ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 3, Issue 11, November 2016

Content-Based Image Retrieval Using Local Orientation Gradient XoR Patterns

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***Abstract*— This paper presents a novel feature extraction method, local orientation gradient XoR patterns (LOGXoRP) for image indexing and retrieval. The LOGXoRP encodes the exclusive OR (XoR) operation between the center pixel and its surrounding neighbors of quantized orientation and gradient values. Whereas local binary patterns (LBP) and local gradient patterns (LGP) encode the relationship between the gray values of center pixel and its neighbors. We show that the LOGXoRP can extract effective texture (edge) features as compared to LBP and LGP. The performance of the proposed method is tested by conducting two experiments on Corel-5K and Corel-10K databases. The results after being investigated the proposed method shows a significant improvement in terms of their evaluation measures as compared to LBP, LGP and other existing state-of-art techniques on respective databases.**

Keywords — Feature Extraction; Local Binary Patterns (LBP); Local Gradient Pattern (LGP); Content Based Image Retrieval (CBIR); Texture

INTRODUCTION

Image retrieval is an active research topic in image processing and pattern recognition. Initially, text based image retrieval was being used for this purpose. To reduce the amount of labor for image annotation and different interpretation of image by different persons, the content based image retrieval (CBIR) came into existence. Still, there remain some challenging problems that attract the researchers' interest towards CBIR.

The feature extraction plays an important role in CBIR whose effectiveness depends upon the method adopted for extracting features from given images. The visual content descriptors are either global or local. A global descriptor represents the visual features of the whole image, whereas a local descriptor represents the visual features of regions or objects to describe the image. These are arranged as multidimensional feature vectors and construct the feature database. For similarity distance measurement many methods have been developed like Euclidean distance (L2), L1 distance, etc. Selection of feature descriptors and similarity distance measures affect retrieval performances of an image retrieval system significantly. The previously available literature on CBIR is presented in [1], [2], [3], [4] and [5].

Recently, active researchers in image retrieval using a combination of color and texture features have been performed [6], [7]. Liu et al. [6] Have integrated the color and texture features called multi-texton histogram (MTH) for image retrieval. MTH integrates the advantages of the co-occurrence matrix and histogram by representing the attribute of the co-occurrence matrix using histogram. Further, they introduced the micro-structure descriptor (MSD) [7] which is built based on the underlying colors in micro- structures with similar edge orientation.

Mahmoudi et al. [8] Have proposed the shape based feature which classifies image edges based on two factors: their orientations and correlation between neighboring edges. They proved that the proposed scheme is effective and robustly tolerates translation, scaling, color, illumination, and viewing position variations. Qi et al. [9] Have proposed an effective shape description method which includes contour-based shape descriptor and Zernike moments. In addition, they present a new feature matching strategy to compute the dissimilarity value between the feature vectors extracted from images.

In this paper, we focus on pattern based features for image retrieval. Ojala et al. [10] Proposed the local binary patterns (LBP) which can show better performance as well as less computational complexity for texture classification. Success of LBP variants in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification [10, 11], face recognition [12, 13], object tracking, image retrieval, fingerprint matching and interest point detection.

Jun and Kim [12] have proposed the local gradient patterns (LGP) for face detection. LGP representation is insensitive to global intensity variations like the other representations such as local binary patterns (LBP) and modified census transform (MCT), and to local intensity variations along the edge components. Xie at al. [13] have proposed the local Gabor XOR patterns (LGXP) operator for face recognition.

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 3, Issue 11, November 2016

The LGXP which is proposed in [13] and LGP in [12] are motivated us to propose the local orientation gradient XoR patterns (LOGXoRP) for image retrieval. The main contributions of the proposed method are given as follows: (a) the quantization of Gabor responses for LGXP operator is very difficult because the range of Gabor coefficients is different for each image, whereas the LOGXoRP uses the quantized gradient and orientation responses whose range (Orientation: 0° to 360° and Gradient: 0:255) is always constant. (b) We prove that the LOGXoRP can extract effective texture (edge) features as compared to LBP and LGP. The performance of the proposed is tested by conducting two experiments on benchmark Corel-5K and Core-10K databases.

LOCAL PATTERNS

Local Gradient Patterns (LGPs)

Jun and Kim [12] have proposed the LGP for face detection. Given a center pixel in an image, the LGP value is computed by comparing its gray scale value with its neighbors based on Eq. (1) and Eq. (2).

$$LGP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f_1(|g_i - g_c| - T_h) \tag{1}$$

$$T_h = \frac{1}{P}\sum_{i=1}^{P} |g_i - g_c| \tag{2}$$

More details of LGP can be found in [12].

The proposed LGP is almost similar to the completed LBP magnitude (CLBP_M) [11]. The only difference between these two features is that the LGP calculates the threshold (T_h) from the mean/average of local difference operator (LDO) for a given pattern whereas CLBP_M calculates from the mean/average of entire image LDO.

Proposed Method

The idea of LBP [10], LGP [12] and LGXP [13] has been adopted to define the local orientation gradient XoR patterns (*LOGXoRP*).Given a center pixel in an image, the gradients (*P*=8) are calculated as:

$$I_{g_c}^{h} = g_1 - g_5 \tag{3}$$

$$I_{g_c}^{v} = g_3 - g_7 \tag{4}$$

Where, $\{g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8\}|_{P=8}$ are the gray values of neighbors for a given center pixel, g_c .

The orientation and gradient values are calculated as follows:

$$I_{g_c}^{G} = \sqrt{\frac{(I_{g_c}^{h})^2 + (I_{g_c}^{v})^2}{2}} \tag{5}$$

$$\theta_{g_c} = Tan^{-1}\left(\frac{I_{g_c}^{v}}{I_{g_c}^{h}}\right) \tag{6}$$

$$I_{g_c}^{O} = \begin{cases} 0° + \theta_{g_c} & I_{g_c}^{h} \geq 0 \; and \; I_{g_c}^{v} \geq 0 \\ 180° - \theta_{g_c} & I_{g_c}^{h} < 0 \; and \; I_{g_c}^{v} \geq 0 \\ 180° + \theta_{g_c} & I_{g_c}^{h} < 0 \; and \; I_{g_c}^{v} < 0 \\ 360° - \theta_{g_c} & I_{g_c}^{h} \geq 0 \; and \; I_{g_c}^{v} < 0 \end{cases} \tag{7}$$

The gradient XoR patterns (LGXoRP) and orientation XoR patterns (LOXoRP) are calculated as:

$$LGXoRP = \begin{bmatrix} \{Q(I_{g_1}^{G}) \otimes Q(I_{g_c}^{G})\}, \\ \{Q(I_{g_2}^{G}) \otimes Q(I_{g_c}^{G})\}, \\ \ldots\ldots\ldots\ldots, \\ \{Q(I_{g_P}^{G}) \otimes Q(I_{g_c}^{G})\} \end{bmatrix} \tag{8}$$

$$LOXoRP = \begin{bmatrix} \{Q(I_{g_1}^{O}) \otimes Q(I_{g_c}^{O})\}, \\ \{Q(I_{g_2}^{O}) \otimes Q(I_{g_c}^{O})\}, \\ \ldots\ldots\ldots\ldots, \\ \{Q(I_{g_P}^{O}) \otimes Q(I_{g_c}^{O})\} \end{bmatrix} \tag{9}$$

Where, $Q(x)$ denotes the quantized value of x and $\otimes$ represents the exclusive OR (XoR) operation.

Similarly, orientation and gradient patterns are calculated using diagonal directions also.

For the local pattern with *P* neighborhoods, 2^P combinations of local binary patterns are possible, resulting in a feature vector length of 2^P. The computational cost of this feature vector is very high. In order to reduce the computational cost we consider the uniform patterns [11]. The uniform pattern refers to the uniform appearance pattern that has limited discontinuities in the circular binary representation. In this paper, those patterns which have less than or equal to two discontinuities in the circular binary representation are referred to as the uniform patterns and remaining patterns are referred to as non-uniform. Thus, the distinct uniform patterns for a given query image would be $P(P-1)+2$. The possible uniform patterns for *P*=8 can be seen in [11].

After identifying the local pattern, *PTN* (LBP or LGP or LOGXoRP (LGXoRP+LOXoRP)) the whole image is represented by building a histogram using Eq. (10)

$$H_S(l) = \frac{1}{N_1 \times N_2}\sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f_2(PTN(j,k), l); \; l \in [0, P(P-1)+2] \tag{10}$$

$$f_2(x,y) = \begin{cases} 1 & if \; x = y \\ 0 & else \end{cases} \tag{11}$$

Where, $N_1 \times N_2$ represents the size of input image.

FEATURE EXTRACTION AND ANALYSIS

Fig. 1 illustrates the flow chart of proposed feature extraction method and algorithm for the same is given bellow:

Algorithm:

Input: Image; *Output: Feature vector*

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 3, Issue 11, November 2016

1. Load the image, and convert it into gray scale.
2. Calculate the gradient and orientation values.
3. Quantize the gradient and orientation values.
4. Calculate the XoR patterns for gradients and orientations.
5. Calculate the histograms.
6. Construct the feature vector by concatenating the histograms.

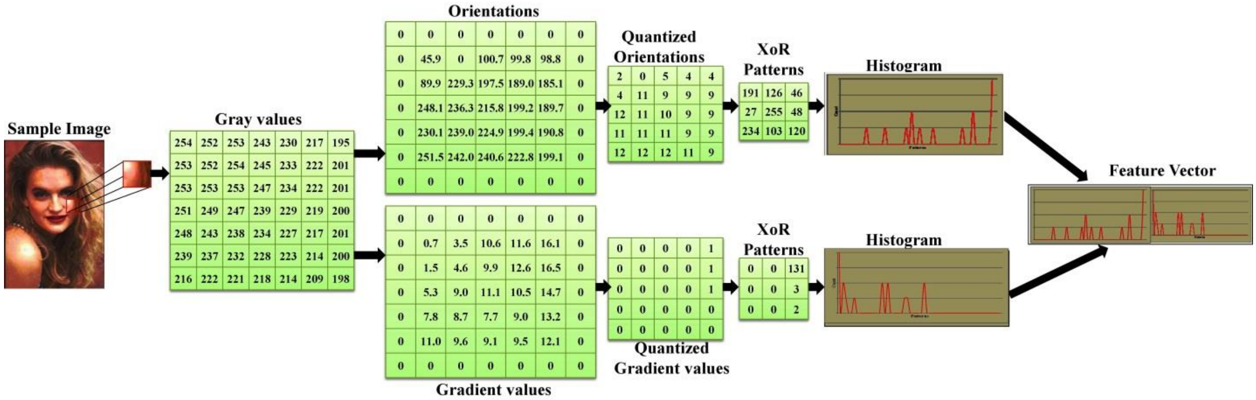

Fig. 1: Proposed feature extraction method

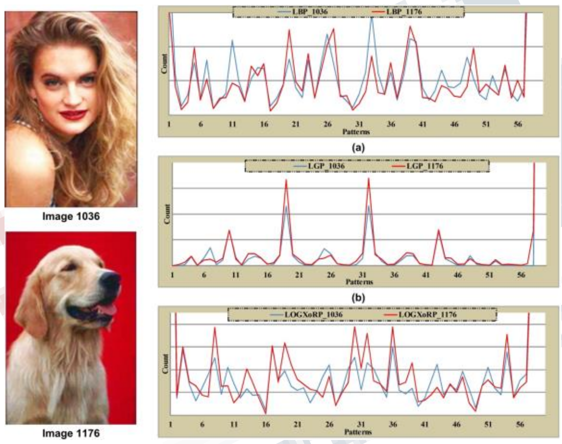

Fig. 2: Comparison of various features on two sample images from Corel-10K database.

Fig. 2 illustrates the comparison between the various features of two sample images which are selected from the different categories of the Corel-10K database. Form Fig. 4, it is clear the proposed method (LOGXoRP) is able to differentiate the two sample images as compared to LBP and LGP.

Similarity Measure

Feature vector of query image Q is represented as $f_Q = (f_{Q_1}, f_{Q_2}, \ldots\ldots f_{Q_{Lg}})$ obtained after the feature extraction. Similarly each image in the database is represented with feature vector $f_{DB_j} = (f_{DB_{j1}}, f_{DB_{j2}}, \ldots\ldots f_{DB_{jLg}});\ j = 1, \quad 2, \ldots, |DB|$.

The goal is to select n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between query image and image in the database $|DB|$.

In this paper d_1 similarity distance metrics is used for image retrieval.

$$D(Q, DB) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{ji}} - f_{Q,i}}{1 + f_{DB_{ji}} + f_{Q,i}} \right| \tag{12}$$

Where $f_{DB_{ji}}$ is i^{th} feature of j^{th} image in the database $|DB|$.

Evaluation Measures

The performance of the proposed method is measured in terms of average precision or average retrieval precision (ARP), average recall and average retrieval rate (ARR) as shown below:

For the query image I_q, the precision is defined as follows:

$$P(I_q, n) = \frac{1}{n} \sum_{i=1}^{|DB|} \left| \delta\left(\Phi(I_i), \Phi(I_q)\right) | Rank(I_i, I_q) \leq n \right| \tag{18}$$

Where n indicates the number of retrieved images, $|DB|$ is the size of an image database, $\Phi(x)$ is the category of *'x'*, $Rank(I_i, I_q)$ returns the rank of image I_i (for the query

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ISSN (Online) 2394-2320

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image I_q) for all images of $|DB|$ and

$$\delta\left(\Phi\left(I_i\right),\Phi\left(I_q\right)\right)=\begin{cases}1 & \Phi\left(I_i\right)=\Phi\left(I_q\right)\\ 0 & else\end{cases}.$$

Recall is defined as:

$$R(I_q,n)=\frac{1}{N_G}\sum_{i=1}^{|DB|}\left|\delta\left(\Phi\left(I_i\right),\Phi\left(I_q\right)\right)|Rank(I_i,I_q)\le n\right| \quad (13)$$

where, N_G is the number of relevant images in the database. The average precision for the j^{th}similarity category of the reference image database is computed using Eq. (14)

$$P_{ave}^{j}(n)=\frac{1}{N_G}\sum_{i\in G}P(I_i,n) \quad (14)$$

Finally, the total average retrieval precision (ARP), and average retrieval rate (ARR) for the whole reference image database are computed using Eq. (15) and (16) respectively.

$$ARP=\frac{1}{|DB|}\sum_{i=1}^{|DB|}P(I_i,n) \quad (15)$$

$$ARR=\frac{1}{|DB|}\sum_{i=1}^{|DB|}R(I_i,n)\Big|_{n\le 100} \quad (16)$$

EXPERIMENTAL RESULTS AND DISCUSSIONS

In this paper, Corel database is used for experimentation. Corel database [14] comprises of large amount of images of various contents ranging from animals, outdoor sports to natural images. These images are preclassified into different categories of size 100, by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content. For Corel-5K database, 5000 images are collected which consists of 50 different categories. Each category has 100 images and all these have sizes either 126×187 or 187×126.

In this experiment, Corel-5K database is used. The performance of the proposed method is measured in terms of ARP and ARR. The results are considered to be better, if average values of precision and recall are high.

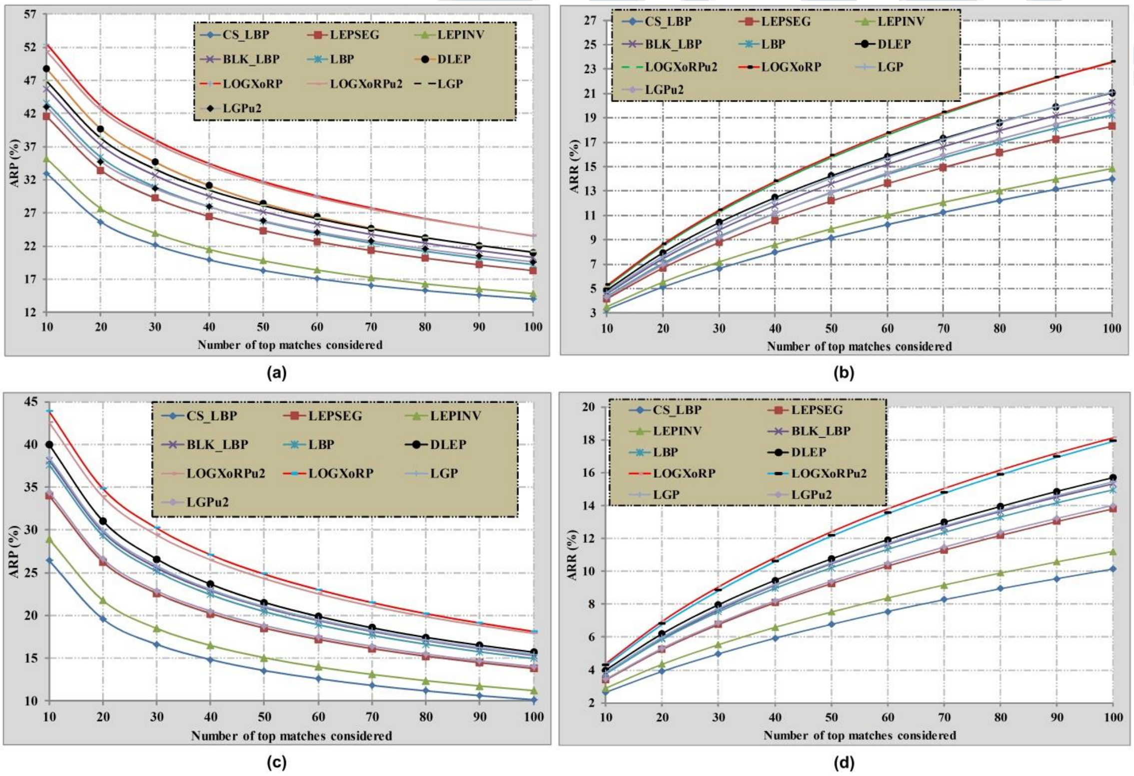

Fig. 3: Comparison of LOGXoRP with other existing methods in terms of ARP and ARR: (a), (b) on Corel-5K and (c), (d) on Corel 10K database.

PERFORMANCE OF VARIOUS METHODS IN TERMS OF PRECISION AND RECALL ON COREL-5K AND COREL-10K DATABASES.

Database	Performance	Method									
		CS_LBP	LEPSEG	LEPINV	BLK_LBP	LBP	DLEP	LGP	LGPu2	LOGXoRP	LOGXoRPu2
Corel–5K	Precision (%)	32.9	41.5	35.19	45.7	43.6	48.8	46.8	42.9	**52.5**	51.4
	Recall (%)	14	18.3	14.8	20.3	19.2	21.1	21.1	19.6	**23.6**	23.6
Corel–10K	Precision (%)	26.4	34	28.9	38.1	37.6	40	38.4	34.4	**43.8**	42.6
	Recall (%)	10.1	13.8	11.2	15.3	14.9	15.7	15.4	14	**18.1**	17.9

PERFORMANCE OF PROPOSED METHOD WITH VARIOUS QUANTIZATION LEVELS IN TERMS OF PRECISION AND RECALL ON COREL-5K DATABASE.

Performance	Method	Quantization Levels of Orientations and Gradients							
		18	12	9	8	7	6	5	4
Precision (%)	LOGXoRP	50.6	51.4	52	51.9	52.2	52.2	52.2	**52.5**
	LOGXoRPu2	49.2	49.9	50.4	50.4	50.8	50.7	51	**51.4**
Recall (%)	LOGXoRP	22.6	22.9	23	23.1	23.3	23.3	23.3	**23.6**
	LOGXoRPu2	21.9	22.3	22.5	22.6	23	22.9	23.1	**23.6**

Table I illustrates the retrieval results of proposed method (LOGXoRP) and other existing methods (CS_LBP, LEPSEG, LEPINV, BLK_LBP, LBP, LGP and DLEP) on Corel–5K database in terms of average precision and recall. Fig. 3 (a) and (b) show the performance of various methods in terms of ARP and ARR on Corel–5K database. From Table I and Fig. 3 (a) and (b), it is clear that the LOGXoRP outperforms the other existing methods in terms of ARP and APP on Corel-5K database. The performance of the proposed method is analyzed with different quantization levels of gradient and orientation responses as shown in Table II. From Table II, it is observed that the four quantization levels are showing better performance as compared to other quantization levels. Fig. 4 illustrates the query results of proposed method on Corel-5K database (top left image is the query image).

Fig. 6: Query results of proposed method on Corel-5K database (top left image is the query image).

CONCLUSION

In this paper, a new image indexing and retrieval algorithm is proposed using local orientation gradient XoR patterns (LOGXoRP). The LOGXoRP encodes the images based on the XoR operation between the center pixel and its neighbors of quantized orientation and gradient responses.

The performance improvement of the proposed method has been compared with the LBP, and the LGP on grayscale images and has been detailed below.

1. The average precision has significantly improved from 43.6%, and 46.8% to 52.5%, as compared with the LBP, and the LGP, respectively, on Corel-5K database.

2. The average recall has improved from 19.2%, and 21.1% to 23.6%, as compared with the LBP, and the LGP, respectively, on Corel-5K database.

Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

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