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TEXTURE CLASSIFICATION BY LOCAL SPATIAL PATTERN MAPPING BASED ON COMPLEX NETWORK MODEL

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Abstract. *This paper proposes a method for image texture classification based on a complex network model. Finding relevant and valuable information in an image texture is an essential issue for image classification and remains a challenge. Recently, a complex network model has been used for texture analysis and classification. However, with current analysis methods, important empirical properties of image texture such as spatial information are discarded from consideration. Accordingly, we propose local spatial pattern mapping (LSPM) method for manipulating the spatial information in an image texture with multi-radial distance analysis to capture the texture pattern. In experiments, the feature properties under the traditional complex network model and those with the proposed method are analyzed by using the Brodatz, UIUC, and Outex databases. As results, the proposed method is shown to be effective for texture classification, providing an improved classification rate as compared to the traditional complex network model.*

Keywords: Complex network, Spatial arrangement, Spatial information, Texture analysis, Texture classification

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, 2]. 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 [2]. Texture analysis has played an important role in texture discrimination by quantifying image properties. There are a growing number of techniques described in the literature for texture characterization. These techniques are able to extract and to characterize texture information using first-order features [1], Fourier descriptors [3], Gabor filters [4], graph theory [5, 6], and complex networks (CN) [7].

In recent years, graph-based representation and complex network model have been efficiently applied in texture analysis [8, 9]. Backes et al. [9] proposed a traditional complex network model for texture analysis and classification. Graph-based representations have been used to characterize the topological structure of networks, including image pixels [6]. Vertex 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. However, other empirical properties of image texture such as spatial arrangement are discarded from the statistical properties by the conventional vertex measurement.

Based on the flexibility of complex networks for characterizing textural structures, it is interested in applying standard pattern recognition techniques to the complex network model of [9] in order to improve texture descriptors. Regarding the pattern analysis techniques, local binary pattern (LBP) operator is employed in this work. Ojala et al. [10, 11] 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. The original LBP has been extended to improve the rotation invariance which calls this operator $\mathrm{LBP}^{\mathrm{riu2}}$ [12]. The $\mathrm{LBP}^{\mathrm{riu2}}$ operator is great measures of the spatial structure of local image texture and therefore the advantage of the $\mathrm{LBP}^{\mathrm{riu2}}$ operator has been used in this paper.

This paper proposes a method to characterize texture primitives by considering spatial information based on the complex network model of [9] for texture classification. The $\mathrm{LBP}^{\mathrm{riu2}}$ method is adopted to analyze the spatial arrangements of spatial patterns in the texture elements. Three standard texture databases, Brodatz [13], UIUC [14], and Outex [15] are used for evaluation. The experimental results show the effectiveness of the proposed method compared to the traditional complex network model [9] and texture analysis based on conventional methods. The remainder of the paper is organized as follows. Section 2 explains our proposed method, which is based on image graph-based representation and includes the spatial information analysis. The feature descriptors are explained in Section 3 followed by experimental results and discussions in Section 4. Finally, Section 5 concludes this work.

2. **Proposed Method.**

2.1. **Image graph-based representation.**

2.1.1. *Weights of edges.* Image textures can be represented as pixel networks based on graph theory [6]. Figure 1 shows an example of the image graph-based representation. Suppose, image I with a resolution of $M \times N$ pixels. Let $I(i,j) = g$, $i = 1,\ldots,M$ and

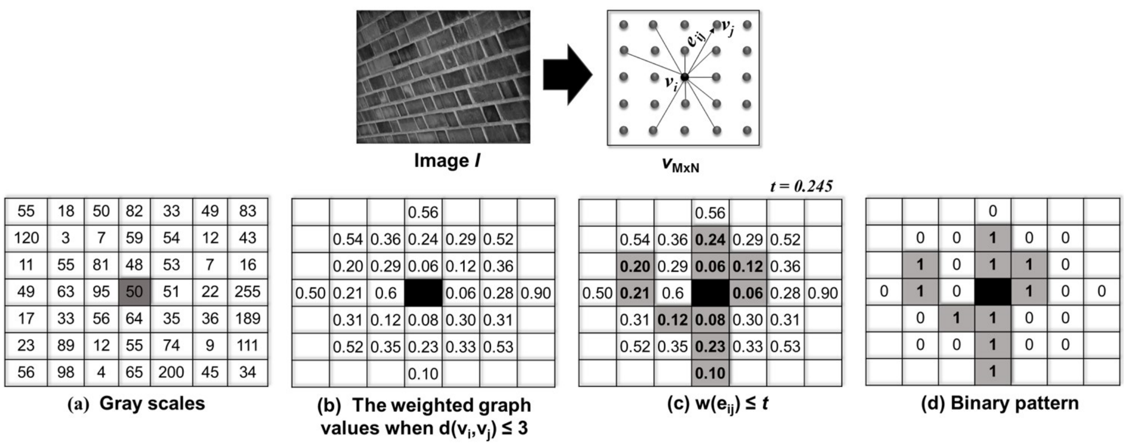

FIGURE 1. Image pixel representation based on graph theory: (a) each pixel of the image is a vertex in the graph, (b) two vertices are connected if $d(v_i, v_j) \leq r$ ($r = 3$ in this example), whereas a weighted graph is defined by Equation (1), (c) a threshold t is applied to imitating a transformation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

$j = 1, \ldots, N$, 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 [9], the weight of the edges e_{ij} is defined as

$$W(e_{ij}) = \begin{cases} \dfrac{\|\mathbf{r_i} - \mathbf{r_j}\| + r^2 \frac{|I(i)-I(j)|}{L}}{r^2 + r^2} & \text{if } d(v_i, v_j) \leq r \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $\mathbf{r_i}$ and $\mathbf{r_j}$ 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.

2.1.2. *Threshold.* A threshold (t) is a parameter related to the property of being an edge in graph theory [5, 6]. In the traditional complex network model [9], 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:

$$W_b^{(t)}(e_{ij}) = \begin{cases} 1 & \text{if } W(e_{ij}) \leq t \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

2.2. **Spatial pattern analysis.** In the traditional complex network model [9], the texture properties are characterized by the distribution of vertex degree. However, some informative properties such as spatial arrangement should be determined among the extracted topological features. To our knowledge, spatial information was never previously been analyzed in texture analysis based on a complex network model. Therefore, spatial arrangement is the focus of this paper.

2.2.1. *Local spatial pattern mapping.* Multi-radial distance analysis is employed for feature representation as defined below. After the binary pattern transformation, the neighbors of a vertex v_i which have Euclidean radial distances r_1, r_2 and r_3 equal to 1, 2, and 3 are constructed by the radial symmetric neighborhood as in Figure 2. This approach enables us to describe local context information about pixel surroundings, (indicated in gray in the figure). The results of these binary row records are used for encoding the spatial arrangement in the next process.

A set of binary features for a radial distance r is denoted by

$$k^{(t)}(e_{ij}) = \begin{cases} \left[W_b^{(t)}(e_{i1}), W_b^{(t)}(e_{i2}), \ldots, W_b^{(t)}(e_{ip_1})\right] & \text{if } d(v_i, v_j) < r_1 \\ \left[W_b^{(t)}(e_{i1}), W_b^{(t)}(e_{i2}), \ldots, W_b^{(t)}(e_{ip_2})\right] & \text{if } r_1 \leq d(v_i, v_j) < r_2 \\ \left[W_b^{(t)}(e_{i1}), W_b^{(t)}(e_{i2}), \ldots, W_b^{(t)}(e_{ip_3})\right] & \text{if } r_2 \leq d(v_i, v_j) < r_3 \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where $j = 1, 2, \ldots, p_n$, $n = 1, 2$ and 3. The p_n is denoted as vertices neighborhood of a vertex v_i in the Euclidean radial distances r_1, r_2 and r_3. In this paper, the vertices

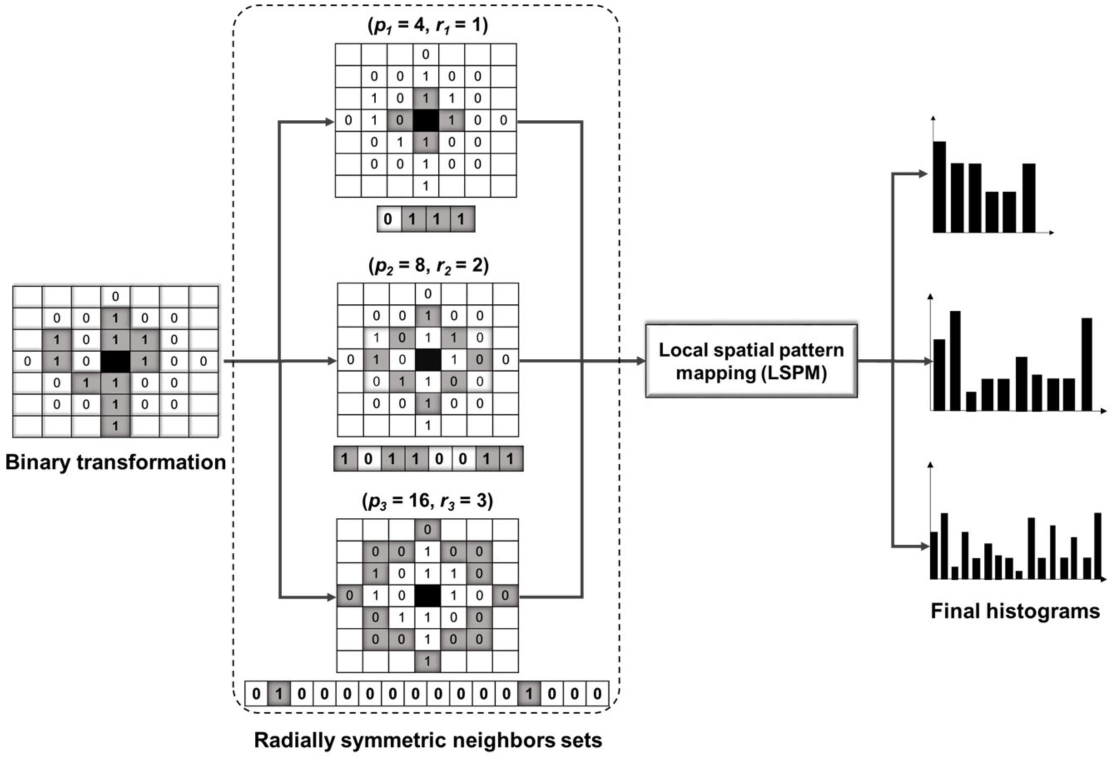

FIGURE 2. Local spatial pattern mapping with the radially symmetric neighbor sets for different (p, r)

neighborhood p_1, p_2, and p_3 are equal to 4, 8, and 16, whereas the radial distances r_1, r_2 and r_3 equal to 1, 2 and 3, respectively.

A spatial arrangement analysis is performed by local spatial pattern mapping or LSPM. The uniformity of LBP mapping [10, 12] is adapted for spatial mapping at different radial distances. The LSPM method is used to describe the uniformity of texture primitives when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1 in the same way as uniformity in LBP theory [10]. We define the LSPM method as follows:

$$lspm(e_{ij}) = \sum_{j=1}^{p_n} k^{(t)}(e_{ij})2^{(j-1)}, \tag{4}$$

where $p_n = p_1$, p_2 and p_3, which are equal to 4, 8, and 16, respectively. For considering the uniformity of $lspm$, the following equation is used:

$$\text{LSPM}(p_n, r_n) = \begin{cases} lspm(e_{ij}) & \text{if } U(lspm(e_{ij})) \leq 2 \\ p+1 & \text{otherwise,} \end{cases} \tag{5}$$

where U is the uniform pattern of $k^{(t)}(e_{ij})$ in Equation (3), which is determined when the binary pattern of a binary row record contains at most two bit-wise transitions between 0 and 1. For example, the pattern of 00000000 shows the U value of 0, whereas the binary pattern of 11000001 shows U equal to 2 as justified by [10]. This equation means that if the $lspm(e_{ij})$ has $U > 2$, it defines for non-uniform pattern. This step enables us to analyze the uniform pattern of pixel surroundings, which can refer to local texture analysis. In practice, LSPM is implemented by using a look-up table of 2^{p_n} elements. In this case, there are $p_n + 2$ output bits for each final histogram. The feature properties as histogram for the radial analyses $\mathrm{LSPM}(p_n, r_n)$ are defined as follows:

$$F^{(t)}(v_i) = \begin{bmatrix} \mathrm{LSPM}(4,1) \\ \mathrm{LSPM}(8,2) \\ \mathrm{LSPM}(16,3) \end{bmatrix}^{\top}. \tag{6}$$

3. **Feature Descriptors.** The feature properties in the system analyzed herein are given by (6). A probability density function of histograms is computed to obtain statistical properties. The set of statistical descriptors is given by [9] and comprises the mean, contrast, energy, and entropy, which are defined by

$$p(i) = \frac{\mathrm{LSPM}(p_n, r_n)}{\sum_{i=1}^{p_n+2} \mathrm{LSPM}(p_n, r_n)}, \quad n = 1, 2, 3, \tag{7}$$

where p_1, p_2, and p_3 are equal to 4, 8, and 16, whereas r_1, r_2 and r_3 equal to 1, 2 and 3, respectively. For vertex characterization using the histogram of LSPM, the following set of features was evaluated:

$$\begin{gathered} \mu = \sum_{i=0}^{p_n+2} ip(i) \qquad C = \sum_{i=0}^{p_n+2} p(i)i^2 \\ E = \sum_{i=0}^{p_n+2} \left[p(i)^2\right] \qquad H = -\sum_{i=0}^{p_n+2} p(i)\log_2[p(i)]. \end{gathered} \tag{8}$$

The set of complex network properties in terms of LSPM with a threshold set $\{t_0, t_1, \ldots, t_{\mathrm{end}}\}$ is given by

$$\begin{aligned} \text{Mean} &= \left[\mu\left(F^{(t_0)}(v_i)\right), \mu\left(F^{(t_1)}(v_i)\right), \ldots, \mu\left(F^{(t_{\mathrm{end}})}(v_i)\right)\right] \\ \text{Contrast} &= \left[C\left(F^{(t_0)}(v_i)\right), C\left(F^{(t_1)}(v_i)\right), \ldots, C\left(F^{(t_{\mathrm{end}})}(v_i)\right)\right] \\ \text{Energy} &= \left[E\left(F^{(t_0)}(v_i)\right), E\left(F^{(t_1)}(v_i)\right), \ldots, E\left(F^{(t_{\mathrm{end}})}(v_i)\right)\right] \\ \text{Entropy} &= \left[H\left(F^{(t_0)}(v_i)\right), H\left(F^{(t_1)}(v_i)\right), \ldots, H\left(F^{(t_{\mathrm{end}})}(v_i)\right)\right]. \end{aligned} \tag{9}$$

In order to evaluate our proposed method, a discrimination function for texture classification was generated by a support vector machine (SVM). In the implementation of this work, the *Classification Learner* app of MATLAB 2016a version with default parameter values was used for multi-class classification with the one-versus-all strategy. An SVM with a quadratic kernel was integrated for evaluation following 10-fold cross-validation.

4. **Experimental Results.** For the present study, three experiments were conducted to compare the results between the traditional complex network texture descriptor (CNTD) [9] 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. The last experiment was a comparison with other conventional methods which include Gabor filters, Fourier descriptors, LBP, $\mathrm{LBP}^{\mathrm{riu2}}$, and CNTD.

TABLE 1. Threshold sets for experiments

Set	Thresholds			CNTD [9]	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

TABLE 2. Results for Brodatz database by threshold set

Feature Descriptors				Threshold Set	CNTD [9]		Proposed	
Mean	Contrast	Energy	Entropy		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

4.1. **Databases.** Three standard texture databases were used for evaluation in this study. First, the Brodatz texture album [13] is a benchmark for evaluating methods. This dataset is composed of 111 classes, each class containing 10 grayscale samples of 100×100 pixels which are 10 non-overlapping of sub-images. Second, the UIUC database [14] 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, 128×128-pixel 40 grayscales images were considered. Finally, the Outex database Suite (Outex_TC_0013) [15] has 68 classes, each class containing 20 images, totaling 1360 grayscales images, each 128×128 pixels.

4.2. **Comparison of results from different threshold sets.** The first experiment determined the appropriate set of threshold values to be used. The most meaningful information could be extracted when $t \leq 0.590$. We followed [9] in defining t_{step} as 0.015. Table 1 defines the threshold sets T1, T2, and T3 and lists the numbers of features separately for CNTD and the proposed method. The proposed method generates three times as many features compared with the CNTD method because the radial distance r here sets equal to 3, as shown in Equation (6). Using the threshold sets in Table 1, an experiment on statistical descriptors was performed using the Brodatz database. The results in Table 2 indicate that the number of features affects the success rate. Based on the success rates, we chose the T3 configuration for the CNTD method in the second experiment, whereas the T1 configuration was chosen for the proposed method because the numbers of features and success rates were close to those of CNTD with T3. Table 2 shows the proposed method produced significantly better results for all feature descriptors. In a spectrum of textures from regular textures to stochastic textures on the Brodatz database, the proposed method can describe irregular, near-stochastic, and stochastic textures better than the CNTD method. These reasons imply the efficiency of using spatial arrangement to improve texture classification based on a complex network model.

4.3. **Results by combination of feature descriptors.** The selected threshold configurations as explained in Section 4.2 were used in the second experiment for evaluating combinations of feature descriptors. Table 3 lists the numbers of features by combination of feature descriptors, and Figure 3 shows the classification results for the Brodatz, UIUC, and Outex databases for CNTD and the proposed method. For the Brodatz database, good performance was obtained for all combinations of descriptors for the same reasons as discussed with reference to Table 2. In order to clarify the performance of the proposed method, this second experiment evaluated it with respect to the UIUC database. The UIUC database is more challenging because it was collected the database in uncontrolled environments including viewpoints (rotations) and scale changes. Based on the UIUC results in Figure 3, the proposed method outperformed CNTD. This is because LSPM can extract more important information from local image texture. For example, an arrangement of neighbors at the same radial distance is identified as a radially symmetric set for encoding the spatial arrangement. Moreover, the uniformity of texture patterns has been

TABLE 3. Number of features by combination of feature descriptors

Feature Descriptors					CNTD [9]	Proposed
No.	Mean	Contrast	Energy	Entropy	No. feature (T3)	No. feature (T1)
1	✓	✓	–	–	54	60
2	✓	–	✓	–	54	60
3	✓	–	–	✓	54	60
4	–	✓	✓	–	54	60
5	–	✓	–	✓	54	60
6	–	–	✓	✓	54	60
7	✓	✓	✓	–	81	90
8	✓	✓	–	✓	81	90
9	✓	–	✓	✓	81	90
10	–	✓	✓	✓	81	90
11	✓	✓	✓	✓	108	120

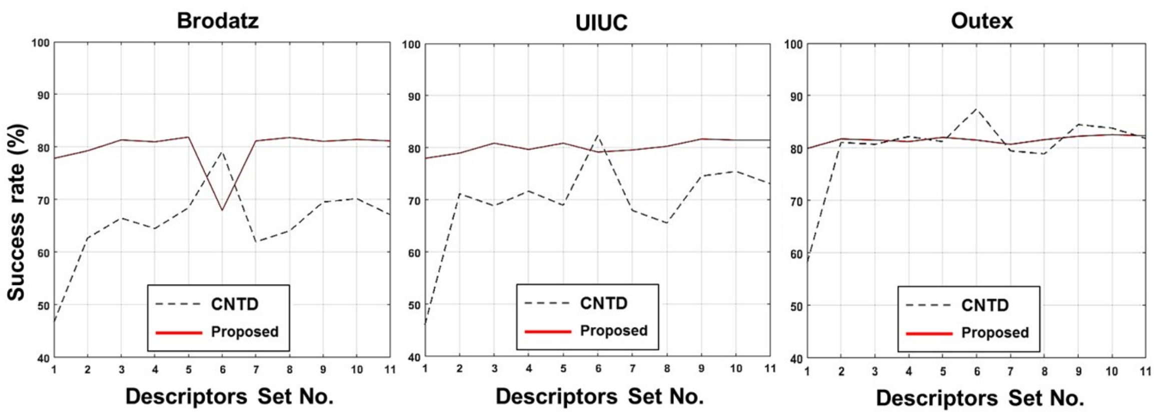

FIGURE 3. Experimental results for the CNTD [9] and proposed methods

analyzed based on the LBP^{riu2} mapping. Thus, LSPM can characterize the texture of significant feature patterns by using their spatial arrangement. As a result, we can conclude that the proposed method is invariant to scale and rotation. For the Outex database, the performance was obtained in the same scale as compared with CNTD method was obtained for all combinations of descriptors as shown in Figure 3. The texture images of the Outex database are obtained under the various illumination condition which influenced the performance. Although this condition has an effect on the system, this approach was good to compare with other texture analysis methods.

4.4. **Comparison with other methods.** The success rates and numbers of features of the third experiment are listed in Table 4. The success rates of the CNTD and the proposed method are shown for descriptors set No. 9 (Table 3). For more evaluating our proposed method, the additional conventional texture analysis methods are chosen for comparison which include, Gabor filters [4], Fourier descriptors [3], LBP and LBP^{riu2} texture operators [10, 11] and CNTD [9]. 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. The Fourier descriptors are computed 90 descriptors from the shifted spectrum. For LBP and LBP^{riu2} operators, the histograms were concatenated for $(P, R) = (2, 8)$ to characterize texture, resulting in a total of 256 and 10 descriptors, respectively.

Table 4. Comparison of the proposed and other methods

Method	No. features	Success rate (%)		
		Brodatz	UIUC	Outex
Gabor filters	40	76.58	60.00	74.26
Fourier descriptors	90	78.02	72.40	72.13
LBP	256	82.52	51.30	71.47
LBP^{riu2}	10	81.90	75.90	73.81
CNTD	81	69.55	74.60	84.49
Proposed method	90	81.08	81.70	82.28

As the results in Table 4, the LBP and LBP^{riu2} 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 image is difficult to distinguish between each class. The complex network model can extract the meaningful information on the local textural pattern by a set of thresholds as we described in Section 4.2, whereas the result is shown to be effective in the Outex database. On the other hand, the LBP and LBP^{riu2} methods 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 CNTD and the proposed method. These points can indicate the set of thresholds has influences on the performance of the CNTD and the proposed method, which can be a promising in the future work. For the UIUC database, the proposed method outperformed the other methods. The different viewpoints with respective distortion and non-rigid transformation are manipulated by the proposed method. Accordingly, these results confirm that the proposed method can perform efficiently for traditional complex networks applied to challenging environments relative to conventional methods.

5. **Conclusion.** In this paper, we proposed a method for image texture classification based on a complex network model. We used an approach which we refer to as local spatial pattern mapping (LSPM) to describe the spatial arrangement of neighbors in a network. 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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