Classification of Texture Using Multi Texton Histogram and Probabilistic Neural Network

Agus Eko Minarno¹, Yuda Munarko¹, Arrie Kurniawardhani² and Fitri Bimantoro³

¹Department of Informatics, Universitas Muhammadiyah Malang, Malang, Indonesia
²Department of Informatics, Faculty of Industrial Technology, Universitas Islam Indonesia, Jl. Kaliurang Km. 14.5 Yogyakarta, 55584, Indonesia
³Universitas Mataram, Mataram, Indonesia

e-mail: agoes.minarno@gmail.com

Abstract. Image classification plays an important rule for other image domains such as image retrieval, object recognition, image annotation and relevance feedback. In this paper, we describe our work in image classification using Multi Texton Histogram (MTH) and Probabilistic Neural Network (PNN). The result shows that the proposed method reaches 92% accuracy for Batik dataset and 98% for Brodatz dataset. This indicates that the use of MTH and PNN for image classification for Batik dataset and Brodatz dataset are effective.

1. Introduction
A number of research have been conducted for pattern recognition and classification of images. One of those research is the texture classification of Songket images by Cheong and Loke. They used six multispectral co-occurrence matrix in order to extracting colour features. After that, they incorporated Tchebichef orthogonal polynomial to compute coefficient moment and then extracting features based on co-occurrence. They showed that the used method is powerful for differentiate texture colour of Songket [1]. Continue their research, Cheong and Loke tried to reducing features using Principal Component Analysis (PCA). It may reduce 2% of features without any issue in classification accuracy [2]. A similar research is conducted by Nurhaida et al. [3], which also focus on Batik features extraction. They compared three methods, those are Gray Level Co-occurrence Matrices (GLCM), Canny Edge Detection, and Gabor filters. They found that the performance of GLCM is best to other methods for image classification.

In general, image classification is built based on colour, texture and shape features which are used independently or in combinatorial. From those features, colour feature becomes the most dominant and is broadly used for discriminating images. Almeida et al. has been proposed a method that used colour feature and distance between pixels by creating image index on three dimensional table. The table illustrates the spatial relationships in the image colour change. The objective of colour indexing is compare an image query to images in the database [4].

Research on texture features has also been widely proposed in the field of pattern recognition clustering, classification and object detection. Julesz, in his research on the analysis of texton interaction to discriminate textures, found that by using texton combined with simple statistical methods, visual perception to distinguish the texture of the image can be obtained significantly
Research on texture has also been done by Haralick using Gray Co-Occurrence Matrix (GLCM). GLCM is using statistical methods of order one and two to produce 14 features. Including in these features are mean, variance, correlation, energy and homogeneity. From some research above, we see that the accuracy of the image classification using either statistical or texton methods could be improved. Therefore, this study was proposed to develop a method for feature extraction using Multi Texton Histogram (MTH) and Probabilistic Neural Network (PNN) as a classifier. PNN is chosen as the classifier because it has a relatively lower complexity compared to Neural Network.

2. Dataset
The datasets in this study are the 950 images of Brodatz colour dataset and the 300 images of Batik dataset. Brodatz dataset consists of 50 classes where each class consists of 19 images. While Batik dataset consists of 50 classes where each class consists of 6 images. Figure 1 is an example of the Brodatz’s images (a) and Batik’s images (b). The dimensions of each image is 128x128 pixels.

3. Multi Texton Histogram
MTH basic idea is texton theory proposed by Julesz. MTH is using four types of texton to detect the micro structure of an image. Those four types of texton are shown in Figure 3. MTH approach does not involve segmentation process and training data. MTH extracts image features by utilizing a colour histogram in RGB colour space and detects the edge orientation of an image using Sobel operator. MTH stages can be described into four steps. First, perform edge orientation detection using Sobel operator. Edge orientation detection results are then quantized into 18 bins. Since MTH is using 1-180
degrees in representing edge orientation value, so if the value is quantized into 18 bins, then the quantized value is a multiplication of 10. Second, do a quantization to the image’s colour in RGB colour space. For each RGB component, the value is quantized into 4 bins: R = 4 bin, G = 4, bins, and B = 4 bins. Third, detect texton on the results of quantized edge orientation and quantized colour using four different textons. Detection process is conducted from left to right and from top to bottom, by two pixels of each shift. The result of texton detection is colour histogram and edge orientation histogram. Finally, colour histogram and edge orientation histogram are combined becoming a single histogram. The combined histogram is consisted of 82 features which composed by $4 \times 4 \times 4 = 64$ colour features and 18 edge orientation features.

4. **Probabilistic Neural Network**

Probabilistic Neural Network (PNN) was chosen because of its speed and accuracy in patterns recognition and classification. PNN is developed from Neural Network method which based on Bayes Classification Parzen. PNN architecture as can be seen in Figure 2. The PNN consists of four layers, namely input layer, pattern layer, the summation layer, and the layer decision.

![FIGURE 2. PNN Architecture](image)

The input layer is consisted of several node which are vectors. The vector is a hallmark of input image. The pattern layer is consisted of the sum of the total number of neuron of training data. In the pattern layer, the input features are calculated using Gaussian function and probability density function (PDF) based on Parzen window. The summation layer is a layer that calculates total of the highest probability from pattern layer. Lastly, the decision layer, which responsible for determining an image to the most similar target and decide to a specific class.

5. **Feature Extraction and Classification**

5.1. **Extraction of Edge Orientation Feature**

The first stage is performing an extraction of edge orientation feature using Sobel operator. Sobel operator produces vector and magnitude which are then quantized into 18 bins. The selection of bin size is based on previous studies by [5][7][8][9][10][12]. This stage is resulting 18 edge orientation features.

5.2. **Extraction of Colour Feature**
The second stage is the extraction of RGB colour feature. In this stage, colour is separated into RGB colour component. Then, each value of RGB colour component is quantized into 4 bins, so there are $4 \times 4 \times 4 = 64$ bins. These features will be used in the next stage along with edge orientation features.

5.3. Texton Detection

The next stage is the detection of texton on the result of colour quantization and edge orientation quantization. The 2x2 element size is used in this paper to increase texture discrimination, because the texture gradients contain only at texture boundaries [6]. The types of texton that detected can be seen in Figure 3., named T1, T2, T3 and T4. Those texton types are chosen because the co-occurring probability of two same-valued pixels is bigger than that of three or four same-valued pixels in a 2x2 grid element size.

Features are extracted by convoluting each texton on pixels that contains quantized colour and quantized edge orientation information. The convolution is performed from the top left of image to the right side of image and from the top downwards by two pixels per detection. MTH uses grids with dimension 2x2 pixels which are marked as V1, V2, V3 and V4. When a grid contains two similar pixels which have similar pattern with a particular texton, then, that grid is calculated as a texton. Two pixels are considered similar when the value of quantized colour or quantized edge orientation are equal. For example, a grid is considered to texton T1 when the 2 top pixels have quantized colour value 10. Consequently, the number of texton T1 with quantized colour value 10 is increased by 1. Total number of texton such as T1 with quantized colour value 10 is then stored in a histogram. An illustration of texton detection is shown in Figure 4.

![FIGURE 3. Four types of MTH’s texton. (a) 2x2 Grid; (b) T1 ; (c)T2 ; (d) T3; (e) T4](image)

![FIGURE 4. An illustration of texton detection in MTH (a) original image; (b) 4 texton detection; (c) texton type; (d) result of detection.](image)

6. PNN Classification

The classification experiment is conducted using 950 images of Brodatz dataset, which 900 images is set for training data and 50 image as testing data. PNN is selected as classification method because PNN is relatively faster and may perform good accuracy compared to Neural Network. PNN is a combination of Neural Networks and Probability Density Function (PDF). This method is fast since it uses probability approach for activation. PDF is calculated using Equation 1 and Equation 2.
\[
\phi_{ki}(x) = \frac{1}{\sqrt{(2\pi)^d \sigma^d}} \exp\left(-\frac{\|x_i - \bar{x}_k\|^2}{2\sigma^2}\right)
\]  
(1)

Where \(x_i\) is a vector of features, \(x_k\) is a set of training data, \(k\) indicates the class and \(\sigma\) is smoothing parameter.

\[
g_k(x) = \frac{1}{\sqrt{(2\pi)^d n\sigma^d}} \sum_{i=1}^{n} \exp\left(-\frac{\|x_i - \bar{x}_k\|^2}{2\sigma^2}\right)
\]  
(2)

Where \(n\) is the number of training data, then likelihood can be calculated from features which classified to class \(k\). The last calculation is to compute the maximum probability at the output layer of the PNN using Equation 3.

\[
C(x) = \arg \max \{g_k(x), k = 1,2,...,m\}
\]  
(3)

Where \(k\) is a class and \(m\) is the number of classes and \(x\) is a feature.

7. Performance Measure

The accuracy of features extraction and classification is calculated using Equation 4.

\[
Accuracy = \frac{M}{N} \cdot 100\%
\]  
(4)

Where \(M\) is the number of data test which are classified correctly, whereas \(N\) is the total number of data test.

8. Result and Discussion

To measure the performance of the proposed method, an experiment was conducted using Brodatz dataset and Batik dataset. The total number of Brodatz dataset is 950 images, consists of 50 classes, each class composed of 19 images. 900 images are used for training data and 50 images are used for testing data. While the total number of Batik dataset is 300 images, consists of 50 classes, each class composed of 6 images. For each class, 4 images are used for training data and two images are used for testing data.

Features that feed on PNN are detected using texton. The number of features that related to colour is 64 while the number of features that related to edge orientation is 18. Those features are represented as a histogram. An example of the result of edge orientation detection using Sobel operator can be observed in Figure 5. Figure 5(a) is the original image while Figure 5(b) is the result of edge detection using Sobel operator. An example of MTH histogram that are detected using texton is shown in Figure 6. MTH histogram represents the number of co-occurrence pixel successful detected using 4 types of texton. The Y axis is representing the number of co-occurrence of a particular feature with a particular value in a pair of pixels.

![FIGURE 5. An example of the result of edge orientation extraction using Sobel operator (a) original image; (b) the result of Sobel operator.](image)

Table 1 is the result of classification using MTH and PNN. From the experimental results in Table 1, we can see that features extraction method using MTH and PNN classifier is able to classify the image properly. For Batik dataset, the accuracy reaches 92% for 250 training data and 50 testing data. While,
for Brodatz dataset, the accuracy is 6% higher by Batik dataset, reaches 98% for 900 training data and 50 testing data. The nature of Brodatz dataset and Batik dataset are a reach variety of feature values, so these datasets are appropriate to use for examining the reliability of the proposed method. Still based on Table 1, the number of training data that used does not contribute a significant influence. Therefore, we can see that MTH and PNN are able to present a good performance.

| Testing Scenario                                      | Dataset | Accuracy |
|-------------------------------------------------------|---------|----------|
| Batik 250 training data, 50 testing data              | Batik   | 92%      |
| Brodatz 900 training data, 50 testing data           | Brodatz | 98%      |

Moreover, Table 1. indicate that the 2x2 texture element can represent the Batik features well. The 2x2 texture elements can discriminate the texture patterns within an image based on texton gradients. Texton gradients are used to represent texture pattern because those represent the texture bundaries.

9. Conclusion
This study was elaborated a features extraction method using Multi Texton Histogram and an image classification method using Probabilistic Neural Network on Brodatz dataset and Batik dataset. The accuracy of classification is relatively high which reaches 92% for Batik dataset and 98% for Brodatz dataset. Based on the experiment results, we may conclude that Multi Texton Histogram and Probabilistic Neural Network are reliable for extracting features and classifying images, especially images that contains texture character. Future studies can be developed to improve performance of the detection of co-occurrence of pixels and edge orientation.

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