IJETST- Vol.||02||Issue||06||Pages 2569-2574||June||ISSN 2348-9480 2015

Open access Journal International Journal of Emerging Trends in Science and Technology

Content Based Image Retrieval Using Local Directional Pattern (LDP) Image Descriptor

Authors

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Abstract

We present an approach for image retrieval using Local Directional Pattern (LDP) and efficient on-line learning. This paper presents an image retrieval using novel local feature descriptor, the Local Directional Pattern (LDP), for describing local image feature. A LDP feature is obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. Each bit of code sequence is determined by considering a local neighborhood hence becomes robust in noisy situation. A rotation invariant LDP code is also introduced which uses the direction of the most prominent edge response. Finally an image descriptor is formed to describe the image (or image region) by accumulating the occurrence of LDP feature over the whole input image (or image region). Experimental results on the UW database show that LDP impressively outperforms the other commonly used dense descriptors (e.g., Gabor-wavelet and LBP).

Keywords: *Grey-Level Co-occurrence matrix(GLCM),Local Binary Pattern (LBP),k-NN,Rotation Invariant LDP.*

1. INTRODUCTION

Content- based means that the search will analyze the actual contents of the image. The term 'content' in this context might refer colors, shapes, textures, or any other information that can be derived from the image itself. Without the ability to examine image content, searches must rely on metadata such as captions or keywords. Such metadata must be generated by a human and stored alongside each image in the database.

Content-based image retrieval (CBIR) has been more and more important in the last decade. Visual information systems are radically different from conventional information systems. Many novel issues need to be addressed. A visual information system should be capable of providing access to the content of image. Where symbolic and numerical information are identical in content and form, images require a delicate treatment to approach their content. To search and retrieve items on the basis of their content requires a new visual way of specifying the query, new indices to order the data and new ways to establish similarity between the query and the target. A major problem stems from the fact that an interpretation of an image has no unique meaning. The gap between high-level semantic concepts and low-level visual features hinders further performance improvement. The problem of online feature selection is critical to really bridge this gap. Wei et al. proposed a similarity based online feature selection in Content-based image Retrieval system. An investigation is based on online feature selection in the relevance feedback learning process to improve the retrieval performance of the region-based image retrieval system. The contributions are mainly in three areas.

1) A novel feature selection criterion is proposed, which is based on the psychological similarity between the positive and negative training sets.

2) An effective online feature selection algorithm is implemented in a boosting manner to select the most representative features for the current query concept and combine classifiers constructed over the selected features to retrieve images.

3) To apply the proposed feature selection method in region-based image retrieval systems, Wei Jiang and Q. Da propose a novel region-based representation to describe images in a uniform feature space with real-valued fuzzy features. The system is suitable for online relevance feedback learning in CBIR by meeting the three requirements: learning with small size training set, the intrinsic asymmetry property of training samples, and the fast response requirement .Extensive experiments, including comparisons with many state-of-the-arts, show the effective-eness of algorithm in improving the retrieval performance and saving the processing time.

Local image descriptors are employed in many real world applications like object detection and view matching using local invariant features, texture classification using micro textons , face detection and recognizing using local features, etc. Every image descriptors attempt to describe the image robustly in adverse imaging condition like lighting variation, changed view point, alteration due to rotation, zooming etc. Descriptors found in literature can be classified into two groups: sparse descriptor and dense descriptor The sparse first detects the interest points from a given image for sampling local image patch around detected interest points then it generates a feature vector capable to describe the patch. On the other hand, the dense descriptors extract local image features pixel by pixel over the whole input image without identify the interest points.

Scale invariant feature transform (SIFT) is the most notable descriptor in terms of distinctiveness which generates the descriptors with a 3D histogram of gradient location and orientation. Several researchers make an effort to improve the SIFT descriptor and consequently proposed Gabor wavelet and local binary pattern are two most popular dense descriptors. The first technique applies a number of Gabor filters on the image to capture small changes in frequency and orientation; finally statistics of these micro-features are used to describe the underlying texture. Recently LBP feature is gaining much attention as a local image descriptor due to its simplicity and excellent performance in texture analysis and face image analysis . Though LBP is robust to monotonic illumination change but it is sensitive to non-monotonic illumination variation and also shows poor performance in the presence of random noise . Local Directional Pattern (LDP), a more robust facial feature, is proposed by Jabid et al., which demonstrated better performance in different application of facial image analysis .

This paper introduces LDP as a local image descriptor that can work as a dense descriptor. LDP feature considers relative edge response value in eight directions around a pixel to encode the local neighborhood property of image pixel with a binary bit sequence. In this work, we also proposed a rotation invariant LDP code which uses the largest edge response direction as a starting bit location to normalize the orientation change. It is nearly impossible that most significant edge response will corrupt in any kind of noise or photometric changes, hence generates a robust rotation invariant LDP code.

2. FEATURE EXTRACTION USING LOCAL DIRECTIONAL PATTERN DESCRIPTOR

The local directional pattern (LDP) operators use the edge response values of neighborhood pixels and encode the image texture. Kirsch edge detector is used to find edge responses.Figure 3.2 shows eight Kirsch masks to detect edge response values.

$$\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}$$

$$\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}$$

Fig 1: Kirsch Edge Response masks in eight directions

The LDP is computed as follow. The LDP assigns an 8-bit binary code to each pixel of an input image. This pattern is then calculated by comparing the relative edge response values of a pixel by using Kirsch edge detector. Given a central pixel in the image, the eight-directional edge response values m_i (i= 0,1,2……,7) are computed by Kirsch masks. Since the presence of a corner or an edge shows high response values in some particular directions, thus, most prominent directions of k number with high response values are selected to generate the LDP code. In other words, top-k directional bit responses, b_i, are set to 1, and the remaining $(8-k)$ bits are set to 0. Finally, the LDP code is derived by equation (1).

$$LDP_k = \sum_{i=0}^{7} b_i\,(m_i - m_k) \times 2^i \qquad (1)$$

$$b_i(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Where m_k is the k –th most significant directional response.

m_3	m_2	m_1
m_4	$\times$	m_0
m_5	m_6	m_7

b_3	b_2	b_1
b_4	$\times$	b_0
b_5	b_6	b_7

Fig 2: Edge Response and LDP Binary Bit Positions

85	32	26
53	50	10
60	38	45

→

313	97	503
537	X	393
161	97	161

→

0	0	1
1	X	1
0	0	0

Fig 3: LDP code with k=3

Then LDP binary code is calculated starting from binary bit position 0 from right to left, calculated as

LDP Binary Code : 00010011

LDP Decimal Code: 19

2.1 Rotation invariant LDP

Rotational change of any image will lead to alter the spatial intensity distribution of that image. As a result edge response values of each direction will change and in consequence generate completely different LDP code. But observing the response values minutely we can conclude that relative position of these response values compared to strongest edge response will not affected by this rotation of the image. For example consider a particular image patch with eight edge response value. If the image is rotated by 90^0 anticlockwise then intensity value of that image patch change which leads to change of edge response values. The rotated image patch along with edge responses. If we compare these two figures out that edge response values changes their corresponding direction by 90^0 anticlockwise. Observing this, we proposed a simple method for achieving rotation invariant LDP feature by applying a circular shift operation on the original binary code value. For achieving this shift operation, the direction of highest edge response is termed as the dominant direction of the LDP code. The bit value associated with the dominant direction is moved to the right most bit of the code. Then, the other bits are circularly shifted with the same number of bit position as the dominant direction bit shifted to get the right most position. For example, if the bit position original code is ''abcdefgh'' and dominant directional bit is at ''c'' location then bit value of 'c' position should be shifted 5 place to positioned into right most bit. So all other bit will also circularly shifted by 5 places and finally the normalized code will be ''defghabc''. This procedure generates rotation invariant LDP code which is denoted by LDP. This normalization method is based on the assumption that to compare similarity between two textures, they should be rotated so that their dominant directions are the same. It has been proved that image rotation in spatial domain is equivalent to circular shift of feature vector elements.

3. k-NEAREST NEIGHBOR(kNN)

To make the classification-Nearest Neighbor (kNN) transforms the target images into representational feature vectors which have same formation with training samples. Then it calculates Euclidean distance between the target images and the selected k-neighbors. Finally the category of target image is determined according to their neighbors'class.

The Euclidean distance between two images a and b, is calculated by equation (2).

$$D\,(a, b) = \sqrt{\sum_{i=1}^{n}(b_i - a_i)^2} \quad (2)$$

Where $a = (a_1, a, \ldots . a_n)$ and $b = (b_{1,} b_2, \ldots . b_n)$ are two points in Euclidean n-space. Choose nearest k neighbors as the reference ,then the category C_j which includes most neighbors, calculated by equation (3).

$$p(\bar{x}, C_j) = \sum_{\overline{d_\imath} \epsilon kN} Sim\left(\bar{x}, \overline{d_\imath}\right) y(\overline{d_\imath}, C_j) \quad (3)$$

Where $\overline{d_\imath}$ is the i^{th} training image, Sim(a,b) is the similarity of image a and image b, and y(α, β) represent the probability of image α belong to class β.

4. DATABASE

The database created at the University of Washington (UW) consists of a roughly categorized collection of 780 images. The images are of various sizes and mainly include vacation pictures from various locations. There are 19 classes, for example "spring flowers", "Barcelona", and "Iran" etc. The relevance assessment for the experiments with this database is performed using test images. The database is freely available.

Texture classification is done with a total of 91 (13*7=91) rotated textures of size 512*512 which are achieved by rotating the original image into seven different orientations of 0^0, 30^0, 60^0, 90^0, 120^0, 150^0 and 200^0. The rotated textures are of size 256x256, derived from the center portion of respective 512x512 size rotated textures. The second group of textures comprises all the 112 textures of size 512x512 from UW Dataset (D1–D112). They are rotated in steps of 10^0 up to 360^0 and used for classification, i.e., texture classification is done with a total of 4032 rotated texture images (112x36 = 4032). The rotated textures are of size 256x256, derived from the centre portion of respective 512*512 size rotated textures.

5. EXPERIMENTAL SETUP

In the following section Feature extraction is performed on the three datasets and these results have been stored in the feature database made in MS Office Excel. This database includes mainly image features extracted from images. After the features have been stored in the databases, image classification has been performed by the means of the proposed Adaboost based kNN algorithm.In this section, some of the screenshots are given from the software implementation used for displaying the result, after puts test image.

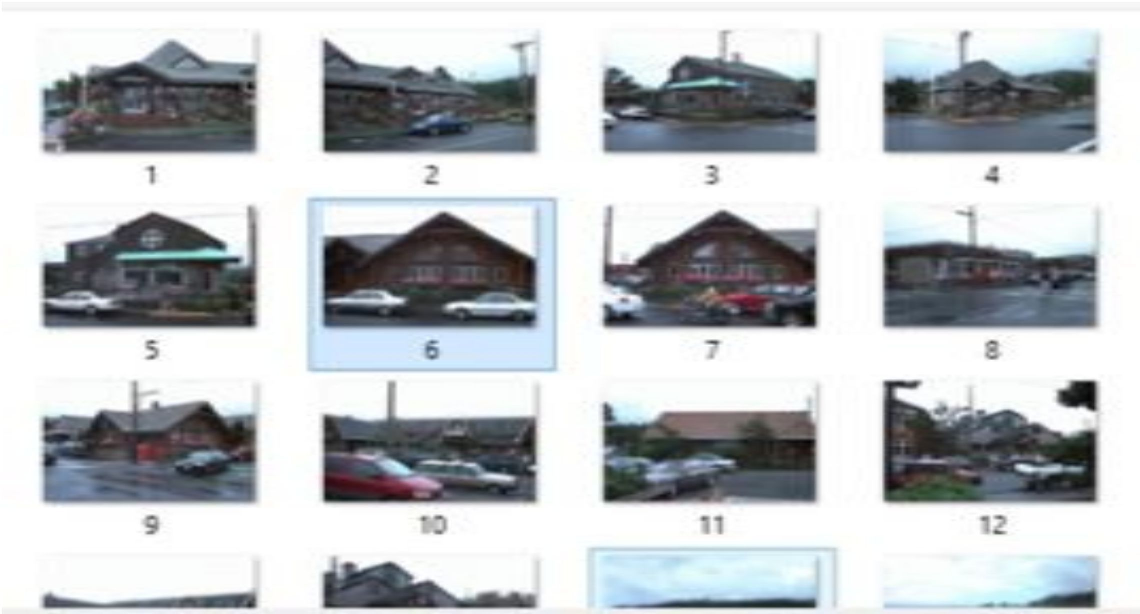

Figure 4: Result Images for UW database after Classification

6. PERFORMANCE ANALYSIS

Let the database $\{x_1,\ldots. x_n,\ldots\ldots.,x_N\}$ be a set of images represented by features. To retrieve images similar to a query image q, each database image x_n is compared with the query image using an appropriate distancefunction $d(q, x_n)$. Then, the database images are sorted according to the distances such that $d(q, x_{n_i}) \leq d(q ,x_{n_{i+1}})$ holds for each pair of images x_{n_i} and $x_{n_{i+1}}$ in the sequence $(x_{n_1}\ldots.,x_{n_i}\ldots x_{n_N})$. If a combination of different features is used, the distances are normalized to be in the same value range and then a linear combination of the distances is used to create the ranking. To evaluate CBIR, several performance evaluation measures as F-measure has been proposed based on the precision P and the recall R:

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

$$R= \frac{\text{No. of relevan timages retrieved}}{\text{Total number of relevant images}} \quad (5)$$

$$\text{F-Measure} = \frac{2*P*R}{P+R} \quad (6)$$

No. of Iterations	Average Precision	Average Recall	F-Measure
1	95.5	94.6	95.0478
2	95.5	94.6	95.0478
3	95.5	94.6	95.0478
5	95.5	94.6	95.0478

Table 1: Performance analysis using Precision, Recall and F-Measure for UW Database

The precision and recall values have been improved using LDP. An average precision value using LDP for UW database is 95.6%, an average recall value for UW database is 94.7% .The LDP gives better result than other image descriptor.

7. CONCLUSION

This paper introduces a local feature descriptor LDP for object detection. LDP code which compute the edge response values in different directions and use this to encode the local image property. The discriminative power of the LDP descriptor mainly lies in the integration of local edge response into a single binary pattern that makes it robust and insensitive to noise and non-monotonous illumination changes. Experimental results show that LDP descriptor shows better classification accuracy on UW database.

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