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Texture characterization via deterministic walks' direction histogram applied to a complex network-based image transformation

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ABSTRACT

Texture classification involves acquiring descriptive features from the image. This work proposes a descriptor based on statistics from a complex network inspired transformation of the texture. The descriptor is generated by performing a deterministic walks algorithm on the image transformation, focusing on the representation of the shape of the walks to build the feature vector. The first innovation of the proposed approach involves creating a complex network from an image and performing walks using the values of the network of node degrees, instead of on the intensity of the original image's pixels. The second meaningful improvement is in the information that is obtained from the walks: instead of walk sizes or demanding fractal dimension computations, the proposed method derives shape information in the form of a walk direction histogram. Experiments applying the method for texture classification on several widespread data sets show that the proposed method improves correct classification rates compared to other state-of-the-art methods while using a smaller feature vector.

1. Introduction

Textures are complex visual patterns with particular characteristics that can be powerfully discriminating between images [1], and texture-based features can be employed in several tasks such as content based image retrieval [2], image segmentation [3], synthesis [4], clustering and classification [5–7], to name a few examples. To enable these tasks, it is necessary to appropriately represent an image's texture, using a model that extracts relevant and descriptive information from the visual data. Among the categories of texture description methods are geometric, signal processing-based or model-based methods [8,9], although a number of texture description methods are statistical in nature [10,11]. These last methods study the distribution and statistical behavior of local features [7,12,13], while other methods aim to characterize textures through processes dealing with identifying and analyzing higher-level elements of a texture [14].

Images can be modeled as complex networks [15], which are graphs that present distinct, non-trivial topological features. This allows for the use of graph specific metrics and analyses that yield information on the image [16,17]. The work found in [15] offered a method to create a complex network from a given image, using complex network metrics [16] to extract information from it.

Works such as [5,18–20] use deterministic walks (sometimes referred to as crawlers [21]) to characterize images, employing mainly an analysis of the size of the walks. Recent efforts such as in [21–25] have explored analyzing textures using measures of fractal dimension as a robust discriminating feature, often combined with walks in an endeavor to go beyond the size of the walks and analyze their shapes.

This work proposes a novel approach to texture classification by extracting directional information from deterministic walks applied on a proposed image transformation. The complex network metric of a vertex's degree is used to generate a transformation of the original image. The proposed improved deterministic walks method is applied on the transformed image, extracting from the resulting walks new directional information that is more descriptive than the commonly used walk size and more performance efficient than the fractal dimension strategy.

Experiments in classification show that the method is robust for texture classification and showcases high precision and recall for several texture databases, outperforming other state-of-the-art descriptors while maintaining a manageable number of dimensions on the feature vector. Section 2 of this paper describes how an image is transformed by the creation of a complex network from its data, from which a second average node degree image is derived. Section 3 goes into how we use an improved version of determin-

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istic walks to extract a feature vector from the average node degree matrix while including rotation-invariant walk shape information. Section 4 presents the classification experiments performed on widely used data sets and displays the results, followed by conclusions on Section 5.

2. Complex network-based image transformation

In this section we propose an image transformation that encapsulates information on the original pixels' neighborhood in the value of the transformed pixel. The transformation is based on complex network metrics. In order to analyze an image using this approach, the first step is to model the image as a network. The work by Backes et al. [15] achieves this by considering each pixel $I(x,\ y)$ in grayscale image I to be a vertex (or node) $v_{x,\ y} \in V$ in a graph $G = (V, E)$. As for E, the set of edges from G, the decision whether a given vertex v has an edge to vertex v' (that is to say, whether $(v,\ v') \in E$) is based on a measure of dissimilarity $w(v,\ v')$ of the pixels the vertices represent, given by Eq. (1), which takes into account the distance between their x and y coordinates (column and row, respectively) and their difference in intensity $I(x,\ y)$, a value in the $[0,\ L]$ interval.

$$w(v_{x,y}, v_{x',y'}) = (x - x')^2 + (y - y')^2 + r_G^2 \frac{|I(x,y) - I(x',y')|}{L} \tag{1}$$

Edges are attributed to vertices whose dissimilarity is below a threshold value t, and vertices with edges between them are defined as connected. To improve performance, and since the chances of pixels yielding connected vertices decreases as the Euclidean distance between pixels increases, a maximum distance r_G is established for two vertices to be considered candidates for connection, as in (2). In practice, this works as a circular kernel inside which pixels are considered:

$$E = \left\{ (v_{x,y}, v_{x',y'}) \in I \times I \mid \sqrt{(x - y')^2 + (x - y')^2} \le r_G \right\} \tag{2}$$

We are ultimately interested in the degree of the vertices on such graphs (the degree of a vertex being defined as the number of vertices connected to it) because that is the data we will consider when applying the deterministic walks algorithm later on.

Different thresholds values for t provide different graphs with different vertex degrees. In Backes et al. [15] a range of values for t is used, generating multiple graphs (one for each t value). A higher threshold is more judicious and results in lower degrees for nodes, while lower thresholds are less selective and result in higher degrees. The set of neighbors $\partial(v_t)$ of a node v for a given t is given by (3). Notice that $\partial(v_t)$ is a subset of E. Therefore, the degree $deg(v_t)$ of a vertex v_t, that is, the number of edges connected to it, is given by (4):

$$\partial_{v_t} = \{v' \in V | (v, v') \in E \quad \text{and} \quad w(v, v') \le t\} \tag{3}$$

$$deg(v_t) = |\partial(v_t)| \tag{4}$$

Let D_t be the matrix of degrees of the nodes $v_{x,\ y} \in V$ for a given t. Every $v_{x,\ y}$ has a corresponding $D_t(x,\ y) \in D_t$, where $D_t(x, y) = deg(v_t(x, y))$. It would be unruly and slow to perform statistical analysis on all $|S|$ graphs generated from an image, while selecting a single value for t is potentially less representative, therefore we define the average degree matrix D as the average of D_t for all t in the range S, with $S = \{t_0, t_1, \ldots t_s\}$, as shown in (5):

$$D = \frac{1}{|S|} \sum_{t \in S} D_t \tag{5}$$

This also grants the additional benefit of helping avoid ties in the deterministic walk next step decision, since it is significantly less likely that $D(x,\ y)$ values are exactly the same for different $(x,\ y)$ compared to the $D_t(x,\ y)$ values. For instance, considering r_G equal to $\sqrt{3}$ yields 28 possible values for vertex degrees in D, while in D_t the possibilities are many orders of magnitude more. The average degree of a vertex is a meaningful indicator of how the corresponding pixel relates to its neighborhood, which is key in describing texture patterns and features. This approach is called local texture analysis, and is the concept behind successful texture descriptors such as Local Binary Patterns (LBP) [26]. Taken as a whole, the average degree graph expresses high level taxonomic properties of a texture such as period, anisotropy (direction), regularity, granularity, contrast, roughness, among others [1,27,28].

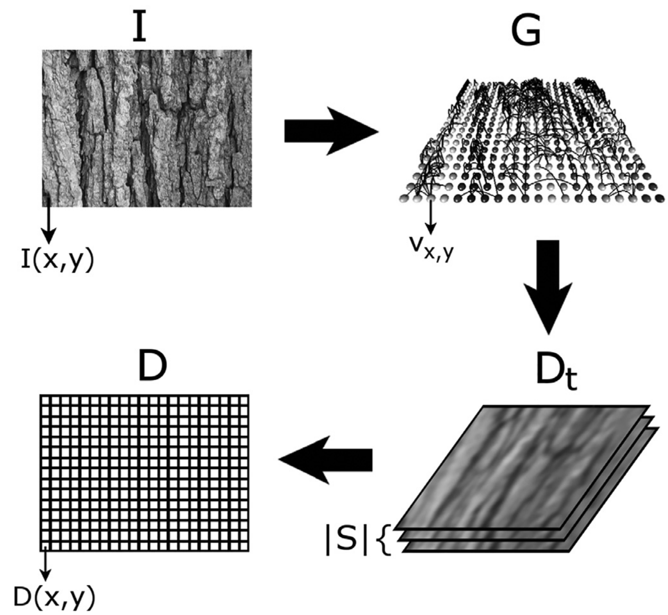

Fig. 1. Steps towards acquiring the average degree matrix D. A graph G is created based on the intensities of pixels from original image I. Analysis of the topology of G for different thresholds t yields several D_t. The average of values in D_t yields D.

Note that D has the same dimensions as the image I, and we can think of D as an image transform of I with every indexed value $(x,\ y)$ in D representing, in short, the average degree of the $v_{x,\ y}$ node that represents the pixel $(x,\ y)$ in I in the complex network described by graph G, as shown in Fig. 1. Treating D as an image will be useful when performing deterministic walks.

3. Deterministic walks and descriptor

A statistical approach emphasizes periodic information. The major challenge in statistically representing an image lies in extracting periodic information that is discriminative. Since we do not know the period of the texture we are evaluating, we need a method which is able to represent features from several image neighborhood sizes. Methods such as LBP solve this problem by employing a multi-resolution approach [12]. Others try to garner statistics from larger scale features of the image via means such as fractal analysis [22]. We propose an approach similar in to the latter in that it attempts to statistically highlight large scale features, but without resorting to the computationally intensive fractal analysis.

3.1. Deterministic walks

Walks are data analysis methods often associated with graph analysis. They are similar to the concept of a path in a graph, but with the difference that they can contain repeated vertices [16].