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Recognition of Toraja Carving Motifs Using Texture Features with GLCM

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Abstrak

Indonesia terdiri dari beragam kelompok etnis dan budaya. Setiap kelompok etnis memiliki motif ukiran unik yang kaya akan makna filosofis. Motif Toraja adalah salah satu yang paling khas di dunia. Motif-motif ini sering ditemukan di rumah-rumah tradisional, tekstil, dan ornamen arsitektur. Namun, pemahaman orang-orang tentang nilai simbolis dari ukiran ini masih terbatas, sehingga berisiko erosi budaya. Penelitian ini bertujuan untuk mengenali motif ukiran Toraja menggunakan pengolahan citra digital, khususnya melalui ekstraksi fitur tekstur Gray Level Co-occurrence Matrix (GLCM), yang meliputi kontras, korelasi, energi, dan homogenitas pada orientasi 0°. Dataset ukiran Toraja diproses melalui tahap prapemrosesan, ekstraksi fitur, dan klasifikasi berbasis threshold. Penelitian ini berkontribusi pada kombinasi GLCM dan threshold yang dapat meningkatkan akurasi sekaligus memberikan solusi komputasi yang efisien untuk pengenalan pola motif tradisional. Hasil eksperimen menunjukkan bahwa threshold 0,002 dan 0,004 menghasilkan akurasi pengenalan masing-masing sebesar 100% dan 82%.

***Kata kunci**—GLCM, threshold, pengolahan citra digital, Toraja, carving*

Abstract

Indonesia comprises a diverse array of ethnic groups and cultures. Each ethnic group has unique carving motifs rich in philosophical meaning. Toraja motifs are among the most distinctive in the world. These motifs are often found in traditional houses, textiles, and architectural ornaments. However, people's understanding of the symbolic value of these carvings remains limited, thereby risking cultural erosion. This study aims to recognize Toraja carving motifs using digital image processing, specifically through the extraction of Gray Level Co-occurrence Matrix (GLCM) texture features, which include contrast, correlation, energy, and homogeneity at 0° orientation. The Toraja carving dataset was processed through preprocessing, feature extraction, and thresholding-based classification stages. This study contributes to the combination of GLCM and thresholding that can improve accuracy while providing a computationally efficient solution for traditional motif pattern recognition. Experimental results show that thresholds of 0.002 and 0.004 produce recognition accuracies of 100% and 82%, respectively.

***Keywords—**GLCM, threshold, digital image processing, Toraja, carving*

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1. INTRODUCTION

Indonesia possesses a vast variety of carving motifs inherited from its many ethnic groups, and this cultural legacy must be safeguarded for future generations. Unfortunately, only a limited number of people genuinely understand the symbolic significance of these motifs. Long before the existence of written language, Indonesian ancestors used carved symbols as a medium of communication. Among the many traditional motifs, Toraja carvings stand out for their distinctiveness and artistic excellence. These motifs are commonly found in traditional Toraja houses [1], [2], woven fabric crafsmen [3], and wall decorations, each carrying profound cultural significance. The challenge lies in the fact that few people today are familiar with these motifs. One way to preserve them is by utilizing digital image processing for pattern recognition. Such methods can help document and disseminate knowledge about the symbolic meanings embedded in the carvings. This research is particularly urgent, as fewer people can interpret Toraja motifs. The lack of sufficient studies on pattern recognition—especially concerning Toraja carvings—underscores the need for documentation, so that present and future generations can appreciate the cultural depth of these artifacts.

Although there have been attempts to analyze Toraja carvings, most publications remain scarce and limited in access. Previous studies was identifiying traditional house of Toraja carving on ethnomathematical [1], [2], geometry transformation type [4][5], and Toraja community handycraft [6]. Other works have examined development research that analyse the level of validity and practicality of teaching materials for transformation geometry based on visual ethnomathematics of Toraja carvings [7].

Several studies on pattern recognition have been conducted on Indonesian carvings as part of efforts to preserve cultural heritage, especially in addressing the limited knowledge of younger generations about motif meanings. A significant number of these works focus on classification of Toraja wood carvings. One study applied the Convolutional Neural Network (CNN) algorithm optimized with the ResNet50 architecture, achieving strong results in deep learning, especially pattern recognition. Using Canny feature extraction, the study attained 96.8% accuracy with a resolution of 224 x 224 pixels, learning rate of 0.00001 and epoch 400 yields the highest F1-Score [8]. Another study in classifying seven traditional Toraja Carving motifs to evaluate the effectively of four Convolutional Neural Network (CNN) architecture – VGG-16, DenseNet121, ResNet50V2, and EfficientNetB0. The highest validation accuracy of 98% achieved in EfficientNetB0 [9]. Other study also using CNN for comparing performance of ResNet Architectures for Toraja Carving to classify image with data augmentation. Their experimental result showed that the highest validation accuracy of 97% achieved in ResNet101V2 [10].

Beyond carvings, a wide range of studies have focused on batik patterns and other fabric designs, which often resemble carvings. Some studies using Gray Level Co-occurrence Matrix (GLCM), such as extracting texture features in image retrieval of batik motifs [11], comparing the effectiveness of GLCM and LBP features with Multikernel SVM for classify batik [12]. Additional works also using GLCM to classify of traditional Sambas woven cloth “Kain Lunggi” based on texture features [13].

This study focuses explicitly on Toraja carving motifs within the scope of Digital Image Processing. The objective is to identify Toraja carving patterns using Gray Level Co-occurrence Matrices (GLCM) for feature extraction. The methodology consists of data collection, data processing, and testing. This research contributes to the field by utilizing thresholding to enhance the accuracy of pattern recognition in Toraja carving motifs, while also promoting cultural preservation by providing a framework for documenting and analyzing ethnic art forms. The novelty of this research is the use of thresholding to enhance recognition accuracy, with GLCM feature extraction applied at a 0° orientation to analyze Toraja carving patterns. This research seeks to preserve culture by offering a digital framework for the documentation and analysis of ethnic art, as well as opening up opportunities for further development using deep learning techniques to expand its application to other Indonesian carving motifs.

2. METHODS

Figure 1 illustrates that the research process is divided into two main stages: training and testing. In the training stage, a collection of images is prepared by preprocessing, segmenting into smaller parts, extracting features using GLCM, and storing the extracted data. During the testing stage, a test image undergoes similar preprocessing, segmentation, and GLCM feature extraction, followed by numerical analysis. The extracted features from the test image are then compared with those stored in the database. To determine whether the test image corresponds to a Toraja carving pattern, the comparison is performed using the Euclidean Distance method.

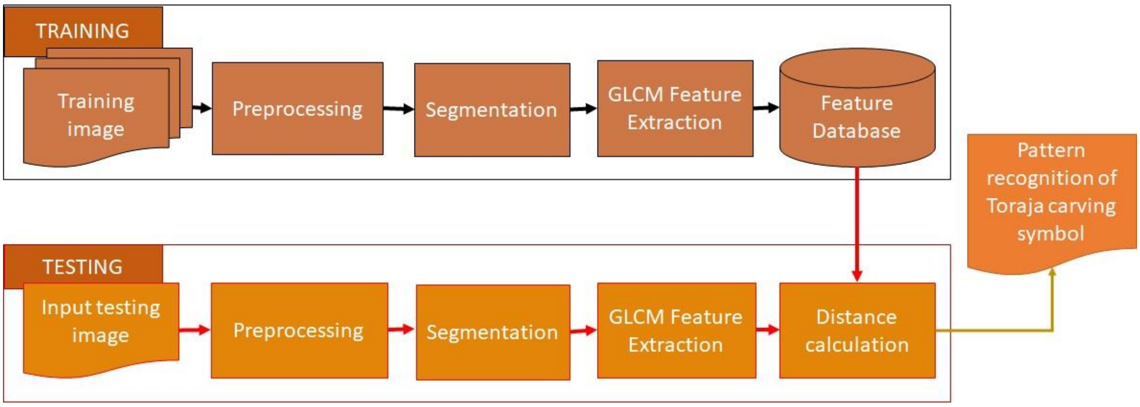


Figure 1 Proposed method

2. 1 Training

The training process is carried out in sequential stages, which are described in detail. The first stage involves preparing image data. A total of 200 images is used for training, obtained by dividing the dataset into training portions. Figure 2 shows the dataset employed in this study, consisting of 10 types of Toraja carving motifs selected from a previously established dataset [14]. The motifs, arranged from left to right, include: 1) Ne' Limbongan, 2) Pa' Barre Allo, 3) Pa' Kapu' Baka, 4) Pa' Kadang Pao, 5) Pa' Sulan Sangbua, 6) Pa' Bulu Londong, 7) Pa' Sissik Bale, 8) Pa' Tank Pattung I, 9) Pa' Tank Pattung II, and 10) Pa' Horn Repe.

Algorithm 1 is used to generate both training and testing datasets, which are designed to differentiate one image from another by placing a small circle at varying positions within each image. The dataset is divided with 80% allocated for training and 20% for testing, resulting in 200 images for training and 50 images for testing in this study.

Figure 2 Initial Dataset

The next stage of training focuses on preparing the images for display. This stage involves cropping them into square or rectangular shapes and standardizing their dimensions to 287 × 290 pixels. Once resized, the images are converted into grayscale and categorized into 10 distinct Toraja carving patterns. At this stage, thresholding is also applied. Several threshold values were tested, and two effective values were identified: 0.002 and 0.004.

The next stage is feature extraction, which is carried out using the Gray Level Co-occurrence Matrix (GLCM) method in the 0° direction. GLCM is a widely used technique for texture analysis and feature extraction. As one of the earliest methods for analyzing image textures, GLCM relies on two parameters: distance (d) and angle (θ). It is commonly applied to extract texture features from digital images for tasks such as segmentation, classification, and analysis. Feature extraction in GLCM can be performed at four different orientations: 0°, 45°, 90°, and 135°. However, this study focuses explicitly on features obtained at the 0° direction, as shown in Figure 3. The GLCM procedure is carried out as follows [15]:

a. Construct the initial GLCM matrix using pixel pairs aligned at 0°, 45°, 90°, and 135°.
b. Generate a symmetric matrix by adding the initial GLCM matrix to its transposed version.
c. Normalize the GLCM matrix by dividing each element by the total number of pixel pairs.
d. Extract statistical features such as contrast, correlation, energy, and homogeneity.

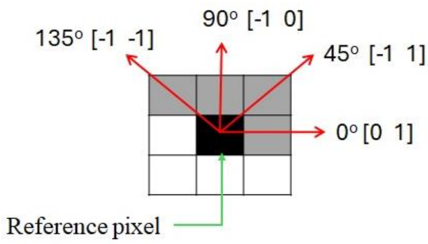


Figure 3 GLCM Angle Direction [15]

In GLCM, contrast represents the statistical measure of intensity variation, indicating the difference between the brightest and darkest pixel pairs in the matrix. Contrast can be expressed mathematically using equation (1), where:

- i = gray level at the i-th row
- j = gray level at the j-th column
- $p(i, j)$ = the probability of occurrence of gray levels i and j at a specified distance and orientation

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \tag{1}$$

In GLCM, correlation indicates the degree of association between pixel pairs within the matrix. This relationship is calculated using equation (2), where:

- μi = mean gray level of row i
- μj = mean gray level of column j
- σi = standard deviation of gray levels in row i
- σj = standard deviation of gray levels in column j

This feature reflects the degree to which different regions of an image are interrelated.

$$Correlation = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma i \sigma j} \tag{2}$$

In GLCM, energy represents a statistical measure that reflects the overall strength or uniformity of pixel pair intensities at specific gray levels within the matrix. It is expressed mathematically in equation (3), where:

- i = gray level at the *i-th* row
- j = gray level at the *j-th* column
- $p(i, j)$ = probability of the occurrence of gray levels i and j at a given distance and orientation

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \tag{3}$$

In GLCM, homogeneity is a statistical measure that indicates the level of uniformity or consistency in the variations of gray intensity within the matrix. It is formulated in equation (4), where:

- i = gray level at the *i-th* row
- j = gray level at the *j-th* column
- $p(i, j)$ = probability of gray levels i and j occurring at a specified distance and orientation

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{4}$$

Equation (5) shows G is the normalized Gray Level Co-occurrence Matrices (GLCM). GLCM is a popular representation for texture in an area. GLCM contains a count of the number of times a given feature (e.g., a given grey level) occurs in a particular spatial relationship with other given features. G(i,j) is the probability of occurrence of i and j valued pixel pairs from matrix G. n is the number of GLCM elements. i and j are rows and columns in G. P(i,j) is the value of the GLCM matrix at index i,j. G(i,j) can be calculated by equation (5).

$$G(i,j) = \frac{P(i,j)}{\sum_{i=0}^{n} \sum_{j=0}^{n} P(i,j)} \tag{5}$$

The Gray Level Co-occurrence Matrix (GLCM) can be constructed in four orientations: 0°, 45°, 90°, and 135°. An example of GLCM formation in the 0° and 45° directions is shown in Figure 4.

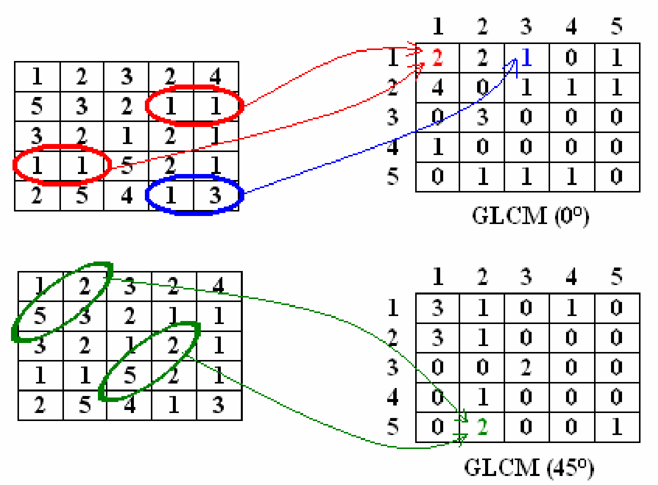


Figure 4 Example GLCM in 0° and 45° angle

The fifth stage of training involves building the feature database, where all extracted feature values are stored. Each image is represented by four GLCM features: contrast, correlation, energy, and homogeneity. These values are saved in matrix form. This study applies four feature extraction measures: contrast, correlation, energy, and homogeneity. We only choose 0° orientation because it is enough to analyse these feature in this orientation.

2. 2 Testing

The testing process is explained sequentially. The first stage is preparing the testing images. A total of 50 images is used; all placed in a single folder to simplify the testing process.

The second stage is preprocessing, which involves cropping images either into rectangles or squares. Rectangular cropping is considered more flexible since the length and width do not need to be equal to each other. After cropping, the images are resized uniformly to 287 × 290 pixels.

The third stage is segmentation, where the images are converted to grayscale, followed by thresholding. Threshold values are determined experimentally, with two values selected: 0.002 and 0.004.

Algoritma 1 Thresholding algorithm

1. Compute the GLCM values for each training dataset.
2. Select two features—correlation and homogeneity—each consisting of four values arranged in a 1 × 4 array (a, b, c, d).
3. Calculate the mean for each of a, b, c, and d. The mean values are then compared with the original values to establish upper and lower limits. The smallest absolute difference is chosen as the threshold. The same procedure is applied to homogeneity values, represented as a 1 × 4 matrix (e, f, g, h), to determine its threshold.
4. For each test image, the correlation and homogeneity values are compared with the mean thresholds obtained from the training data.

The fourth stage is feature extraction, where GLCM in the 0° direction is used to extract four features: contrast, correlation, energy, and homogeneity. These extracted values for each test image are stored in an array form.

The fifth stage is distance calculation using the Euclidean Distance method, chosen because it provides the most reliable results in measuring similarity [15]. The Euclidean Distance is computed between the feature values of training and test images.

The final stage of testing is motif recognition. The outcome identifies the Toraja carving motif by comparing the test image with the database and selecting the motif whose values are closest to the labeled patterns.

3. RESULTS AND DISCUSSION

The recognition interface for Toraja carving motifs shown in Figure 6. The process begins with image acquisition by selecting an image through the *Open Image* button. Next, preprocessing is performed by cropping with the rectangle tool, pressing *Select*, and then resizing to standardize the dimensions. The third step is segmentation, activated by pressing the *Segmentation* button, which converts the image into grayscale. Fourth, feature extraction is performed using the *Feature Extraction* button, applying the four GLCM features: contrast, correlation, energy, and homogeneity. Fifth, recognition is executed by pressing the *Classification* button, with the results displayed in the *Toraja Carving Motif Recognition Result* box. Finally, the *Reset* button clears the screen and memory to allow testing of another motif.

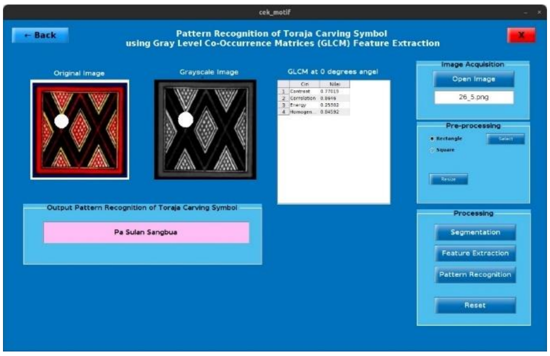
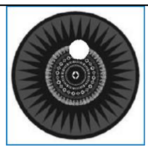
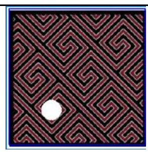
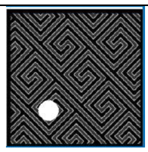
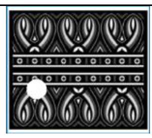
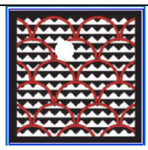
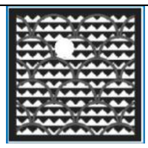
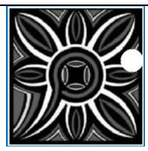


Figure 6 Interface display showing the recognition results of Toraja carving motifs

Table 1 summarizes the experimental results when thresholding is applied to improve recognition accuracy. The caption column (*Note*) uses the symbol √ to indicate correct recognition and X to indicate incorrect recognition shown in Table 1. A threshold value of 0.002 achieved 100% accuracy, while a value of 0.004 achieved 82%.

Table 1 Experimental outcomes of applying thresholds to GLCM feature extraction

No.	Name	Image	Grayscale	GLCM				Result	Note
				Contrast	Correlation	Energy	Homogeneity		

1.	42_1			1.4199	0.91012	0.14898	0.84922	Ne Limbo ngan	√
2.	20_2			0.57724	0.96487	0.1889	0.88951	Pa Barre Allo	√
3.	25_3			1.1659	0.81298	0.21791	0.82912	Pa Kapu Baka	√
4.	50_4			2.4962	0.64164	0.14027	0.71681	Pa Kadang Pao	√
5.	26_5			1.0687	0.86566	0.2479	0.84598	Pa Sulan Sangbu a	√
6.	41_6			2.3305	0.82888	0.17768	0.7726	Pa Bulu London g	√
7.	19_7			1.8397	0.86196	0.20145	0.81961	Pa Sissik Bale	√
8.	31_8			1.5448	0.8832	0.20391	0.81477	Pa Tangki Pattung I	√
9.	47_9			1.1823	0.92241	0.23978	0.86685	Pa Tangki Pattung II	√
10.	20_10			1.1339	0.87504	0.16892	0.82204	Pa Tanduk Repe	√

4. CONCLUSIONS

This study successfully identified Toraja carving patterns through feature extraction using Gray Level Co-occurrence Matrices (GLCM) at 0° orientation. The use of a threshold algorithm proved effective in improving recognition accuracy. Experimental results showed that applying a threshold value of 0.004 resulted in an accuracy rate of 82%, while a lower threshold value of 0.002 achieved a perfect accuracy rate of 100%. These findings underscore the crucial role of threshold selection in enhancing pattern recognition performance. Further research is recommended for the application of alternative techniques and advanced methods that contribute to the development of digital image processing, particularly in the recognition of cultural motifs.

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