Shape-Based Image Retrieval of Songket Motifs

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Abstract

Songket is a traditional hand woven cloth of the Malays and its beauty lies on the design of the songket motifs intricately woven on the cloth. The objectives of this paper are to create a digitized archive of traditional songket motifs and test the efficiency of retrieving these motifs using geometric shape descriptors. Images of traditional songket patterns are digitally acquired and pre-processed into binary images. The processes involved are contrast enhancement, noise removal, binarization and morphological operations. After the pre-processing operation, the shape features of the motifs are extracted using five geometric shape descriptors. These shape features are stored as feature vectors together with the motifs images in the archive. To test the effectiveness of image retrieval, fifty songket motifs are selected as sample queries. Similarities of these images are measured using Euclidean distance and performance of the retrieval effectiveness is evaluated using recall and precision rate. Results of the experiment showed that geometric shape descriptors are effective in retrieving the songket motifs.

Keywords: Songket motifs, image retrieval, geometric shape descriptors, digital archive.

1 Introduction

Songket is an exquisite hand woven cloth of the Malays made by hand weaving silver, gold and silk threads on a handloom. The beauty of songket lies in the elaborate design of the patterns and combination of motifs that are intricately woven on the cloth. Motif is the main element of designing songket patterns (See Figure 1). When several motifs are arranged within parts of the songket, patterns are created on the songket cloth. During the process of designing new songket pattern, a designer normally has to determine the concept of the design and refer to existing collections of motifs. Currently, a profile of all these motifs and designs are being stored physically in a filing system or produced into slides. Other than the problem of finding physical space for storage, the task of finding certain motifs or designs for references is incredibly tedious. With an image retrieval system that stores new and old motif designs in digital form, the task of searching, storing and retrieving these motifs will be much easier and faster.

In content-based image retrieval (CBIR), the low-level visual features are color, texture, shape and spatial localization. However, among these features, shape is the most important criteria because it represents significant regions or relevant objects in an image (Bouet et al. 1999). Shape is also the utmost criteria in differentiating these songket motifs as these traditional motifs are woven in either gold or silver threads only, thus color and texture are not significant features. Previous works of CBIR have experimented with several methods of representing images using shape descriptions. Wenyin et al. (2000) presented a hierarchical characterization of the image content from coarse level using eccentricity, compactness and solidity to fine level features using Normalized Fourier descriptors. Fourier Descriptor is also used in (Rafiei and Mendelzon 2002) to describe and index hand-written digits data. A robust affine invariant descriptors for shape based on the convex hull and the curvature of a set of dominant points along a shape contour was used by Horace et al. (2002). In SHREW (Riley and Eakins 2002), aspect ratio, circularity, convexity, triangularity, ellipticity, rectangularity, and 8 normalized Fourier descriptors are extracted as shape feature descriptions to retrieve historical watermark images. In SQUID (Mokhtarian and Abbasi 2002); (Mokhtarian and Mackworth 1992), every image is processed to recover the boundary contour, which is then represented by three global shape parameters and the maxima of the curvature zero-crossing contours in its Curvature Scale Space image. Jain and Vailaya (1995) proposed a shape representation based on a histogram of the edge directions.

Figure 1: Songket Patterns (Source: National Musuem of Terengganu, Malaysia).

In this paper, the geometric shape descriptors: convexity, rectangularity, compactness, eccentricity and solidity are

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chosen to represent the songket motifs. They are chosen because they are simple to implement, compact, indexable, and invariant to translation and rotation. These criteria are very important since the songket motif database is growing from time to time, thus automatic extraction of feature vectors and real-time indexing can be computed efficiently. Furthermore, since matching is done on-line, the simple Euclidean distance can be used to compute similarity measures of these descriptors.

2 Methodology

Similar to other CBIR retrieval systems, image retrieval system for the songket motifs have two basic components: Archive module and Retrieval module as can be seen from Figure 2.

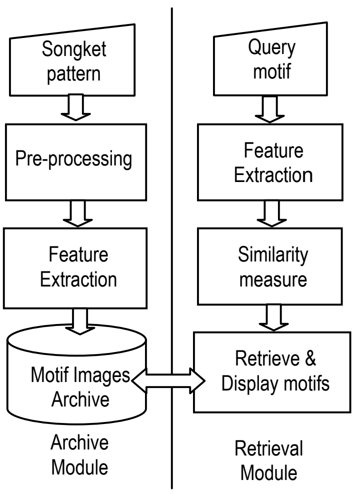


Figure 2: Image Retrieval System Model

There are two major processes involve in creating the Archive module, that is image pre-processing and feature extraction. Retrieval module, on the other hand, requires feature extraction, similarity measure and retrieving processes. In this section, this paper will discuss the methods used in image pre-processing, feature extraction and similarity measure.

2.1 Image Pre-processing

Images of songket patterns are captured using digital camera and pre-processing processes such as motif extraction, contrast enhancement, noise filtering, binarization and morphological operations are applied to produce binary songket motifs.

2.1.1 Motif Extraction

The first step in pre-processing is to allow cropping of motifs from the pattern. During the cropping process, unwanted objects or partial objects may be cropped together with the intended motif. Thus, removal of these extraneous details needs to be done by filling in the selected region of interest with the values on the boundary of the region. The motif is also converted to greyscale image for further processing. Another method used for cleaning image is by suppressing light objects connected to the image border using morphological operations. However, this method tends to reduce the overall intensity level in addition to suppressing border structures.

2.1.2 Contrast Enhancement

Contrast enhancement is important because cleaning and removing unnecessary details during pre-processing may deteriorate brightness level of the image. The pre-processed image may be subjected to histogram stretching, equalization and sliding. Histogram stretching and sliding will be based on intensity values of the input image entered by the user.

2.1.3 Noise Filtering

Noise is any unwanted information that contaminates an image; normally arise during digital image acquisition process such as scanning. It is almost impossible to remove noise totally without distorting an image, but it is imperative that noise is reduced to a certain acceptable level for further analysis of the image. This paper experimented on three different types of noise filtering: adaptive filter adaptive, median, and linear filters.

2.1.4 Binarization

After noise filtering, the greyscale image is converted to binary image by thresholding. The program accepts a threshold value between 0.0 and 1.0 and all pixels with luminance less than this value is converted to 0 (black) while others will be set to 1 (white). An automatic thresholding is also provided as an option. It is done by computing a global threshold using Otsu's method.

2.1.5 Morphological Processing

Morphological operations available in the system are dilation, erosion, opening and closing, filling, clearing and majority operations. Different morphological processes are applied on the images depending on the results of the binarization. Each operation may be applied repeatedly on the images to produce the best-desired result.

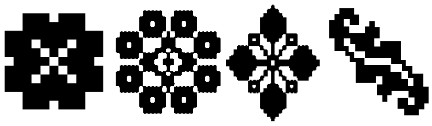
2.2 Feature Extraction

To represent the songket motifs, five geometric shape descriptors: eccentricity, compactness, convexity, rectangularity and solidity are chosen. During calculations of the shape descriptors, area of the motifs is defined as the net area not the filled area because the net area represents the songket motif's shape better than the filled area.

2.2.1 Eccentricity

Eccentricity of the boundary can be defined as the ratio of the major to minor axis, calculated with moments using Equation 1. The value is always between 0 and 1. Below (Figure 3) are some examples of the songket motifs and its corresponding eccentricities. Note that a more elongated motif will have a higher value of eccentricity.

$$Eccentricity = \frac{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}{(\mu_{20} + \mu_{02})^2} \quad (1)$$



0.0 0.09691 0.58400 0.93259

Figure 3: Eccentricity measurements

2.2.2 Compactness

Compactness is the ratio of the area of the image object to the area of a circle with the same perimeter, calculated by Equation 2. The maximum value of compactness will be 1 if the motif is a circle. This value will decreases for elliptical-shaped motifs and motifs with irregular, complicated boundaries. Figure 4 shows some measurements of the motifs compactness**.**

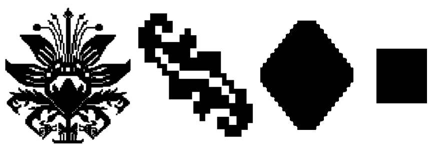
$$Compactness = \frac{4\pi . Area_{image}}{Perimeter^2_{image}} \quad (2)$$

0.00796 0.03974 0.23317 0.87708

Figure 4: Compactness values

2.2.3 Convexity

Convexity is the relative amount that an image object differs from a convex object. A measure of convexity can be obtained by forming the ratio of perimeters of the object's convex hull to the object's perimeter itself. See Equation 3. A convex motif such as the *Gigi Belalang* motif shown rightmost in Figure 5 has convexity value of 1. The more erratic the motif's boundary is, the less its convexity value is. For example, the *Bunga Bogan* motif shown leftmost in Figure 5 has the least convexity value due to its irregular boundaries.



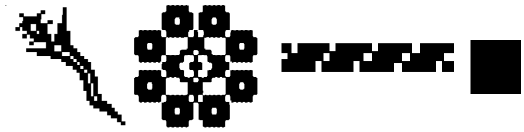
0.15700 0.33965 0.77240 1.0

Figure 5: Songket motifs and its corresponding convexity values.

$$Convexity = \frac{Perimeter_{convexhull}}{Perimeter_{image}} \quad (3)$$

2.2.4 Rectangularity

Rectangularity or extent of an object can be defined as the proportion of the pixels within the minimum bounding rectangle of the object that are also in the object (The Mathworks 1997). Thus, the *Gigi Belalang* motif has the highest rectangularity value of 1 and the *Keris Parung Sari* motif has the lowest rectangularity value of 0.18634. Other examples presented in Figure 6 are the *Bunga Mangga* and *Kendik Tali* with rectangularity values of 0.56499 and 0.8397, respectively. See Equation 4 for calculation of rectangularity measures.



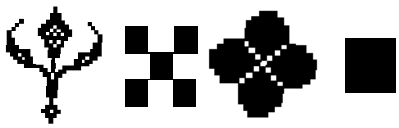
0.18634 0.56499 0.83970 1.0

Figure 6: Rectangularity measurements

$$Rectangularity = \frac{Area_{image}}{Area_{MBR}} \quad (4)$$

2.2.5 Solidity

Solidity measures the density of an object. A measure of solidity can be obtained as the ratio of the image object's area to the area of the object's convex hull. Refer Equation 5. A value of 1 signifies a solid object, and a value less than 1 will signify an object having an irregular boundary, or containing holes (Wirth 2005). Figure 7 shows examples of solidity measurements of the motifs.



0.3637 0.5384 0.8126 1.0

Figure 7: Solidity values

$$Solidity = \frac{Area_{image}}{Area_{convexhull}} \quad (5)$$

2.3 Similarity Measures

Similarity measures are computed between features of the query motif images and motifs images in the database. Output will then be sorted and displayed according to their similarity values. Computation of similarity measure should not only be efficient, but also the degree of similarity calculated should produce visual ranking of shapes which is similar to human perception. Latecki and Lakämper (1999) said that the similarity measure used should be consistent with human visual interpretation:

1. A shape similarity measure should permit recognition of perceptually similar objects that are not mathematically identical.
2. It should abstract from distortions.
3. It should not depend on scale, orientation, and position of objects.

In this paper, images are represented by a feature vector, thus Euclidean distance (Equation 6) is used to measure the similarity values of the query and target motif images.

$$d(Q,I)=\sqrt{\sum_{j=1}^{n}(f_j^Q - f_j^I)^2} \quad (6)$$

where n is the number of features, f^Q is the feature vector for the query image and f^I is the feature vector for the database image.

2.4 Motifs Retrieval and Display

Fifty selected motif images are used as the query images in this paper. For each of the query image, the experiment retrieves relevant shapes from the database and displays them in decreasing order of similarity to the query shapes. The query shapes are compared individually in a linear search against each shape in the database using Euclidean distance measure. The database consists of 300 contour shapes of songket motifs. A relevance judgment list or ground truth database is first created by several songket experts to be compared with the experiment's results. Two shapes are considered similar if a human judges that they represent the same image.

For retrieval evaluation, the common precision and recall (del Bimbo 1999) are used and calculated as follows:

$$\mathrm{Re}call = \frac{Number of\ relevant\, documents\, retrieved}{All\, relevant\, documents} \quad (7)$$

$$\mathrm{Pr}ecision = \frac{Number of\ relevant\, documents\ retrieved}{All\, retrieved\, documents} \quad (8)$$

Recall indicates the robustness of the retrieval performance. Precision indicates the accuracy of the retrieval. For each query, the precision of the retrieval at each level of the recall is obtained.

3 The Experiments

The experiments are divided into two parts. The first part involves creating the Archive module and the second part tests the efficiency of the retrieving the motif images using five simple shape descriptors.

3.1 The Archive Module

There are five steps involved in creating the traditional songket motifs archive: (1) motif extraction, (2) contrast enhancement, (3) noise filtering (4) binarization and (5) morphological processing. For each steps (2)-(5), the process can be performed repeatedly until the desired results are achieved. At the time of writing there are over 300 motifs collected in the archive. In this paper, however, only 25 of them are tested in the experiment of the Archive module.

3.2 The Retrieval Module

Previous experiment (Nursuriati and Zainab 2004) on each of the five single features indicated that eccentricity feature has the highest recall-precision value followed by rectangularity, compactness, convexity and solidity. Thus, the first part of this paper experiments on the combinations of the first three features with different weights of percentage applied. The methods are as follows:

Method1. Eccentricity, Rectangularity, Compactness.
Method2. 70%Eccentricity, 20%Rectangularity, 10%Compactness.
Method3. 50%Eccentricity, 30%Rectangularity, 20%Compactness.

The second part of the paper tests another three methods using different combinations of the geometric features. These methods are:

Method4. Eccentricity, Rectangularity, Compactness.
Method5. Eccentricity, Rectangularity, Compactness, Convexity.
Method6. Eccentricity, Rectangularity, Compactness, Convexity, Solidity.

4 Results and Discussion

Since the experiments are divided into two parts, their results are also presented separately in this section.

4.1 Contrast Enhancement

Based on the estimated grey level value, the motif images can be divided into three categories. Forty-eight percent of the motif images have estimated grey level values ranging from 0–255, twenty-eight percent from 25-255, and twenty-four percent from 0-150. This indicates that seventy-six percent of the original motifs grey values are equally distributed and the others are low-contrast images. For each image then, a number of different ranges of grey values are tested on them. The results show that fifty-six percent best grey values lies in the range 25.5-255, twenty eight percent in the range 0-200, and sixteen percent in the range 0-100. See Figure 8.

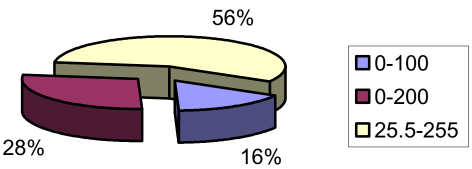


Figure 8: Estimated best grey level values after contrast enhancement

Even though the image can be clustered into three groups, contrast enhancement has to be done individually on each motif. As shown in the result of the experiment, there is no specific range of grey scale values that can be generally applied on all motif images. Even for images in the same category of estimated grey-level range, the best grey values vary significantly. The low and high brightness value has to be determined by looking at the histogram and this range of values are to be used as guideline for the input and mapped to the output range of 0 to 255. This histogram stretching process will lighten the light toned areas and darken the dark toned areas. However, choosing the appropriate brightness value is vital to produce the best contrast differences between the object and the background.

4.2 Noise Filtering

Removal of noises from the songket motifs is tested using average, median and adaptive filters. Different sizes of filters are also used to achieve the best representation of the original motif. A summary of the noise filtering experiments is shown in Table 1. The results show that sixty percent of the motifs are best filtered using average filter type, followed by twenty-four percent using adaptive filter and sixteen percent using median filter.

The type of filter chosen to remove the noise depends on the type of noise that exists in the motifs. For example, a motif with grain noise is better filtered using an averaging filter. Each pixel in the image is set to the average value of its neighbourhood thus reducing local discrepancies caused by the grain noise. However, this method causes blurring of the motif's edges. To reduce the problem of edge blurring using average filter, adaptive filter can be used instead. The adaptive filter changes its filtering behaviour based on the local image variance. It preserves edges or details when the local variance of the image is higher than the noise variance, otherwise it performs smoothing by averaging. On the other hand, motif with irregular distinct intensities is best filtered using median filter. This type of noise is suppressed by eliminating pixels with dissimilar intensity to be similar to its surrounding pixels.

Table 1: Noise Filtering Results

Image No.	Best Filter Type	Filter size
8,11,19	Average	3x3
13	Average	5x5
5	Average (Disk Filter)	3x3
1,4,7,9,10, 22,23	Average (Disk Filter)	5x5
2, 21, 25	Average (Disk Filter)	7x7
14,16,17	Adaptive	3x3
15,18,20	Adaptive	5x5
6,12,24	Median	3x3
3	Median	5x5

4.3 Binarization

In this paper, the digitized songket motifs are to be stored in binary format for minimal storage space usage. Thus, all the colour and greyscale motif images are converted to binary based on a threshold value determined by experimenting with the images individually. The results of experimentation are summarized in the pie chart shown in Figure 9.

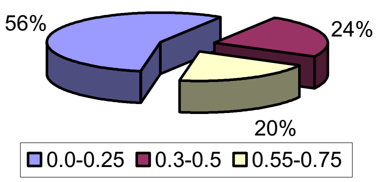


Figure 9: Best threshold values for binarization

The chart shows that fifty-six percent of the images use threshold value in the range of 0.3-0.5, followed by twenty-four percent in the range of 0-0.25 and twenty percent in the range of 0.55-0.75. From observation, the images that use low threshold values are dark contrast images, while high contrast images use high threshold values. All twenty-five motif images are also subjected to a global threshold value calculated using Otsu's method. However, this method does not produce the desired result due to the existence of noise in the images.

4.4 Morphological Operations

All twenty-five motifs require different morphological operations in different sequences depending on the results after binarization process. Table 2 summarizes the sequence of morphological operations applied on all twenty-five motifs.

Table 2: Morphological OperationResults

Image No.	Morphological Operations
1	Erode(3x), Dilate(3x), Majority-Close(4x)
2	Erode(2x), Dilate(3x)
3	Majority-Close(2x)
4	Erode, Dilate
5	Majority-Close (5x)
6	Majority-Close
7	Erode, Fill, Majority-Close(4x), Open
8	Erode, Close, Dilate, Fill, Majority
9	Dilate, Open, Dilate
10	Majority-Close(3x), Erode
11	Close
12	Majority
13	Erode(3x), Dilate(3x), Close-Majority, Close
14	Close-Majority(3x)
15	Close
16	Fill
17	Fill
18	Fill, Erode, Dilate
19	Majority, Erode, Dilate, Fill
20	Majority, Erode, Dilate
21	Erode(3x), Dilate(5x)
22	Dilate(4x), Close
23	Majority, Close, Dilate
24	Majority-Close(2x)
25	Dilate(2x), Close, Dilate

Out of the six morphological operations applied on the motif images, close is the most used operation followed by dilate, majority, erode, fill and open. Even though each of the operation can be applied individually, combinations of two or more operations applied in sequence can substantially enhanced the motif image. For example, combinations of majority and close done in sequence will smooth edges and fill tiny holes in the image. Image 3, 5, 6, 7, 10, 14, 23 and 24 all uses the combination of close and majority to improve their appearances. Another notable combinations of operations are erode and dilate. An image that has a lot of diminutive noise speckles can be greatly enhance if erosions are done repeatedly on it, then followed by dilations to reinstate the motif shape again. Image 1, 2, 4, 13, 18, 19, 20, 21 utilize these operations to attain the best-desired appearance of the songket motif.

4.5 Motifs Retrieval

Recall and precision as discussed in Section 2.4 assume that all images have been received and examined at the time of calculation. However, the motifs images retrieved are first sorted according to the degree of relevance in ascending order. In this situation, the recall and precision vary as the images are examined from top to bottom of the relevance list. Thus, proper evaluation of the retrieval performance requires plotting a precision versus recall curve or table. For each query, the precision of the retrieval at each level of the recall is obtained. To evaluate the retrieval performance over all queries, the average precision at each recall level is calculated as follows:

$$\overline{P}(r) = \sum_{i=1}^{N_q} \frac{P_i(r)}{N_q} \qquad (9)$$

where $\overline{P}(r)$ is the average precision at the recall level r, N_q is the number of queries used, and $P_i(r)$ is the precision at recall level r for the i-th query.

The first part of the Retrieval module experiments on combinations of three features of different weights. Table 3 shows that the average recall-precision value of Method1 is 0.336203, Method2 is 0.338745 and Method3 is 0.337942. Method1 has the highest precision rate at 10% recall level, followed by Method3 and Method2. However, at 20% recall level, Method3's precision rate precedes the other methods. Nevertheless, the difference precision value is very trivial, thus can be assessed as insignificant.

Table 3: Recall-precision rate at every 10% recall level

Recall (%)	Method1	Method2	Method3
10	0.955334	0.936875	0.94990
20	0.658745	0.638165	0.661703
30	0.400411	0.395717	0.401898
40	0.33947	0.357889	0.331935
50	0.272717	0.277093	0.273948
60	0.213765	0.222794	0.215973
70	0.180955	0.182192	0.185387
80	0.147823	0.162697	0.156384
90	0.103888	0.116385	0.109445
100	0.08892	0.097644	0.09285
Mean	0.336203	0.338745	0.337942

The second experiment tests different integration of geometric shape descriptors. From the R-P curve in Figure 10, Method6 has the highest precision rate of 97% at 10% recall level, while Method4 has the lowest precision rate at 91%. At 20% recall, Method6's precision recall dipped to 70% and Method4 at 65%. Method6 that integrates five shape descriptors, seems to outperform Method4 that integrates three descriptors only. The outcome seems to indicate that the more descriptors used, the higher the retrieval rate is. However, Method5 that integrates four descriptors has the same mean retrieval (33%) with Method4 that only integrates three shape descriptors. Upon closer analysis, it shows that convexity feature does not contribute significantly towards the effectiveness of the retrieval rate.

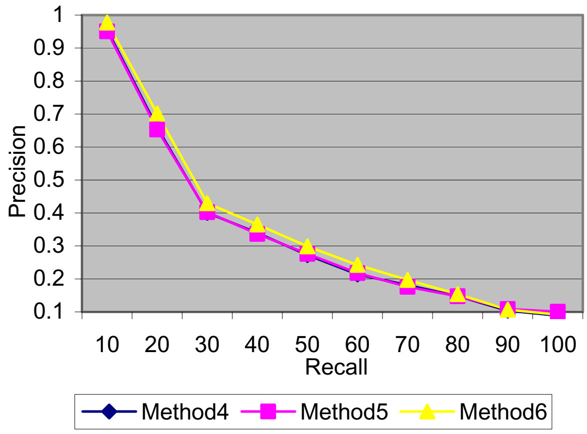


Figure 10: Recall-Precision curve

An example of a Method6's query and its results of the 10 most similar motifs arranged in decreasing order of similarity are shown in Figure 11.

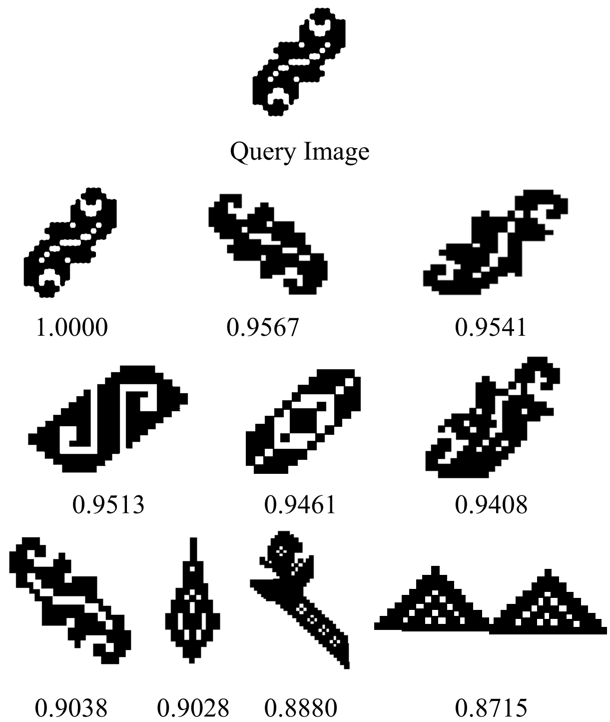


Figure 11: A query and its retrieval results

5 Conclusions

Based on the results presented earlier, there are no conclusive techniques for enhancing the songket motif images. Instead, guidelines and recommendations for each contrast enhancement, noise reduction, binarization and morphological operations are presented. For contrast enhancement, the image histogram has to be viewed beforehand to determine the low and high brightness value. These values are then used to uniformly expand or stretch the image histogram to cover the full range of values from 0 to 255. Choosing the brightness range of values is very crucial and the appropriate range can only be identified through experimentation on each image.

The primary objective of noise filtering is to reduce noise as much as possible without altering the shape of the original motif. Result of noise filtering showed that the best filter for songket motif is average filter as majority of the images contain Gaussian noise. Filtering can also be improved by using the correct filter size. However, motifs that have a lot of intricate details are better filtered using adaptive filter to maintain its unique shape. For motifs with erratic dissimilar intensities, they are best filtered using median filter.

Binarization is done manually by supplying a threshold value to convert the image into binary. For dark images, the recommended choice of threshold value is between the ranges of 0.15 to 0.25, while for high contrast images the suitable value is within 0.55 to 0.70. On the other hand, a proper value for normal contrast images is between the ranges of 0.30 to 0.40.

The single most used morphological operations in this project are close, dilate, majority and erode. Even though on their own these operations can contribute in enhancing the motif images, combination of majority-close and erode-dilate are able to significantly improve their appearance.

The suggestions and guidelines given here are based on the experimental results of this paper. It can be conclude that there is not a single optimally suited method for all songket motif images. It is often best to experiment with the images differently to achieve the best representation of the final binary image that resembles the actual motif.

Even though there are many existing shape descriptors that can be used in image retrieval, this paper experiments on geometric shape descriptors because of its fast and simple computations. The first part of the retrieval experiment tests on the combinations of eccentricity, rectangularity and compactness with different weights of percentage applied. Method1 that uses equal weight of the three features has the highest precision rate at 10% recall level. However at 20% recall, Method3 surpasses Method1 and the average value of Method1 is slightly lower than Method3. Even though eccentricity proved to produce the highest recall-precision value compared to the others, placing a greater weight on it (Method2) did not produce a significant higher performance of retrieval.

The second part of the retrieval experiment tests another three methods that integrates different combinations of the shape descriptors. At 10% and 20% recall, Method6 produced the highest precision values of 97% and 70% respectively, compared to the other five methods. This shows that combining five features has a higher retrieval efficiency compared to using fewer features.

The precision rate of 97% at 10% recall and 70% precision at 20% recall showed that using simple shape descriptors to retrieve songket motifs are considerably accurate. Furthermore, the calculations of these shape descriptors are simple and fast. Future research should be done to experiment on more combination of these five features or integrating other method such as Fourier descriptor to improve accuracy of the retrieval rate.

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