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Angular descriptors of complex networks: A novel approach for boundary shape analysis

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ABSTRACT

We introduce a method for shape recognition based on the angular analysis of Complex Networks. Our method models shapes as Complex Networks defining a more descriptive representation of the inner angularity of the shape's perimeter. The result is a set of measures that better describe shapes if compared to previous approaches that use only the vertices' degree. We extract the angle between the Complex Network edges, and then we analyze their distribution along with a network dynamic evolution. The proposed approach, named Angular Descriptors of Complex Networks (ADCN), presents a high discriminatory power, as evidenced by experiments conducted in five datasets. It is rotation invariant, presents high robustness against scale changes and degradation levels, overcoming traditional methods such as Zernike moments, Multiscale Fractal dimension, Fourier, Curvature and the degree-based descriptors of Complex Networks.

1. Introduction

In a general sense, shape is a preeminent property of almost every entity in the physical world. A large range of objects can be discriminated by their shape, including not only natural circumstances but also synthetic phenomena. In computer vision and pattern recognition, the shape is considered one of the most important features for the identification and distinction of objects in various scenarios (Loncaric, 1998). The principle of shape-oriented analysis is to extract information able to characterize the elements of specific domains, leading to methods used in a wide scope of applications, in areas such as medicine (Shen, Rangayyan, & Desautels, 1994), biology (Neto, Meyer, Jones, & Samal, 2006), and people tracking (Wang, Tan, Hu, & Ning, 2003).

Shape descriptors can be divided into two main categories: those based on contours, and those based on regions (Mehtre, Kankanhalli, & Lee, 1997; Zhang & Lu, 2004). Contour-based approaches focus on extracting information located at the edges of the shape, while region-based approaches consider all the pixels of a certain region of the shape. Among the contour-based techniques, we can cite descriptors based on the Fourier transform (Persoon & Fu, 1977), on Curvature (Wu & Wang, 1993), on Zernike moments (Zhenjiang, 2000), on multiscale fractal dimension (Torres, Falcão, & Costa, 2004), and on multiscale triangle representation (Mouine, Yahiaoui, & Verroust-Blondet, 2013). The region-based descriptors are based on Zernike moments (Kim & Kim, 2000), on invariant moments (Chen & Tsai, 1993), and on histograms of gradients (Xiao, Hu, Zhang, & Wang, 2010), to name a few.

In the last decade, the concept of Complex Network (CN) has been employed in the field of shape analysis, as described in the work of Backes, Casanova, and Bruno (2009). In this approach, a shape is represented by a CN in which each pixel corresponds to a vertex, and the Euclidean distance, along with a threshold, is used to define edges between pairs of vertices. Over one such CN, it becomes possible to use several methods and metrics from Graph Theory in order to characterize the shapes. In the work of Backes et al., the authors introduce a descriptor based on vertex degree; they use the max and the average mean degree as global features. This descriptor, though simple, presented promising results, corroborating that CN has potential in pattern recognition.

In the present work, we proposed a new shape descriptor based on CNs and geometric concepts. Our method can be applied after the image segmentation step; so, given the shape boundary pixels, we build a CN. We explore the fact that the use of global

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measures limits the discriminating potential of CN-based descriptors. In a different course of action, we contribute by introducing a shape characterization that takes into account the angle between the connected vertices (pixels), a local feature that brings a finer discrimination to the descriptor. We also describe how to automatically set the threshold used to define the edges, which presented superior results compared to the use of constant threshold values. As shown in the experiments, the proposed methodology improved the classification results in most of the cases, including with variations on rotation, scale, noise, and contour degradation. We compared our results to traditional contour and region-based descriptors, and to other CN descriptors.

The paper is organized as follows. Section 2 presents an overview of the CN theory and its application for shape representation. The proposed approach is defined in Section 3, where our techniques for angular analysis and automatic threshold selection are presented. Section 4 details all the experimental protocol, the datasets and the classification results achieved in each experiment, along with the comparison to other descriptors. Finally, in Section 6 an overview of the angular descriptors and its results are presented.

2. Complex network theory

CN has emerged in the past decade combining concepts from graph theory and statistics (Costa, Rodrigues, Travieso, & Villas Boas, 2007). It is a research field that heavily relies on mathematics, computer science, and physics, leading to a large range of applications (Costa et al., 2011). The popularity of CNs can be explained by its ease in modeling many kinds of problems and natural phenomena. As CNs are represented by graphs, every entity-relationship problem can be straightly modeled, such as social interaction, physics simulation, or image representation.

We can cite three main developments that have contributed for the CN research (Costa et al., 2007): (i) investigation of the random-network model (Erdos & Rényi, 1959; 1960); (ii) investigation of small-world networks (Watts & Strogatz, 1998); and (iii) investigation of scale-free networks (Barabási & Albert, 1999). Moreover, works from various fields of science have focused on the statistical analysis of such networks (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Costa et al., 2007; Dorogovtsev & Mendes, 2013; Newman, 2003).

Most of the works using CNs have two main steps: (i) model the problem as a network; and (ii) extract topological measures to characterize its structure. These features can be useful for discriminating different categories/classes, and, therefore, for creating techniques for pattern recognition. In this context, current works focus on exploring concise strategies for representing the CN according to the problem at hand.

Although the field of CNs is gaining a lot of attention from many areas, such as physics and biology, it is still an under-explored field in computer vision. Only a few works can be found in the literature which uses CNs as a supporting method. In computer vision, examples include texture analysis (Chalumeau, Meriaudeau, Laligant, & Costa, 2008; Gonçalves, Machado, & Bruno, 2015; Scabini, Gonçalves, & Castro Jr, 2015), nanoparticle agglomeration analysis (Machado et al., 2017), face recognition (Gonçalves, de Jonathan de Andrade Silva, & Bruno, 2010), and shape analysis (Backes et al., 2009); this last work presented good results, but its simplicity renders for limited discrimination, as we demonstrate in our comparative experiments.

2.1. Complex network representation and measures

As previously discussed, graphs are used to represent CNs. Specifically, in our work, we use undirected weighted graphs. In this representation, a graph $G = \{V, E\}$ accounts for $V = \{v_1, \dots, v_n\}$, a set of n vertices; $E = \{e = (v_i, v_j) | v_i \in V \textit{ and } v_j \in V\}$, a set of edges that connects pairs of vertices v_i and v_j; and values $e_{v_i,v_j} = weight(v_i, v_j)$ representing the edge weight of the connection between two vertices v_i and v_j.

There is a large number of measures that can be extracted from a CN, as presented in the work of Costa et al. (2007), in which the authors review different classes of measures. A simple but important one is the degree distribution. The degree of a vertex v_i is the number of its connections, which describes its interplay with neighbor vertices:

$$k(v_i) = \sum_{v_j} \begin{cases} 1, & \text{if } e_{v_i,v_j} \in E \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Most works use the degree distribution for the characterization of CNs, using measures such as the max and the average degree. However, although the degree is an important measure, using simple statistical measures from its distribution can limit the task of describing the properties of a network. For a more thorough analysis, other measures that consider the local properties of the vertices have the potential for a finer description.

2.2. Shapes as complex networks

The technique to model a shape as a CN was proposed in the work of Backes et al. (2009). Given a set of n_c pixels belonging to the contour of a shape in an image, a network $G = \{V, E\}$ is modeled so that each pixel is mapped to a vertex of the set $V = \{v_1, \dots, v_{n_c}\}$. The next step is the definition of the set of edges E. We connect each pair of vertices to define edges whose weights come from the Euclidean distance considering the position of the pixels. The distance between two pixels i and j represented by vertices v_i and v_j is given by:

$$d(v_i, v_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

Next, we normalize the weights as follows:

$$e_{v_i,v_j} = \frac{d(v_i, v_j)}{d_{max}} \tag{3}$$

where $d_{\max}$ is the largest distance between all pixels. This normalization is performed so that the connections' weights are kept in the interval [0, 1]. It also keeps the edge's weights invariant to the scale of the shape.

At this point, the topology is regular – all the vertices have the same number of connections; a selective procedure is necessary, keeping only the edges that are more relevant. A simple and widely used approach is to remove edges according to a threshold. Given a threshold t, a new network $G^t = \{V, E^t\}$ is obtained by discarding edges that have a weight greater than t, as follows:

$$E^t = \{(v_i, v_j) | e_{v_i,v_j} \le t, v_i \in V, v_j \in V\} \tag{4}$$

The resulting G^t network fits into the Watts and Strogatz small-world model (Watts & Strogatz, 1998), and can be used as a representation of a given image's shape. Fig. 1 shows an example of a *shape network* after the threshold operation.

2.3. Dynamic analysis of complex networks

The threshold value t directly affects the network topology resulting in dense or sparse networks, as observed in Fig. 2. Moreover, a CN cannot be fully characterized without considering the interplay between structural and dynamic aspects (Costa et al., 2007). In our methodology, we access the dynamics of the network by using a set of thresholds $T = \{t_1, t_2, \dots, t_n\}$. This analysis covers the network evolution since its creation (low thresholds) to its stabilization (high thresholds). The result is a shape represented by a