern is proposed to perform the image retrieval application using color and texture features. An empirical result that is presented in section IV shows that the proposed BLECoP descriptor is preferred, since its improved performance of image retrieval accuracy, precision and recall, when compared with existing method LEPINV + Color hist, Joint LEP + Color hist, TCM, MTH, MSD, LECoP. In Fig.5 LECoP outperform the proposed BLECoP descriptor slightly for the dinosaur, flower, mountains and food categories of Corel 1k database, because all those four categories are flat images with fewer texture details. In the future, we will work on flat image categories as well to improve image retrieval accuracy. Overall the proposed method outperforms LEPINV + Color hist, Joint LEP + Color hist, TCM, MTH, MSD, LECoP by 10.87%, 8.21% 24.4% , 13.92, 11.16% and 4.76 % respectively, in terms of its average retrieval accuracy rate.

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