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Texture recognition based on diffusion in networks

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ABSTRACT

Much work has been done in the field of texture analysis and classification. While promising classification methods have been proposed, most of them rely on classical image analysis approaches. This paper presents a texture classification method based on diffusion in directed networks. First, an image is modeled as a directed network by mapping each pixel as a node and connecting two nodes up to a maximum distance *r*. To reveal texture properties, links between two nodes are removed based on the pixel intensity difference. Once such a network is obtained, the activity of each node is estimated by random walks and combined into a histogram to describe the image. The main contribution of this paper is the use of directed networks, which tends to provide better performance than in undirected cases. Also, we have shown that the activity induced on these networks can be effectively used as texture descriptor. Experimental results show that the proposed method is favorably compared to traditional texture methods on widely used texture datasets. The proposed method is also found to be promising for plant species classification using samples of leaf texture.

1. Introduction

Texture has become a fundamental cue for recognizing objects and scenes in different applications of computer vision, including industrial inspection, remote sensing of earth resources, medical imaging, object recognition and content-based image retrieval. Generally speaking, visual texture can be described as patterns that exhibit a high degree of similarity in the image. Despite the intense research in the last decades and recent advances, texture analysis still presents many challenges to be addressed, especially regarding the classification of textures in different viewpoints [65]. The main drawback of most texture methods is to assume that the texture images are acquired from the same viewpoint (e.g. same orientation or scale). Since it is very difficult to ensure the same viewpoint in practical applications, texture methods should be invariant under contrast, translation, rotation, scale and perspective changes. As we show in the following sections, the proposed method deals effectively with images in different viewpoints.

Recently, texture methods using networks to represent images have emerged as promising approaches [6,7,25,27]. Many measurements can be used to extract meaningful features from networks such as topological [6], random walks [28,41], and

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deterministic walks [25]. Unlike previous works [7,25,27], our method represents an image as a directed network, which tends to stabilize induced random walks after few steps. In addition, we extract features from networks based on the diffusion process which estimates an activity for each node. This activity showed to be correlated to texture in the image, thus an effective measure for texture classification.

Specifically, this paper proposes a novel approach to characterize texture images based on diffusion in directed networks, following recent findings that diffusion in directed networks can reveal clustering in the structure versus dynamics space [16]. In this method, a texture image is mapped into a regular directed network by mapping each pixel to a node of the network and connecting two nodes in a given radius. Then, a function is applied to transform the regular directed network into a t-scaled directed network that enhances different properties of the texture. Given the t-scaled network, random walks are performed in each node in order to estimate its activity. Finally, the histogram of activities for different values of thresholds and radius of connection is used to obtain the respective feature vector.

Experiments were performed in four widely used texture image datasets that present challenges as scaling, lighting, rotation, among others. Experimental results on these datasets showed the effectiveness of the proposed method compared to existing texture methods. Furthermore, the proposed method was applied to a real-world challenging problem consisting in the classification of plant species by leaf texture. Promising results have been achieved in the classification of 20 plant species.

The paper is structured as follows. Related work is discussed in Section 2 and the mathematical details of networks and diffusion are described in Section 3. In Section 4, we show how to model images into networks, as well as the diffusion process in directed networks. Section 5 discusses the invariance of the proposed method under different viewpoints. Texture image datasets, experiments and results are described in Section 6. Finally, Section 7 concludes the paper and presents suggestions for further investigation.

2. Related work

Many methods for texture analysis have been proposed in the literature. According to [25,65], these methods can be divided into five categories: (i) structural, (ii) statistical, (iii) spectral, (iv) model-based and (v) agent-based. A sixth category can be considered to include (vi) graph-based methods. Structural methods (i) consider the texture as a set of textural elements organized according to some spatial rule. Usually, mathematical morphology operations are successively applied on the image in order to describe the evolution of textural elements [2,32,52]. Recently, some methods proposed the use of keypoint detectors and descriptors to characterize the texture elements [39,64]. Lazebnik et al. [39] suggested the use of the affine Harris and Laplacian regions as texture elements. Then, these texture elements are characterized by the spin image and the RIFT descriptors. Despite promising results, these approaches may discard important texture elements as a consequence of using only some pixels of the image. Moreover, the keypoint detectors may incur instability and redundancy of existing keypoints [57].

Statistical methods (ii) describe the texture image using properties that govern the spatial distribution of gray-levels in a given neighborhood. To capture the spatial distribution of gray-levels, co-occurrence matrices [33] and their rotation invariance version proposed by Davis [20] are usually employed. More recently, the local binary patterns [29,43] were proposed. This method achieved interesting results by calculating the co-occurrence of gray-levels on circular neighborhoods. In this context, the method proposed here analyzes the co-occurrence of gray levels in the path taken by the agent when performing the walk. In [40] the texture is represented by random projecting measurements.

Spectral methods (iii) model the texture image in the power spectrum domain. One of the most popular texture method is based on the convolution of the image with a bank of Gabor filters [34,35,50]. Varma and Garg [57] and Zisserman [58] achieved interesting results by convolving the image with the Maximum Response filter bank – MR8, which consists of 38 filters at multiple orientations but only 8 filter responses since their outputs are reduced by storing only the maximum filter response across all orientations. Also, methods of the spectral-based category have been focused on developing different sub-band decompositions of the image, such as wavelets [45,55].

In model-based methods (iv), a texture image is described using mathematical models. Fractal geometry has shown impressive results on texture classification [4,57,60]. The fractal methods calculate the fractal dimension of the texture image or use the process of dilation as feature vector, which provides texture methods invariant to the bi-Lipschitz transformations: multiscale fractal dimension [4], multifractal spectrum [60] and local fractal dimension [57]. Also in the model-based methods, rotation invariant autoregressive models for texture recognition were proposed by Kashyap and Khotanzad [36]. Many studies have analyzed the texture models as Markov Random Fields (MRF), where images are modeled as undirected graph, nodes are variables, edges are the model's functions and a joint distribution over these variables specifies the model MRF [19,47,66].

More recently, agent-based methods (v) have emerged as a new category of texture characterization methods. This new category includes methods that use autonomous entity to act upon a texture image, e.g. random walks processes on graphs [22,23,28,41], deterministic tourist walks [7,8,25,26] and ant systems [38].

Graph-based methods (vi) represent the image as a graph where each pixel represents a vertex and the edges are generated according to the location and intensity between two pixels. Graph-based learning methods have been extensively proposed for image segmentation [1,9,10,18,37,53,54,56,59] and classification [49,61–63]. Additionally, texture images have