A Survey on Recent Image Indexing and Retrieval Techniques for Low-level Feature Extraction in CBIR systems

Komal Juneja
M.Tech Scholar
Department of CSE
AKGEC, Ghaziabad
komaljuneja504@gmail.com

Akhilesh Verma
Asssistant Professor
Department of CSE
AKGEC, Ghaziabad
akhilesh.verma@hotmail.com

Savita Goel
Senior System
Programmer
CSC, IIT Delhi
savita@iitd.ac.in

Swati Goel
M.Tech Scholar
Department of CSE
AKGEC, Ghaziabad
swatigoel043@gmail.com

***Abstract-* In the modern era, with the explosive growth of image databases, huge amount of image and video archive led to rise of a new research and development of efficient method to searching, locating and retrieving of image. For this purpose, an efficient tool for searching, locating and retrieval of image is required. This paper presenting a survey on low-level feature description techniques for Content Based Image Retrieval is presented with its various applications.**

Keywords- Content-Based Image Retrieval (CBIR); Texture Feature; Feature Extraction; Similarity measurement and Performance Parameters.

I. INTRODUCTION

With increasing development of image acquisition devices, the volume of image database is expanding rapidly. An efficient image retrieving tool is required by the users of various domains such as remote sensing, crime prevention, fashion, medical diagnosis etc. Basically, image retrieving tools are defined using following terms: query, result presentation, features, and matching. For image retrieval purpose, the various image retrieving tool has been developed, see [42]. For image retrieving purpose, two frameworks were developed, text-based image retrieval (TBIR) and content-based image retrieval (CBIR) [1].

CBIR extracts the image from database by analyzing its contents. The content might refers to texture, color, shape or spatial layout of an image. Fig. 1 shows the block diagram of CBIR. It performs two main tasks:-

1. Feature Extraction
2. Similarity Measurement

The effectiveness of CBIR Systems depends on the performance of algorithm for extracting the features of image [2]. In this, the visual characteristics of the images are represented by feature vectors and hence form a feature database.

The descriptors for finding the feature vector using visual content can be local or global. A global descriptor represents the image features as a whole whereas local or low-level descriptor utilizes the feature of objects or region to represent the whole image. Low-level features consist of texture, color and shape. Color feature is unchangeable with respect to size and orientation of objects, hence it is easy to analyze and extracted using color moments [3]-[4], color correlogram [5]-[7], color model [8]-[9], and [10], color histograms [11]-[13], and color-coherence [14] and [15]. Texture is characterized as a structural layout of surfaces and objects of image. The previous methods for calculating texture feature are co-occurrence matrix, texture histograms, wavelet-based, Gabor Features etc. [16]-[18]. Shape represents the layout of an object. The methods for extracting the shape features are boundary descriptors, like, chain code, signatures, Fourier descriptors etc., and region descriptors, like, grid-based, moments-based etc. [2], [19]-[21].

J. Y. Choi et al. [22] used color texture features for face recognition that outperforms the methods that based on only color or texture information.

This paper gives introduction to numerous image analysis techniques that extract the local patterns of image. The local binary pattern (LBP) and local ternary pattern (LTP) that consider the relationship between centre pixel and neighbourhood pixels. [23]-[25]. S. Liao et al. [26] extend the LBP approach, that only consider uniform patterns that is inadequate to capture high curvature edges or corners, dominant local binary pattern (DLBP) approach that consider the frequencies of all patterns that capture information like, high curvature edges, corners or crossing boundaries [26]. Z. Guo et al. [27] extend LBP, which used sign of gray-level difference among the given pixel and its neighbourhood pixels, completed local binary pattern (CLBP) consider both the sign component and magnitude component of gray level difference among the given pixel and its neighbors. The Local Derivative Pattern (LDP), encodes the directional pattern based on the variations of local derivative is capable of describing more accurate information [28]. S. Murala et al. [29] introduces higher order Local Tetra Patterns (LTrPs), for texture analysis, has higher capability to extract more definite information from image. S. Murala et al. [30] introduces Local Mesh Patterns (LMeP) that encodes the relationship between the surrounding neighbours of centre pixel and it outperforms LBP with respect to retrieval rate.

This paper also introduces the application area such as medical diagnosis, trademark registration, web searching, remote sensing etc. where CBIR support the user for analysing the image content [31]-[36].

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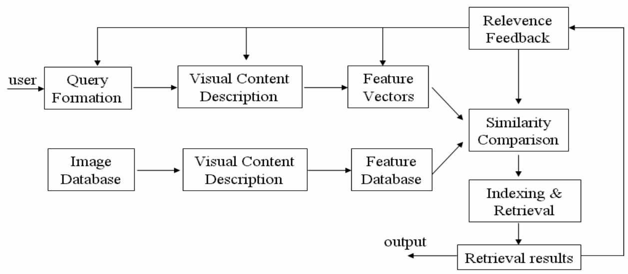


Fig. 1 Block Diagram of CBIR System [44].

II. LOW-LEVEL FEATURE EXTRACTION TECHNIQUES

A. *Feature Extraction using Local Binary Pattern (LBP)*

T. Ojala et al. [23] proposed LBP as a grayscale rotation invariant local pattern measure operator that was introduced for image indexing. Given a centre pixel of an image, the LBP value of pixel is calculated by comparing its gray-level value with its neighbours, shown in Fig. 2 using (1) and (2).

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \tag{1}$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

where g_c is the gray-scale value of centre pixel, g_p is the gray value of its neighbourhood pixel, P denotes the no. of neighbours and R is the radius of neighborhood [23].

LBP outperform in image indexing and it has been used in various applications because it is highly discriminative, gray-scale invariant and rotation invariant. They only consider the uniform patterns for calculating feature vector like, 10001111 that has almost two transitions from 0 to 1 or 1 to 0. It recognizes the microstructures such as, flat areas, lines, spots, edges, and histogram distribution is used to measure these microstructures [23]. LBP is also applied for face description because faces seem to be the combination of micropatterns which can easily recognize by LBP [23].

B. *Feature Extraction using CLBP*

T. Ojala et al. [23] proposed LBP to use sign component, instead of magnitude component of the difference among gray-level value of centre pixel and neighbourhood pixels to represent local pattern.

Z. guo et al. [27] proposed CLBP that consider the sign component and the magnitude component for calculating local patterns. Given a centre pixel g_c of image and its neighbours P, that is circularly and evenly spaced, g_p, $p=0,1,...,P-1$, as shown in Fig. 3, CLBP compute the difference between g_c and g_p as $d_p = g_p - g_c$. The difference vector $[d_0,.....,d_{p-1}]$ characterizes the local structure of image at g_c. Because the gray value of centre pixel g_c is removed,

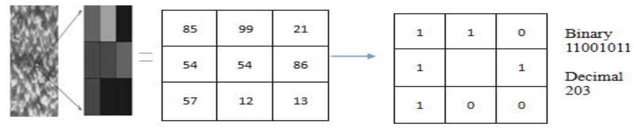


Fig. 2 Calculation of LBP

$[d_0,\ldots,d_{p-1}]$ is more robust to illumination. Now, d_p is decomposed into two components i.e. magnitude and sign components shown in Fig. 4 using (3).

$$d_p = s_p * m_p \, and \begin{cases} s_p = sign(d_p) \\ m_p = \mid d_p \mid \end{cases} \tag{3}$$

In LBP and CLBP, the centre pixel value is taken as threshold; hence, it is perceptive to noise. Figure 5 shows noise sensitivity behaviour of LBP.

N. Shrivastava et al. [38] introduce local structure pattern (LSP) that used centre pixel value and magnitude of local differences as threshold. Hence, it is less susceptible to noise.

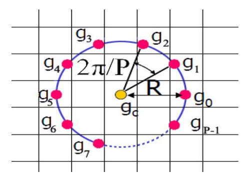


Fig .3 Central pixel and its *P* neighbours with radius *R* [27].

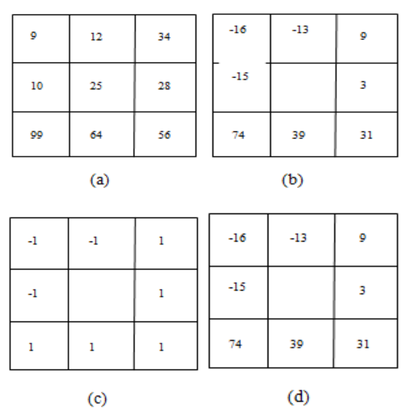
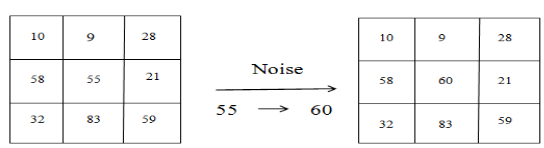


Fig. 4 (a) 3 x 3 sample block; (b) local differences; (c) sign component; and (d) magnitude component [27].



LBP: 00001011 LBP: 00000010

Fig. 5 Noise sensitivity of LBP [37]

C. Feature Extraction using Dominant LBP

In LBP, uniform patterns are consider that capture the information like, low curvature edges or straight edges but some images has complicated structure that contain high curvature edges, corners or crossing boundaries which is complicated to extract using uniform LBPs.

S. Liao et al. [26] proposed dominant local binary patterns that consider all possible patterns instead of only uniform patterns. Hence, capture the sophisticated shapes in an image.

D. Feature Extraction using Local Ternary Pattern (LTP)

LBP operator is highly discriminative for texture classification and proves to be more resistant to lighting effects. Hence it is consistent to gray-level transformations but perceptive to noise in approx-uniform image regions.

X. Tan et al. [25] proposed LTP that is 3-valued codes (-1, 0, 1), where the gray-levels are in a zone of width *-t* to *+t* around i_c are quantized to zero, above and below are quantized to 1 and -1 respectively, as shown in Fig. 6 i.e., the function *s(x)* from (2) is replaced by a 3-valued function given as:-

$$s'(u, i_c, t) = \begin{cases} 1, u \geq i_c + t \\ 0, |u - i_c < t \\ -1, u \leq i_c - t \end{cases} \tag{4}$$

where *t* is user-defined threshold. The feature extracted using LTP are robust and more resistant to noise in near-uniform regions where LBP fails, but variant to gray-level transformations [25]. After calculating the ternary code, each ternary pattern is decomposed into two LBP codes shown in Fig. 7.

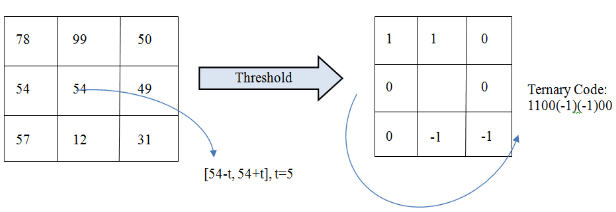


Fig. 6 Calculation of LTP pattern [25]

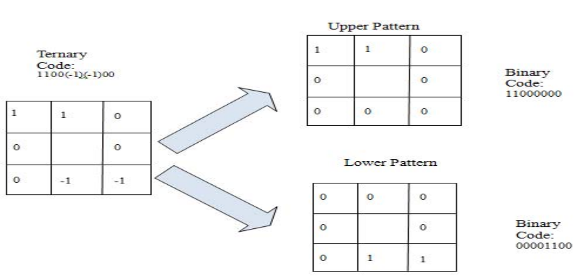


Fig. 7 Decomposition of LTP code in positive and negative LBP code [25]

E. Feature Extraction using Local Derivative Patterns (LDP)

Zhang et al. [28] proposed LDP that encodes the directional pattern based on the variations of local derivative is capable of describing more accurate information that the first-order local binary pattern (LBP) unable to obtain from an image.

Let *I(Z)* be an image shown in Fig. 9, the first-order derivatives along direction α (0^0, 45^0, 90^0, and 135^0) are expressed as $I'_\alpha(Z)$. Let Z_0 be a point in *I(Z)*, and Z_i, where $i = 1, \ldots, 8$ be the neighbors of Z_0
The four first-order derivatives at $Z = Z_0$ can be defined as:-

$$I'_{0^\circ}(Z_0) = I(Z_0) - I(Z_4) \tag{5}$$

$$I'_{45^\circ}(Z_0) = I(Z_0) - I(Z_3) \tag{6}$$

$$I'_{90^\circ}(Z_0) = I(Z_0) - I(Z_2) \tag{7}$$

$$I'_{135^\circ}(Z_0) = I(Z_0) - I(Z_1) \tag{8}$$

The second-order LDP, $LDP^2_\alpha(Z_0)$, in direction α at $Z{=}Z_0$ is given as:-

$$LDP^2_\alpha(Z_0) = \{ f(I'_\alpha(Z_0), I'_\alpha(Z_1)), f(I'_\alpha(Z_0), I'_\alpha(Z_2)) \\ \ldots, f(I'_\alpha(Z_0), I'_\alpha(Z_8)) \} \tag{9}$$

where,

$$f(I'_\alpha(Z_0), I'_\alpha(Z_i)) = \begin{cases} 0, I'_\alpha(Z_i) \,.\, I'_\alpha(Z_0) > 0 \\ 1, I'_\alpha(Z_i) \,.\, I'_\alpha(Z_0) \leq 0 \end{cases} \tag{10}$$

Finally, the second-order LDP, $LDP^2(Z)$, is represent by the concatenation of the four 8-bit directional LDPs and it is given as:-

$$LDP^2(Z) = \{ LDP^2_\alpha(Z) \mid \alpha = 0^\circ, 45^\circ, 90^\circ, 135^\circ \} \tag{11}$$

The LDP operator labels each pixel of image using four directions separately and gives 32-bit binary sequence by concatenating four 8-bit binary sequences.

The benefit of using high-order local patterns is that it provides a stronger discriminative capability and gives detailed information and results in higher retrieval rate than LBP.

Z1	Z2	Z3
Z8	Z0	Z4
Z7	Z6	Z5

Fig. 9 Neighbourhood around Z_0 [28].

F. Feature Extraction using Local Tetra Pattern (LTrP)

S. Murala et al. [29] proposed LTrP that encodes the relationship among the centre pixel and its neighbourhood pixels using derivatives in vertical and horizontal directions that results in 13 patterns of a single image. Let g_c be a centre pixel of image I, the first order derivative along 0° and 90° directions denoted as I_0^1 and I^1_{90} is given as:-

$$I^1_{0^\circ}(g_c) = I(g_h) - I(g_c) \tag{12}$$

$$I^1_{90^\circ}(g_c) = I(g_v) - I(g_c) \tag{13}$$

where g_v and g_h denote the vertical and horizontal neighborhood of g_c respectively. The direction assign to the centre pixel is computed as:-

$$I^1_{Dir.}(g_c) = \begin{cases} 1, I^1_{0^\circ}(g_c) \geq 0 \text{ } and \text{ } I^1_{90^\circ}(g_c) \geq 0 \\ 2, I^1_{0^\circ}(g_c) < 0 \text{ } and \text{ } I^1_{90^\circ}(g_c) \geq 0 \\ 3, I^1_{0^\circ}(g_c) < 0 \text{ } and \text{ } I^1_{90^\circ}(g_c) < 0 \\ 4, I^1_{0^\circ}(g_c) \geq 0 \text{ } and \text{ } I^1_{90^\circ}(g_c) < 0 \end{cases} \tag{14}$$

The direction assign to each centre pixel can be 1, 2, 3, or 4, using (14) and whole image is changed into four directions. The second order $LTrP^2(g_c)$ is calculated as:-

$$\begin{aligned} LTrP^2(g_c) = \{ & f_3(I^1{}_{Dir}(g_c), I^1{}_{Dir}(g_1)), \\ & f_3(I^1{}_{Dir}(g_c), I^1{}_{Dir}(g_2)), \\ & \ldots, f_3(I^1{}_{Dir}(g_c), I^1{}_{Dir}(g_P))\} |_{P=8} \end{aligned} \tag{15}$$

where,

$$f_3(I^1{}_{Dir}(g_c), I^1{}_{Dir}(g_P)) = \begin{cases} 0, & I^1{}_{Dir}(g_c) = I^1{}_{Dir}(g_P) \\ I^1{}_{Dir}(g_P), & else. \end{cases} \tag{16}$$

Equation (15) and (16) results in 8-bit tetra pattern correspond to each pixel. After that, segregate all patterns into four parts (directions). Then, each tetra pattern in all directions is represented by three binary patterns. Let the centre pixel direction ($I_{Dir}{}^1(g_c)$) obtained using (14) be 1, the 3 binary pattern is calculated in direction 2, 3 and 4.

In same manner, the 3 tetra patterns correspond to remaining three directions of given center pixel are transformed to binary patterns. Hence, we get 12 (4 * 3) binary patterns. LTrP also use magnitude pattern that can be calculated from the magnitude of vertical and horizontal first-order derivative of image pixel which is given as:-

$$M_{I^1}(g_p) = \sqrt{\left(I^1_{0^0}(g_p)\right)^2 + \left(I^1_{90^0}(g_p)\right)^2} \tag{17}$$

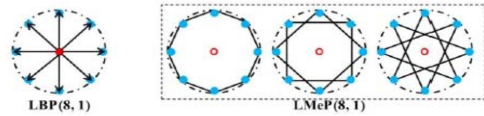


Fig. 10: The LBP and the first three LMeP calculations for a given (P, R).

$$LP = \sum_{p=1}^{P} 2^{(p-1)} \times f_1\left(M_{I^1(g_p)} - M_{I^1(g_c)}\right) \tag{18}$$

In this way, 13 local patterns are calculated in LTrP technique.

It is observed that second order LTrP gives better results as compared with higher order LTrPs because higher order LTrPs are noise sensitive [29].

G. Feature Extraction using Local Mesh Pattern (LMeP)

In LBP, T. Ojala et al. [23] encodes the interrelation among the centre pixel and its neigborhood pixels but in LMeP S. Murala et al. [30] encodes the interrelation between the neighbourhood pixels of given pixel shown in Fig. 10.

It considers the uniform patterns to decrease the cost of computation as in LBP. The LMeP technique outperforms LBP with respect to retrieval rate when applied to biomedical images [30].

III. SIMILARITY MEASUREMENT

After extracting the feature vector, a function is used that measure the similarity among the query image and database images feature vector in CBIR systems. Generally, the similarity measure function used is distance metric. The value of distance metric indicates the level of similarity among the query image and database image. A database image is said to be similar to query image if the calculated distance is 'small'. Some of the methods for similarity measurement are Euclidean Distance, Mean Square Error, Sum of Absolute Differences, NN Classifiers, K-Nearest Neighbor Algorithm, Mahalanobis Distance, Bhattacharya Distance [39].

IV. PERFORMANCE EVALUATION

The idea behind performance evaluation is to make a prediction on the CBIR system performance with respect to retrieval rate. The common methods used to measure the performance are *User comparison, rank of best match, Average rank of retrieval images, Recall* and *Precision, Error rate* etc. [40].

Most of the researchers used Recall rate and Precision rate as a performance metric in CBIR systems. Precision rate gives the proportion of relevant images retrieved and the recall rate gives proportion of relevant images that are retrieved [41]. Let Iq be the query image, recall rate and precision rate are defined as:

$$\text{Precision: } P(Iq) = \frac{\text{Count of Relevant images retrieved}}{\text{Total images retrieved}}$$

$$\text{Recall: } R(I_q) = \frac{\text{Count of Relevant images retrieved}}{\text{Total Relevant images in database}}$$

Precision rate measure the system accuracy whereas Recall rate measure the robustness. Average Retrieval Rate (ARR) and Average Retrieval Precision (ARP) judging the CBIR systems, are defined mathematically as follows [30]:

$$ARP = \frac{1}{|DB|}\sum_{i=1}^{|DB|} P\left(I_q\right) \tag{25}$$

$$ARR = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R\left(I_q\right) \tag{26}$$

where $|DB|$ denote database size. The high value of ARR and ARP indicates the better performance of CBIR [30].

V. APPLICATIONS

A. *Trademark Registration*

In this, a new mark is matched with stored marks in the data store to remove the possibility of confusion [31].

B. *Medical Diagnosis*

With the development of diagnostic techniques such as radiology, histopathology, results in huge medical image database. In this case, CBIR tool is used by radiologist for analysing Magnetic Resonance (MR) images of the brain [32, 33].

C. *Crime Prevention*

Law enforcement agencies maintain huge database of visual evidence, including past suspect's facial photographs, fingerprints, footprints and shoeprints. Whenever a crime takes place, CBIR assist them to match the evidence from the scene of the crime to records in their databases for its similarity.

D. *Web Searching*

Various social sites, for example, Facebook, Twitter, LinkdIn etc., consist of immense amount of multimedia content, like image, audio, video and text. Analysing and mining that content is a complex task that can be managed by CBIR systems.

E. *Historical Research*

The Historians from various fields such as, medical, sociology, art, etc. use visual data to carry their research activities. Sometimes the visual record from art galleries, museums etc. is only evidence available. Various organizations maintain slide and photographic collections that include public and academic libraries. To categorize objects that share some characteristic can be helpful to researchers demanding to mark out historical influences.

VI. CONCLUSION

CBIR is a wide area under Computer vision systems and achieves a great attention of many researchers. Since, feature extraction play a major role in CBIR systems, many researchers works on feature description techniques. In this survey, we introduce various feature description techniques such as LBP, LDP, LTP, LTrP, and LMeP. The performance evaluation metrics such as Recall rate and Precision rate for measure the effectiveness of above mentioned CBIR techniques.

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