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# A hybrid approach for texture classification based on complex network

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**Abstract**

This paper proposes a method for image texture classification based on a complex small world network model. Finding important and valuable information in the context of an image is a big problem for image classification. In current analysis methods, image texture features such as spatial information are left out and color histogram is mostly used. In this article, the multi-radial distance analysis method is used to select the nodes, and then based on the identified nodes and calculating the shortest distance between adjacent nodes, a complex network is created to record the texture pattern. In the next step, the topological characteristics of the network such as the number of nodes, the number of triple triangles, the length of the edges and the average diameter of the network are identified and used for evaluation. Brodatz, UIUC and Outex databases have been used to test the system. The results of the proposed method show that this method is effective for texture classification and improves the classification rate compared to the usual traditional methods.

Keywords: Texture analysis, Texture classification, Dynamic complex network, Network similarity
2020 MSC: 68U10, 68M15

## 1 Introduction

Texture is important information for characterizing the appearance of an image. The attributes of a texture can be described qualitatively in such terms as coarseness, orientation, and spatial relationship appearing as uniformity of image intensity [1, 8]. Coarseness and directionality are two important attributes of textures which aid in discrimination. Coarseness relates to the size of the texture elements, whereas directionality corresponds to the orientation and spatial arrangement of the texture elements [1].

Texture analysis has played an important role in texture discrimination by quantifying image properties. There are a lot of techniques to characterize the texture. These techniques are able to extract and characterize texture information using first-order features [8], Fourier descriptors [2], Gabor filters [5], and graph theory [6, 9]. In recent years, graph-based representation and network model have been efficiently applied in texture analysis [3, 13].

Backes et al. [3] proposed a traditional network model for texture analysis and classification. Graph-based representations have been used to characterize the topological structure of networks, including image pixels [9]. Vertex

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measurement is obtained in terms of the distribution vertex degree or number of edges incident on a particular vertex. This numerical measure of connectivity between a vertex and its neighbors can be used to characterize the texture attributes of an image. The coarseness and orientation of an image structure can be described in terms of the topological properties of the network. According to the pattern analysis techniques, the local binary pattern operator (LBP) has also been used.

Ojala et al. [11, 12] proposed the LBP texture operator for classification, which analyzes differences between a central pixel and its neighbors by a thresholding which considers the intensities as binary numbers.

This paper proposes a method to characterize texture primitives by considering spatial information based on the complex network model of [3] for texture classification. Three standard texture databases, Brodatz [4], UIUC [7], and Outex [10] are used for evaluation. The experimental results show the effectiveness of the proposed method compared to the traditional network model [3] and texture analysis based on conventional methods. The remainder of the paper is organized as follows. In section 2, the basics of the complex network and its parameters are mentioned. Section 3 explains our proposed method, which is based on image graph-based representation and includes the spatial information analysis. Section 4 represents the Simulation and analysis results. Finally, Section 5 concludes this work.

## 2 Basic Concepts of Complex Networks

A complex network, a graph with a set of vertices connected by edges. Complex networks can be classified into three main models: 1- Random networks 2- Small world networks 3- scale Free networks. In the random networks, which is the simplest model, the edges are added randomly. Each complex network has a specific topological design that determines how it is connected. Therefore, the analysis of complex networks depends on the use of measurements, which leads to the extraction of appropriate topological designs and their classification. Grade distribution is an important attribute of the vertex in the graph. Given vertex degrees, many measures can be formulated, with the two most straightforward measurement techniques as seen in (2.1) and (2.2):

$$K_{\max} = \max_i K_i \tag{2.1}$$

$$K_{avg} = \frac{1}{n}\sum_{i=1}^{n} K_i \tag{2.2}$$

where $K_i$ indicates the degree of node $i$. Structural and dynamic networks can be principally characterized by connectivity degree distribution, including: i) entropy, ii) energy, and iii) average connection degree. The entropy of connectivity degree distribution can be determined as seen in (2.3):

$$K_{jd}(k,k') = -\sum_{k,k'=1}^{K_{\max}} p(k,k')\log(p(k,k')) \tag{2.3}$$

the normal distribution-associated energy can be determined as seen in (2.4):

$$E = \sum_{k,k'=1}^{K_{\max}} p(k,k') \tag{2.4}$$

one way to detect the loop is through the clustering coefficient, which is beneficial for network analysis like degree. Two different clustering coefficients are typically used, the first of which, according to the definition of non-directional networks, is as follows:

$$E = \frac{3N_\Delta}{N_3} \tag{2.5}$$

where $N_\Delta$ represents the number of triangles on the grid and $N_3$ represents the triangles. A triangle has three vertices, with an edge between each pair, a triangular connected set of three vertices, whose two vertices are adjacent to a third one (i.e., central vertex). Clustering factors can be obtained for a grid by calculating the mean clustering factor for each vertex. The clustering factor of vertex $i$ can be measured as follows:

$$C_i = \frac{N_\Delta(i)}{N_3(i)} \tag{2.6}$$

where, $N_{\Delta}(i)$ denotes the number of triangles with vertices $i$ and $N_3(i)$ denotes the number of triangles, i.e., the central vertex. The clustering coefficient of a network can be defined as follows:

$$\overline{C} = \frac{1}{N}\sum_{i} C_i \tag{2.7}$$

the distance is an important size, depending on the overall network structure. We can measure the network as the mean of the shortest distance by calculating the mean distance of the shortest line (path) for each pair of vertices, such as the following formula:

$$d_G = \frac{1}{N(N-1)}\sum_{i+j} d_{ij} \tag{2.8}$$

$d_{ij}$ represents the shortest line distance from vertex $i$ and vertex $j$.

## 3 Proposed Method

Weights of Image texture edges can be represented as pixel networks based on graph theory [9]. Figure 1 shows an example of the image graph-based representation.

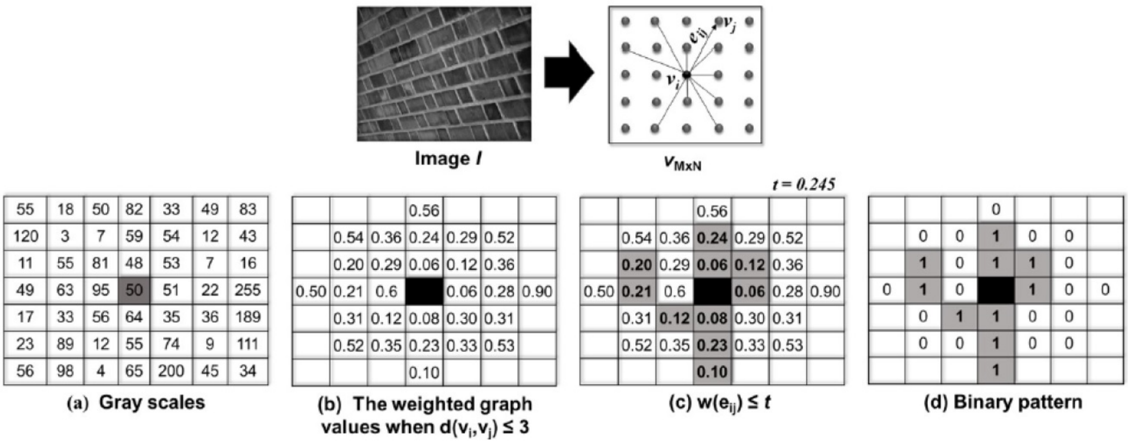


Figure 1: Image pixel representation based on graph theory: (a) each pixel of the image is a vertex in the graph, (b) two vertices are connected if $d(v_i, v_j) \leq r$ ($r = 3$ in this example), whereas a weighted graph is defined by Equation (2.1), (c) a threshold t is applied to imitating a transformation in the network ($t = 0.245$ in this example), and (d) the binary pattern transformation after passing thresholding.

Suppose, image $I$ with a resolution of $M \times N$ pixels. Let $I(i,j) = g,\ i = 1, ..., M$ and $j = 1, ..., N$ where $i$ and $j$ are the pixel indices of $I(i,j)$. Let $G = (V, E)$ be the graph comprising the set of vertices $V$ and the set of edges $E$. Each pixel in the image is a vertex $v_i \in V$. The two vertices are connected by a non-directed edge $e \in E$, $e = e_{ij}$, when the Euclidean radial distance between them is less than or equal to $r$ (see Figure 1(b)). Based on [3], the weight of the edges $e_{ij}$ is defined as:

$$w(e_{ij}) = \begin{cases} \frac{||r_i - r_j|| + r^2 \frac{|I(i) - I(j)|}{L}}{2r^2}, & if\ d(v_i, v_j) \leq r \\ 0, & otherwise \end{cases} \tag{3.1}$$

where $r_i$ and $r_j$ are the coordinates of pixels $i$ and $j$ in image $I$. The intensities of pixels $i$ and $j$ are denoted by $I(i)$ and $I(j)$. L is the maximum value of intensity at a radial distance $r$ from either $v_i$ and $v_j$.

### 3.1 Threshold

A threshold ($t$) is a parameter related to the property of being an edge in graph theory [6, 9]. In the traditional network model [3], a set of thresholds is used to construct a network that imitates dynamic transformation for the purpose of texture analysis. Thus, we can determine the spatial relationships of the attributes of textures when applying threshold parameters in the complex network model. The threshold $t$ value is applied to the original set of edges, as illustrated in Figure 1(c).

In this study, threshold values are obtained through an experiment. Then, the binary pattern transformation process is performed by converting the vertices whose weights are less than or equal to threshold $t$ to 1, while the remaining vertices are converted to 0 as in Figure 1(d). This process is defined as follows:

$$w_b^{(t)}(e_{ij}) = \begin{cases} 1, & w(e_{ij}) \leq t \\ 0, & otherwise \end{cases} \tag{3.2}$$

In graph $G = (V, E)$, $E$ and $V$ indicate the set of edges and vertices, respectively. $|E|$ and $|V|$ denote the number of edges and nodes of the graph $G$, respectively. The network model can be defined as $GN = (V_N, E_N)$ for the $G$ graph. Each edge of the graph $G$ is a vertex $GN$. The weighting vector for each vertex can be measured by evaluating the relationship between and geometric position of the edges, as shown in Figure 2, the weighting vector for vertex $i$ can be measured as seen in (3.3):

$$e_i = (l_i, d_i, d_{1i}, d_{2i}, x_i, y_i) \tag{3.3}$$

where $l_i$ represents edge length, $d_i$ represents the distance between the edge center and graph center (Point $o$), $d_{2i}$ and $d_{1i}$ the intervals from the beginning of the edge to the center of the graph (point $o$) and from edge end to graph center (point $o$) and $x_i$ and $y_i$ are the center point coordination of the edges.

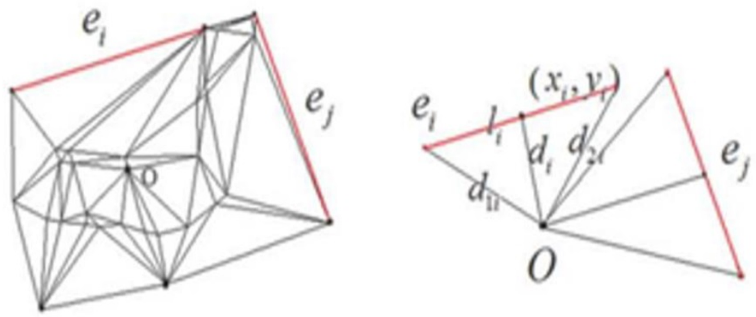


Figure 2: Schematic representation of a graph based on a complex network

The network is formed by a set of non-directional edges $E$ that connects each pair of vertices. The value of the edge of vertex $i$ to vertex $j$ can be calculated using the Euclidean distance between $e_i$ and $e_j$:

$$W_{ij} = d(e_i, e_j) \tag{3.4}$$

therefore, the network can be mapped as $|E| \times |E|$ and show the weight $w$ with the matrix.

$$W_{ij} = W([e_i, e_j]) \tag{3.5}$$

and then normalize it to form:

$$W = \frac{W}{\max(w_{ij} \in W)} \tag{3.6}$$

The network model $GN = (V_N, E_N)$ is initially a regular network that connects the set of edges of $E_N$ to each node of the network; although however, this regular network does not offer any good useful features for the program. Hence, this regular network must be transformed into a complex network with appropriate characteristics. Here we carry this transition using the method applied in [13] and define the threshold $t$. This transition is performed to create a new edge set for the network by choosing a subset of performed the $\hat{E}_N$ of $E_N$ which eliminates the need for the edges of the $E_N$ to have a lower weight than the threshold of $t$. This can be defined as:

$$G^t_{CN} = \delta(G_N, t) = \begin{cases} w_{ij} = 0, & if\ w_{ij} \geq t \\ w_{ij} = 1, & if\ w_{ij} < t \end{cases} \tag{3.7}$$

where $t$ varies between $t_0$ and $t_f$ and the first and final thresholds $(t_f, t_0)$ are user-defined. Given a graph $G = (V, E)$, we first model the graph structure using network $G_N$ and then extract measurements from networks $G^t_{CN} = \delta(G_N, t)$ by varying the threshold $t$. Afterwards, our CNCRG is performed as the concatenation of these measurements. Three distinct feature vectors are proposed, i.e., degree descriptors, joint degree descriptors, and clustering-distance descriptors. Using formulas described in (2.1)–(2.3), $\varphi_t$ denote degree descriptors as follows:

$$\varphi_t = (K_{\max}(t), K_{avg}(t), K_d(t)) \tag{3.8}$$

using formulas described in (2.3) and (2.4), $\gamma_t$ denote joint degree descriptors as follows:

$$\gamma_t = (H_{jd}(t), E_{jd}(t)) \tag{3.9}$$

using formulas described in (2.7) and (2.8), $\xi_t$ denote clustering-distance as follows:

$$\xi_t = (\overline{C}(t), G_d(t)) \tag{3.10}$$

the final feature vector for $G^t_{CN}$ can be computed as

$$f_t = [\varphi_t, \gamma_t, \xi_t] \tag{3.11}$$

with the feature vector for $G^t_{CN}$, our CNCRG can be computed as the concatenation of $f_t$ at different stages of the evolution of the network, according to the following:

$$CNCRG = f_{t0}, f_{t1}, ..., f_{tj} \tag{3.12}$$

this approach is used to convert the regular network to the complex network, as illustrated in Figure 3.

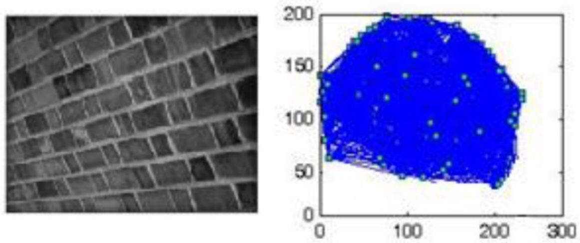


Figure 3: The image of a texture and its complex network

In [3], they showed the complex network $G^{t_0}_{c_n}$ is as suitable for the small-world model. This complex network model has two main characteristics: i) high clustering coefficient and ii) small-world property that can be based on the discussed issues. The clustering coefficients listed in (2.7) can be used to evaluate the characteristics of high clustering coefficients. The small-world property is quantified based on whether an average shortest distance is present on the network (2.8).

## 4 Simulation and analysis results

Using the concepts introduced in section 2 and according to the nodes identified in section 3, the method of doing the work can be described as follows:

1. The image is read and convert into a gray scale image.
2. The weight of the image texture nodes is determined.
3. Based on the introduced threshold, some nodes are selected and their corresponding edges are created.
4. Based on the existing graph, the resulting complex dynamic network is formed using the introduced threshold limit.
5. Triple triangles in the graph are identified.
6. The parameters related to the complex network and other specifications are calculated based on formula (3.3).
7. Input Image is compared with existing images based on the obtained parameters and then it is classified.

Three standard texture databases were used for evaluation in this study. First, the Brodatz texture album [4] is a benchmark for evaluating methods. This dataset is composed of 111 classes, each class containing 10 grayscale samples of $100 \times 100$ pixels which are 10 non-overlapping of sub-images. Second, the UIUC database [7] is a very challenging database for evaluation of texture recognition because the images were obtained in an uncontrolled environment, viewpoint, and scale. For each of 25 classes, $128 \times 128$-pixel 40 grayscales images were considered. Finally, the Outex database Suite (Outex TC 0013) [10] has 68 classes, each class containing 20 images, totaling 1360 grayscales images, each $128 \times 128$ pixels.

Table 1: Threshold sets for experiments

| set | Thresholds | | | NTD [3] | Proposed |
|---|---|---|---|---|---|
| | $t_0$ | $t_{step}$ | $t_{end}$ | No. feature | No. feature |
| T1 | 0.2 | 0.015 | 0.335 | 10 | 30 |
| T2 | 0.2 | 0.015 | 0.485 | 20 | 60 |
| T3 | 0.2 | 0.015 | 0.590 | 27 | 81 |

For the present study, three experiments were conducted to compare the results between the traditional network texture descriptor (NTD) [3] and our proposed method. The first experiment was a comparison of threshold sets as listed in Table 1.

The objective of this experiment was the selection of the best threshold set by using Brodatz as the validation database. The results are shown in Table 2. The second experiment examined combinations of feature descriptors by using the threshold set which was selected based on the first experiment. Along with Brodatz, this experiment used the additional two texture databases, UIUC and Outex for the evaluation. In order to evaluate our proposed method more precisely, the additional conventional texture analysis methods are chosen for comparison which include, Gabor filters [5], Fourier descriptors [2], LBP texture operator [11, 12] and NTD [3]. For the experiments, we used a total of 40 filters (combination of 8 rotation filters and 5 scale filters) a frequency range from 1.2 to 1.4 by using energy as a descriptor for the Gabor filters method. As the results in Table 3, the LBP methods outperformed the other methods in the Brodatz database. In this work, we built the new Brodatz dataset by cropping ten subsections with non-overlapping of a larger Brodatz image. Thus, some images are difficult to distinguish among each class.

Table 2: Results for Brodatz database by threshold set

| Threshold Set | NTD [3] | | Proposed | |
|---|---|---|---|---|
| | No. features | Success rate (%) | No. feature | Success rate (%) |
| T1 | 10 | 36.22 | 30 | 76.76 |
| T2 | 20 | 38.83 | 60 | 77.84 |
| T3 | 27 | 42.25 | 81 | 80.36 |
| T1 | 10 | 37.30 | 30 | 77.12 |
| T2 | 20 | 44.23 | 60 | 79.37 |
| T3 | 27 | 46.31 | 81 | 81.98 |
| T1 | 10 | 62.07 | 30 | 63.78 |
| T2 | 20 | 70.63 | 60 | 65.68 |
| T3 | 27 | 73.24 | 81 | 77.21 |
| T1 | 10 | 62.16 | 30 | 63.42 |
| T2 | 20 | 75.14 | 60 | 63.96 |
| T3 | 27 | 77.84 | 81 | 79.28 |

The complex network model can extract the meaningful information on the local textural pattern by a set of thresholds as we described in Section 3, whereas the result is shown to be effective in the Outex database. On the other hand, the LBP method extract local features using the sign of the difference between a central pixel and its neighbors for thresholding, whereas the results turn to be effective in the Brodatz database more than the NTD and the proposed method. These points can indicate that the set of thresholds has influences on the performance of the NTD and the proposed method, which can be promising in the future work. For the UIUC database, the proposed method outperformed the other methods. Accordingly, these results confirm that the proposed method can perform efficiently for traditional networks applied to challenging environments relative to conventional methods.

Table 3: Comparison of the proposed and other methods

| Method | Success rate (%) | | |
|---|---|---|---|
| | Brodatz | UIUC | Outex |
| Gabor filters | 76.58 | 60.00 | 74.26 |
| Fourier descriptors | 78.02 | 72.40 | 72.13 |
| LBP | 82.52 | 51.30 | 71.47 |
| NTD | 69.55 | 74.60 | 84.49 |
| Proposed method | 81.08 | 81.70 | 82.28 |

## 5 Conclusion

In this paper, we proposed a method for image texture classification based on a complex network model. The experimental results show that the performance of our method in analyzing spatial information based on a complex network model improves the accuracy of texture classification as compared to the original and other methods. Therefore, spatial information analysis based on a complex network is a promising direction for further research.

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