

# Iban plaited mat motif classification with adaptive smoothing

Silvia Joseph, Irwandi Hipiny, Hamimah Ujir

Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, Sarawak, Malaysia

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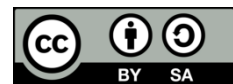
Probabilistic hough line transform

Random sample consensus

## ABSTRACT

Decorative mats plaited by the Iban communities in Borneo contains motifs that reflect their traditional beliefs. Each motif has its own special meaning and taboos. A typical mat motif contains multiple smaller patterns that surround the main motif hence is likely to cause misclassification. We introduce a classification framework with adaptive sampling to remove smaller features whilst retaining larger (and discriminative) image structures. Canny filter and probabilistic hough transform are gradually applied to a clean greyscale image until a threshold value pertaining to the image's structural information is reached. Morphological dilation is then applied to improve the appearance of the retained edges. The resulting image is described using binary robust invariant scalable keypoints (BRISK) features with random sample consensus (RANSAC). We reported the classification accuracy against six common image deformations at incremental degrees: scale+rotation, viewpoint, image blur, joint photographic experts group (JPEG) compression, scale and illumination. From our sensitivity analysis, we found the optimal threshold for adaptive smoothing to be 75.0%. The optimal scheme obtained 100.0% accuracy for JPEG compression, illumination, and viewpoint set. Using adaptive smoothing, we achieved an average increase in accuracy of 11.0% compared to the baseline.

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## Corresponding Author:

Silvia Joseph

Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak

94300 Kota Samarahan, Sarawak, Malaysia

Email: [silvia.joe8@gmail.com](mailto:silvia.joe8@gmail.com)

## 1. INTRODUCTION

Borneo is widely known as a home to the world's richest and aesthetically appealing plait work traditions. These traditions derive from the island's diverse cultural history and a product of creativity as well as ingenuity of its different communities [1]. Decorative mat plaiting is a craft skill known in most indigenous communities in Borneo. Plaited mats are used for basic floorcovering, for sitting, for sleeping and for ritual purposes during religious ceremonies. Sleeping and ritual mats tend to be the most elaborately decorated and may feature sacred motifs that are believed to be carrying spiritually powerful patterns that establish link between humans and the gods [2]. Modern practice of naming plaited mat motifs has suffered from a relative neglect in material culture studies, often resulting to a devoid of meaning. The relation between a motif and the name by which it is called is often not relevant. Thus, it is specious to interpret motifs only through their names [3]. Our previous work [4] investigated the use of an invariant image-based feature descriptor for recognizing Iban plaited mat motifs. We argue that this is the best route (i.e., image-based classification) to automate the mat motif recognition task. With modern smartphones being equipped with camera(s) as standard, we can integrate feature into educational and edutainment app. Such apps will be an excellent way to promote and educate the public about this invaluable cultural heritage to the masses.

This paper focuses on plaited mat work by the Iban communities. Plaited mats contain unique motifs that are either simple or complex. The motifs are mostly stylized beyond recognition. Most motifs are plaited based on loose categories that include natural elements such as plants, animals, firmaments, and faerie [5]. The main motif plays a dominant role for determining the specific meaning, whereas the smaller motifs only serve as fillers for filling in the empty areas surrounding the main motif. These motifs are usually arranged repeatedly to illustrate the mat pattern as a whole see Figure 1. Each motif has its own distinctive features. Thus, to recognize a plaited mat motif, we need to extract discriminative as well as robust visual features. Nevertheless, due to the diversity of appearances, variety of positions, scales and rotations of the major and minor motifs, the recognition task is non-trivial. Furthermore, the image captured by the camera may undergo common image deformations hence making the task harder.



Figure 1. An example of an Iban plaited mat motif, i.e., *Buah Tungku*. The (1) and (2); small ornament that act as a filler, *Buah Mata Punai*. The image was sourced from [4]

To date, a significant amount of research had been done on the robust detection, description and matching of invariant features related to motif and pattern classification. Features extraction algorithm and classification methods were applied to batik motif and batik making using convolutional neural network (CNN) model architectures [6]–[10], using multiwindow and multiscale extended center symmetric local binary patterns (MU2ECS-LBP) [11] and [12], using scale invariant feature transform (SIFT) [13], [14] using gray level co-occurrence matrices (GLCM) [15], [16], fine arts [17]–[19], for license plate recognition [20], [21], and tattoo recognition [22]–[24]. Even though the reported performance was quite high but these methods still suffer from false positives due to similar features that contain more than one pattern and noisy background. In order to deal with the mentioned problems, we introduce a classification framework with adaptive smoothing to remove small image features whilst protecting the discriminative structural information (i.e., edges). The appearance of the retained edges is enhanced using morphological dilation. The rest of this paper is organized: section 2 details out the data collection and pre-processing phase, section 3 outlines the proposed method. The results and analysis are presented in section 4 whilst the conclusion is provided in section 5.

## 2. DATA COLLECTION AND PRE-PROCESSING

Red, green and blue (RGB) images of the decorative plaited mat motifs were captured indoor using a setup consisting of a downward-facing camera with normal setting. For this initial work of ours, only 20 motifs were used in the experiments out of the possible 50. We labelled the class by the most prominent motif visible on the plaited mat upon consultation with the experts. The images were resized to a resolution of 800×533 pixels (original resolution is 5,184×3,456 pixels) for performance reason. The resized RGB images were then cropped and perspective-corrected to produce synthetic images. Following the decision made during our previous work [4] synthetic images are used as the target image instead of the actual photographed images to prevent background noises from polluting the resulting image descriptor. Examples of synthetic plaited mat motif images of different classes are shown in Figure 2.

Common image deformations [25] of incremental degrees were applied to the synthetic images to produce our query sets. We used the same set of incremental degree values as in our previous work [4]. Since we have a total of 20 classes, the precision of random classification by chance is  $\frac{1}{20}=0.05$ .



Figure 2. Examples of synthetic images, i.e., *Buah Lang Antu*, *Buah Burung Garuda*, *Buah Bandau*, *Buah Lintan Tanah* and *Buah Nabau Besundang* (from left to right)

### 3. PROPOSED METHOD

The proposed method utilizes adaptive smoothing and morphological dilation to not only remove noises but also to recover lost image information and to enhance image details. We start by convolving the 800×533 greyscale image with a Gaussian kernel of size 5×5, with the 1<sup>st</sup> derivation of 2D Gaussian smoothing filter function. The purpose of this smoothing function is to destroy the small image features that we considered as noise. The smoothed image is then converted into an edge image using Canny filter. In our proposed classification framework with adaptive smoothing, we gradually reduce the number of remaining edges by iteratively applying Canny filter of increasing low threshold value to the original edge image. We use a fixed increment of 5 units. By setting a higher value for the Canny filter's low threshold parameter, the number of kept edges is lower as the algorithm becomes more stringent in rejecting weak candidates. We stop the iteration once the percentage of remaining edges (PoRE) is lower or equal to the set threshold values (i.e., 100.0%, 90.0%, 85.0%, 80.0%, 75.0%, 70.0%, 50.0%, and 20.0%). These threshold values are selected randomly as it is possible to tune the threshold and locate the optimal value directly. These thresholds are evaluated using a validating set. PoRE is calculated using,

$$\text{PoRE} = \frac{\text{Current number of detected edges using PHT}}{\text{Initial number of detected edges using PHT}} \times 100 \quad (1)$$

We calculate the current percentage at each iteration using probabilistic hough transform (PHT) to extract the image's structural information. The iteration will stop once PoRE is equal or less than the target value, as shown in Figure 3 for a flowchart of the adaptive smoothing function. This function is implemented inside our classification framework.

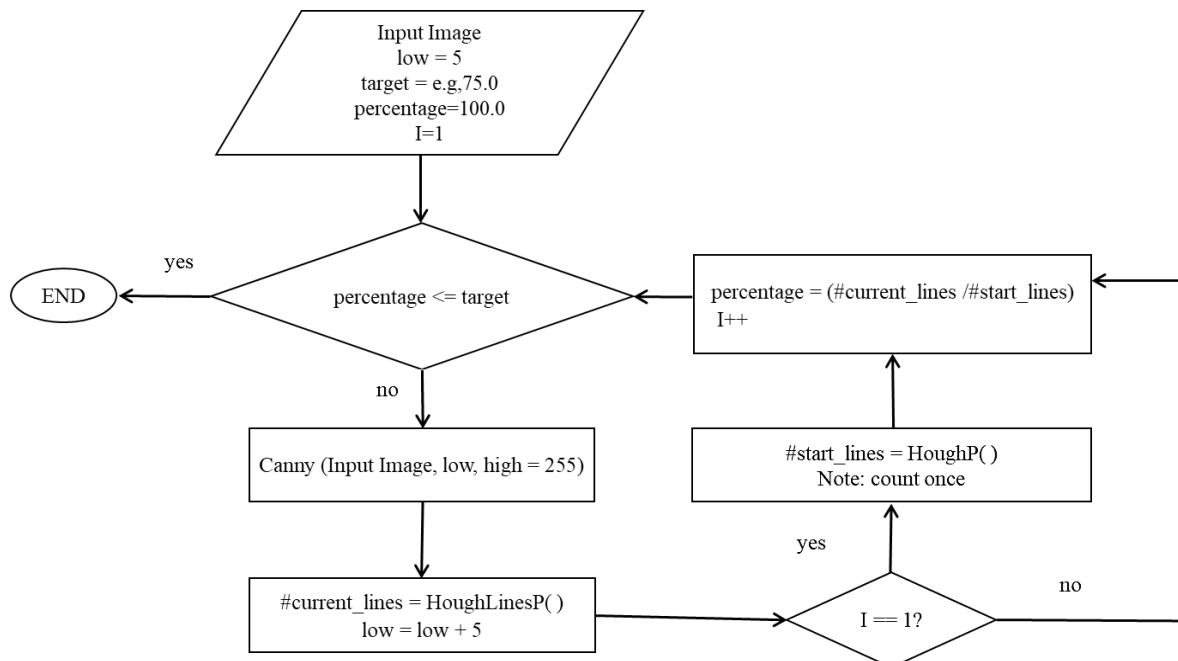


Figure 3. Our classification framework with adaptive smoothing

To validate our classification framework, we conducted an experiment for motif image classification against the following common image deformations, i.e., image blur, illumination changes, JPEG compression, viewpoint changes, scale+rotation changes, and scale changes. Using our dataset, we prepared a test sequence (i.e., query images) for each motif class. A test sequence contains five images. Each image exhibits a gradual increment of geometric and/or photometric transformation of the initial image. Following the recommendation by [25], we used the same 6 image deformation types as in our previous work [4]. For each motif class, both test image (i.e., synthetic image) and the test sequence's images were converted into edge images at different PoRE values. The final edge images were used during the classification exercise. As a comparison set, we also produced a second set by applying PHT on the final edge images.

In total, we have 20 motif classes x 6 image deformation types x 5 deformation levels x 8 sets of PoRE values range of (100%, 90%, 85%, 80%, 75%, 70%, 50%, and 20%), yielding a final total of 9,600 query images. Figure 4(a) shows examples of query image produced at different PoRE values, whilst Figure 4(b) shows the corresponding query images with dilation (to improve appearance of edges). Figure 5 shows selected query images with incremental degrees of image deformation. For the feature matching and classification of the prepared target and query images, binary robust invariant scalable keypoints (BRISK) [26] were used. BRISK detects corners using adaptive and generic accelerated segment test (AGAST) algorithm [27] and perform filtering with features from accelerated segment test (FAST) corner score while searching for maxima inside the scale space pyramid. Outlier-rejection from matched features was performed using random sample consensus (RANSAC). RANSAC estimates the homography matrix and use that information to eliminate any mismatches/possible false key points. We used the ready implementation of BRISK and RANSAC in VLFeat Version 0.9.21 library [28]. This work was implemented on a Windows laptop with the following specifications: Intel Core i7-8550U @ 1.80GHz processor and 8 GB RAM.

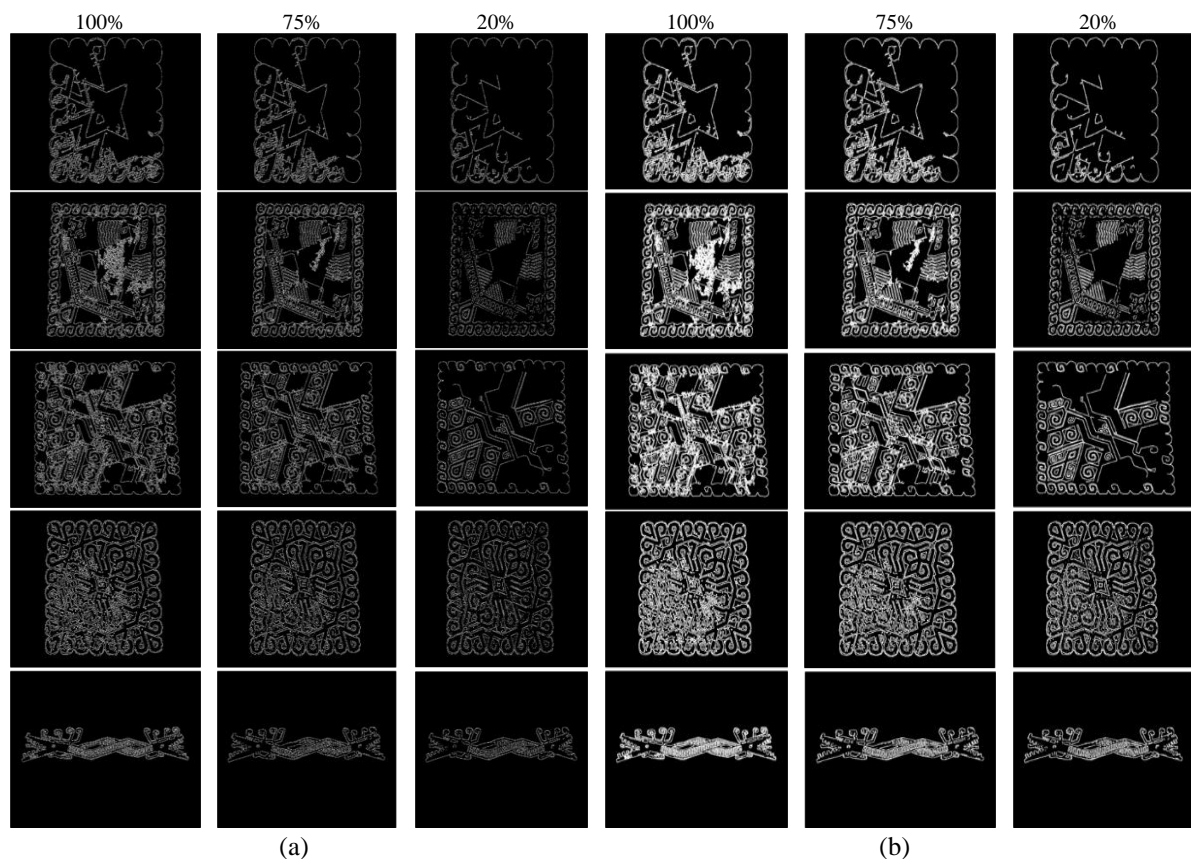


Figure 4. From left to right, query images produced using PoRE values of 100.0%, 75.0%, and 20.0% for the following motif classes (top to bottom row) *Buah Lang Antu*, *Buah Burung Garuda*, *Buah Bandau*, *Buah Tungku Lebur* and *Buah Nabau Besundang*. Two versions are shown, i.e., (a) without dilation and (b) with dilation



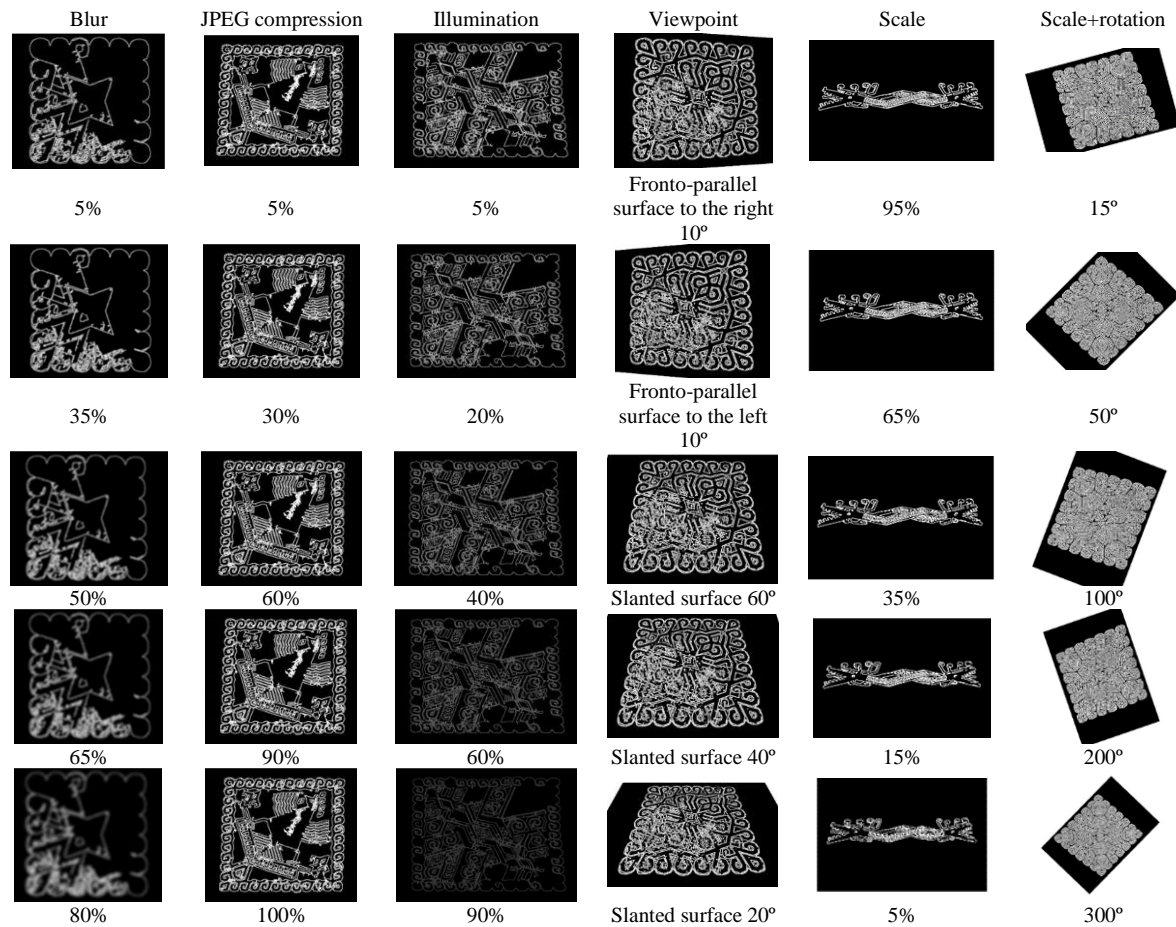


Figure 5. From top to bottom, selected query images with incremental degrees of image deformation. From left to right, a column showing query images of *Buah Lang Antu* sequence for blur changes, *Buah Burung Garuda* sequence for JPEG compression changes, *Buah Bandau* sequence for illumination changes, *Buah Tungku Lebur* sequence for viewpoint changes, *Buah Nabau Besundang* for scale changes, and *Buah Tangkai Gajai Besembah* sequence for scale + rotation changes

#### 4. RESULTS AND ANALYSIS

We recorded the number of detected BRISK key points inside the query vs. template image, the number of correspondences, and number of correct matches after RANSAC. For image blurring, when the level of distortion increases, the number of detected BRISK+RANSAC key points decreases dramatically especially at the 5<sup>th</sup> level of deformation without dilation, shows in Table 1. However, with dilation enabled of PoRE=75.0%, the decrease in number does not correlate with a loss of accuracy. False matches only started at the 3<sup>rd</sup> deformation level for image blurring, while for scale+rotation, we observed that the BRISK+RANSAC is able to detect a considerable number of key points, even at increasing degrees of deformation. We also found that that our method performed well for viewpoint with front parallel surface images at a value of 10° (left/right) and slanted surface images, at a value ranging from 20° to 60°. BRISK+RANSAC managed to detect enough key points, even at the worst deformation level of scale+rotation changes. Clearly it is demonstrated that BRISK+RANSAC using our proposed method performed well against JPEG compression, viewpoint and illumination changes, shows in Table 2. The unique properties of symmetrical, repetitive, similar and complex motifs, i.e., *Buah Tangkai Gajai Bersembah* and *Buah Tungku Lebur* creates a challenge for the classification task that leads to some errors during the matching process as shown in Figures 6(a) and 6(b). Motifs with simpler features, i.e., *Buah Mata Punai* that sometimes act as a filler for other motifs, have a smaller number of strong edges resulting to a reduced number of discovered key points, shows in Figure 6(c).

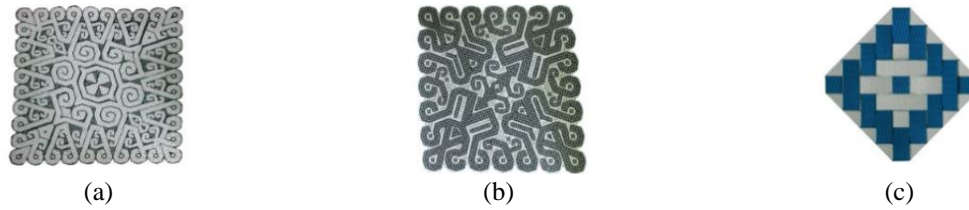


Figure 6. Three motifs with high misclassification rate (a) *Buah Bulan Bekarung*, (b) *Buah Tangkai Gajai Besembah*, and (c) *Buah Mata Punai*

Table 1. Number of detected BRISK+RANSAC keypoints using the optimal PoRE value of 75.0% for each image deformation category, with and without morphological dilation

Image deformation	w/o dilation		w/ dilation	
	1 <sup>st</sup> level	5 <sup>th</sup> level	1 <sup>st</sup> level	5 <sup>th</sup> level
Blur	155	0	7882	164
Illumination	117275	50991	140871	64996
Viewpoint	457	36	2994	231
JPEG compression	82992	1300	128084	10379
Scale+rotation	397	30	1307	122
Scale	795	138	2516	527

The following metrics were calculated:

- True positives (TP): the number of query images being correctly classified with a similarity score higher than the threshold.
- False positives (FP): the number of query images being incorrectly classified with a similarity score higher than the threshold.
- False negatives (FN): the number of instances where multiple top matches were returned, or the top matches similarity score is lower than the threshold.

Table 2. Comparative failure point of using BRISK+RANSAC with optimal PoRE value of 75.0%, for each image deformation category. We show the failure point (a) w/o morphological dilation, and (b) w/ morphological dilation

(a)							
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale+rotation	Scale	
Image1	FN	TP	TP	TP	FN	FN	
Image2	FN	TP	TP	TP	FN	FN	
Image3	FN	TP	TP	TP	FN	FN	
Image4	FN	TP	TP	FN	FN	FN	
Image5	FN	TP	TP	FN	FN	FN	
(b)							
Level of image deformation	Blur	Illumination	JPEG _Compression	Viewpoint	Scale+rotation	Scale	
Image1	TP	TP	TP	TP	TP	TP	
Image2	TP	TP	TP	TP	FN	TP	
Image3	FN	TP	TP	TP	TP	TP	
Image4	FN	TP	TP	TP	FN	TP	
Image5	FN	TP	TP	TP	FN	FN	

The results of keypoint matching from both query and template image were summarized in the form of confusion matrix as shown in Figures 7(a) to 7(f). We have 20 actual classes and 20+1 predicted classes. The additional predicted class, i.e., class unresolved, represent cases where our classification returns multiple top matches or a similarity score is lower than the threshold. We consider such cases as a FN to penalise the configuration. Based on the confusion matrix obtained from the classification results using our proposed framework with optimal PoRE value of 75.0% + dilation, for Blur set as in Figure 7(a) shows the highest number of unresolved classes, followed by scale set as in Figure 7(d), and scale+rotation set, in Figure 7(f). Most of the results in class unresolved for blur set are due to the false top matches produced by simple motif *Buah Mata Punai* and complex motifs of *Buah Bulan Bekarung*, *Buah Kandung Nibung Berayah*, *Buah Sebayon* and *Buah Tangkai Gajai Besembah*. From our experiment, we observed that blurring is the most destructive image deformation type (compared to the rest) as its application produces many false top matches. There is no class unresolved for JPEG compression set, illumination set, and viewpoint set, see



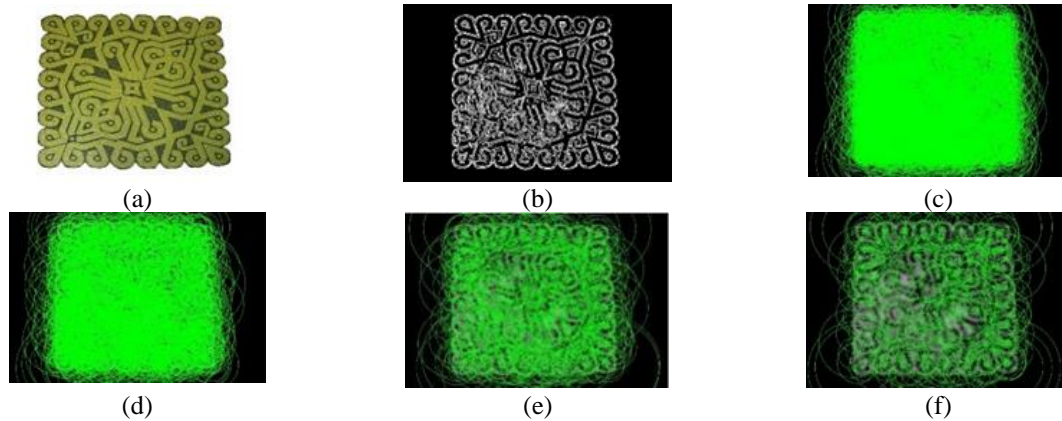


Figure 8. Synthetic image of (a) *Buah Tungku Lebur*, (b) the resulting edge image produced by Canny filter, detected BRISK key points when using optimal PoRE value of 75.0% at (c) blur level 1, (d) level 2, and (e) level 3, and (f) level 5

In Figure 10, we presented the average matching accuracy achieved by the following schemes: scheme 1: synthetic image and BRISK+RANSAC; scheme 2: synthetic image and BRISK+RANSAC with Canny filter; scheme 3: synthetic image and BRISK+RANSAC with Canny filter and PoRE (without dilation); and scheme 4: synthetic image and BRISK+RANSAC with Canny filter, PoRE (with dilation) the average accuracy is 85.0%, 95.0%, 79.0% and 96.0% respectively. As for dilation vs no dilation, we observed that with dilation enabled, the average accuracy increases by 17.0%. The optimal scheme, i.e., scheme 4 offers an average increase of 11.0% compared to the baseline, i.e., scheme 1, and an average increase of 1.0% compared to scheme 2. Figure 11, illustrate the average matching accuracy using BRISK+RANSAC at different PoRE values for each image deformation type. The optimal PoRE value is observed to be 75.0% with a comparably higher average matching accuracy of 83.0%, 100.0%, 100.0%, 100.0%, 92.0% and 99.0% across all image deformations (blur, illumination, JPEG compression, viewpoint, scale+rotation and scale) compared to the rest.

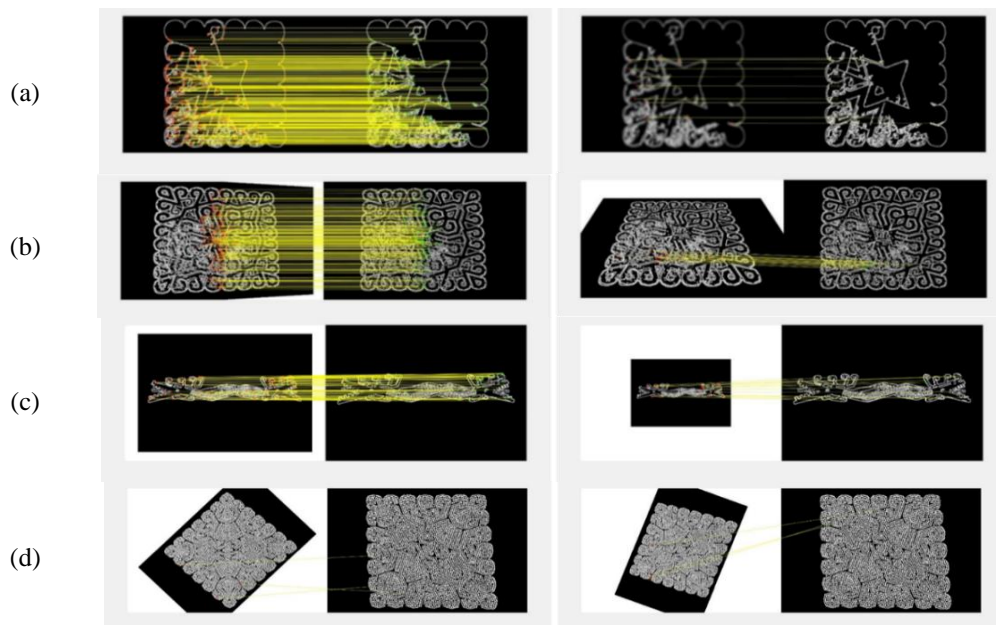


Figure 9. Side-by-side comparisons of visualized matching results of *Buah Lang Antu*, *Buah Tungku Lebur*, *Buah Nabau Besundang* and *Buah Tangkai Gajai Besembah* using BRISK+ RANSAC at deformation level 1 (left column) vs. level 5 (right column). We show a sample matching result (optimal PoRE=75.0%, dilation enabled) each for the following image deformation types, i.e., (a) blur, (b) viewpoint, (c) scale, and (d) scale+rotation



Performance comparison of average matching accuracy using BRISK+RANSAC at different scheme following six image deformations.

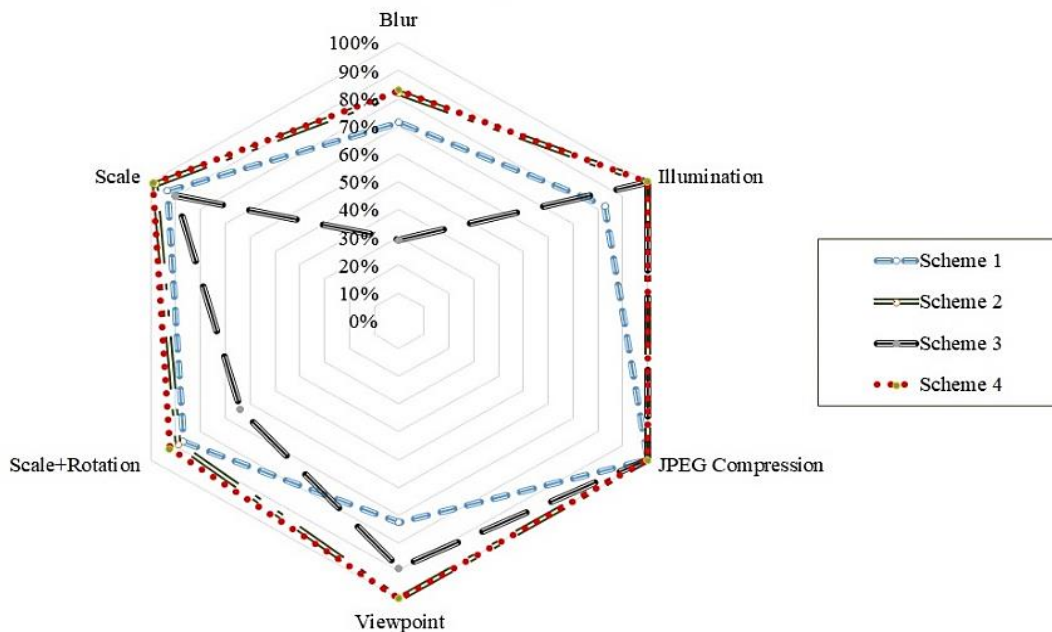


Figure 10. Performance comparison of average matching accuracy using BRISK+RANSAC at different schemes, following six image deformations

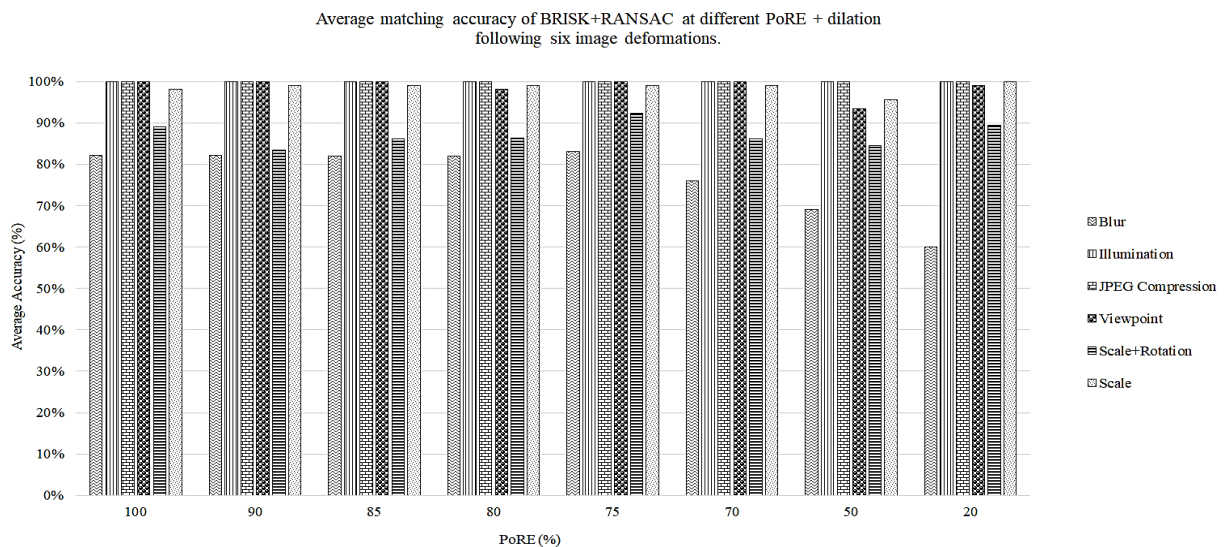


Figure 11. Average matching accuracy of BRISK+RANSAC at different percentage of PoRE+dilation values following six image deformations

## 5. CONCLUSION

In this work, we presented an adaptive smoothing scheme consisting of Canny edge detector and PHT to gradually remove smaller image structures from a given mat motif greyscale image. Dilation is then used to restore broken edges after the application of the smoothing scheme to improve detection. Motifs are matched using BRISK features and RANSAC against six common image deformations: combination of scale and rotation, viewpoint, image blur, JPEG compression, scale and illumination changes. Varying degrees of each deformation type were applied to all cropped and perspective-corrected mat motif images. The optimal PoRE value is 75.0% with a reported 100.0% matching accuracy for JPEG compression, illumination and

viewpoint change set. Our optimal scheme achieved an average increase in accuracy of 11.0% compared to classification using only BRISK+RANSAC on synthetic RGB images (i.e., baseline method). It is observed that the proposed scheme improves the classification accuracy of mat motif images with complex motif across common image deformation types.

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## BIOGRAPHIES OF AUTHORS






**Silvia Joseph**    is currently a postgraduate student at the Faculty of Computer Science and Information Technology (FCSIT), Universiti Malaysia Sarawak (UNIMAS). Working as an Information Technology Officer at Government Hospital, Ministry of Health, Malaysia. She obtained her Master in Advanced IT (MAIT) in 2016. Silvia's research interests are on features recognition in fields of pattern analysis, image processing applications and image retrieval system. She can be contacted at email: [silvia.joe8@gmail.com](mailto:silvia.joe8@gmail.com).



**Dr Irwandi Hipiny**    is a Senior Lecturer at the Faculty of Computer Science and Information Technology (FCSIT), Universiti Malaysia Sarawak (UNIMAS). He obtained his PhD in Computer Vision from University of Bristol in 2014. Irwandi's current research interests are in computer vision and animal re-identification. He can be contacted at email: [mhihipni@unimas.my](mailto:mhihipni@unimas.my).



**Ts. Dr Hamimah Ujir**    is a Senior Lecturer at the Faculty of Computer Science and Information Technology (FCSIT), Universiti Malaysia Sarawak (UNIMAS). She obtained her PhD in the School of Electronic, Electrical and Computer Engineering, University of Birmingham, United Kingdom in 2013. Hamimah's research interests lay in the interdisciplinary field of computer vision, with related interests being in computer graphics, image processing, and mathematical methods. Her previous and current works include 3D physical simulation and 3D static as well as dynamic facial expression. She can be contacted at email: [uhamimah@unimas.my](mailto:uhamimah@unimas.my).