# SVM Ensemble Approaches for Improving Texture Classification Performance Based on Complex Network Model with Spatial Information

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***Abstract*—This paper proposes an SVM ensemble approach for improving textural classification performance. Finding informative patterns in an image texture is an important issue for image classification and remains a challenge. Local spatial pattern mapping (LSPM) method has been proposed for texture classification based on a complex network model. The purpose of the method was manipulating the spatial distribution in an image texture with multi-radial distance analysis. Although the classification performance was improved, there is a limitation by using a single support vector machine (SVM) as a classifier. Accordingly, we propose an SVM ensemble method with Bagging technique to overcome the limitation by showing improved textural classification performance. In experiments, the SVM ensemble classification performance is compared to the single SVM, SVM with cross-validation and k-NN classifiers by using the Brodatz, UIUC and Outex texture databases. As results, the SVM ensemble is shown to be effective for improving textural classification performance as compared to the other classifiers.**

***Keywords*—SVM ensemble, complex network model, texture classification**

## I. Introduction

Ensemble methods are learning models that achieve high performance by combining the opinions of multiple learners. The advantage of ensembles is that it can lead to significant improvement in the performance of new data. In our previous work [1], we proposed the local spatial pattern mapping (LSPM) method to characterize texture primitives based on the complex network model of [2] with considers spatial information for texture classification. A support vector machine (SVM) for multi-class classification was applied to evaluate the proposed method. Although the classification performance improved as compared to traditional methods, there is a limitation by using single SVM as a classifier.

To overcome the limited classification performance of the single SVM, this paper proposes an ensemble method based on SVM classifier for improving the textural classification performance based on our previous work [1]. The SVM ensemble can improve the classification performance more significant than the single SVM by the following fact on [3]. In experiments, each SVM has been trained through randomly chosen feature samples which extracted by using LSPM method [1]. We can expect that a combination of several SVMs will expand the correctly classified area incrementally. The SVM ensemble classification performance is compared to the single SVM, SVM with cross-validation and k-NN classifiers by using the Brodatz, UIUC, and Outex texture databases. As results, the SVM ensemble is shown to be effective for improving textural classification performance as compared to the other classifiers.

To describe the proposed method, the remainder of the paper organizes as follows. Section 2 explains backgrounds that relate to this work, which based on complex network model and the spatial arrangement analysis. The SVM ensemble classifier explains in section 3, followed by experimental results and conclusion in sections 4 and 5.

## II. Backgrounds

### A. Texture images based on complex network model

Texture pixels are represented based on graph theory [4]. Let $G = (V, E)$ be the graph comprising the set of vertices $V$ and the set of edges $E$. An edge $e_{ij}$ is constructed when the Euclidean distance between pixels $i$ and $j$ is less than or equal to radius $r$. Based on [2], the weight of the edges $e_{ij}$ is defined as

$$W(e_{ij}) = \frac{\parallel r_i - r_j \parallel + r^2 \frac{|I(i)-I(j)|}{L}}{r^2 + r^2}, \tag{1}$$

where $r_i$ and $r_j$ are the coordinates of pixels $i$ and $j$ in image $I$, and $L$ is the maximum intensity within Euclidean distance $r$ between pixels $i$ and $j$.

Fig. 1(a) shows an example of representing image texture based on the complex network model. Each pixel of an image is denoted as a vertex in the graph. Two vertices are connected when Euclidean distance $r$ between them no more than $r$ value ($r = 3$ for this example), whereas a weight of each pixel defined by equation (1). Then the threshold $t$ value ($t = 0.245$) is applied to the original set of edges, where weight $W(e_{ij}) \leq 0.245$ is indicated by orange. Then, the binary pattern transformation process, which is performed

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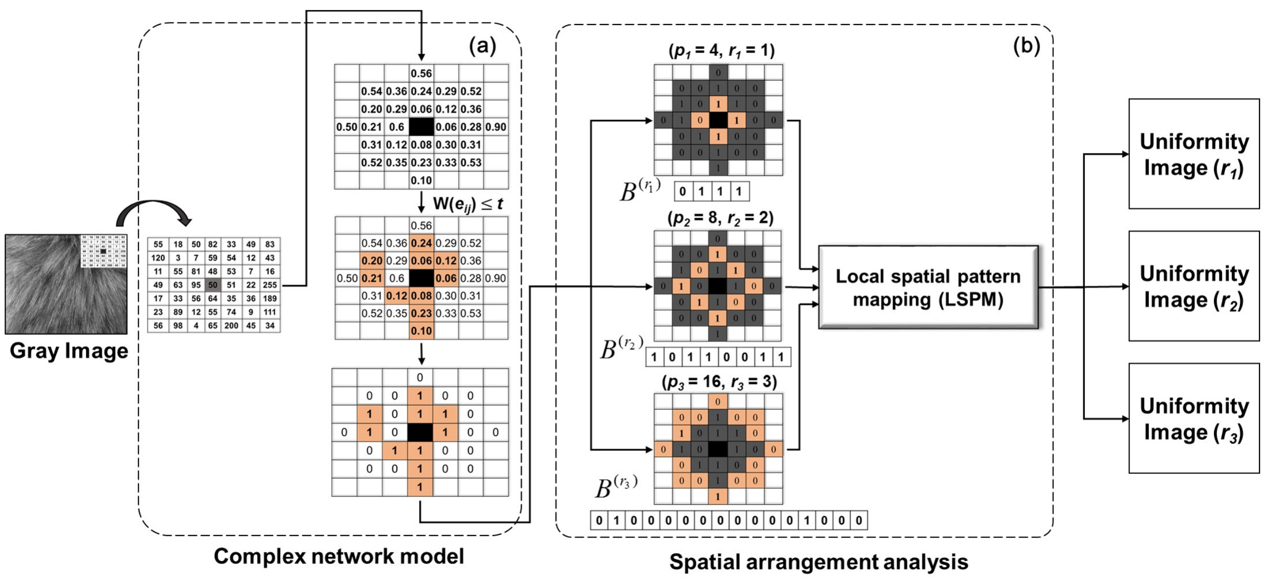


Fig. 1. Example of representing texture as pixel network based on complex network model with spatial arrangement analysis

by converting the vertices whose weights are less than or equal to threshold $t$ to 1, while the remaining vertices are converted to 0. In this study, a set of thresholds is used to construct a network that imitates dynamic transformation for the purpose of texture analysis. It means that we can obtain context information of texture by a set of thresholds values. In this work, threshold values obtains through the experiments.

### *B. Spatial arrangement analysis*

In our previous work [1], we proposed a method to characterize texture primitives based on the complex network model of [2] that considers spatial information. We briefly explain the details in this subsection. A spatial arrangement analysis was performed by local spatial pattern mapping which denoted as LSPM. The LSPM approached to describe the spatial arrangement of neighbors in a network by adapting local binary pattern (LBP) [5] method for pattern mapping. After the complex network model in Fig. 1(a), the multi-radial distance analysis is applied after the binary transformation process. The neighbors of a vertex $v_i$ which have Euclidean radial distance $r$ = 1, 2, and 3 are determined (indicated in orange in the figure). Then, the radially symmetric mapping is approached to construct binary row records for encoding the spatial arrangement (illustrated in Fig. 1(b)). Then, LSPM method is employed 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$^{riu2}$ theory [5]. The outputs are derived as three uniformity images based on radius $r$ = 1,2 and 3. The feature sets are obtained through the concatenated histograms in term of statistical descriptors (energy and entropy) on multiple radial distances $r$.

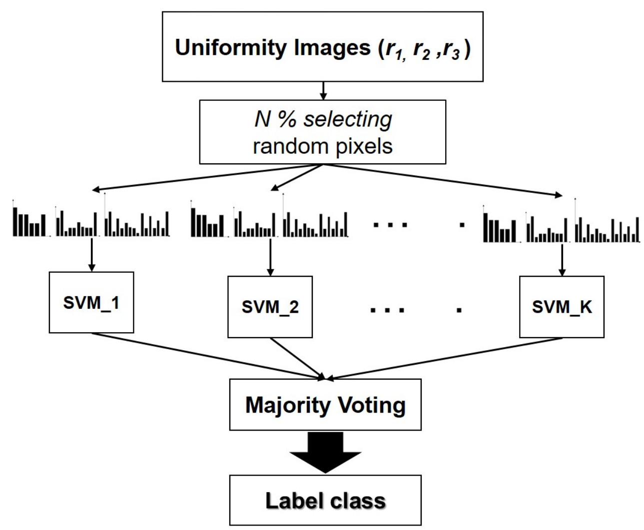


Fig. 2. An architecture of the SVM ensemble process

## III. SVM ENSEMBLE CLASSIFIER

Ensemble methods are learning models that achieve excellent performance by combining the opinions of multiple or same learners for making strong decision [3]. The advantage of ensembles is that it can lead to significant improvement performance by analyzing the bias-variance decomposition of the learning models. The error of models can be decomposed into two components bias and variance. To construct an ensemble, same classifiers is used for training new data in this paper as illustrated in Fig. 2. A subset of training data is collected via a bootstrap aggregation or bagging with replacement method, $N\%$ of random pixels are selected for reducing bias problem. Class labels are predicted using majority voting approach based on the number of SVMs.

## IV. Experiment results

### A. Databases

Three standard texture databases were used for evaluation in this study. First, the Brodatz texture album [6] 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 [7] is a very challenging database for evaluation of texture recognition because the images were obtained in an uncontrolled manner in terms of environment, viewpoint, scale, and illumination. For each of 25 classes, 128×128-pixel 40 grayscales images were considered. Finally, the Outex database Suite (Outex_TC_0013) [8] has 68 classes, each class containing 20 images, totaling 1360 grayscales images, each 128×128 pixels.

### B. Results

In experiments, we collected 80% random pixels as training data for bagging technique. We noted that the number of random pixels is fixed in this paper. For the number of SVM classifier, the 100 ensembles of SVM are used for manipulating in the process. In the implementation of this work, the Classification Learner app of MATLAB 2016a version with default parameters is used for multi-class classification with the one-versus-all strategy. An SVM with a quadratic kernel integrates for evaluation. The ratio of training and testing samples are 90: 10 percents from the number of each database. To evaluate the proposed approach, the conventional classifiers are used as the comparison which including nearest neighborhood (k-NN), single SVM and SVM with cross-validation.

The experimental results showed in Table 1 with the success rate of each classifier, 10-NN, the single SVM and SVM with 10 folds cross-validation classifiers. We obtained the number of features for comparison in each classifier as 60 dimensions through the statistical measurements which including energy and entropy. Based on the results in Table 1, the proposed method was shown to have improved success rates compared with the others classifiers for all three databases, especially in the challenging UIUC database, because the images of this database were obtained from significantly different viewpoints and at significantly different scales.

For considering the bias-variance decomposition viewpoints, discrimination model is expected to be low-bias and low-variance model for creating good predictive accuracy that is based on the sensitivity [9]. In our previous work, the texture classification method based on complex network model was high dimensional data with high variance by applying a set of thresholds to construct a network property and texture analysis. Then, the feature vectors are obtained by concatenating histograms, which means increasing the dimensional data. Based on the improved classification performance of our feature model [1], we assume that the model can be represented as a low-bias model with complex and unstable properties. Based on the advantage of the ensemble approach, bootstrap aggregation or bagging technique can reduce overfitting problem on the low-bias model by averaging the data together to create stability on the model. Accordingly, the classification performance can improve by applying the proposed method based on above clarification.

TABLE I
Comparison of each classifier as classification performance

| Classifiers | No. features | Success rate (%) | | |
|---|---|---|---|---|
| | | Brodatz | UIUC | Outex |
| 10-NN | 60 | 61.50 | 57.50 | 73.68 |
| Single SVM | 60 | 76.58 | 80.00 | 80.88 |
| Single SVM with 10-CV | 60 | 78.82 | 76.50 | 81.25 |
| **100-SVM ensemble** | **60** | **84.69** | **86.00** | **86.77** |

## V. Conclusion

In this paper, we proposed an SVM ensemble approach for improving textural classification performance based on complex network model with spatial information. We used our previous approach which we refer to as local spatial pattern mapping (LSPM) [1] to describe the spatial arrangement of neighbors in a network. The experimental results show that the performance of SVM ensemble classifier is confirmed to be effective for improving textural classification performance as compared to the other classifiers.

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