Image Retrieval Technique Using Local Binary Pattern (LBP)

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Abstract: ***The increased need of content based image retrieval technique can be found in a number of different domains such as Data Mining, Education, Medical Imaging, Crime Prevention, Weather forecasting, Remote Sensing etc. An image retrieval system allows us to browse, search and retrieve the images. In early days because of very large image collections the manual annotation approach was more difficult. In order to overcome these difficulties content based image retrieval was introduced. This paper presents the content based image retrieval, using local binary pattern (LBP). The local binary pattern encodes the relationship between the referenced pixel and its surrounding neighbors by computing the gray-level difference. The objective of the proposed work is to retrieve the best images from the stored database that resemble the query image.***

Keywords: Content based image retrieval (CBIR), Local binary pattern (LBP).

1. Introduction

During the last decade there has been a rapid increase in volume of image and video collections. A huge amount of information is available, and daily gigabyte of new visual information is generated, stored and transmitted. However, it is difficult to access this visual information unless it is organized in a way that allows efficient browsing, searching, and retrieval. Traditional methods of indexing images in database rely on a number of descriptive keywords, associated with each image. However, this manual annotation approach is subjective and recently, due to the rapidly growing database sizes, it is becoming outdated. To overcome these difficulties in the early 1990s, content-Based Image Retrieval (CBIR) emerged as a promising means for describing and retrieving images. According to its objective, instead of being manually annotated by text-based keywords, images are indexed by their visual content, such as color, texture, shape, and spatial layout.

The local binary pattern (LBP) feature has emerged as a silver lining in the field of texture classification and retrieval. Ojala *et al.* proposed LBPs [2], which are converted to a rotational invariant version for texture classification [3], [4]. Various extensions of the LBP, such as LBP variance with global matching [5], dominant LBPs [6], completed LBPs [7], joint distribution of local patterns with Gaussian mixtures [8], etc., are proposed for rotational invariant texture classification. The LBP operator on facial expression analysis and recognition is successfully reported in [9] and [10]. Xi Li *et al.* proposed a multiscale heat-kernel-based face representation as heat kernels are known to perform well in characterizing the topological structural information of face appearance. Furthermore, the LBP descriptor is incorporated into multiscale heat-kernel face representation for the purpose of capturing texture information of the face appearance [11].

Local Binary Pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by threshold the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

2. Literature Review

[1] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 971–987, Jul. 2002.

This paper introduces a theoretically and computationally simple yet efficient multiresolution approach to gray-scale and rotation invariant texture classification based on uniform local binary patterns and nonparametric discrimination of sample and prototype distributions. This paper developed a generalized gray-scale and rotation invariant operator LBP, which allows for detecting uniform patterns in circular neighborhoods of any quantization of the angular space and at any spatial resolution. They also presented a simple method for combining responses of multiple operators for multiresolution analysis by assuming that the operator responses are independent.

[2] S. Liao, M.W. K. Law, and A. C. S. Chung, “Dominant local binary patterns for texture classification,” *IEEE Trans. Image Process.*, vol. 18, no. 5, pp. 1107–1118, May 2009.

This paper proposes the dominant local binary patterns (DLBP) as a texture classification approach. The DLBP approach on one side guarantees to be able to represent the dominant patterns in the texture images. On the other side, it retains the rotation invariant and histogram equalization invariant properties of the conventional LBP approach. It is simple and computationally efficient. This paper proposes a novel approach to extract image features for texture classification. The proposed features are robust to image rotation, less sensitive to histogram equalization and noise. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses. The dominant local binary pattern method makes use of the most frequently occurred patterns to capture descriptive textural information, while the Gabor-based features aim at supplying additional global textural information to the DLBP.

[3] Z. Guo, L. Zhang, and D. Zhang, “A completed modeling of local binary pattern operator for texture classification,” *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1657–1663, Jun. 2010.

In this paper, a completed modeling of the local binary pattern (LBP) operator is proposed and an associated completed LBP (CLBP) scheme is developed for texture classification. A local region is represented by its center pixel and a local difference sign-magnitude transform (LDSMT). The center pixels represent the image gray level and they are converted into a binary code, namely CLBP-Center (CLBP_C), by global thresholding. LDSMT decomposes the image local differences into two complementary components: the signs and the magnitudes, and two operators, namely CLBP-Sign (CLBP_S) and CLBP-Magnitude (CLBP_M), are proposed to code them. The traditional LBP is equivalent to the CLBP_S part of CLBP, and they show that CLBP_S preserves more information of the local structure than CLBP_M, which explains why the simple LBP operator can extract the texture features reasonably well. By combining CLBP_S, CLBP_M, and CLBP_C features into joint or hybrid distributions, significant improvement can be made for rotation invariant texture classification.

[4] T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with local binary patterns: Applications to face recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

This paper presents a novel and efficient facial image representation based on local binary pattern (LBP) texture features. It is based on dividing a facial image into small regions and computing a description of each region using local binary patterns. These descriptors are then combined into a spatially enhanced histogram or feature vector. The texture description of a single region describes the appearance of the region and the combination of all region descriptions encodes the global geometry of the face. The LBP operator has been widely used in different applications such as texture classification, image retrieval, etc.

[5] G. Zhao and M. Pietikainen, “Dynamic texture recognition using local binary patterns with an application to facial expressions,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 6, pp. 915–928, Jun. 2007.

Dynamic texture (DT) is an extension of texture to the temporal domain. Description and recognition of DTs have attracted growing attention. In this paper, it introduces a novel approach for recognizing DTs and its simplifications and extensions to facial image analysis are also considered. First, the textures are modelled with volume local binary patterns (VLBP), which are an extension of the LBP operator widely used in ordinary texture analysis, combining motion and appearance. To make the approach computationally simple and easy to extend, only the co-occurrences of the local binary patterns on three orthogonal planes (LBP-TOP) are then considered.

3. Methodology

3.1 Local Binary Pattern (LBP)

LBP method provides a robust way for describing pure local binary patterns in a texture. The original 3×3 neighborhoods thresholded by the value of the center pixel. This threshold neighborhood pixel values are multiplied by binomial values of the corresponding pixels. Resulting pixel value is summed for the LBP number of this texture unit.LBP method is gray scale invariant and can be easily combined with a simple contrast measure by computing for each neighborhood the difference of the average gray level of those pixels which have the value 1 and those which have the value 0 respectively as shown in Figure 1 [12].

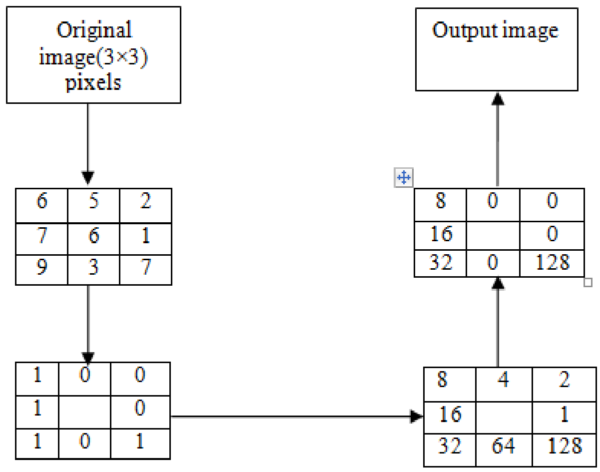

Figure 1: Block diagram of Local Binary Pattern

LBP is a two-valued code. The LBP value is computed by comparing gray value of centre pixel with its neighbors, using the below equations (1) and (2).

$$LBP_{P,R} = \sum_{p=1}^{p} 2^{(p-1)} \times X(Gp - Gc) \quad \text{........(1)}$$

$$X(x) = \begin{cases} 1, x \geq 0 \\ 0, else \end{cases} \quad \text{..............(2)}$$

Where,
Gc – Gray value of the centre pixel
Gp – Gray value of its neighbors
P - Is the number of neighbors
R - Is the radius of the neighborhood.

Example

6	5	2
7	6	1
9	8	7

Binary Pattern

1	0	0
1		0
1	1	1

Weights

1	0	0
128		0
64	32	16

LBP Value

	241	

LBP = 1+16+32+64+128=241

Figure 2: Computation of LBP value**.**

4. Experimental Results

This database consists of large number of images of various contents ranging from animals to outdoor sports to natural images. These images have been pre-characterized into different categories each of size 100 by domain experts. The 4 query retrievals by the proposed method are shown in figure 4-7 with an average retrieval time as 1min.

Figure 3: Sample image from database DB (one image per category)

Figure 4: Sample retrieved results from database for given query image (Bus)

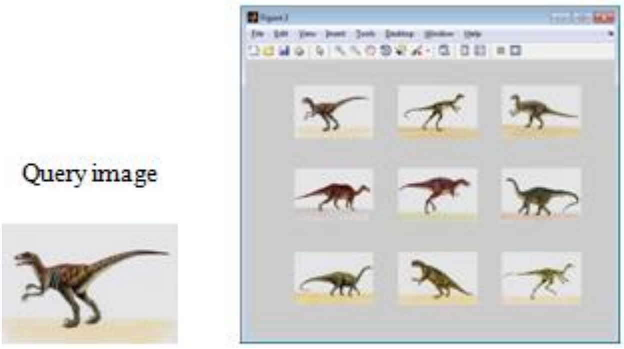

Figure 5: Sample retrieved results from database for given query image (Dinosaur)

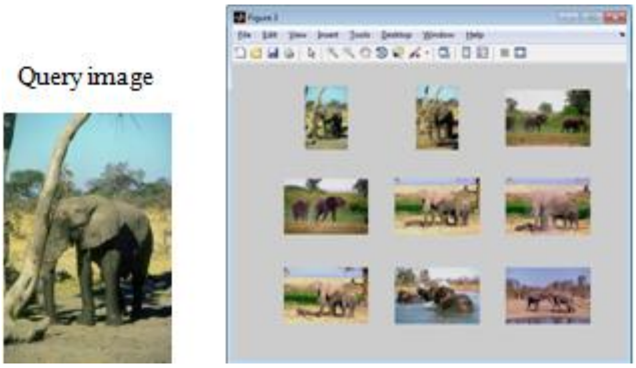

Figure 6: Sample retrieved results from database for given query image (elephant)

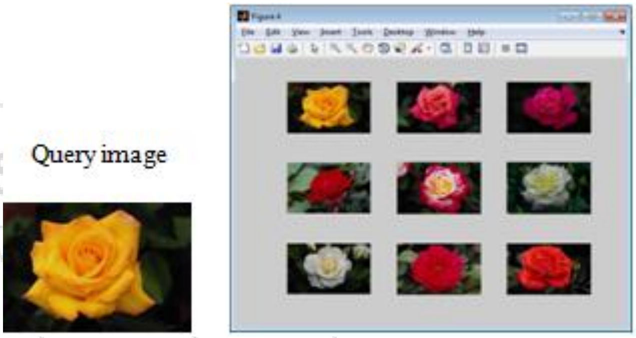

Figure 7: Sample retrieved results from database for given query image (rose)

5. Conclusion

The proposed method has been implemented using Matlab and tested on a general-purpose WANG database [13] containing 1,000 images of the Corel stock photo, in JPEG format of size 384x256 and 256x386 as shown in Figure 3. The search is usually based on similarity rather than the exact match. We have followed the image retrieval technique, as described in the methodology. The 4 query retrievals by the proposed method are shown in Figures 4-7, with an average retrieval time as 1min. The whole indexing time for the 1000 image database takes 5-6 minutes. The current work is based on Local binary pattern. So, in future Local ternary pattern, local tetra pattern can be used for image retrieval, it will give better and effective retrieval of an image.

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