A Complex Network-Based Approach for Texture Analysis

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Abstract. In this paper, we propose a novel texture analysis method using the complex network theory. It was investigated how a texture image can be effectively represented, characterized and analyzed in terms of a complex network. The propose uses degree measurements in a dynamic evolution network to compose a set of feasible shape descriptors. Results show that the method is very robust and it presents a very excellent texture discrimination for all considered classes.

1 Introduction

Texture analysis is a basic issue in image processing and computer vision. It is a key problem in many application areas, such as object recognition, remote sensing, content-based image retrieval and so on. Even though there is no exact definition for the term texture, this is an attribute easily comprehended by humans and it is a wealthy source of visual informations (when considered the tri-dimensional nature of physical objects) [15].

Generally speaking, textures are complex visual patterns composed by entities, or sub-patterns, which present characteristics such bright, color, deepness, size, etc. So, texture can be considered as a group of similarities on a image [15]. Due this characteristic, the definition of a texture class must take into account not just the isolated primitives, but the relation among pixels and its neighbors [12]. Consequently, texture characterization and identification requires a methodology capable to express the context surrounding each pixel, joining local and global texture characteristics.

Numerous methods have been proposed in the literature and, several of them use implicitly the approach of joining local and global texture characteristics. These methods, in general, are based the spectral analysis of the pixels of the

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image (e.g., Fourier desciptors [2] and Gabor Filters [14]), statistical analysis of the pixels (e.g., co-ocorrence matrices [11]) and complexity analysis (e.g., Fractal Dimension [13]).

This paper proposes a novel approach to represent and characterize the relation among these structural elements using the Complex Networks Theory. To accomplish this task, is necessary to represent texture as a complex network, incorporating to the vertices and edges the information about image pixels and their neighbors, followed by an analysis of the topological features of the computed network. These features may be used to discriminate different classes of images. In the fact, every discrete structure such as lists, trees, networks, texts [1] and images [9] can be suitably represented as graphs. Taking this into account, various studies include investigations of the problem representation as a Complex Network, followed by an analysis of its topological characteristics and its features extraction [6,4,3,7,8].

In [4,3] the shape analysis is performed using the complex network theory. After the modeling of the shape as an complex network, simple measurements are extracted. Thoses measurements are used to classify shapes in differents classes. In [6,7] and [8], the problem of texture characterization is presented in terms of complex networks: image pixels are represented as nodes and similarities between such pixels are mapped as links between the network nodes. It is verified that several types of textures present distinct node degree distributions, suggesting complex organization of those textures. Traditional measurements of the network connectivity are then applied in order to obtain feature vectors from which the textures can be characterized and classified.

The idea of this work is similar of the cited works above, model the texture as a complex network and the posterior feature extraction. The main difference are in the manner as complex network is modeled, and in what measurements used. The works of [6,7] and [8] uses an hierarchical representation as model. We propose use direct pixels relations to model the texture and use a set of thresholds values to characterize the network. The work of [6,7] and [8] uses the degree and clustering coeficient to characterize the network. We will use only degree, due the high computational time of the clustering coeficient. In this time we can say that the idea proposed here is more similar with [4,3], but applied in texture analysis context.

2 Texture as a Pixel Network

A graph representation of the texture is built as $G = (P, E)$, where each pixel corresponds to a vertex in the graph G. In this graph, two pixels $p = (i, j) \in P$ and $p' = (i', j') \in P$ are connected when the Euclidean distance between them is no longer than a r value:

$$E = \left\{((i,j),(i',j')) \in P \times P | \sqrt{(i-i')^2 + (j-j')^2} \leq r\right\} \quad (1)$$

For each non-directed edge $e \in E$ is associated a weight, which is defined by the square of the Euclidean distance between two connected vertexes, when considered the pixels intensity $v_{i,j}$ and $v_{i',j'}$:

$$d(e) = (i - i')^2 + (j - j')^2 + (v_{i,j} - v_{i',j'})^2 \ \forall e = \{(i,j),(i',j')\} \in E \quad (2)$$

This approach allows to include context information about pixel surrounding, which refers to a local texture analysis.

Once the connection between pixels depends on the parameter r, which is associated to the covering radius of an pixel in the image, the weight function $d(e)$ may assume a very large range of values. It makes necessary to normalize this weight into the interval $[0, 1]$, which is performed using the largest value possible in a connection. This value corresponds to the maximum difference of intensity between two pixels that are to a distance of r:

$$w(e) = \frac{d(e)}{255^2 + r^2} \quad (3)$$

Initially, each network vertex presents a similar number of connections, so the computed network presents a regular behavior. However, a regular network is not considered a complex network, and it does not present any relevant property. It is necessary to transform this network in a complex network that owns relevant properties. More explanation about this can be read in [4].

An interesting approach for achieving additional information about structure and dynamic of complex networks is to apply a transformation over the original network and then to compute the properties of the resulting network [10]. Figure 1 shows an example of a transformation δ applied over a network, so a set of features are computed.

There are several possibilities to perform this transformation. A straight and simple way is applying a threshold t over the original set of edges E, so as to

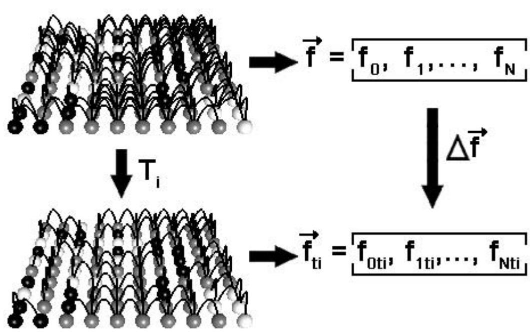

Fig. 1. Difference $\boldsymbol{\Delta f}$ between feature vectors $\boldsymbol{f}$ and $\boldsymbol{f}_{T_i}$ after applying a T_i transformation over the original network. This difference can be used as additional information about the proprieties of the network. Adapted from [10].

select a subset E^*, $E^* \subseteq E$, where each edge of E^* has a weight equal or smaller than t. This transformation δ_T, henceforth represented as

$$E^* = \delta_t(E) = \{e \in E | w(e) \leq t\} . \quad (4)$$

In this case, the δ_t transformation can be interpreted as a intermediate step on network dynamics. So, a richer set of measurements that describes the network dynamics involves to take into account several instances along its degradation. A feature is computed at each time instant t. Figure 2 shows four instances of an evolving network. In such a way, the evolution of a network can now be investigated in terms of a trajectory in dynamical evolution of δ transformation.

In other words, the network characterization is performed using various δ transformations, where the threshold T_i is incremented in a regular interval T_{inc}. Also can be interpreted as acquisition of several samplings of complex network throughout it life (between it creation and extinction).

2.1 Network Characterization

Several measurements can be computed through analysis of the network. One measurement particularly relevant for texture characterization is the average degree of G, $Av(G)$:

$$Av(G) = \sum_{p \in P} \frac{deg(p)}{|P|} \quad (5)$$

where $deg(p)$ is the *degree* (or *connectivity*) of a node p, i.e., the number of neighbors of p and $|P|$ denotes the cardinality (number of nodes).

Note that such measurements are particularly relevant for texture characterization because they provides a good compromise between local (i.e. the measurements are centered at each image point) and global (i.e. the measurement take into account the immediate context of the image properties around the reference point) information.

Considering $f(x, y)$ the texture under analysis and G the network built using Equations 1,2 and 3, the feature vector consists of the average degree in several δ_t transformations. This process is better understood through Figure 2. There, a texture is modeled as a complex network and different δ_{T_i} transformations are applied over the resulting network. For each threshold T_i a numeric value representing the average degree $(Av(\delta_{T_i} G))$ of the network is computed and used as a feasible texture signature. Figure 3 shows two complex networks computed from different textures using the same threshold value.

3 Evaluation

In order to evaluate the proposed method, signatures have been calculated for different configurations and they have been used in a texture analysis context. For this, an image database have been prepared selecting a set of 111 natural textures obtained from Brodatz texture album [5]. This database is broadly used

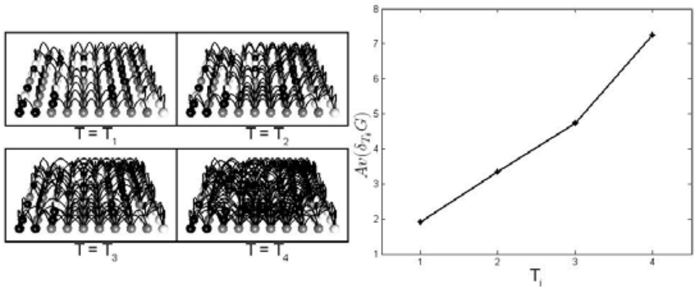

Fig. 2. Complex network characterization through dynamical evolution investigations

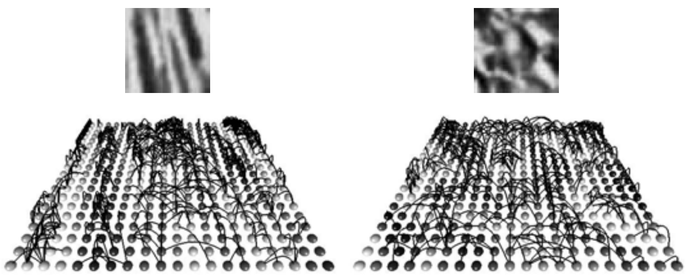

Fig. 3. Example of resulting complex network for two different texture samples

in computer vision and image processing literature as benchmark for texture analysis. Each texture image is of size 640×640 with 256 gray levels. A database constituted of 1110 image regions of 111 texture classes was constructed by subdivided each image into 10 sub-images of 200×200 size.

In addition, to corroborate properties such rotation invariance, an additional database was built by rotating of the original textures in 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135° and 150° degrees.

The analysis has been carried out by applying the Linear Discriminant Analysis (LDA) in a leave-one-out cross-validation scheme.

3.1 Experiments

Experiments have been idealized to show the high potential of the method to analyze and characterize texture images, and its results have been compared with others descriptors found in the literature:

Fourier descriptors[2]: composed by the 99 coeficients of Fourier Transform, were each one corresponds to the sum of the spectrum absolute values placed to a radial distance from the center of the bi-dimensional transformation.

Co-occurrence matrices[11]: distances of 1 and 2 pixels with angles of -45°, 0°, 45°, 90° were used. Energy and entropy were computed from resulting matrices, totalizing a set of 16 descriptors. A non-symmetric version has been adopted.

Gabor filters[14]: we use a family of 16 filters (4 rotation and 4 scale), with frequency lower than 0.01 and superior than 0.3. Definition of the individual parameters of each filter follows mathematical model presented in [14].

4 Results and Discussion

A important characteristic in the proposed method is that it has only two parameters to be configured when it is applied in the texture recognition task: the radius r and the number of evolutions periods T. Several tests have been performed in order to evaluate the method behavior for different values of r and different T periods. Table 1 summarizes the results for 9 vectors $(F1, F2, \dots, F9)$.

Table 1. Result for the proposed method under different parameter values. T_{ini} and T_Q are, respectively, the initial and final threshold defined by user, while T_{inc} is the increment used to go from T_{ini} to T_Q.

Set	Parameters				N° of descriptors	Images correctly classified	Success rate(%)	Maximum error rate (%) per class
	r	T_{ini}	T_{inc}	T_Q				
F1	2	0.005	0.005	0.333	66	1066	96.03	60.00
F2	3	0.005	0.005	0.333	66	1067	96.12	60.00
F3	4	0.005	0.005	0.333	66	1071	96.48	50.00
F4	5	0.005	0.005	0.333	66	1071	96.48	40.00
F5	5	0.005	0.005	0.166	33	1058	95.31	60.00
F6	5	0.166	0.005	0.333	33	1017	91.62	70.00
F7	5	0.333	0.005	0.500	34	927	83.51	100.00
F8	5	0.005	0.010	0.333	33	1054	94.95	60.00
F9	5	0.005	0.015	0.333	22	1033	93.06	80.00

We observed no significant improvement in performance for $F1$, $F2$, $F3$ and $F4$ sets, although they are using different r values. Even though a higher r value be able to model a more dense network, this does not affect straight the results.

We see that the chosen sequence of T values should have a small influence over the final results. This affirmation is corroborated by $F4$, $F8$ and $F9$ parameters set, where we notice a satisfactory classification rate, even when it is used different sampling (T values with intervals of 0.005, 0.010 e 0.015 respectively). We see too that most part of information lies on the beginning of the dynamic evolution process. This is validated by $F5$, $F6$ and $F7$ parameters set. $F5$, whose set yielded the best result among these three (95.31%), uses only the beginning of dynamic evolution process to compose its feature vector ($T \leq 0.166$). Otherwise, the $F7$ set, which uses only the final stages ($0.333 \leq T \leq 0.500$), yielded the worst result (83.51%). As expected, the $F6$ set, which uses intermediate stages ($0.166 \leq T \leq 0.333$), yielded an average result (91.62%).

For comparison, the proposed method have been compared with traditional texture analysis methods described in Section 3.1. Table 2 shows the yielded results presented by each method. The our method presents a superior success rate. Even though the number of descriptors is higher than in other methods, this presents a discrimination ability also higher when it uses only the initial

Table 2. Comparison of the proposed method with traditional texture analysis methods

Method	N° of descriptors	Images correctly classified	Success rate (%)	Maximum error rate (%) per class
Gabor Filters	16	992	89.37	100.00
Fourier	99	888	80.00	90.00
Co-occurrence	16	968	87.21	80.00
Complex Network	66	1071	96.48	40.00

Table 3. Result for the proposed method over rotated textures database

Method	N° of descriptors	Images correctly classified	Success rate (%)	Maximum error rate (%) per class
Gabor Filters	16	885	79.73	100.00
Fourier	99	966	87.02	50.00
Co-occurrence	16	751	67.66	90.00
Complex Network	66	1106	99.64	10.00

stages of dynamic evolution. This is corroborated by result archived with only 16 descriptors (e.g. $T = (0.005 \leq 0.005 \leq 0.08)$, the same number os descriptors used for Gabor filters and Haralick methods), with a success rate of 92.97%.

Due the texture model used here, using Euclidean distance, a small error is added to the distance between a pairs of rotated pixels. Considering the intensity of the pixel too, and the fact that this does not change during image rotation we have method invariant to the rotation. Table 3 shows the result from when the method is applied over rotated textures database.

5 Conclusion

In this paper, we have proposed a novel method of texture analysis using the complex network theory. It was investigated how a texture image can be effectively represented, characterized and analyzed in terms of complex network.

Although the method uses two configuration parameters, they do not have a great influence in the final results. Investigations about the influence of the radius r and the set of thresholds T in texture discrimination show that most of texture information lays in the beginning of the dynamic evolution process. However, using a large sampling of thresholds and/or higher values for r parameter also yield a excellent success rate in spite of a superior computational cost.

Results show that the method is very robust, because it presents a very excellent texture discrimination for all considered classes, it has a great capacity to work with both micro and macro texture, overcoming traditional texture methods, and is invariant a rotataion. So, it have been shown that, besides the compromise between local and global proprieties, the interplay between structural and dynamical aspects can provide precious informations about the structure under analysis. Concerning of Complex Networks theory, the sucess on discrimination of Brodats textures demonstrates the potential of the application of this approach in computer vision problems and digital imaging processing.

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