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Comparison of Methods for Batik Classification Using Multi Texton Histogram

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Abstract

Batik is a symbol reflecting Indonesian culture which has been acknowledged by UNESCO since 2009. Batik has various motifs or patterns. Because most regions in Indonesia have their own characteristic of batik motifs, people find difficulties to recognize the variety of Batik. This study attempts to develop a system that can help people to classify Batik motifs using Multi Texton Histogram (MTH) for feature extraction. Meanwhile, k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM) algorithm were employed for classification. The performance of those classifications is then compared to seek the best classification method for Batik classification. The performance is tested 300 images divided into 50 classes. The results show the optimum accuracy achieved using k-NN with k=5 and MTH with 6 textons is 82%; however, SVM and MTH with 6 textons denote 76%. According to the result, MTH as feature extraction, k-NN or SVM as a classifier can be applied on Batik image classification.

***Keywords**: batik, classification, multi texton histogram, k-nearest neighbor, support vector machine*

1. Introduction

Indonesia is a country rich with diverse cultural heritages from its ancestors. One of the symbols reflecting Indonesian culture is Batik. Batik is the techniques, symbolism, and culture surrounding hand-dyed cotton and silk garments [1]. Batik motif has symbolic meaning and high aesthetic value for Indonesians [1]. The existence and uniqueness of Batik have been acknowledged by UNESCO on October 2, 2009 as an Intangible Cultural Heritage of Humanity [2]. Most Indonesians, however, cannot recognize the characteristic of Batik motifs due to its diversity richly exhibited in each Indonesian region. Batik motifs depict the character, custom, and virtuous value from which they are originated [3-4]. This study attempts to develop Batik classification.

Feature extraction method based on textons has been successfully conducted in Batik image analysis [4-9]. Textons are the elements of texture perception proposed by Julez [10]. One of the method based texton that is capable to show faster performance is Multi Texton Histogram (MTH) [11-13]. Originally, MTH is developed to analyze natural images. Moreover, MTH can also work well in image retrieval study [9],[14-16]. MTH can represent shape, color, and texture correlation through spatial correlation without prior process of any image segmentation process. Support Vector Machines (SVM) and k-Nearest Neighbor (k-NN) classifier are employed to compare which one becomes the optimal classifier that can be used as Batik classification.

SVM and kNN are well-known and powerful classifiers that can simultaneously handle many attributes and large data [17-20]. Both of them are classifiers that are based on statistical theory. SVM can avoid over-fitting and local minimal on the other hand, k-NN is simpler but more sensitive to noise. According to the previous sentences, this study attempts to develop Batik classification using MTH as feature extraction method. Furthermore, this study performs classification method comparison between k-NN and SVM classifier to seek the best classification method for Batik classification. The rest of this paper is organized as follows:

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Section 2, the dataset used to test the performance is presented; Section 3, MTH scheme is presented; Section 4, the performance of MTH using k-NN as classifier is evaluated and compared with MTH using SVM as classifier; and Section 5, this chapter presents the conclusion of the study.

2. Dataset

In this study, the dataset consists of 300 images divided into 50 classes; hence, each class has 6 images. Those classes refer to the types of Batik motif. The size of each image is 128x128 pixels. Figure 1 shows the images utilized in this study.

Figure 1. Batik images as dataset consists of 50 classes. Dataset is available download at https://github.com/agusekominarno/batik

3. Multi Texton Histogram (MTH)

The extraction process used in this study is Multi Texton Histogram (MTH). MTH is used to extract the feature in an image utilizing texton idea.

3.1 Feature extraction of edge orientation

Edge orientation feature extraction is one of the important processes in pattern recognition [11]. There are many methods used for edge feature extraction. This study uses Sobel operator as edge feature extraction method because it can reduce noise before performing edge detection calculations compared to other gradient operators or other edge detection methods. Thus, it is considered to be more efficient and simpler. To add, Sobel operator could give optimal performance in the previous study [11]. Sobel operator gives emphasis to the neighboring pixels of a pixel, such as giving high weight value to neighboring pixels. Therefore, the effect of neighboring pixels will differ according to their location to a pixel at which the gradient is calculated. Gradient is a function calculating the alteration intensity which an image is viewed as a collection of several continuous intensity functions. The results obtained from Sobel operator are vector and magnitude which afterward are quantized into 18 bins. At this stage, features are generated 18 edge orientation features.

3.2 Feature extraction of color

Color is very useful information for object detection process. Human visual can sense three basic colors and the combination of three basic colors namely red, green, and blue. Moreover, RGB is color space commonly used in digital processing. In the previous study, RGB color space could give optimal performance. Hence, RGB color space is used in this study. Each color component of RGB color space is extracted and quantized into 4 bins of color intensity, R=4 bins, G=4 bins, and B=4 bins. The combination of those color bins produces 64 color variations obtained from 4x4x4 bins. Hence, the proposed generated features are 64 color features.

3.3 Texton detection

Texton was introduced by Julesz as a microstructure of an image [10]. Julesz proposed MTH algorithm as its basic idea coming from texton theory. MTH uses four types of texton to detect the microstructure of an image [11]. Figure 2 and Figure 3 show four-type and six-type texton used for texture detection, respectively. The 2x2 grid texton is used in this study. In addition, each grid is marked with v1, v2, v3, and v4. This is employed to increase the texture difference since the texton gradient only provides texture boundary [11]. Each texton type is convoluted from left to right and from top to bottom through two pixels. The texture is detected when there are two pixels having the same value intensity at the corresponding grid position of the texton, hence, the grid can be called as texton. Those four types of texton will produce two histograms, color feature histogram and edge orientation feature histogram.

Figure 4 illustrates how the convolution of texton works. Initially, the T1 type of texton is chosen. Afterwards, the texton is convoluted on image of RGB color space that has been quantized. When there are two pixels having the same value intensity at the corresponding grid position of T1, the frequency of occurrence of those intensity value of a color component in color feature histogram will be added by one. After all types of texton are convoluted, the information obtained from histogram is called as texton feature.

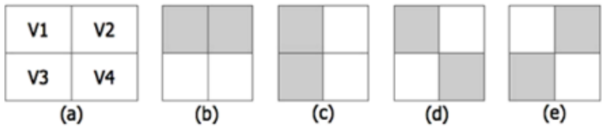

Figure 2. Four-types of texton on MTH used for texture detection, (a) 2x2 grids; (b) T1; (c) T2; (d) T3; (e) T4

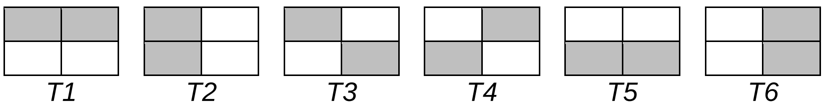

Figure 3. Six-types of texton on MTH used for texture detection

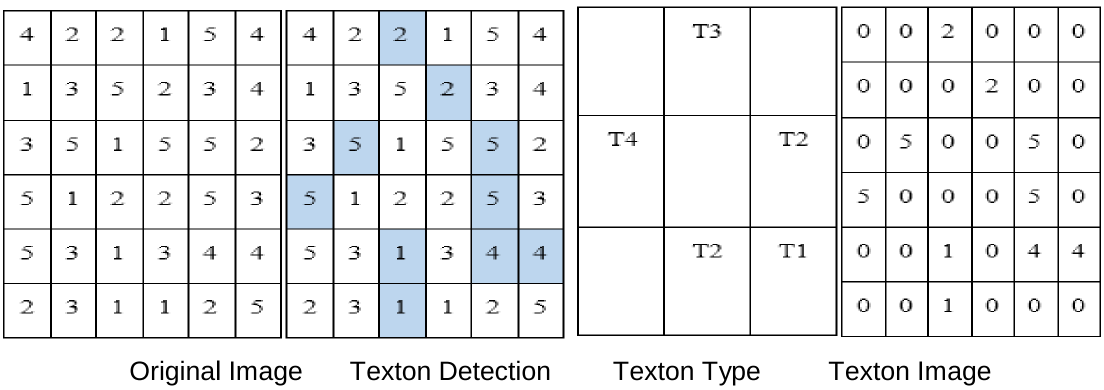

Figure 4. Illustration of texton detection process using four-type textion

3.4 The whole process of feature extraction

MTH is used to extract Batik texture. In the first stage, the color feature extraction at RGB color space and edge orientation feature extraction using Sobel operator are completed separately. Color feature extraction generates 64 features whereas edge orientation feature extraction generates 18 features. Each texton type is convoluted from left to right and from top to bottom through two pixels.

After extracted, textures will be depicted as a vector value in histogram, color feature histogram and edge orientation feature histogram. Histogram is the distribution of several pixels in an image. Furthermore, the color feature histogram and edge orientation feature histogram will be combined to be one histogram concatenatedly. Therefore, the concatenated histogram has 82 features obtained from 64 color features and 18 edge orientation features. Figure 5 shows the workflow of MTH.

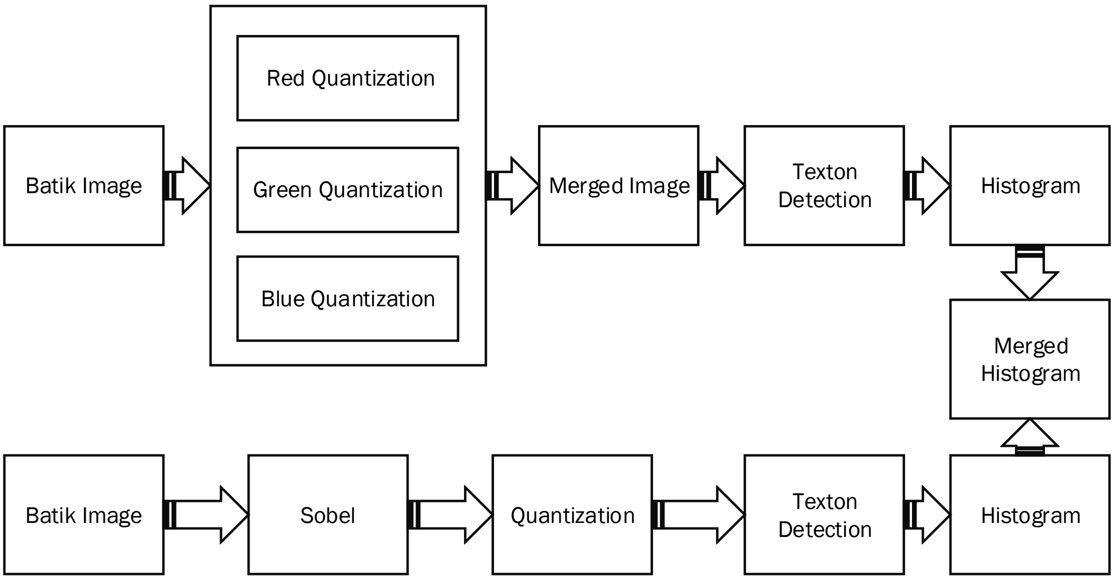

Figure 5. MTH's workflow

4. Result and Discussion

4.1 Color feature extraction

Figure 6 shows one of Batik images used in this study. Each image has intensity value which the range of intensity value in each component in RGB color space is between 0 until 255. Thus, the maximum value of the color component combination is 255 x 255 x255. Figure 7 shows color quantization image. Quantization is a process used for decreasing color intensity value. In this study, each component value of RGB color space is quantized into 4 bins of color intensity, R=4 bins, G=4 bins, and B=4 bins. The combination of those color bins produces 64 color variations obtained from 4x4x4 bins. Figure 7 shows color quantization of images in Figure 6. Meanwhile, Figure 8 shows merged image of RGB channel.

Figure 6. Original Image of Batik

Figure 7. Color Quantized Image

Figure 8. Red, Green, Blue Merged Image.

To perform the previous quantization process, image is separated into three color components of red, green, and blue. After quantization process is completed, those color components are re-combined using equation (1).

$$Merged\ color\ = (B\ bins\ *\ G\ bins\ *\ R\ Quantization) + \ (B\ bins\ +\ G\ Quantization) + B\ Quantization \tag{1}$$

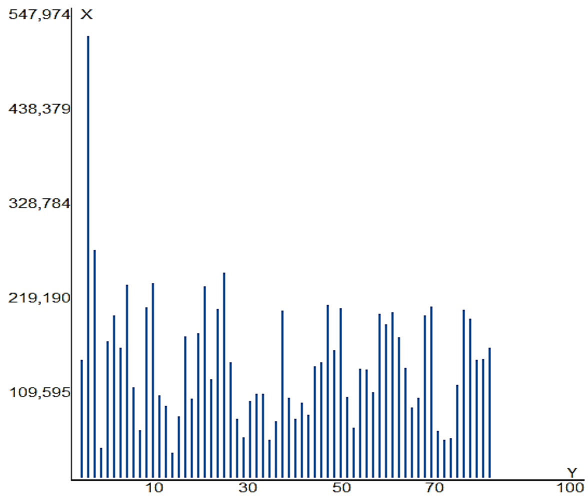

Figure 9. Color Histogram

Texton is an extraction when there are two pixels that have the same intensity value at the corresponding grid position of a texton type. The result of four-type texton extraction on the color quantization image is color feature histogram which is presented in Figure 8.

4.2 Edge orientation extraction

The original image must be converted to grayscale image to extract edge orientation feature. Figure 10 illustrates the grayscale image of Figure 6. The grayscale image attained from previous process is converted to Sobel image using Sobel operator. Sobel image contains edge orientation information of objects in an image. Figure 11 shows the Sobel image of Figure 10. The range of edge orientation information got from previous process is from 0 until 180. In this study, the information of edge orientation is quantized into 18 bins. Thus, at this stage, features that will be generated are 18 edge orientation features. Figure 12 shows the edge orientation quantization image of Figure 11.

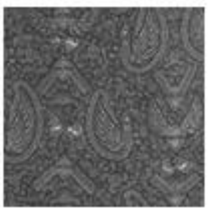

Figure 10. Grayscale Image

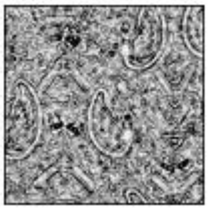

Figure 11. Sobel Image

Figure 12. Edge Orientation Quantized Image

Texton is extracted when there are two pixels having the same edge orientation value at the corresponding grid position of a texton type. The result of four-type texton extraction on the edge orientation quantization image is edge orientation feature histogram which is illustrated in Figure 13.

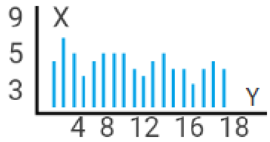

Figure 13. Edge Orientation Histogram

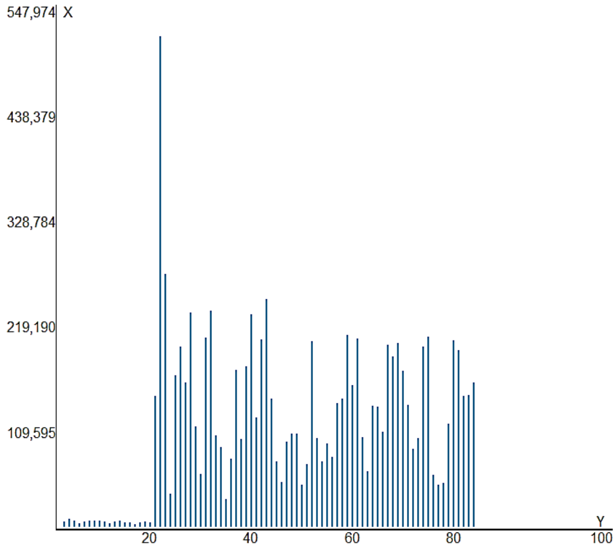

Figure 14. Merged Histogram

4.3 Merged histogram

The histogram obtained from texton extraction on the color and edge orientation features are combined concatenately. Therefore, the concatenated histogram has 82 features obtained from 64 color features and 18 edge orientation features. Those features will be used in the classification process. Figure 14 depicts the merged histogram of color histogram of Figure 9 and edge orientation histogram of Figure 13.

4.4 Experiment scenario of cross validation

Cross validation is executed to perceive the consistency of classification performance [21-25]. Cross validation experiment is completed by varying the data used for training data and testing data. The variation is obtained by randomizing an image, changing an image as training data and testing data. It is intended to alternate all data becoming training data and testing data. Table 1 illustrates the cross-validation experiment results using six-folding.

Table 1. The average accuracy of cross validation experiment

MTH	KNN k = 5	SVM
4 Textons	60 %	54.3 %
6 Textons	64.6%	59.3%

4.5 Experiment scenario of equal distribution 50/50

In this experiment, 300 Batik images are grouped into equal number, 50% as training data and 50% as testing data. Thus, three images in each class are employed as training data, and three other images in each class are used as testing data. Table 2 shows the experiment results of equal distribution scenario.

Table 2. The average accuracy of equal distribution scenario

MTH	KNN k = 5	SVM
4 Textons	57.3 %	49.3 %
6 Textons	62%	59.3%

4.6 Experiment scenario of 60/40 distribution

In this experiment, 300 Batik images are divided into 60% as training data and 40% as testing data. Thus, four images in each class are used as training data, and two other images in each class are used as testing data. Table 3 shows the experiment results of 60/40 distribution scenario.

Table 3. The average accuracy of 60/40 distribution scenario

MTH	KNN k = 5	SVM
4 Textons	62%	58%
6 Textons	68%	65%

4.7 Experiment scenario of 70/30 distribution

In this experiment, 300 Batik images are grouped into 70% as training data and 30% as testing data. Thus, five images in each class are used as training data, and one image in each class is used as testing data. Table 4 shows the experiment results of 70/30 distribution scenario.

Tabel 4. The average accuracy of 70/30 distribution scenario

MTH	KNN k = 5	SVM
4 Texton	70%	64%
6 Texton	82%	76%

From Table 1 to Table 4, the performance of MTH using six-type texton is better than that of the four-type texton. The average accuracy of six-type texton is 6.83% higher than the average accuracy of four-type texton using k-NN classifier. When using SVM classifier, the accuracy of six-type texton is 8.5% higher than the accuracy of four-type texton. Six-type texton has more variation types of texton than four-type texton. Thus, the variation of texture in an image can be more defined using six-type texton. The missing information in an image can be reduced.

Additionally, the best performance of distribution scenario of training data, and testing data is 70% of training data and 30% testing data distribution scenario. The average accuracy from 70/30 distribution is 73%. Meanwhile, the worst performance of distribution scenario of training data and testing data is 50% of training data and 50% testing data distribution scenario. The average accuracy from 50/50 distribution is only 56.98%. It can be implied that to achieve more superior accuracy, the number of training data used for classification should be higher than the number of testing data.

The experiment results show the achived highest accuracy using k–Nearest Neighbor (k-NN) algorithm is 70% and 82% using 4 textons and 6 textons, respectively. Coversely, the highest accuracy that can be achieved using Support Vector Machine (SVM) algorithm is 64% and 76% using 4 textons and 6 textons, respectively. In this study, the performance of k-NN classifier is better than SVM classifier. The average accuracy of k-NN classifier 5.09% higher than that of the SVM classifier

The accuracy achieved in this study is plausible for Batik classification. It can be said that Multi Texton Histogram (MTH), k-NN and SVM are significantly applicable in Batik image classification. MTH algorithm can well represent Batik motifs in texton information. The total number of features used during classification process is 82 features, 62 color features and 18 edge orientation features. It is pretty efficient to represent the information in an image, especially for texture image. Furthermore, it shows that MTH can well extract the feature in any image dataset on a large scale variation.

5. Conclusion

This study attempts to develop a system that can help people to classify Batik motifs using Multi Texton Histogram (MTH) for feature extraction. In addition, this study employs classification method comparison between k–Nearest Neighbor (k-NN) and Support Vector Machine (SVM) classifier to seek the best classification method for Batik classification. The experiment result shows the average accuracy of k-NN classifier is 5.09%, higher than the average accuracy of SVM accuracy. Moreover, the highest accuracy that can be achieved by k-NN and SVM classifier is 82% and 76% using six-type texton, respectively. This study has successfully reached satisfying accuracy for Batik classification. Consecutively, MTH, k-NN, and SVM are pretty good to be applied in Batik image classification.

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