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QUANTIZED NEIGHBORHOOD LOCAL INTENSITY EXTREMA PATTERNS FOR IMAGE RETRIEVAL

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ABSTRACT

Technological advancements in the field of multimedia and digital electronics enable the users create millions of images every moment. Many researchers across the world developed algorithms to retrieve the images from a database. However, obtaining the better accuracy is still an open issue in image retrieval. Texture descriptive features like Local Binary Pattern (LBP) depend on the comparison of central pixel and its neighbors. However, the impact of the adjacent pixels is ignored in encoding the binary information. Our approach primarily relies on the fact that neighbors around a specified pixel hold considerable textural. A Horizontal-vertical-diagonal-anti diagonal structure is created from the image. Sign of difference in the intensity of pixels is used to form the patterns. We propose a novel texture descriptor, termed Quantized Neighborhood Local Intensity Extrema Pattern (QNLIEP). Retrieval efficiency of QNLIEP method is evaluated in the form of Precision as well as Recall. Standard image repositories such as ImageNet-25, Brodatz are used to evaluate the efficiency.

KEYWORDS

Image retrieval, quantization, neighborhood, sign, magnitude patterns.

1. INTRODUCTION

An image is a primary source of information in several real time applications such as Computer Vision, multimedia, Pattern Recognition, etc. Technological advancements enable the users create and share millions of images every moment. Identification of similar images from the database is always a tedious task. To address these issues, researchers have developed different types of algorithms (Ciresan et al., 2012; Sanchez et al., 2013; Krizhevsky et al., 2012). From the study, we observed that the texture plays a significant role in identifying a similar image and propose a local structure dependent CBIR system. In the recent past, researchers explored the role of texture in image retrieval (Kokare et al., 2007; Jhanwar et al., 2004). Any texture feature should yield better results against a range of images of any dataset. Local content descriptors in this paper compare a gray value of pixel with central pixel as well as its neighbors. Pattern extracted from a 3x3 kernel proves to be more effective as compared to other methods.

1.2 Relevant work

A simple and popular method known as local binary pattern became the foundation for many methods of retrieval. In this, texture information is extracted from a 3x3 window. Binary pattern represents the encoded structural information. Extraction of Local binary pattern is illustrated in Figure 1.

Figure 1: Illustration of LBP

K Rao proposed the quantized extrema patterns for image retrieval (Koteswara et al., 2015; Koteswara et al., 2016; Koteswara et al., 2018). H Kaur et. al presented mesh patterns for image retrieval (Kaur et al., 2017). P. Banerjee et al. extracted the mutual relationship among the pixels surrounding the central pixel (Banerjee et al., 2018). Authors proposed parallel cross pattern for retrieval purpose Intensity patterns are extracted for a 3x3 kernel (Feng et al., 2019). In this work, quantization is

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applied to get a HVDA structure as shown in figure 2. Texture information from the adjacent pixels is used to encode the local pattern. For a specified quantized structure, the difference in sign as well as the magnitude is considered.

15		8		14
	19	7	13	
13	6	C	5	7
	16	10	24	
20		17		29

Figure 2: Quantized structure of 5x5 image

Contents of our paper are organized as follows. In Section 2, discussion on LBP and QLNIEP is given. Section 3 describes framework of proposed system. Experimental results are illustrated in Section 4. Important conclusions are given in Section 5.

2. LOCAL PATTERNS

2.1 Review of LBP

Ojala et al. introduced the Local binary pattern (LBP) for texture image classification (Ojala et al., 2002). A small kernel of size 3x3 is considered to explore textural data associated with a specific neighborhood. Binary 0 or 1 is assigned according to the relation between a centre pixel and its neighbor (equation 1). Group of binary bits forms a local textural binary pattern.

$$LBP_{J,K} = \sum_{p=1}^J 2^{(p-1)} \times m(IM(q_p) - IM(q_c)) \dots (1)$$

$$m(x) = \begin{cases} 1 & a \geq b \\ 0 & otherwise \end{cases} \dots (2)$$

Here, J and K depict the no. of neighbors and the radius respectively.

2.2 Quantized neighborhood local intensity extrema pattern

Major limitations in terms of the neighborhood and increased feature vector length influenced us to propose Quantized neighborhood local intensity extrema patterns for texture extraction. Structures in four directions i.e horizontal, vertical, diagonal and Anti-diagonal are taken. In other words, the image is quantized in terms of number of gray levels. We use a 5x5 window in a quantized form. As shown in figure 3, centre pixel P_c is taken as reference. For a specific pixel P_z , number of adjacent neighbors can be either 4 or 2 depending on 'z' value. Here, Sn_z denotes the set of adjacent neighbors as shown in equations 3 and 4. In the first method, mutual textural relationship between centre pixel and neighboring elements is extracted. In our second method, relationship between different pixels of a neighborhood is used. More details of the proposed method are depicted in the figure 3.

$$Sn_z = \{P_{1+\text{mod}(z+5,7)}, P_{1+\text{mod}(z+6,9)}, P_{z+1}, P_{z+9}, P_{1+\text{mod}(z+2,8)}\} \forall z = 1, 3, 5, 7 \dots (3)$$

$$Sn_z = \{P_{z-1}, P_{z+5}, P_{9+2\text{mod}(z,8)}, P_{z+7}, P_{\text{mod}(2z+1,8)}\} \forall z = 2, 4, 6, 8 \dots (4)$$

Figure 3: Illustration of adjacent neighbors for a quantized structure of size 5x5

In the first step, Sign of a relative variation between any one neighbor of central pixel P_c , and neighbors of the same specific pixel Sn_z is identified.

An N-bit pattern is obtained in which N denotes no. of elements in Sn_z . We use the equation 5, 6 to obtain two different binary patterns one related to the central pixel and the other related to P_z .

$$Q_{1,z}(y) = \text{sign}(Sn_z(y), P_c) \text{ where, } y = 1 \text{ to } N \dots (5)$$

$$Q_{2,z}(y) = \text{sign}(Sn_z(y), P_c) \text{ where, } y = 1 \text{ to } N \dots (6)$$

$$\text{sign}(u, v) = \begin{cases} 1 & u \geq v \\ 0 & otherwise \end{cases} \dots (7)$$

In the equation above, u and v are numbers. Logical XoR operation is performed to identify the structural change present in the specified neighborhood. Upon completing the XOR operation, an N bit pattern E_z is extracted as per eqn (8)

$$E_z = \text{xor}(Q_{1,z}, Q_{2,z}) \dots (8)$$

The count of 1s in the pattern helps in deciding the structural change. For any N bit patterns, total no. of positions of difference ranges from 0 to N. Here is $\frac{1}{4}(N)$ is fixed as threshold value, $N=4$ and 2 when $z \in \text{odd}$ and $z \in \text{even}$ respectively. Value of threshold is used in the calculation of a bit for P_z according to the equation (9). For all 8-neighbors, bit pattern is computed. Bit pattern map for centre pixel is extracted using equation (10). Subsequently, a histogram is built to represent the sign pattern.

$$Q(P_z, P_c) = \begin{cases} 1, & \#(E_z = 1) \geq \frac{1}{2}(N) \\ 0, & otherwise \end{cases} \dots (9)$$

$$QNLIEP_{Sn}(P_c) = \sum_{z=1}^8 2^{z-1} \times Q(P_z, P_c) \dots (10)$$

Illustration of the QNLIP pattern is provided in fig.4.

Figure 4: Illustration of quantized neighborhood local intensity extrema pattern (a)-(b) quantized structure highlighting the center and neighboring pixels (iii)-(x) Calculation of sign and magnitude pattern calculation.

A quantized structure example is shown in fig 4 (a). Central pixel is marked in blue color in Fig. 4(b). For the example pattern in figure (b), extraction of the pattern is illustrated in the figures ((c)-(j)). Center pixel is shown in blue, pixel under consideration are colored in orange and neighboring elements are colored in pink. Initially, orange pixel and group of pink pixels are compared. Binary value '0' or '1' is labeled according to comparison. As depicted in Fig. 4(c), P_1 and P_c are compared with P_2, P_3, P_7, P_8 and P_9 . Since P_c is less than P_2, P_3, P_7, P_8 and P_9 we get a pattern 11111 and since P_c is lesser than P_2 and P_8 and P_c is greater than P_3 and P_7 , the binary string 10101 is formed. Bit-wise XoR operation is performed between the binary strings 11111 and 01001, which results in a string 10110. In this case, three bits are different, which is more than threshold 2. Therefore, the bit meant for P_1 is 0.

3. FRAMEWORK OF PROPOSED RETRIEVAL SYSTEM

Detailed block diagram of retrieval system is shown in Fig.5, followed by algorithm. An image is considered as input and a feature vector is obtained in the output.

Figure 5: Schematic diagram of proposed approach

Algorithm

- 1) Get image from database and make it gray, if it is in color form
- 2) Extract QNLEP_{Sn} to build histogram.
- 3) Extract QNLEP_{Mg} to build histogram.
- 4) Create a final feature vector by concatenating histograms in step 2 step 3.
- 5) Take a query image as input.
- 6) Derive the sign patterns and magnitude patterns as given in step 2 and 3
- 7) Calculate the similarity for query and database image.
- 8) Arrange the similarity indices in descending order from highest to lowest.
- 9) Apply the evaluation metrics such as Precision and recall

3.1 Image Similarity measurement

For any retrieval system, apart from feature vector extraction, similarity measure equally has a significant role. Subsequent to calculation of feature vector, distance between a query and database images is computed to determine the level of similarity. Five different types of distance metrics are used for similarity calculation.

d1 distance

$$distMes_{s,tz} = \sum_{k=1}^o \left| \frac{D_s^z(k) - D_{tz}(k)}{1 + D_s^z(j) - D_{tz}(k)} \right| \dots \dots \dots (17)$$

4. EXPERIMENTAL RESULTS AND DISCUSSION

Performance of retrieval framework primarily relies on effective retrieval of similar images. Algorithm has to be tested with varying content of imagery data and the most similar image are to be arranged in descending order of similarity. For this purpose, we have used Precision and Recall as evaluation metrics. Definition of evaluation metrics and the related equations are specified below in the equations,

$$Pr_{avg}(C) = \frac{1}{I} \sum_{x=1}^I Pr_x \dots \dots (21)$$

$$Re_{avg}(C) = \frac{1}{I} \sum_{r=1}^I Re_r \dots \dots (22)$$

Total precision and recall are calculated using the equations (23), (24) given below.

$$Ps_{total}(C) = \frac{1}{K} \sum_{c=1}^K ps_{avg}(C) \dots \dots (23)$$

$$Re_{total}(C) = \frac{1}{K} \sum_{c=1}^K Re_{avg}(C) \dots \dots (24)$$

4.1 Database 1

ImageNet-25k is used to test efficiency of proposed method. Similar to the procedure in experiment 1, each image of database becomes a query. Precision, recall are evaluation metrics used here to determine the effectiveness of algorithm. LTrDP by 2.05%, LEPSEG by 5.5%, CSLBP by 4.7%, LBP by 11.18 %, LEPINV by 4.87%, LNDP by 3.79%, LNIP by 2.05 % Comparison of recent methods w.r.t proposed method is given in fig.6. Images retrieved for a given query are shown in fig.9.

Figure 6: Evaluation metrics calculated on database 1

Query ----- Images Retrieved -----

Figure 7: Retrieval results for a query from the database 1

4.2 Database 2

Brodatz dataset consists of 112 images of size 640x 640. Each Image is divided into 25 images each of size 128x128. Therefore, there exist 112 classes. Each class has 25 images. Efficiency in terms of Precision and Recall are used to test effectiveness of method. In the experiment, initially 25 images are retrieved. In the next step, it is increased in parts of 5. Proposed method surpasses the other methods such as LTrDP by 3.73%, LEPSEG by 10.86%, CSLBP by 21.54 %, LBP by 27%, LEPINV by 20.87%, LNDP by 4.37 %, LNIP by 2.08 % against the Avg. retrieval rate as depicted in table below. Comparison of recent methods w.r.t proposed method is given in Fig.8, Images retrieved for a given query are shown in Fig.9.

Figure 8: Evaluation metrics calculated on database 2

Query ----- Images Retrieved -----

Figure 9: Retrieval results for a query from the database 2

Table 1: Feature vector length and CPU time values of relevant methods

	CPU Time	Time for feature Extraction	Feature vector length
LTrDP	0.0332	0.0305	768
LEPSEG	0.0330	0.0371	512
CS_LBP	0.0322	0.0196	16
LBP	0.0325	0.0192	256
LEPINV	0.0323	0.0720	72
LNDP	0.0321	0.0369	64
LNIP	0.0345	0.0348	512
QNLIEP (Proposed)	0.0281	0.0310	256

A novel feature descriptor, quantized neighborhood local intensity extrema pattern is presented for retrieval. In contrast to many of the existing methods, local relationship among a group of pixels is extracted at a time instead of comparing limited number of pixels. Sign as well as magnitude patterns are derived. Local extrema is also calculated to extract more discriminating information when more than two 3 pixels are present. Precision and recall result show considerable increase in performance. In future, the number of pixels under consideration can be increased further to extend this work. Further, the method can be tested with many face recognition databases.

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