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ROBUST TEXTURE CLASSIFICATION BASED ON HYBRID FEATURES OF COMPLEX NETWORKS

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Abstract. *Recently, complex network theory has emerged as a novel approach for texture analysis. These methods map a texture image into complex networks. Statistical features of the networks are then calculated for texture analysis tasks. Nevertheless, the lack of the use of multifarious network metrics makes it hard to get a more comprehensive texture description. What is more, the preference for regional continuity in most existing modeling strategies makes them sensitive to noise. This paper proposes a novel approach for texture classification using hybrid features of two different kinds of complex networks. Experimental results using real textures and their noise corrupted variants have demonstrated a high classification accuracy and robustness of proposed method.*
Keywords: Texture classification, Complex network, Texture representation, Rotation invariance

1. **Introduction.** Texture perception in human vision is one of the most important early steps towards identifying objects and understanding a scene. As a result, texture analysis has become a basic issue in computer vision and also a key problem in many application areas, such as object recognition, remote sensing, and content-based image retrieval.

Many methods of texture analysis have been developed over the years. Statistical methods represent a texture image by properties that govern the distribution of gray-levels. One of the most popular statistical methods is co-occurrence matrix [1] and its multi-scale rotation invariance version [2]. Another popular statistical method is local binary pattern [3] and its variants [4], which achieve impressive results by calculating the co-occurrence of gray levels on circular neighborhoods. Spectral methods model the texture image by means of spectral information. Gabor filters [5, 6] are representatives of these methods which focus on developing filter banks to efficiently analyze textures. Agent based methods [7, 8, 10] use autonomous entity to act upon a texture image and then use the shape or size of the walks as a discriminating feature. More recently, methods based on complex networks theory have gained a lot of attention for texture analysis. These methods map a texture image into complex networks and calculate their statistical features for texture feature extraction [9, 10, 11].

When expressing texture features, most complex network based descriptors use limited network metrics which are all about the vertex degree. This makes it hard to get a more comprehensive texture description. Further more, the preference for regional continuity in most modeling strategies makes existing complex network based methods sensitive to noise. In this paper we propose a novel texture descriptor in order to improve the robustness and accuracy of texture analysis further. The main contributions of this letter are summarized as follows. Firstly, a novel complex networks model, namely, the high-pass networks model is proposed to capture the rapidly spatial varying information which has been unwitnessed in other complex network based methods. Secondly, several novel measures of complex networks including weighted degree, clustering coefficient and weight distribution difference are proposed to describe the local features of textures more accurately. Thirdly, a modified low-pass networks model is used to work with high-pass networks model to generate hybrid texture features which could obtain more overall information during the phase of texture signature generation. Besides widely used data sets like Outex and CUReT, the UIUC data set which is considered as the most challenging database by far is used to show the robustness and accuracy of texture discrimination of the proposed approach.

The remainder of this paper is organized as follows. Section 2 gives a brief review of the complex network theory, as well as its properties and the definitions of several network measures. Section 3 shows the process of networks generation for the modeled texture and the texture signature generation. In Section 4 the experimental results are presented and discussed. Conclusions of the work are drawn in Section 5.

2. **Preliminaries.** Complex network theory, which is frequently applied to the fields of physics and sociology, is an intersection between graph theory and statistics. Owing to its flexibility to model and express different kinds of problems, complex network theory has been gaining in popularity in a wide range. Usually there are two main steps when using complex networks: modelling the problem as networks and extracting measurements from them. To build a complex network with N vertices, a weighted and undirected graph $\mathsf{G}(\mathsf{V},\mathsf{E})$ is often defined, where $\mathsf{V} = \{v_1, v_2, \ldots, v_N\}$ is a set of vertices and $\mathsf{E} = \{\mathbf{e}_{v_i,v_j} | i \neq j\}$ a set of edges with the weight $w(\mathbf{e}_{v_i,v_j})$. In the rest of this article, $\mathbf{e}_{v_i,v_j}$ and $w(\mathbf{e}_{v_i,v_j})$ are remarked as e_{ij} and w_{ij} for brevity. To characterize the structure of complex networks, vertex measures are often used for their powerful ability to describe topological features of networks. For vertex v_i, its degree k_i, weighted degree k_i^w, clustering coefficient c_i and weight distribution difference y_i^w are defined as follows.

$$k_i = \sum_{e_{ij} \in \mathsf{E}} 1 \tag{1}$$

The degree of v_i corresponds to the number of edges attached to v_i.

$$k_i^w = \sum_{e_{ij} \in \mathsf{E}} w_{ij} \tag{2}$$

The weighted degree of v_i is the sum of weights of edges attached to v_i.

$$c_i = \frac{\sum_{e_{im} \in \mathsf{E}, e_{in} \in \mathsf{E}, e_{mn} \in \mathsf{E}} 1}{k_i(k_i - 1)/2} \tag{3}$$

The clustering coefficient of v_i corresponds to a ratio: the number of triangles including v_i to the number of possible triangles centered on v_i. It can be interpreted as the probability for an edge to exist between two randomly picked neighbors of v_i.

$$y_i^w = \sum_{e_{ij} \in \mathsf{E}} (w_{ij}/k_i^w)^2 \tag{4}$$

The weight distribution difference of v_i describes the effect of the difference of edge weight distribution around v_i on the vertex itself.

3. Proposed Method.

3.1. Complex networks generation for texture representation. Image texture is defined as a bi-dimensional structure of pixels. So in the first step of the proposed method, an image I with $m \times n$ pixels and gray levels between 0 and 255 is modeled as a network $\mathsf{G}(\mathsf{V}, \mathsf{E})$, where $\mathsf{V} = \{v_1, v_2, \ldots, v_{m*n}\}$ is the set of vertices such that each vertex corresponds to one pixel and $\mathsf{E} = \{\mathbf{e}_{v_i,v_j} | i \neq j\}$ is the set of edges. Two vertices v_i and v_j are connected if the Euclidean distance of their corresponding pixels p_i and p_j is smaller than r, namely, the connection radius.

In this stage, as shown in Figure 1(b), the network presents a regular topology which cannot demonstrate the texture variation. Thus, it is necessary to transform this regular network G_r into a series of complex networks $\mathsf{G}_{th,r}$ that have relevant properties for texture analysis, where r is the connection radius and th is a weight threshold. A new complex network is generated from the original regular one when its edges that have weight greater (or less, see the second strategy in next subsection) than th had been discarded. The threshold affects directly the topology, and can result in networks with dense or sparse connections, as shown in Figure 1(c).

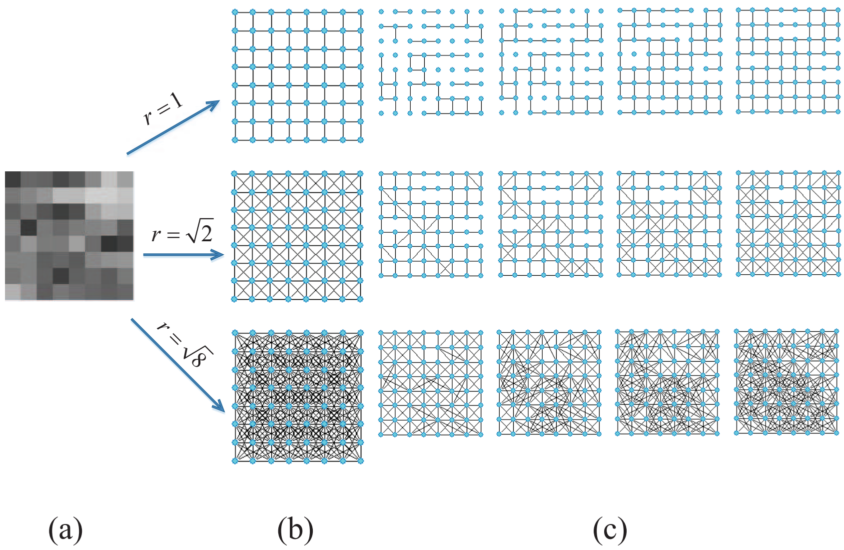


FIGURE 1. Texture image (a) is represented as: (b) regular networks using different r and (c) complex networks with different weight threshold th.

3.2. LP networks and HP networks. From the last subsection we can learn that a series of complex networks $\mathsf{G}_{th_1,r}, \mathsf{G}_{th_2,r}, \ldots, \mathsf{G}_{th_{\max},r}$ can be obtained by using a series of thresholds $th_1, th_2, \ldots, th_{\max}$ with a given r. These networks generated with the same strategy of weight decision and edge discarding are marked as a cluster of graphs G^s. The proposed method generates two clusters of graphs G^{s_1} and G^{s_2} using different strategies.

The first strategy for edge weight decision can be expressed as

$$w^{s_1}(\mathbf{e}_{v_i,v_j}) = \sqrt{\frac{1}{2}\left[\left(\frac{1}{r}d_{p_i,p_j}\right)^2 + \left(\frac{1}{255}|I(p_i) - I(p_j)|\right)^2\right]} \tag{5}$$

where w^{s_1} is the weight of edge $\mathbf{e}_{v_i,v_j}$ when using the strategy s_1, d_{p_i,p_j} is some kind of distance measurement between pixels p_i and p_j which correspond to the vertices v_i and v_j respectively. In this letter, the Euclidean distance is used. $I(p_i)$ is the intensity of pixel p_i and $I(p_i) \in [0, 255]$. From Equation (5) we can learn that $w^{s_1} \in (0, 1]$ for any $i \neq j$.

The corresponding strategy for edge discarding can be expressed as

$$\mathsf{E}_{th}^{s_1} = \mathsf{E} - \bigcup_{\mathbf{e}\in\mathsf{E}} \{\mathbf{e}|w^{s_1}(\mathbf{e}) \geq th\} \tag{6}$$

where th is a weight threshold. In other words, a complex network of the first cluster is generated from the original regular one when its edges that have weight greater than th had been discarded.

From the combination of Equation (5) and Equation (6), we can learn that the first strategy tries to generate a cluster of complex networks by keeping the connections between vertices which are close enough to each other, both in distance and pixel intensity. The resulting networks keep the slow-varying of the expressed texture well, acting like low-pass filters. Thus, this cluster of complex networks are marked as low-pass networks (LP networks). We rewrite G^{s_1} as G^{LP}.

Correspondingly, another cluster of complex networks, namely, high-pass networks (HP networks) could be generated by the following strategy

$$w^{HP}(\mathbf{e}_{v_i,v_j}) = \frac{1}{255}|I(p_i) - I(p_j)| \exp\left(-\frac{d_{p_i,p_j}^2}{2\sigma_r}\right) \tag{7}$$

and

$$\mathsf{E}_{th}^{HP} = \mathsf{E} - \bigcup_{\mathbf{e}\in\mathsf{E}} \left\{\mathbf{e}|w^{HP}(\mathbf{e}) \leq th\right\} \tag{8}$$

where $\sigma_r \propto r^2$ is the distance factor which affects the changing speed of w^{HP} with d_{p_i,p_j}.

According to Equation (7), $w^{HP} \in (0, 1]$ for any $i \neq j$, is positively associated with the difference of pixel intensity, and has a reverse relation with the distance between two vertices. Combined with Equation (8), HP networks keep connections between vertices which are close enough to each other with a relatively large difference of pixel intensity.

Thus, two clusters of complex networks have been modeled from the input texture image for texture feature extraction. Figure 2 shows the HP and LP networks generated from two texture images with different r and th. Texture images in (a) are 32×32 down-sampled images of D43 (first row) and D71 (second row) of normalized Brodatz texture data set. Networks in (b) and (c) are high-pass networks generated with $r = 2$ and $r = 3$ respectively ($th = 0.140$ for all HP networks). Networks in (d) and (e) are low-pass networks generated with $r = 2$ and $r = 3$ respectively ($th = 0.325$ for all LP networks).

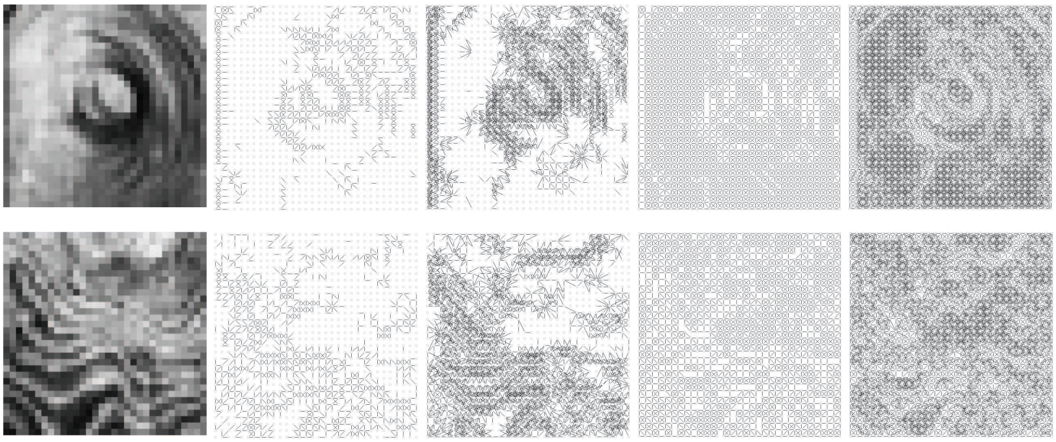
3.3. **Texture signature generation.** Given r and th for each cluster (e.g., the LP networks), one complex network $\mathsf{G}_{th,r}^{LP}$ is built. Texture features are then expressed as a unit feature vector of $\mathsf{G}_{th,r}^{LP}$

$$\varphi_{th,r}^{LP} = \left\{\overline{k}, \overline{k^w}, \overline{c}, \overline{y^w}\right\} \tag{9}$$

where $\overline{k}, \overline{k^w}, \overline{c}, \overline{y^w}$ are means of the measures defined in Equations (1)$\sim$(4) over all vertices in $\mathsf{G}_{th,r}^{LP}$.

Thus, given an r and a set $\{th_1, th_2, \ldots, th_{\max}\}$, the signature of the input texture can be obtained by a feature vector ψ that is calculated as

$$\psi = \left\{\varphi_{th_1,r}^{LP}, \varphi_{th_1,r}^{HP}, \varphi_{th_2,r}^{LP}, \varphi_{th_2,r}^{HP}, \ldots, \varphi_{th_{\max},r}^{LP}, \varphi_{th_{\max},r}^{HP}\right\} \tag{10}$$



(a) (b) (c) (d) (e)

FIGURE 2. HP and LP networks generated from two texture images with different r and th

4. Experimental Results and Discussion.

4.1. **Experimental setting and results.** In order to evaluate the proposed method, the signatures were calculated for appropriate configurations for texture classification. Three texture data sets are used in this evaluation.

Outex TC10 [12]**.** This data set is used to evaluate the rotation invariance of algorithms. It contains 24 classes of texture images captured under 9 rotation angles. There are 20 images with the resolution of 128×128 for each rotation angle. The 20 images of rotation angle $0°$ in each class were adopted as the training data and the 160 images of other 8 rotation angles are used for test.

CUReT [13]**.** This data set is used to evaluate the illumination invariance of algorithms. It contains 61 texture classes each with 92 selected images (200×200) under different illumination directions. We randomly choose 46 texture images from each class as training samples, while the remaining 46 images for testing.

UIUC [14]**.** This data set is used to evaluate performance of algorithms under the condition of complex variations. It contains 25 classes with 40 images (640×480) each, captured under varying viewpoints. We randomly choose 20 texture images from each class as training samples, while the remaining 20 images for testing.

To objectively evaluate the robustness against additive Gaussian noise for the proposed approach, texture images without noise in CUReT and UIUC serve as training set. Each texture sample of testing set is added Gaussian noise with different SNR values.

After evaluating different configurations, we choose the following parameters in the experiments: $\sigma_r = \frac{1}{2}r^2$; $r = 2$ for Outex TC10, $r = \sqrt{8}$ for CUReT and $r = 3$ for UIUC; $th_1 = 0.08$, $th_{\max} = 0.53$ and the threshold interval $\Delta th = 0.03$ for all G^{LP} of Outex TC10; $th_1 = 0.03$, $th_{\max} = 0.18$ and $\Delta th = 0.01$ for all G^{HP} of Outex TC10; $th_1 = 0.25$, $th_{\max} = 0.7$ and $\Delta th = 0.03$ for all G^{LP} of CUReT; $th_1 = 0.05$, $th_{\max} = 0.20$ and $\Delta th = 0.01$ for all G^{HP} of CUReT; $th_1 = 0.325$, $th_{\max} = 0.625$ and $\Delta th = 0.02$ for all G^{LP} of UIUC; $th_1 = 0.01$, $th_{\max} = 0.16$ and $\Delta th = 0.01$ for all G^{HP} of UIUC. Thus, for each image, 1 radius and 32 thresholds (16 for LP networks and 16 for HP networks) were given and 4 measures were used in each network. So there were $1 \times 32 \times 4 = 128$ descriptors in total to express the texture of an image.

Our feature vector analysis is carried out by applying a Linear Discriminant Analysis (LDA) to the data. In the classification, the Nearest Neighbours Classifier (NNC) is used.

We have chosen a simple classifier rather than a sophisticated one in order to highlight the importance of texture descriptors.

The results are compared with other well-known descriptors: LBP [3], Circular Gabor [6], LTP [15], Multi-scale GLCM [2] and existing comlex network based methods including Single-Cluster Complex Networks (SCCN) [9], Deterministic Walks on Complex Networks (DW+CN) [10] and Complex Network Descriptors using Bag-of-Words Framework (BoW+CN) [11]. In order to show the effect of hybrid features of two clusters complex networks, the results of using LP and HP networks separately are also present. Due to space limitations, all the experimental results including classification accuracy, rotation invariance, illumination invariance, complex variation invariance and the robustness against additive Gaussian noise are summarized in Table 1.

TABLE 1. Texture classification results (%) achieved by proposed and other well-known descriptors for different data sets. Top 3 results of each data set are in bold and the best one is in underline & bold.

Method	Rotation Invariance	Illumination Invariance & Robustness Against Noise			Complex Variation Invariance & Robustness Against Noise		
	Outex	CUReT 46:46			UIUC 20:20		
	TC10	No Noise	SNR=50	SNR=30	No Noise	SNR=50	SNR=30
LBP	**98.15**	<u>**94.20**</u>	**86.28**	74.24	79.01	66.36	48.04
C-Gabor	81.42	79.09	78.87	77.43	72.02	71.05	69.37
LTP	<u>**98.64**</u>	**92.66**	<u>**90.90**</u>	<u>**83.78**</u>	**82.34**	**80.83**	<u>**77.22**</u>
M-GLCM	89.45	86.91	85.03	**81.75**	81.72	**77.97**	**70.71**
SCCN	89.67	87.39	81.66	72.33	78.73	71.01	60.19
DW+CN	90.08	91.23	82.87	71.25	80.10	72.23	60.88
BoW+CN	85.47	82.06	75.67	67.51	76.29	69.04	58.33
LP-CN	92.53	90.75	84.37	75.21	**83.27**	75.40	65.98
HP-CN	89.36	86.24	79.07	68.55	78.26	69.64	57.22
proposed	**96.58**	**94.18**	**90.28**	**81.07**	<u>**87.25**</u>	<u>**81.11**</u>	**73.03**

4.2. **Discussion.** From the distribution of data in bold in Table 1 we can learn that both LTP and proposed descriptor achieve good performance in all tests. LBP does well under noiseless or low noise conditions but present a significant drop when noise increasing. On the contrary, multi-scale GLCM performs well in different challenges of noise.

When compared with other traditional vertex degree based complex network descriptors (SCCN, DW+CN and BoW+CN), the approach that only uses LP networks in this paper wins out thanks to the usage of more comprehensive measures defined in Equation (9). Although the HP networks just achieve mediocre performance, they provide important supplemental information of the statistical characteristics of textures for the LP networks. As a result, the final proposed descriptor using hybrid features of the LP and HP networks presents an excellent texture discrimination overcoming traditional complex network based methods and a solid robustness under conditions of rotation and illumination variations, significant viewpoint changes and different noises.

5. **Conclusions.** In this letter, we proposed a novel method of texture analysis using the complex network theory. We investigated how a texture image can be effectively represented, characterized and analysed by two types of complex networks, namely the low-pass networks and the high-pass networks. Results showed that the method was very robust to environmental change and also presented an excellent discrimination in

different challenging texture data sets, outdoing other complex network based descriptors for texture classification.

As future works, we intend to use more different statistical frameworks such as bag of features model to fuse local texture information more effectively. Besides, a multi-scale analysis should be explored in the context of complex network based approaches.

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