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Two novel local binary pattern descriptors for texture analysis

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ABSTRACT

The recent developments in the image quality, storage and data transmission capabilities increase the importance of texture analysis, which plays an important role in computer vision and image processing. Local binary pattern (LBP) is an effective statistical texture descriptor, which has successful applications in texture classification. In this paper, two novel descriptors were proposed to search different patterns in images built on LBP. One of them is based on the relations between the sequential neighbors with a specified distance and the other one is based on determining the neighbors in the same orientation through central pixel parameter. These descriptors are tested with the Brodatz-1, Brodatz-2, Butterfly and Kylberg datasets to show the applicability of the proposed $nLBP_d$ and $dLBP_\alpha$ descriptors. The proposed methods are also compared with classical LBP. The average accuracies obtained by ANN with 10 fold cross validation, which are 99.26% (LBP^{u2} and $nLBP_d$), 94.44% (dLBP_α), 95.71% ($nLBP_d^{u2}$) and %99.64 ($nLBP_d$), for Brodatz-1, Brodatz-2, Butterfly and Kylberg datasets, respectively, show that the proposed methods outperform significant accuracies.

1. Introduction

Texture analysis, which plays an important role in image processing and computer vision systems, has been widely employed in applications such as remote sensing, medical image analysis, document analysis, face identification, finger print identification and classification of real outdoor images. In the last decades, numerous methods were proposed for extracting texture features, and the most common used methods in practice are: local binary patterns (LBP) [1], gray level co-occurrence matrices (GLCM) [2], Gabor filters (GF) and wavelet methods. These methods can be mainly categorized into structural, statistical, transform and model based methods. The LBP, which is one of the simplest approaches for describing texture, was proposed by Ojala et al. [1]. It utilizes statistical intensity of an image or local structure. LBP compares each pixel with its neighbors, which are located on a circle around the pixel. These relationships are represented by a binary pattern and converted to a histogram [3,4]. The main advantages of LBP are: (1) it is a powerful discriminator, (2) it requires less computational cost depending on its simplicity than other texture methods such as GLCM, (3) it is less sensitive to changes in illumination than many other descriptors, and (4) it can be easily implemented [5,6].

Because of these advantages, LBP has been employed in many applications successfully, such as texture recognition and segmentation [1,7], face and facial expression recognition [8–11], dynamic texture recognition [9], environment modeling [12], face classification [8], biomedical image analysis [13], smoke detection, segmentation of remote-sensing images [14], finger print identification [15], classification of real outdoor image [16] and human detection. Despite the significant success of LBP in computer vision, the traditional LBP operator has some drawbacks and limitations: (1) it generates long histograms and the histograms are sensitive to image rotation, (2) it has small spatial support, (3) the LBP operator cannot properly detect large-scale textural structures in its basic form, and (4) it is sensitive to noise [17]. Various versions of traditional LBP descriptors were proposed to overcome these drawbacks. One of them is dominant local binary patterns (DLBP), which aims to extract the dominant local structures in texture images [18]. In another study, LBP descriptors were used in Gabor transform domain (LGBP) [19]. In 2002, Ojala et al. [20] proposed a dynamic version of LBP for video texture extraction and another version of it, multi-resolution LBP (MLBP). Furthermore, Ahonen et al. [21] introduced soft histograms, and Tan and Triggs [22] proposed local ternary patterns (LTP), using tertiary numbers instead of binary. Guo et al. [23] proposed completed LBP (CLBP) by combining the traditional LBP with the measures of local intensity difference and central gray level. Zhao et al. [10] proposed a robust framework of LBP, named completed robust local binary pattern (CRLBP), in which the value of

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each center pixel in a 3×3 local area is replaced by its average local gray level. Since the LBP and its extensions use both statistical and structural characteristics of texture, they are powerful tools for texture analysis that have been successfully utilized in texture analysis and give better performance than other methods, on the other hand, they still have a serious disadvantage: they cannot capture spatial relationships among local textures [17].

The objective of this research is to obtain novel texture searching approaches based on the spatial relation of pixels in different directions or distributions. In this paper, two novel versions of LBP, which may be more useful to understand the image than traditional LBP for the textures that have a special spatial relationship, were proposed. In the first descriptor, the histogram is based on relations between the neighbors around the center pixel. In the other one, the histogram was formed by using the comparison between the values of the center pixel with its neighbors in a defined orientation. The Brodatz-1, Brodatz-2 [24], Butterfly [25] and Kylberg [26] datasets were used to validate these descriptors. The obtained experimental results show that the proposed methods outperform significant accuracies.

This paper is organized as follows. Section 2 describes the datasets used in this study. Also the methodology of the traditional LBP operator and new descriptors, which are local binary patterns by neighborhoods ($nLBP_d$) and directional local binary patterns ($dLBP_\alpha$), are presented in this section. In Section 3, obtained accuracies of four dataset, which are the Brodatz 1, Brodatz 2, butterfly and Kylberg datasets, are assessed. The last section concludes the paper.

2. Material and methods

2.1. Datasets

Four datasets were used in the validation of methods proposed in this study. The first dataset consisted of 15 Brodatz texture classes (Brodatz-1), which totally contains 111 different classes, as shown in Fig. 1. The second one contains 50 Brodatz texture classes (Brodatz-2), which were not used in the first dataset, as shown in Fig. 2. For these two dataset a 9 different 213×213 sub images were extracted from each image.

The third dataset is Butterfly dataset that consisted of 10 images for each one of the 14 butterfly species. The butterflies were collected in Van (Turkey) between May, 2002 and August 2003, and in the attitudes of 1800–3200 m [27–29], are illustrated in Fig. 3.

The last dataset is Kylberg Texture dataset, which consists of 160 images (samples) for each one of the 28 class and it includes totally 4480 images. In this study, only the first 30 images of each class were employed. Fig. 4 shows example images from each class.

2.2. Traditional local binary pattern operator

The LBP operator, which was proposed to measure the local contrast in texture analysis [20], searches micro-textons in a local region. A binary pattern was obtained by thresholding the neighboring pixels with the pixel in the center of them, as shown in Fig. 5 [1,6]. This operator is defined as a gray scale invariant texture measure and derived from a general definition of texture in a local neighborhood [30]. Only eight neighbors of a pixel were taken into account in the basic version of the LBP, but it has been extended to include all circular neighborhoods with any number of pixels [1,20,3].

As seen in Fig. 5, different LBP histograms can be obtained according to any desired rule of selecting neighbors, where R indicates the radius of the model and P is the number of neighbors in $LBP_{P,R}$. For each pixel position, (x_k, y_k), the LBP operator labels every pixel around them by using the value of the center pixel as a threshold value. If the neighboring pixel value is greater than or equal to the value of the center pixel, this pixel takes the value 1, otherwise it takes 0. The process of determining the decimal value for a pixel is demonstrated in Fig. 6.

In Fig. 6, the implementation process of basic LBP, where P and R are 8 and 1, respectively, is presented. The decimal value of obtained binary code gives the local structural information around the given pixel. The mathematical formulation of LBP for a pixel is as follows [31,32]:

$$LBP(x) = \sum_{i=0}^{P} S(G(x_i) - G(x))2^{i-1} \quad (1)$$

$$S(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases} \quad (2)$$

where x is the location of the center pixel. x_i is the location of the ith neighboring pixel and $G(.)$ is the pixel intensity value. Note that, each bit (0 or 1) in the binary value has the same significance level

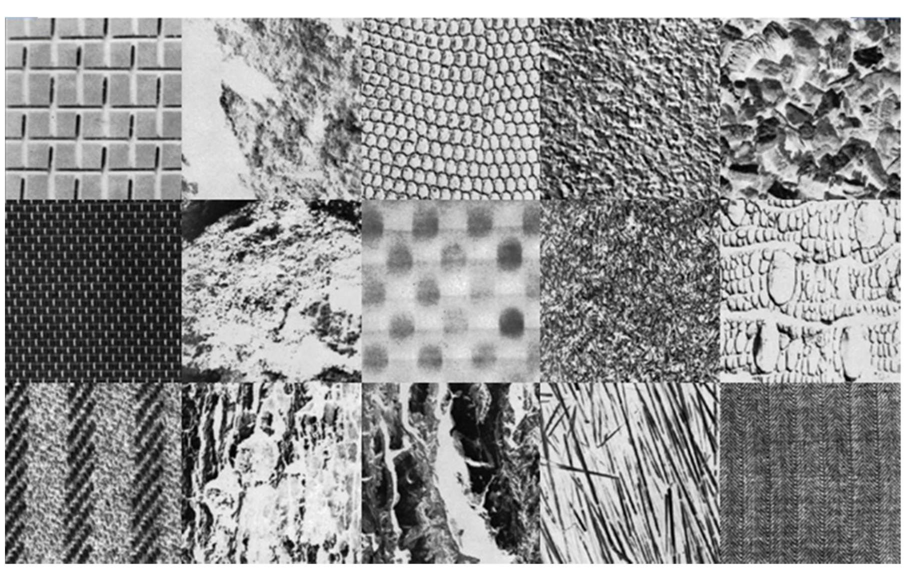

Fig. 1. The Brodatz texture dataset from the USC-SIPI image database.