Pattern Recognition of Balinese Carving Motif Using Learning Vector Quantization (LVQ)

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Abstract. Bali is a world tourism destination with its cultural uniqueness, one of the Balinese cultural products that need to be maintained is the art of Balinese carvings in traditional buildings and sacred buildings, to inherit the culture it needs a management, documentation and dissemination of information by utilizing technology. Digital image processing and pattern recognition can be utilized to preserve arts and culture, the technology can be utilized to classify images into specific classes. Balinese carving is one of the carvings that have many variations, if these carvings are analyzed then required an appropriate method for feature extraction process to produce special features in the image. So they can be recognized and classified well and provide information that helps preserve Bali. The aim of this research is to get the right feature extraction method to recognize and classify Bali carving pattern image based on the accuracy of HOG feature extraction method with PCA trained using LVQ. The results of the test data obtained the best accuracy of HOG is 90% with cell size 32×32 and block size 2×2, PCA obtained 23.67% with threshold 0.01 and 0.001, from training input with learning rate = 0.001 and epoch = 1000.

Keywords: Balinese carving motif · Learning Vector Quantization (LVQ) · Histogram of Oriented Gradient (HOG) · Canny edge detection · Principal Component Analysis (PCA)

1 Introduction

The era of globalization has made Indonesia one of the fastest growing countries in technology, Indonesia as a developing country faces a serious threat in the cultural field because does not have competitive power equivalent to developed countries and begins to erode the values of Indonesian cultural identity [1]. Bali is the worlds best tourist destination with its unique culture, one of Balinese cultures that needs to be maintained is the Balinese sculpture from traditional and sacred buildings. Digital technology is one way to maintain, inherit and introduce the art and culture of Bali to the world, in an effort to maintain and inherit the culture hence required a management, documentation and dissemination of information by utilizing technology that can be poured in the form of games, educational software, digital music or animated films and others [2], other digital technology areas that can be utilized for preservation of art and culture is the processing of digital images and pattern recognition, one of the problems in the field of

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pattern recognition is the classification of images into a particular class. Balinese carving are very complex and rich with variations on each species, it is a combination of one motif and another, if the pattern of Balinese carvings poured into digital images and analyzed, it would be difficult to make recognition and classification, then it required a method of feature extraction to help obtain the special characteristics of the input image so that later can facilitate the process of recognition and classification to provide information related to Balinese carving motif and contribute to preserve the art and culture of Bali.

This study utilizes a form of Balinese carvings that are dominant containing arches so that the approach used for feature extraction is the gradient of the line. The Histogram of Oriented Gradient (HOG) method is a method of feature extraction that utilizes the distribution of image gradients at a particular orientation by utilizing cells and blocks, but the problem with HOG is to obtain accurate recognition and classification of the selection of cell sizes and blocks must be done manually and randomly selecting cell and block size variations [3]. Another method that can do the gradient calculation is Canny edge detection method, the advantage of this method is to detect the weak edge properly because this method will remove the noise with gaussian filter before detection the edge, but the constraint that occurs is the size of the resulting image before and after the edge detection is the same so that in the introduction process will take a long time if the input image used has a large size, this constraint requires a support method that can accelerate the process of introduction and classification of Balinese carvings, Principal Component Analysis (PCA) is an appropriate method for reducing image size and minimizing memory usage in the data training process so that it takes less time for recognition and classification [4]. Features or characteristics derived from both the feature extraction methods of HOG and PCA are further trained using artificial neural network Learning Vector Quantization (LVQ) that performs competitive and supervised learning and intelligently classifies data into specific classes according to training data, the results of recognition with best accuracy will be chosen as the right method for the pattern recognition of Balinese carving.

2 Methodology

2.1 Digital Image Processing

Digital image is a function of two dimensional light intensity f (x, y), where x and y denote spatial coordinates. The f value at each point (x, y) shows the color level (value) of the image at that point [5].

2.2 Image Acquisition

The result of image acquisition consists of six types of carving motif, karang gajah, karang goak, karang tapel, mas-masan motif, kakul motif, and patra cina. The process of image acquisition used a digital camera with posisition that the main object can meet at least 80% of the size of an image of the acquisition.

2.3 System Overview

The comparison of Balinese carvings recognition used HOG and PCA methods. Overview of the pattern recognition with HOG and PCA methods shown in Figs. 1 and 2.

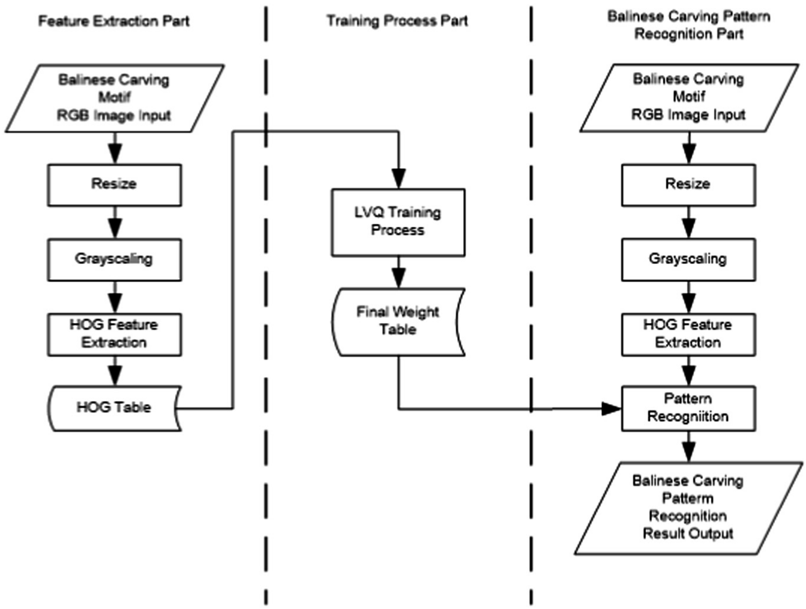

Fig. 1. Pattern recognition of Balinese carvings with feature extraction HOG

The system is designed into three main parts, the establishment of feature data, the data training section, and the pattern recognition of Balinese carvings. In the character forming data section is divided into three main processes, the first process is preprocessing shown in Fig. 1 consists of the process of image size changes or resize, grayscaling and in Fig. 2 added Canny edge detection process. The second process of feature extraction, in Fig. 1 used feature extraction by the HOG method, in Fig. 2 used feature extraction by the PCA method. The third process is the process of storing feature data into tables.

The training section consists of a training process with LVQ and the process of storing the final training weight on the final weight table. The recognition part is the same part as the formation of characteristic data but added recognition process using data from the final weight table to obtain the output data.

2.4 Preprocessing

Preprocessing serves to prepare the image or signal in order to produce better characteristics in the next stage. The process include resize the image, grayscaling or

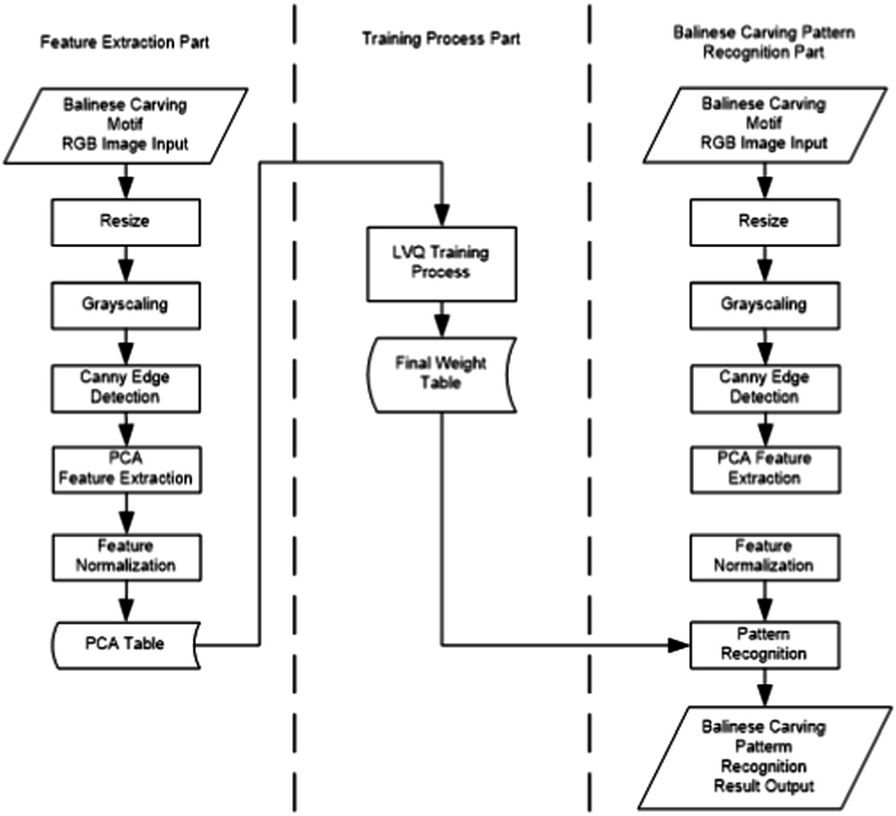

Fig. 2. Pattern recognition of Balinese carvings with feature extraction PCA

changes the image to grayscale, and edge detection process, the process for resizing the image is performed using an interpolation method that obtains the average value of a given region, this process can be illustrated in Fig. 3.

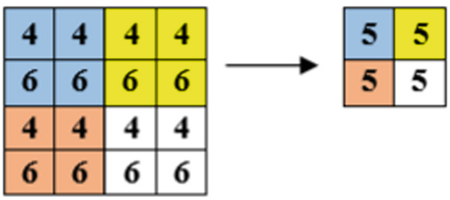

Fig. 3. Rezising image using interpolation

Grayscaling is the process of converting the image composition to one channel value with a range of one value being between 0–255, the process of converting RGB image to grayscale can be calculated by Eq. (1) [6].

$$0.2989 * \mathrm{R} + 0.5870 * \mathrm{G} + 0.1140 * \mathrm{B} \tag{1}$$

Further preprocessing is edge detection using the Canny method, the steps for the Canny edge detection process as follows.

1. Reduce input image noise with gaussian filter.
2. Calculate the intensity of the gradient Gx and Gy with the sobel operator and determine the direction of the edge. The equation used to calculate the gradient is shown in Eq. (2) and to calculate the edge direction is represented by Eq. (3) [5].

$$G(x, y) = \sqrt{(G_x)^2 + (G_y)^2} \tag{2}$$

$$\theta = tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{3}$$

3. Directions based on the obtained angle are:

$$Degree(\theta) = \begin{cases} 0, & 0 \le angle < 22,5 || angle \ge 157,5 \\ 45, & 22,5 \le angle \le 67,5 \\ 90, & 67,5 \le angle < 112,5 \\ 135, & 112,5 \le angle < 157,5 \end{cases}$$

4. Streamline the edge with non-maximum suppression.
5. Binaries with two thresholding T1 and T2.

2.5 Feature Extraction

The feature extraction process used two ways with HOG method and PCA method as a comparison. The HOG method describes the intensity distribution or direction of the edge gradient of an object in the image. The steps for the HOG feature extraction process are as follows [7].

Calculate the gradient value of each pixel input image, it is grayscale image using filter [−1 0 1] and $[-1\ 0\ 1]^T$ that shown in Eqs. (2) and (3).

1. Divide the image into several cells with size n × n pixels.
2. Determining the number of orientation bins used in histogram creation or also called spatial orientation binning.
3. Then the cells grouped into larger sizes and named block.
4. The subsequent process of overlapping normalization of blocks can be calculated by Eq. (4).

$$v = \frac{v_{i,j}}{\sqrt{||v_{i,j}||^2 + \epsilon^2}} \tag{4}$$

The result of the HOG is a feature used for the recognition process, the blocks produce a feature vector that will be used as a descriptor, the vector normalization process aims to obtain a data that is normal distribution, v is a normalized vector, $v_{i,j}$ is the Vector obtained from the binning process, ϵ is a small value constant.

The feature extraction with the PCA method is a transformation process that reduces a dimension value of data, PCA represents and selects the optimal base of an image vector given by the eigenvalues and transforms by reducing the image vector of a high-dimensional space into a lower dimension space. The process of feature extraction with PCA is as follows.

1. Change the image matrix of edge detection results into column vectors in a dataset.
2. Looking for the zero mean of the dataset.
3. Calculating the covariance matrix.
4. Looking for the eigenvalues of the covariance matrix.
5. Calculate the principal component.

The PCA feature extraction results will be normalized to make the data at a certain interval, the feature normalization process can be calculated by Eq. (5) [8].

$$X_{normal} = \frac{X - X_{min}}{X_{max} - X_{min}} * (S - R) + R \tag{5}$$

X_{normal} is normalized features, X is a not yet normalized feature, X_{max} is maximum feature, X_{min} is the minimum feature, S is the upper limit of normalization ($S = 1$), R is the lower limit of normalization $(R = 0)$.

2.6 Training Process

Training process use to obtain the final weight that will be used as a reference in the pattern recognition process. The steps for training the data on LVQ are as follows [9].

1. The first step is to determine each output class, determine the initial weight, and set the learning rate α.
2. Compare each input with each defined weight by measuring the distance between each weight w_0 and input x_p. The equation shown in Eq. (6).

$$\|x_p - w_0\| \tag{6}$$

3. The minimum value of the comparison result will determine the class of input vectors and the new weight $(w_0^{'})$ can be calculated using Eqs. (7) and (8). For input and weight that have the same class calculated by Eq. (7).

   - For input and weight that have the same class calculated by Eq. (7).

$$w_0^{'} = w_0 + \alpha(x - w_0) \tag{7}$$

   - For input and weight that have different class calculated by Eq. (8).

$$w_0' = w_0 - \alpha(x - w_0) \tag{8}$$

4. The new weight replaces the initial weight (step 2), calculations will continue until the weight value does not change with new input, this requires a very large memory to perform calculations, for that performing LVQ calculations determined maximum epoch.

2.7 Pattern Recognition

The process of recognition is done by calculating the minimum value of the calculation between the final weight and the value of the characteristics obtained from the extraction process of the test image feature, the method used is eucledian distance. The equations used for calculating eucledian distance are shown in Eq. (9).

$$d = \sqrt{\sum\nolimits_{k=1}^{n} (x_k - w_k)^2} \tag{9}$$

d the distance between the feature and the final weight, the distance is used to measure the similarity degree between the feature and the final weight, x_k is a feature derived from feature extraction, w_k is the final weight.

3 Results

Results on this research related to training process analysis, testing process analysis, and comparison results of Balinese carving pattern recognition method.

3.1 Training Process Results with LVQ

Training process needs to make the artificial neural network system can learn based on case/pattern until the artificial neural network system can recognize the pattern, if the output produced by the network does not meet the target then the artificial neural network will do the renewal of the weight. The training process will stop if epoch = maximum epoch or previous weight (w_0) = new weights (w_0). Tables 1 and 2 are the training process results of Balinese carving pattern using PCA and HOG feature extraction that was taught by LVQ.

In PCA data obtained the smallest Mean Square Error (MSE) result on upper threshold 0.01 and lower threshold 0.001 with learning rate (alpha) value 0.0010 and epoch 1000.

In HOG data obtained the smallest MSE on the variation of cell 8 × 8 and block 2 × 2 with alpha/learning rate value 0.0010 and epoch 1000, compared with PCA then HOG obtained greater MSE.

The training data will be retested on the basis of the final weights obtained in the training process to get the accuracy. Tables 3, 4 and 5 are test results of training process using PCA and HOG.

Table 1. Training process results with PCA

No	Feature extraction	Up threshold	Low threshold	Alpha	Max epoch	MSE
1	PCA	0.01	0.001	0.0010	1000	2.9463e−13
2	PCA	0.01	0.001	0.0025	1000	2.4815e−11
3	PCA	0.01	0.001	0.0050	1000	1.6307e−09
4	PCA	0.01	0.001	0.0075	1000	2.1968e−07
5	PCA	0.01	0.001	0.0100	1000	1.5407e−06
6	PCA	0.1	0.01	0.0010	1000	9.9373e−09
7	PCA	0.1	0.01	0.0025	1000	6.1007e−07
8	PCA	0.1	0.01	0.0050	1000	2.5490e−06
9	PCA	0.1	0.01	0.0075	1000	5.2965e−06
10	PCA	0.1	0.01	0.0100	1000	8.1809e−06
11	PCA	0.2	0.1	0.0010	1000	5.7268e−09
12	PCA	0.2	0.1	0.0025	1000	5.5475e−07
13	PCA	0.2	0.1	0.0050	1000	3.7159e−06
14	PCA	0.2	0.1	0.0075	1000	9.2270e−06
15	PCA	0.2	0.1	0.0100	1000	1.6278e−05

Table 2. Training process results with HOG

No	Feature extraction	Cell (n)	Block (n)	Alpha	Max epoch	MSE
1	HOG	8	2	0.0010	1000	8.2492e−12
2	HOG	8	2	0.0025	1000	2.2864e−11
3	HOG	8	2	0.0050	1000	2.1923e−11
4	HOG	8	2	0.0075	1000	4.4222e−11
5	HOG	8	2	0.0100	1000	1.3116e−10
6	HOG	16	2	0.0010	1000	5.4179e−11
7	HOG	16	2	0.0025	1000	1.5671e−10
8	HOG	16	2	0.0050	1000	1.5772e−10
9	HOG	16	2	0.0075	1000	2.6711e−10
10	HOG	16	2	0.0100	1000	6.2313e−10
11	HOG	32	2	0.0010	1000	1.0150e−10
12	HOG	32	2	0.0025	1000	1.1398e−10
13	HOG	32	2	0.0050	1000	3.6382e−10
14	HOG	32	2	0.0075	1000	4.8919e−10
15	HOG	32	2	0.0100	1000	8.8085e−10

The highest accuracy obtained by the PCA method was 22% with the upper and lower threshold values of Canny edge detection respectively 0.01 and 0.001 with recognizable images totaling 132 and not recognizing amounting to 468. Increases were obtained when the feature size was increased to 8192 (50% size of the input image). Table 4 is a table of training process accuracy using PCA with feature size 8192.

Table 3. Accuracy of training process with PCA features size 4096

No	Feature extraction	Up threshold	Low threshold	Alpha	Known imagery	Unknown imagery	Accuracy %
1	PCA	0.01	0.001	0.0010	132	468	22.00
2	PCA	0.01	0.001	0.0025	130	470	21.67
3	PCA	0.01	0.001	0.0050	100	500	16.67
4	PCA	0.01	0.001	0.0075	100	500	16.67
5	PCA	0.01	0.001	0.0100	100	500	16.67
6	PCA	0.1	0.01	0.0010	130	470	21.67
7	PCA	0.1	0.01	0.0025	111	489	18.50
8	PCA	0.1	0.01	0.0050	110	490	18.33
9	PCA	0.1	0.01	0.0075	106	494	17.67
10	PCA	0.1	0.01	0.010	105	495	17.50
11	PCA	0.2	0.1	0.0010	124	476	20.67
12	PCA	0.2	0.1	0.0025	123	477	20.50
13	PCA	0.2	0.1	0.0050	114	486	19.00
14	PCA	0.2	0.1	0.0075	113	487	18.83
15	PCA	0.2	0.1	0.010	113	487	18.83

Table 4. Accuracy of training process with PCA features size 8192

No	Feature extraction	Up threshold	Low threshold	Alpha	Known imagery	Unknown imagery	Accuracy %
1	PCA	0.01	0.001	0.0010	146	454	24.33
2	PCA	0.1	0.01	0.0010	134	467	22.17
3	PCA	0.2	0.1	0.0010	135	465	22.50

Table 5. Accuracy of training process with HOG

No	Feature extraxtion	Cell (n)	Block (n)	Alpha	Known imagery	Unknown imagery	Accuracy %
1	HOG	8	2	0.0010	581	19	96.83
2	HOG	8	2	0.0025	564	36	94.00
3	HOG	8	2	0.0050	548	52	91.33
4	HOG	8	2	0.0075	536	64	89.33
5	HOG	8	2	0.0100	527	73	87.83
6	HOG	16	2	0.0010	579	21	96.50
7	HOG	16	2	0.0025	558	42	93.00
8	HOG	16	2	0.0050	545	55	90.83
9	HOG	16	2	0.0075	537	63	89.5
10	HOG	16	2	0.0100	537	63	89.5
11	HOG	32	2	0.0010	600	0	100.00
12	HOG	32	2	0.0025	586	14	97.67
13	HOG	32	2	0.0050	576	24	96.00
14	HOG	32	2	0.0075	575	25	95.83
15	HOG	32	2	0.0100	569	31	94.83

The feature size that changed to 8192 has an accuracy increase of 24.33% with upper threshold 0.01, lower threshold 0.001, and alpha/learning rate 0.001. Table 5 is a table of training process accuracy using HOG.

The highest accuracy obtained from HOG method is 100% with variation of cell size 32 × 32, block 2 × 2, and alpha/learning rate 0.0100 with all images are recognized.

3.2 Testing Process Results

The best five accuracies training data will be used for reference to the testing process, as for the best five accuracy of the PCA training data that will be tested again shown in Table 6.

Table 6. Accuracy of testing process with PCA

No	Feature extraction	Up threshold	Low threshold	Alpha	Known imagery	Unknown imagery	Accuracy %
1	PCA	0.01	0.001	0.0010	71	229	23.67
2	PCA	0.01	0.001	0.0025	58	242	19.33
3	PCA	0.1	0.01	0.0010	40	260	13.33
4	PCA	0.2	0.1	0.0010	51	249	17.00
5	PCA	0.2	0.1	0.0025	50	250	16.67

The highest accuracy obtained in the test from the upper threshold 0.01, the lower threshold 0.001 and alpha value 0.0010 with the recognition accuracy is 23.67%. Improvement efforts were made by changing the feature size from 4096 to 8192, the accuracy from the feature size 8192 shown in Table 7.

Table 7. Accuracy of testing process with PCA features size 8192

No	Feature extraction	Up threshold	Low threshold	Alpha	Known imagery	Unknown imagery	Accuracy %
1	PCA	0.01	0.001	0.0010	55	245	18.33
2	PCA	0.1	0.01	0.0010	40	260	13.33
3	PCA	0.2	0.1	0.0010	49	251	16.33

In the features size 8192 obtained the highest accuracy 18.33% with the recognizable image amounted to 55 and the unrecognized amounted to 245. The highest accuracy obtained from the upper threshold value 0.01 and the lower threshold value 0.001 with the same alpha value 0.001, in this case accuracy not increase when using feature size 8192 with testing process.

The next test is using HOG, the best five accuracy of the HOG training data that tested again with the testing process shown in Table 8.

Table 8. Accuracy of testing process with HOG

No	Feature extraction	Cell (n)	Block (n)	Alpha	Known imagery	Unknown imagery	Accuracy %
1	HOG	8	2	0.0010	191	109	63.67
2	HOG	16	2	0.0010	213	87	71.00
3	HOG	32	2	0.0010	270	30	90.00
4	HOG	32	2	0.0025	229	71	76.33
5	HOG	32	2	0.0050	217	83	72.33

The highest accuracy of the HOG testing process was obtained from the cell size 32×32, image blocks 2×2, and alpha/learning rate 0.001 with 270 recognizable images and 30 unrecognizable images.

3.3 Comparison Analysis for Recognition Patterns of Balinese Carving with HOG and PCA

The best accuracy of testing process with HOG method reached 90%, but the the best accuracy of testing process with PCA only reached 23.67%. This is because PCA used to reduce dataset can not guarantee that the accuracy obtained from matrix reduction results will increase, but PCA reduction can support systems in accelerating computation. Research by [4] mentions that PCA is a method to reduce image dimension that can reduce memory usage and shorten time during data training process.

Another factor that causes the low accuracy obtained from the recognition of Balinese carving patterns with the Canny edge detection and PCA approach is the lack of accurate edge detection of the engraving object, this is because the background is too dirty (the background has many other object or the same light intensity that causes the background detected as an object). [5] states that the edge of an object formed from point one to the next point in the image can be detected by the difference in the intensity of light, if the degree of difference in light intensity is high then the edge can be detected clearly, and if the low light intensity the resulting edge will be unclear. [10] in his research describes PCA as a statistical technique used to convert the dimensions of space from high dimension to low dimension and finds a pattern in the data using standard deviation concepts, mean values, variance, covariance and algebraic matrices from mathematical field statistics, in this case the image is a data that has a high dimension that required a technique or method that can be used to reduce dimensions. As well as the research that has been done [4] the effect of edge detection is very high on recognition accuracy. The separation of objects and backgrounds plays an important role in obtaining good edge detection results.

The HOG method as a descriptor can produce maximum accuracy because the HOG calculates gradient values in a particular orientation, [3] in his research explaining that the selected cell size and block may affect detection quality and recognition time, the best results obtained are the results of an experimental approach based on correction gamma, gradient filter type, and cell size and block size. The best cell size and block determination on HOG does not apply to the whole case, it depends on the dataset. In the case of Balinese carvings pattern recognition the best accuracy of HOG is obtained from the largest cell size of 32 × 32 and 2 × 2 blocks with minimum overlaping blocks, feature length generated from 32 × 32 cell size and 2 × 2 block with 128 × 128 image size is 1 × 324, this size is the smallest of three variation of cell size and block. The 8 × 8 and 2 × 2 blocks feature 1 × 8100, 16 × 16 and 2 × 2 block features 1 × 1764 size, the smallest feature size can help speed up computing and provide shorter time in the data training process.

4 Conclusion

Based on the analysis of training and testing results the recognition of Balinese carvings pattern, it can be taken some conclusions as follows.

1. The test results of the training data with total data is 600 images show that HOG can produce better accuracy than PCA, HOG can recognize the whole data on cell size 32 × 32 and block 2 × 2, while PCA only able to recognize the most amount of 146 image at features size 8192 with upper threshold 0.01 and lower threshold 0.001 for Canny edge detection.
2. The test results of the testing data with total data is 300 images with each motif amounting to 50 images shows that HOG produces a better accuracy than PCA that reached 90% accuracy with 32 × 32 cell size and 2 × 2 block, while the accuracy with PCA only reached 23.67% with features size 4096 (25% of image size), upper threshold and lower threshold value Canny detection is 0.01 and 0.001.
3. The testing process using the training data or testing data of the HOG method produces better accuracy than the PCA method because the feature extraction of HOG method performs gradient calculations on a particular orientation and does not depend on the edge of the image; the HOG feature extraction utilizes gradients on the orientation of specific cells and blocks.
4. In the PCA method the acquisition of accuracy is influenced by the edge detection process, in the case of Balinese carving pattern recognition found a problem that the separation of objects with a background unperfect give a very big influence on edge detection results. The PCA feature extraction also does not provide assurance to improve accuracy, but PCA as a method to reduce the image can accelerate computing and reduce memory usage.

Based on the results obtained, it can be suggested some things for further research such as adding a method that can separate the object and background well so that the edge detection process produces maximum results, can compare other methods to perform feature extraction e.g. comparison of HOG and SIFT.

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