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An Extension to the Local Binary Patterns for Image Retrieval

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Abstract. In this paper, we propose an extension to the local binary patterns for image retrieval. We focus on the spatial distribution information in images, and present a spatial-distribution-information-enhanced local pattern for content-based image retrieval. Differing from traditional local patterns, we group those gray-level varying values according to three directions, and each group is then merged into a local spatial distribution pattern to represent the spatial distribution property of the image. Our preliminary experimental results on a real dataset demonstrate the effectiveness of our algorithm.

Keywords: Content-based Image Retrieval; Local Patterns

1 Introduction

Image retrieval is an important field in image processing and pattern recognition, which is also an important branch of information retrieval. Generally, there are three categories of retrieval methods: text-based, semantic-based, and content-based methods. The text-based method was proposed in 1970s and is still the most widely used one in Web image retrieval [1], however, the text-based method heavily depends on human perception, as the images need to be first manually annotated using text tags, categories, or other information [2]. The semantic-based approaches focus on reducing the semantic gap between the visual features and human perception. People tend to use high-level features to understand images and measure their similarity, but image low-level features such as color, texture, and shape often fail to describe the high level semantic concepts [3, 4]. The content-based image retrieval (CBIR) method aims to organize digital images according to their visual features, such as color, texture, shape, distribution layout, and so on [5]. CBIR needs neither manual image annotation nor semantic labeling, and can rank the retrieved images with respect to their similarity with the query image. Therefore, it has been one of the hottest research topics in recent years.

The key issue in CBIR is to find meaningful features to represent images. One of the most widely-used and important features is the texture of image. Texture

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feature is able to reflect a lot of properties of image, such as smoothness, coarseness, and regularity. Therefore, many approaches have been proposed to describe texture features, among which the most influential one is the local pattern based methods. A local pattern of image refers to the gray-level differences between the referenced pixel of an image and its surrounding pixels. There have been some different local patterns presented in recent years, such as local binary patterns (LBP) and local ternary patterns (LTP), however, one common problem of those previous local patterns is that, they all ignore the spatial distribution property of texture in images. This will lead to the loss of useful texture information of image retrieval in many cases, and our experimental results in this paper will demonstrate this claim.

In this paper, we aim at incorporating the spatial distribution property of image with the traditional local pattern based CBIR methods, and present a new spatial-distribution-enhanced local pattern for texture features, which is called local spatial distribution pattern (LSDP). Compared with various traditional local patterns, LSDP reorganizes the gray-level varying values among pixels in accordance with three directions (horizontal, vertical, and diagonal) so that it can represent the texture feature of an image in different spatial distribution patterns.

The remainder of the paper is structured as follows. Section 2 introduces the local spatial distribution pattern. In Section 3, experiments and comparison between our algorithm and previous ones are given. And the conclusions as well as the future work are in Section 4.

2 Local Spatial Distribution Pattern

Traditional local patterns like LBP, LTP, and LTrP do not pay attention to the spatial distribution property hidden in images. Therefore, our general idea is to incorporate the spatial distribution property with the traditional local patterns, so that we can describe the spatial distribution structure of the local texture. This idea leads to the design of so-called *local spatial distribution pattern* (LSDP).

Given an image *I*, supposing that *p* is the referenced pixel in the image *I*, we use the symbol to denote the gray-level variation pattern along the horizontal and vertical direction, and to represent the pattern along the diagonal direction. Then, we determine and w.r.t Formula (1).

(1)

In Formula (1), *R* is the number of the neighbors around *p* along with the horizontal and vertical direction, *D* is the number of the neighbors around *p* along with the diagonal direction. Fig.1 shows an example of calculating and . In this example, the exemplified image region consists of pixels, and both *R* and *D* are 4.

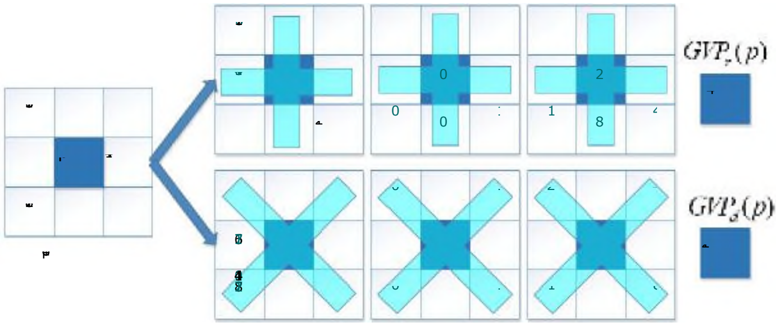


Fig. 1. An example of calculating and

The definition of LDSP is based on and . First, we use a distance vector ***l*** to denote the distance between the referenced pixel *p* and its neighbor pixel *q* in an image, and define ***l*** as ***l*** = (q_x–p_x, q_y–p_y). LSDP of *p* is defined by integrating the horizontal, vertical or diagonal patterns of these pixels together, as defined in Formula (2).

(2)

From Formula (1) and (2), we integrate two 4-bit patterns into 8-bit pattern LSDP value for each referenced pixel. In this paper, we choose the window size of and the distance ***l*** as (0, 1), (1, 0), (1, 1), (-1, 1), so we can finally obtain each four LSDP patterns of the referenced pixel and its neighbor pixel individually on horizontal, vertical and diagonal directions. After identifying the local spatial distribution pattern, the whole image is represented by building a histogram using Formula (3), where represent the size of the input image, *x* is the LSDP level, range from 0 to 255.

$$f(LSDP(p), x), f(x, y) \quad (3)$$

1,

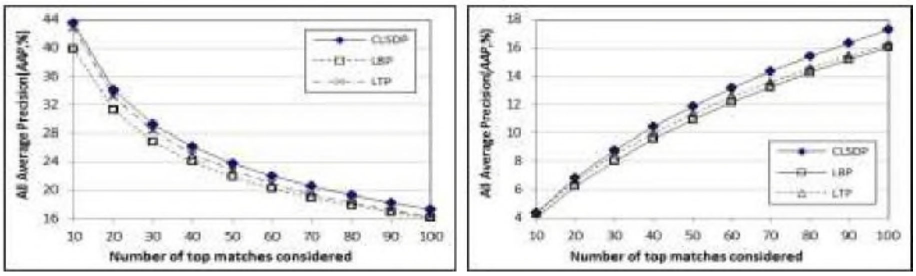
3 Performance Evaluation

In order to evaluate the effectiveness of CLSDP, experiments are implemented on a benchmark databases, named DB1: Corel 10K Database (http://wang.ist.psu.edu/docs/related.shtml). DB1 consists of 100 categories of natural scene images, with 100 images of each category, set up a database with 10,000 images. This database meets all the requirements to evaluate an image retrieval system, due to its large size and heterogeneous content. Each image in this database is considered as the query image.

The performance of LSDP and traditional local patterns is measured in terms of *AAP* and *AAR*, as mentioned in Formula (4).

(4)

The retrieval results are shown in Fig.2. It shows that the *AAP* of LSDP increases from 39.90% to 42.79% (top matches = 10), and the *AAR* increases from 16.06% to 17.28% (top matches = 100).



(a) AAP *(b)* AAR

Fig. 1. *AAP* and *AAR* of LSDP and local patterns on DB1 (Corel 10K Database)

4 Conclusion

In this paper, we present an extension to the local binary patterns for content-based image retrieval. Our extension is focused on the spatial properties of images, and we introduced directional patterns to better describe the textual features of images. Our preliminary results on a real data set demonstrated its effectiveness.

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