Content Based Image Retrieval Using 3D Center Symmetric Local Binary Co-occurrence Pattern

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Ankita Wadhera
Electronics and Communication Engineering
Jaypee Institute of Information and Technology
Noida, India
ankita.wadhera@gmail.com

Megha Agarwal
Electronics and Communication Engineering
Jaypee Institute of Information and Technology
Noida, India
megha.agarwal@jiit.ac.in

***Abstract*—This paper presents a novel algorithm three dimensional center symmetric local binary co-occurrence pattern (3DC-SLBCoP) for retrieval of images. Standard local binary pattern and its forms uses 2D plane of the image. On the other hand, proposed method leads to 3D volume by extracting Gaussian filtered images using multiresolution Gaussian filter banks and computes the relationship between center pixel and its neighbors in five selected directions. Center symmetric local binary pattern (CSLBP) image is formed by encoding the relationship between focus pixel and its center symmetric neighboring pixels. Thus, gray level co-occurrence matrix (GLCM) of the CSLBP map in four directions leads to the formation of feature vector. Experiments are performed and results are analyzed on benchmark datasets. Analyzed retrieval results clearly better than the other well known methods by considering average retrieval precision and average retrieval rate as evaluation measures.**

***Index Terms*—Texture, image retrieval, center symmetric local binary pattern, gray level co-occurrence matrix.**

I. Introduction

In today's era of digital world, massive amount of data is available in internet. These data are expressed as digital images. It becomes very challenging to extract relevant data from this huge amount of digital data in the optimum time. So, this demands an expert content baaed image retrieval (CBIR) system, which retrieves images according to the user's interest [1], [2]. CBIR systems utilize feature extraction technique to retrieve relevant results by comparing the features of query image and dataset of images. A detailed introduction of CBIR is presented in [3], [4]. Local binary pattern (LBP) is a useful technique in the area of image retrieval applications [5], [6]. Instead of all the neighborhood pixels, center symmetric local binary pattern (CSLBP) utilizes only interest region to provide reduced directional pattern [7]. To improve accuracy, author takes gray level co-occurrence matrix (GLCM) of CSLBP for feature vector computation [8]. There is also an extension of LBP from two dimensional to three dimensional in facial expression recognition [9]. SOBEL LBP [10] explores sobel operators to obtain two filtered images and the feature set is formed by calculating the frequency distribution of pixels of both images. Frequency decoded local binary pattern (FDLBP), the combination of high and low frequency pattern has been proposed for face retrieval [11]. The variants based on LBP in face application are surveyed in [12]. Local diagonal extrema pattern (LDEP) expressed the relation amid neighbors in the diagonal in the form of local diagonal extremas [13]. Local neighborhood difference pattern (LNDP) is observed in [14] and it is used in texture image retrieval by combining it with LBP. Two most adjoining pixels along with neighborhood pixels is employed in Local tri-directional pattern (LTriDP) [15]. Further, second order derivatives is explained in local tetra pattern (LTrP) [16]. Further, Local maximum edge binary pattern (LMEBP) extracts features by incorporating differences between the center pixel and surrounding neighborhood pixels to obtain maximum edges [17]. Local ternary co-occurrence pattern (LTCoP) proved to be very useful for medical images [18]. Spherical symmetric 3D local ternary pattern (SS-3D-LTP) included gaussian filter bank to extract multiscale directions and extracts information in five distinct directions [19]. In [20], the author proposed characterize color texture and its robustness against rotation and scaling (LEP-INV). 3D local ternary co-occcurrence pattern (3D-LTCoP) explores the ternary pattern for 3x3 and 5x5 neighborhood pixels. It includes gaussian filter bank to extract multiscale information and extracts information in five distinct directions [21].

A center symmetric local binary co-occurrence pattern in three dimensional (3DCSLBCoP) is proposed for image retrieval application. Main aspects of the proposed feature are:

- Gaussian filter banks efficiently obtains multiscale information from the images.
- CSLBP and GLCM is used to obtained co-occurrence of local patterns.
- The length of feature vector is less as compared to other techniques.

The rest of the paper is arranged in the following manner: Variants of Local binary patterns and GLCM calculation is described in section 2. The methodology of proposed method

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and its implementation is explained in section 3 . Section 4 represents analyzed retrieval results . Finally Section 5 brings conclusion of the paper.

II. Local patterns and GLCM

A. Local binary pattern(LBP)

Ojala et al. incorporate LBP [5], [6] for extracting the local information from the pixels. In this technique, each pixel is considered as center pixel and it is subtracted from surrounding pixels. A binary number that are multiplied by some weights is allocated to each surrounding pixel and the summation of product leads to a pattern value. For a 3x3 neighborhood , LBP value is measured as

$$LBP_{n,d}(x,y) = \sum_{i=0}^{n-1} 2^i \times T_1(I_i - I_c) \tag{1}$$

where n and d indicates number of surrounding pixel around the center and distance of the neighborhood pixels from the center pixel respectively.

$$T_1(x) = \begin{cases} 1 & x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

The histogram (256 bins) is computed by calculating the LBP value for each pixel in the original image . Fig. 1 illustrates LBP calculation for a 3x3 sample window.

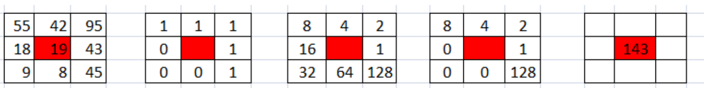

Fig. 1. example of local binary pattern (LBP) calculation for a sample window

B. Center symmetric local Binary Pattern (CSLBP)

In center symmetric local binary pattern (CSLBP), pattern map is based on difference between center symmetric pixels. The center symmetric pixels are subtracted for every center pixel and based on that each center pixel is assigned a binary number which are multiplied by some weights. The summation of product leads to a pattern value, same as LBP. Mathematically CSLBP is defined as:

$$CSLBP_{i,d,t}(x,y) = \sum_{i=0}^{(n/2)-1} 2^i \times T_2(I_i - I_{i+(n/2)}) \tag{2}$$

where t represents threshold parameter, n and d indicates nunber of surrounding pixel around the center and distance of the neighborhood pixels from the center pixel respectively. An example of CSLBP for a 3x3 neighborhood is shown in Fig. 2.

$$T_2(x) = \begin{cases} 1 & x \geq t \\ 0, & \text{otherwise} \end{cases}$$

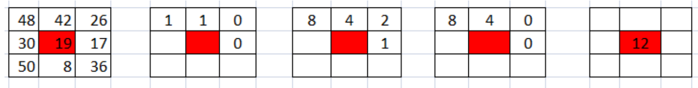

Fig. 2. Example of computation of center symmetric local binary pattern

C. Gray level co-occurrence matrix (GLCM)

It distinguishes the texture of original image and extracts features by calculating the mutual occurrence of pairs of pixel for a distinct value and in a specified direction. GLCM computation for an image is shown in Fig. 3, where the two matrices are original image matrix and glcm matrix respectively. In the gray level co-occurrence matrix shown in Fig. 3, pixel value of 2 is occurred at a position of (0,1). This means the original matrix has 2 pixel pair of (0,1).

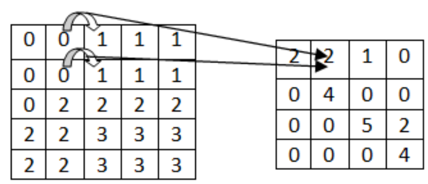

Fig. 3. Example of computation of gray level co-occurrence matrix.

III. Proposed 3DCSLBCoP method

Fig. 4 depicted the proposed 3D based approach. To find the retrieval results, similarity measure is computed of the query image and database images for the proposed system and arrange them in terms of decreasing order of similarity. The detail description of block diagram is mentioned in the following sections. Firstly, Gaussian filters are used to obtain multiscale information. Fig. 5 shows three output of gaussian filtering considered as three planes of the cube. All the images in the dataset are filtered through gaussian filters to form 3D image as shown in Fig. 6 and taking the slice of the volume in five separate directions appeared in Fig. 7. Center symmetric local Binary Pattern (CSLBP) is obtained for the center pixel in each direction and finally, the gray level co-occurrence matrix (GLCM) for each image for unit radius at four distinct angle (0^o, 45^o, 90^o, 135^o) leads to the formation of feature vector. This leads to four matrices and the combination of these four matrices has been transformed into vectors. Thus the final feature vector is computed by concatenating the vector into single feature vector. As, there are five direction for each image, so this method exhibits the length of feature vector of 16x16x4x5.

A. Similarity measurement

The feature matching is done with a similarity metric on the features extracted from query image and database images. To

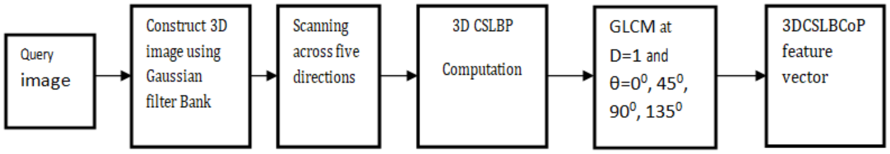

Fig. 4. Proposed algorithm (3DCSLBCoP) framework

15	20	42
33	36	27
56	31	20

55	42	95
18	19	43
9	8	45

25	28	23
10	25	31
19	23	56

Fig. 5. Three output of Gaussian filters considered as three planes of the cube.

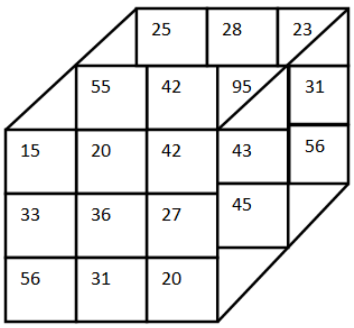

Fig. 6. 3D image formed by Gaussian filtering.

55	42	95
18	19	43
9	8	45

20	42	28
36	19	25
31	8	23

42	95	23
36	19	25
59	9	19

33	18	10
36	19	25
27	43	31

15	55	25
36	19	25
20	45	56

Fig. 7. planes after slicing cube in five directions.

measure the similarity metric between the query images and the database images , we use d1 distance metric [21].

$$d_1(q, ds_i) = \sum_{k=1}^{N} \frac{\mid D_{ds_{ik}} - D_{q_k} \mid}{1 + D_{ds_{ik}} + D_{qk}} \quad (3)$$

where, D_q and D_{ds_i} indicate query image's feature vector and feature vector of i^{th} image in the dataset. N is the feature vector length. In D_{ds_i} , $D_{ds_{ik}}$ is the k^{th} element of feature,$1 \leq i \leq \mid ds \mid$. The total images in the dataset is $\mid ds \mid$.

B. Performance metric

In our experiments, every image in the database is treated as query image. For testing the performance of the system, precision and recall are used as evaluation measure. For a query image, Precision P_Q is defined as,

$$P = \frac{No.\ of\ relevant\ images\ retrieved}{Total\ images\ retrieved} \quad (4)$$

The average retrieval precision (ARP) is defined as

$$ARP = \frac{1}{\mid DS \mid} \sum_{Q=1}^{|DS|} P_Q \quad (5)$$

where $\mid DS \mid$ denotes the total no. of images in the dataset. Recall RR is defined as

$$RR = \frac{No.\ of\ relevant\ images\ retrieved}{Total\ relevant\ images\ available\ in\ the\ database} \quad (6)$$

The average recall rate (ARR) is defined as

$$ARR = \frac{1}{\mid DS \mid} \sum_{Q=1}^{|DS|} RR_Q \quad (7)$$

IV. Analysis of Experimental Results

In order to prove the proficiency of proposed method, experiments are conducted on two benchmark databases and retrieval performance is evaluated. The retrieval results are compared with other techniques to prove its competency.

A. STex texture database

The Salzburg texture database consists of 128x128 size images [22]. It contains 476 classes and each class has 16 colored images thus, total of 7616 images in the database. For the top 16 images retrieved, the proposed method 3DCSLBCoP clearly performs better than other comparative techniques with an average retrieval precision (ARP) of 61%. and average retrieval rate (ARR) of 61%. Fig. 8 and Fig. 9 illustrates the performance of the analyzed results.

B. ESSEX face database

This database is taken from 392 subjects [23]. It has many variations like illumination, scale, different variation of expression and background consisting of total 7616 face images with approximately 20 images in each class. Thus, it is very challenging database. For the top 5 images retrieved, the proposed method 3DCSLBCoP gives an average retrieval precision (ARP) of 97.4% , superior to other techniques. Fig. 10 and Fig. 11 illustrates the performance of the analyzed results.

V. Conclusion

We proposed a novel 3DCSLBCoP technique for retrieval of images. This method efficiently captured directional information of images. CSLBP is used to obtain local information and GLCM is obtained from CSLBP map using co-occurrence of pixel intensities. As compared to histogram, GLCM is more vigorous to extract the frequency information. Finally results are examined on two databases. The proposed method proves its effectiveness while comparing the performance with other advanced techniques.

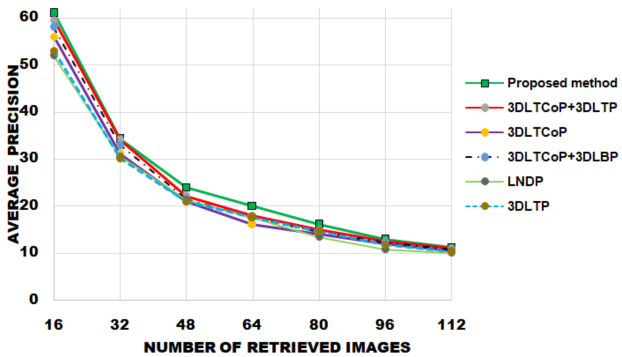

Fig. 8. ARP for STex database

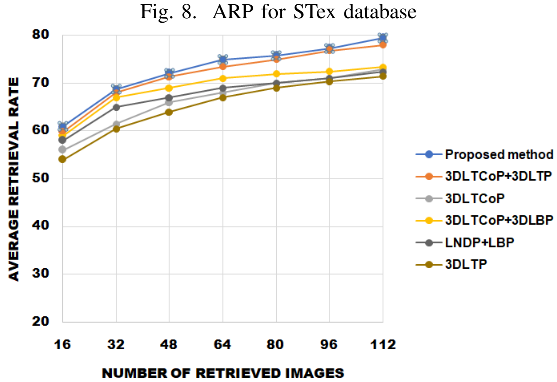

Fig. 9. ARR for STex database

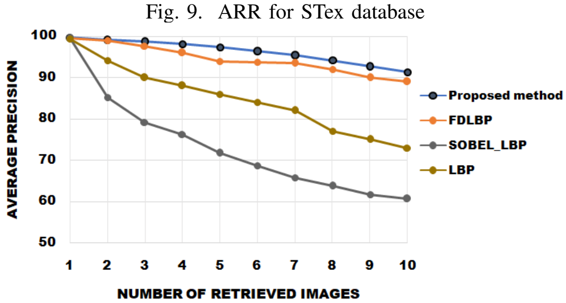

Fig. 10. ARP for ESSEX database

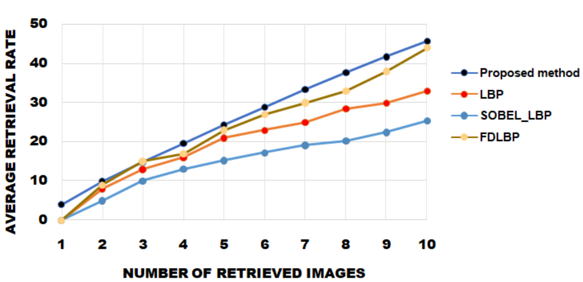

Fig. 11. ARR for ESSEX database

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