Contents lists available at ScienceDirect
Digital Signal Processing
www.elsevier.com/locate/dsp

An optimized shape descriptor based on structural properties of networks

Gisele H.B. Miranda [a], Jeaneth Machicao [b,1], Odemir M. Bruno [b,1]

[a] Institute of Mathematics and Computer Science, University of São Paulo, USP, Avenida Trabalhador são-carlense, 400, 13566-590, São Carlos, SP, Brazil
[b] São Carlos Institute of Physics, University of São Paulo, São Carlos, SP, PO Box 369, 13560-970, Brazil

ARTICLE INFO

Article history:
Available online xxxx

Keywords:
Shape analysis
Shape classification
Network analysis
Pattern recognition

ABSTRACT

The structural analysis of shape boundaries leads to the characterization of objects as well as to the understanding of shape properties. The literature on graphs and networks have contributed to the structural characterization of shapes with different theoretical approaches. We performed a study on the relationship between the shape architecture and the network topology constructed over the shape boundary. For that, we used a method for network modeling proposed in 2009. Firstly, together with curvature analysis, we evaluated the proposed approach for regular polygons. This way, it was possible to investigate how the network measurements vary according to some specific shape properties. Secondly, we evaluated the performance of the proposed shape descriptor in classification tasks for three datasets, accounting for both real-world and synthetic shapes. We demonstrated that not only degree related measurements are capable of distinguishing classes of objects. Yet, when using measurements that account for distinct properties of the network structure, the construction of the shape descriptor becomes more computationally efficient. Given the fact the network is dynamically constructed, the number of iterations can be reduced. The proposed approach accounts for a more robust set of structural measurements, that improved the discriminant power of the shape descriptors.

1. Introduction

In computer vision, shape boundaries are important attributes that can be used for the characterization and the classification of objects. In shape analysis there are many pattern recognition applications covering different areas, such as neuroscience [1–3], agriculture [4–9], medical imaging [10–13], remote sensing [14,15], to mention but a few. Over the last decades many methods were proposed in the literature of pattern recognition which are based on classical approaches, such as, Fourier descriptors [16,17], wavelets [18,19], fractal dimension [9,20–22], curvature scale space (CSS) [23] among others. These methods support a wide range of applications. More recently, methods based on structural properties of shape boundaries have been drawing attention for classification tasks. Such methods are strongly influenced by graph and network theory [20,24–28]. Instead of considering the shape boundaries only as a chain of connected points, this new approach also takes advantage of the topological properties of the network drawn over the shape contour. One advantage of network-based methods for shape analysis is that they are invariant to rotation and can also be invariant to scale [24].

In a paper published in 2009 [24], Backes et al. proposed a method, named as CNDescriptor, for boundary shape analysis based on the connectivity among the contour pixels. In this one-parameter model, each pixel is modeled as a vertex of a graph and the connections between them are established according to that parameter, which represents a distance threshold. For a given threshold value, there is one graph realization and a set of measurements regarding the connectivity of this graph can be obtained. These measurements are the so-called network descriptors which characterize the graph structure, and, consequently, unveil the topological properties of the shape boundary. In the referred paper, the authors also detail some properties of the graphs obtained through the proposed method, e.g., for some thresholds the graphs present a high clustering coefficient, characterizing them as small-world graphs. In addition, the CNDescriptor is invariant to geometric transformations such as rotation and scale and robust for what concerns the presence of noise. This method was also evaluated in the context of image degradation, in which parts of the shape contour were removed. The authors demonstrated that the CNDescriptor is also very robust in such cases, showing

E-mail address: bruno@ifsc.usp.br (O.M. Bruno).
[1] Scientific Computing Group – http://scg.ifsc.usp.br.

https://doi.org/10.1016/j.dsp.2018.06.010
1051-2004/

promising results. It is also possible to find an extension of the method for texture analysis [29].

However, in spite of being well suited for shape analysis tasks, the dynamic evolution signature provided by the method CNDescriptor only accounts for degree-related measurements as feature vectors. However, a much more robust set of measurements could improve the classification performance in different shape recognition applications. Along the last two decades, Complex Networks (CN) has been established as a new research field which integrates graph theory and statistical mechanics [30–32]. Many related studies have provided new insights about the topological characterization of networks leading to a deep understanding of how the connectivity patterns of the nodes are related to the network model [33–35]. Therefore, the measurements extracted from the network structure are important features for the network characterization. In a survey of 2007, Costa et al. emphasize this approach [36]. The authors summarize a huge set of measurements that can be used to describe the topology of a network. They present different categories of measurements, such as, connectivity measurements which include, for instance, mean degree and degree distributions and correlations. Distances and path lengths as well as hierarchical and spectral measurements are other important categories. Centrality measurements can quantify how important is a node to the network topology for what concerns its robustness and noise tolerance, e.g., betweenness, closeness and eigenvector centrality [37,38]. It is also possible to quantify clustering and cycles in a network through measurements like transitivity and the clustering coefficient, which can be used to characterize the small-world property [35]. In addition, Costa et al. also addresses the use of classical pattern recognition techniques for network analysis [39].

In this paper we present an extension of the previous work of Backes et al. [24] and we propose a generalized approach for shape characterization in Computer Vision based on network analysis. This approach accounts for different categories of measurements. We have demonstrated how these measurements are related with the properties of shape boundaries. For this task we used samples obtained through an interpolation process performed between regular shapes. This way, we could analyze, for instance, how the emergence of internal angles of a shape influences the connectivity of the resulting network. Besides, we also performed an analysis of the curvature signal of those shapes and its relationship with structural network measurements. We observed that the pixels of high curvature are not the ones with the highest degree, instead, they present a high clustering coefficient. In addition, we also evaluated the performance of the proposed approach in three different applications concerning shape recognition. The first image dataset contains geometric shapes of ten different classes. The second dataset contains generic shape contours belonging to nine different categories like animals, fishes and tools among others. This dataset has been used as benchmark in many other studies [40,41]. The last dataset evaluated in this paper is the same dataset yielded by Backes et al., which was used for comparing purposes as well as in order to validate the methodology in a real-world application. This dataset contains images of leaf contours from 30 different plant species.

This paper is organized as follows: Section 2 presents a detailed description of the previous work of Backes et al. as well as a basic introduction in what concerns the structural characterization of networks. In Section 3, we present a study regarding structural properties of networks for different geometric shapes using an interpolation approach as well as a curvature analysis. In section 4, we evaluated the proposed approach regarding the classification task for three distinct datasets, and, finally, conclusions are drawn in Section 5.

2. Background

2.1. Previous work

In the work of Backes et al. [24] is introduced a shape descriptor based on the dynamic evolution of a network built from the contour points. This method is based on a distance criterion in order to establish the connections between the pixels. The threshold parameter, T, is used for modeling shape boundaries and to obtain the corresponding feature vectors. All this process is detailed next.

Let S be the contour of an image, such that $S = \{s_1, s_2, \ldots, s_N\}$, where $s_i = [x_i, y_i]$ are the coordinates of point i, represented by discrete values. Given a graph of the form $G = \langle V, E\rangle$, each pixel of the contour represents a node in the graph, and, therefore, $S = V$. The set of non-directed edges E is defined for each pair of nodes and the corresponding weight is calculated by the Euclidean distance, as follows:

$$d(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{1}$$

The adjacency matrix W of this weighted network is represented by the $N \times N$ matrix, such that $w_{ij} = W([w_i, w_j]) = d(s_i, s_j)$, which is then normalized in the interval $[0, 1]$: $W = \frac{W}{\max_{w_{ij} \in W}}$. N is the total number of nodes in the network.

Initially, the network is regular, since each node is connected to all the others. At this step, a threshold transformation, T_l, can be applied in order to obtain a new set of edges E'. This set is composed by the edges whose weights are smaller than T_l. If T_l is small, the number of edges will be also small and the network will be composed of many connected components without intersection. Otherwise, if T_l is large, the network will be almost fully connected. For intermediate values of T_l, other properties begin appearing, such as the small-world property, characterized by the presence of many connected triples. The authors have demonstrated this property for a set of distinct shapes. Therefore, the threshold parameter controls the connectivity of the network. Notice that the same process can be implemented considering the connections which are above the threshold, i.e., two pixels will be connected if the distance between them is greater than T_l.

Based on the properties that arise from the transformations defined by T_l, the shape descriptor is obtained through the connectivity measures extracted from the network topology. The dynamic evolution of the network as a function of T_l provides distinct attributes which are then combined to compose the feature vector. The transformation is formally defined by the δ operation as follows:

$$A_{T_l} = \delta_{T_l}(W) = \forall_W \in W \begin{cases} a_{ij} = 0, & \text{if } w_{ij} \geq T_l \\ a_{ij} = 1, & \text{if } w_{ij} < T_l \end{cases}, \tag{2}$$

where A is the resulting unweighted and thresholded matrix. Therefore, the shape characterization is performed through a series of δ transformations where T_l is regularly incremented by T_{inc}. Fig. 1 illustrates the $\delta_{T_l}(W)$ transformation. The left part of the figure presents the networks obtained by applying the comparison *smaller than*. Therefore, as T_l increases more connections are established. Similar analysis is shown in the right part of the figure, which illustrates the condition *greater than*, $\Delta_{T_l}(W)$, however with the opposite behavior. Given that the distance values are normalized between 0 and 1, the threshold values are defined in the same interval.

The measurements obtained at each $\delta_{T_l}(W)$ are: the *average degree* (k_μ) and the *max degree* (k_κ), which corresponds to the average and to the maximum degree of all the network nodes, respectively. The final feature vector, φ, is represented by