Comparison of Evaluation Image Segmentation Metrics on Sasirangan Fabric Pattern

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ABSTRACT

Sasirangan fabric is a typical fabric from the South Kalimantan area. Sasirangan fabric patterns or motifs have unique archetype that is different from other typical fabrics in Indonesia. The design of Sasirangan fabric is forme from the process of juju or seam. The pattern of Sasirangan fabric that has this uniqueness can be segmented into more meaningful shape so that it is easy to analyze. The image segmentation that will be tested is the basic patter of Sasirangan fabric with a random sample to compare the results of the evaluation of the metric evaluation of th image segmentation process from the Sasirangan fabric pattern. Image segmentation is a different segmentation wit certain characteristics, namely using the compact watershed approach, canny filter, and morphological geodesi active contours method in the evaluation of image segmentation metrics using precision-recall, which serves t evaluate the quality of the classifier's output. After the image segmentation process is evaluated, the Sasiranga fabric pattern is grouped using the K-means algorithm as a different labelling strategy. This labelling process use the K-means algorithm to better match details but can be unstable because it relies on random initializatio. Alternatives to balance the unstable labelling process using the means algorithm can use discretization. The additio of the K-means method with discretization can create fields with geometric shapes that are pretty flat. Th segmentation with Sasirangan fabric with a full motif or data number four 741.78s, results in processing the faste. and the longest computational time on data number two 120.79s.

Keywords: Segmentation; Sasirangan; Pattern; Image; Cluster

INTRODUCTION

Sasirangan fabric is a typical fabric from the South Kalimantan area (Rosyadi, 2017). Sasirangan fabric patterns or motifs have a unique archetype so that they are different from other typical fabrics in Indonesia (Maulida et al., 2019). The pattern of sasirangan fabric is formed from the process of juju or seam (Qur'ana, 2018). The design of sasirangan fabric that has this uniqueness can be segmented into a more meaningful shape so that it is easy to analyze (Muharir, 2018). Image analysis is needed to recognize and explore patterns that exist in an image so that the image can be processed by image processing methods.

In the method of image processing, several stages of the process must be carried out, namely the process of image segmentation (He & Huang, 2020; Marleny & Mambang, 2019). The image segmentation process can use several methods to match the tested image (Danish et al., 2020; Rahaman & Sing, 2021). The segmentation of the image that will be tested is the archetype of sasirangan fabric with a sample of sasirangan fabric pattern with a slight to the full motif of the sasirangan fabric. The process of image segmentation in this article starts from taking samples of the simplest sasirangan fabric motifs, namely taking samples from 2 motif patterns, 3 motifs, 4 motifs, and full motif patterns. Data on these four types of motifs are taken to compare the results of the evaluation of metrics of the image segmentation process from the pattern of sasirangan fabric as crude image segmentation. Rough image segmentation is an important stage for the pattern recognition process in the initial segmentation of objects, and the background of the image is separated so that it can be continued to the stage of fine segmentation, namely the sasirangan fabric pattern data cluster (Bao et al., 2018).

The rough image segmentation compared is a different segmentation with certain characteristics, namely using the compact watershed method approach, canny filter, and morphological geodesic active contours method (Houssein et al., 2021). In the evaluation of image segmentation metrics, using precision-recall evaluates the quality of the classifiers (Lei & Fan, 2019).

After the rough image segmentation process is evaluated, the sasirangan fabric pattern is grouped using the k-means algorithm as a different labelling strategy. This labelling process uses the K-means algorithm to better match

details but can be unstable because it relies on random initialization. Alternatives to balance the inconsistent labelling process using the k-means algorithm can use discretization. The addition of the k-means method with discretization can create fields with geometric shapes that are pretty flat. With labelling using k-means, Spectral grouping can also be used to partition graphics through their spectral insertion.

LITERATURE REVIEW

Metric evaluation is used to measure the quality of a model. In image processing and machine learning how evaluating models when building models is an important stage to measure how accurate the model is in predicting the expected results (Castillo-martínez et al., 2020). Comparison of Evaluation Image Segmentation Metrics on Sasirangan Fabric Patterns is measured using the process stages of digital image processing.

Compact Watershed

The watershed method was originally developed by Lantujeoul and is extensively described together with its many applications by Beucher and Meyer. Since its original development with grayscale images, it has been extended to a computationally efficient form (using FIFO queues) and applied to colour images. The watershed segmentation techniques are one of the most advanced tools offered by image processing for the segmentation of images. A recent and most comprehensive review of various watershed algorithms is presented, and it has various drawbacks (Rahma et al., 2020).

Since watershed segmentation is a well-known algorithm, there are various algorithmic implementations and adaptions. We start from the OpenCV implementation of the algorithm following. OpenCV implements a seeded watershed segmentation (also called marker-controlled watershed). The seeds are externally provided to the algorithm, e.g. as local gradient minima or for superpixel-like segmentation on a uniform grid. The seeds grow pixel iteratively by pixel until they reach a border to the segment around another source. These borders form the watersheds (Ibrahim & El-Kenawy, 2020).

Canny Filter

Edge detection of explosive piles of ore has stricter requirements on the quality of explosive pile images. The Canny operator uses the Gaussian filter function to perform first-order derivation in any direction of the burst image and then convolves with the original image to perform filtering processing to obtain a smooth appearance. Variance ($\sigma 2$) is used as the smoothing and denoising parameter to eliminate external factors' interference. Firstly, a pixel point x(i,j); is determined. In the 3 x 3 neighbourhood of this pixel, the mean l and variance $\sigma 2$ of all pixels in this neighbourhood are calculated by using Eqs (Huang et al., 2022).

$$\mu = \frac{1}{N}\sum_{(i,j)\in w} x(i,j) \qquad (1)$$

$$\sigma^2 = \frac{1}{N}\sum_{(i,j)\in w}[x(i,j) - \mu]^2 \qquad (2)$$

where N is the number of pixels in the neighborhood.

Morphological Geodesic Active Contours

Geodesic active contours are implemented with morphological operators. It can be used to segment objects with visible but noisy, cluttered, broken borders. Preprocessed image or volume to be segmented. This is very rarely the original image. Instead, this is usually a preprocessed version of the original image that enhances and highlights the borders (or other structures) of the object to segment. Morphological geodesic active contour will try to stop the contour evolution in areas where the image is small that the quality of morphological_geodesic_active_contour might greatly depend on this preprocessing inverse gaussian gradient (Medeiros et al., 2019).

K-Means

The K-Means algorithm clusters data by trying to separate samples in n groups of equal variance, minimizing a criterion known as the inertia or within-cluster sum-of-squares. This algorithm requires the number of clusters to be specified. It scales well to many samples and has been used across a large range of application areas in many different fields. The k-means algorithm divides a set of N samples X into K disjoint clusters C, each described by

the mean µj of the samples in the cluster. The means are commonly called the cluster "centroids"; note that they are not, in general, points from X, although they live in the same space (Akram et al., 2017).

The K-means algorithm aims to choose centroids that minimize the inertia, or within-cluster sum-of-squares criterion:

$$\sum_{i-0}^{n} \min_{\mu_j \in C} (||x_i - \mu_j||^2) \qquad (3)$$

Precision and recall

Precision-Recall is a valuable measure of prediction success when the classes are imbalanced. In information retrieval, precision measures result in relevancy, while recalling measures how many truly relevant results are returned. The precision-recall curve shows the tradeoff between precision and recalls for different thresholds. A high area under the curve represents both high recall and high precision, where high precision relates to a low false-positive rate, and high recall relates to a low false-negative rate. High scores for both show that the classifier is returning accurate results (high precision) and a majority of all positive results (high recall). A system with high memory but low precision produces many influences, but most of its predicted labels are incorrect compared to the training labels. A system with high precision but low recall is the opposite, returning very few results, but most of its predicted titles are correct compared to the training labels. An ideal system with high precision and high recall will produce many effects, with all results labelled correctly. Precision (P) is defined as the number of true positives (Tp) over the number of true positives plus the number of false positives (Fp) (Lim et al., 2022).

$$P = \frac{T_p}{T_p + F_p} \qquad (5)$$

Recall (R) is defined as the number of true positives (Tp) over the number of true positives plus the number of false negatives (Fn).

$$R = \frac{T_p}{T_p + F_n} \qquad (6)$$

These quantities are also related to the (F1) score, which is defined as the harmonic mean of precision and recall.

$$F1 = 2\frac{P \times R}{P + R} \qquad (7)$$

METHOD

The segmentation of the proposed image is to use sasirangan fabric image data with simple motifs up to full motifs on sasirangan fabrics. The pre-processing stage is to input RGB image data and then in the process so that it becomes a grayish image. In the pre-processing step of image segmentation used with the compact watershed method approach, Canny Filter and Morphological geodesic active contour as a method for coarse segmentation, from segmentation to these three methods compared metric evaluation of the method. Furthermore, for fine segmentation using the K-means Cluster and K-means discretize methods. Model evaluation measurements use a precision and recall approach to see which models have been used or not. Here is the framework of the proposed segmentation stages.
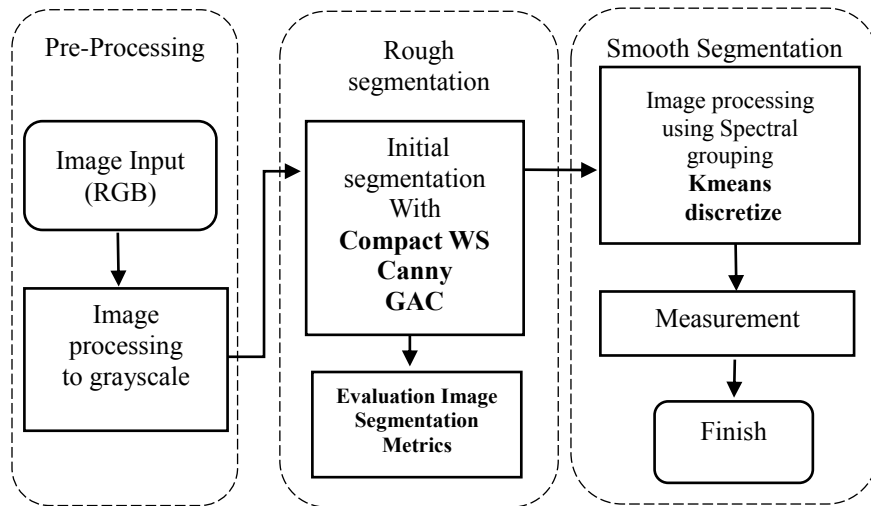
Fig. 1 Proposed image segmentation framework

DISCUSSION

In discussing the stages of the proposed image segmentation framework, there are three process stages. The first pre-processing stage is inputting colour images and image processing to grayscale. Next to the steps of rough segmentation, here is a discussion on coarse segmentation. In the results of image segmentation in the initial stages, there are four image results. Accurate segmentation images are the results of segmentation images at the initial step. The image below will display the segmentation of images with different fabric patterns. Where the image results with the compact watershed method, Canny filter, or edge detection and morphology GAC.
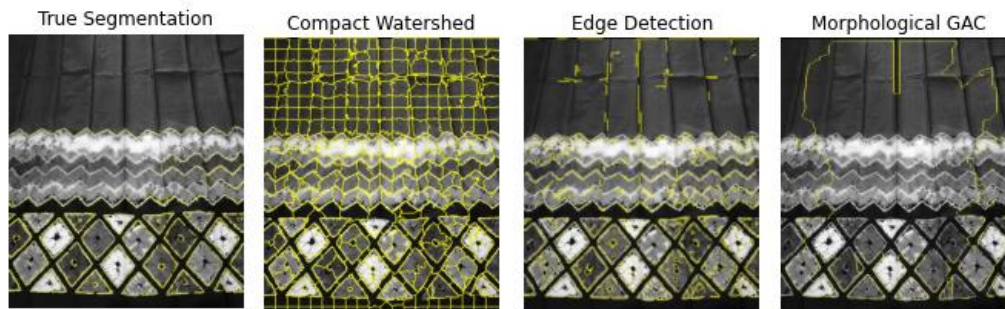

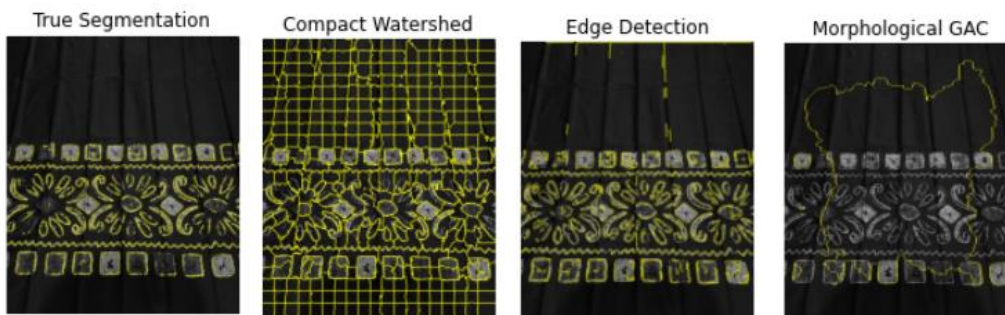Fig. 2 Results of rough segmentation Fabric pattern with two motifs

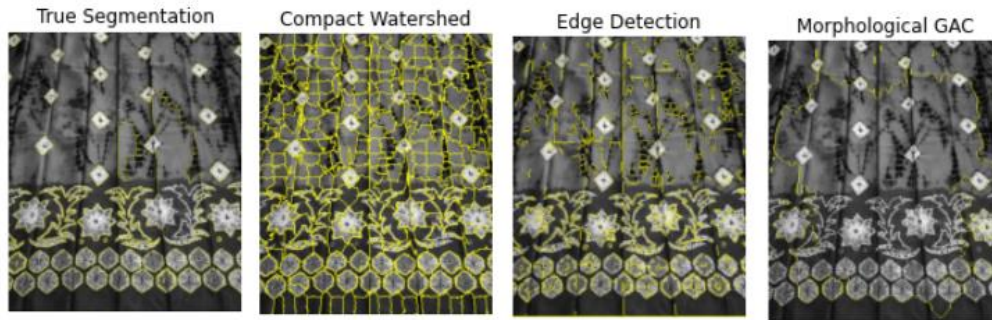Fig. 3 Results of rough segmentation Fabric pattern with 3 motifs

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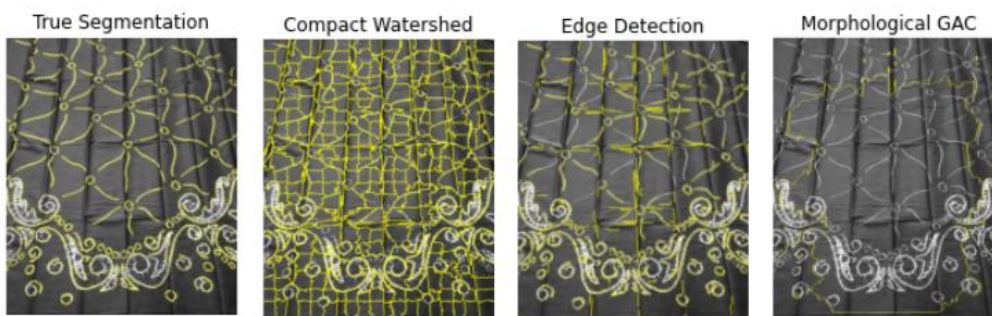Fig. 4 Results of rough segmentation Fabric pattern with 4 motifs

Fig. 5 Results of rough segmentation Fabric pattern with full motifs

The measurement approach used is Precision Measurement and recall. The following is an image of the result of the split variation of information.

(a) the result of measuring the Fabric Pattern with 2 motifs

(b) the results of measuring the Fabric Pattern with 3 motifs

(c) the results of measuring cloth patterns with 4 motifs

(d) the results of measuring fabric patterns with full motifs
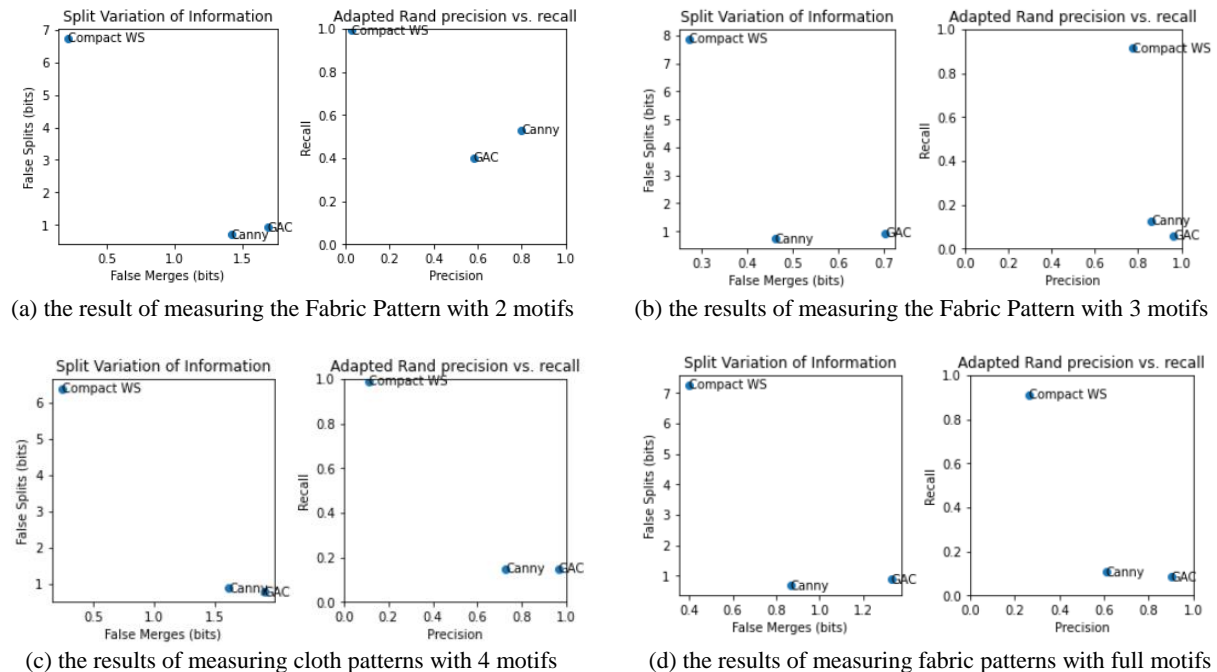
Fig. 6 Results from model measurements

RESULT

Here is a table of comparative results of asymmetric evaluations where precision-recall curves are commonly used in binary classifications to study the output of classifiers. Extending precision-recall curves and average precision to multi-class or multi-label sorts, it is necessary to binarize outputs. One curve can be drawn per label, but we can also draw a precision-recall curve taking into account each element of the label indicator matrix as a binary prediction. The number one image model tested with these three methods has the lowest error result with the Canny method. In figure two, the lowest error test result in the GAC method, in the third trial, the lowest error was obtained in the Canny process, but the range of error numbers was not significantly different. The Compact Watershed method had the lowest error in the fourth image trial.

Tabel 1
The comparison result of the evaluation of the image segmentation metric

No	Metode	error	Precision	Recall	Fales Split	False Merges
1	Compact Ws	0.95185	0.02468	0.99115	6.74151	0.20831
	Canny	0.36328	0.79971	0.52893	0.70263	1.41699
	GAC	0.52494	0.58247	0.40111	0.92682	1.68710
2	Compact Ws	0.98135	0.0095	0.9693	6.70171	0.47266
	Canny	0.19451	0.85890	0.85890	0.83447	1.58433
	GAC	0.35040	0.60931	0.69559	0.89169	1.85475
3	Compact Ws	0.79940	0.11162	0.98805	6.38258	0.24091
	Canny	0.75380	0.72843	0.14812	0.88871	1.61424
	GAC	0.74050	0.96403	0.14992	0.78344	1.90495
4	Compact Ws	0.59304	0.26205	0.91027	7.26305	0.39890
	Canny	0.81926	0.60804	0.10614	0.68369	0.86500
	GAC	0.84738	0.90078	0.08337	0.88147	1.32899

The results of the measurement model in table 1 can vary results. Judging from these results, they can be compared that each different motif will be further from the recommended segmentation method. Edge detection can detect motifs better with irregular patterns. Judging from the irregular patterns, they are recommended to use the GAC method. In the rough segmentation stage, metrics are measured and evaluated, whose results vary in each experiment using the three methods above. The GAC method is recommended for irregular patterns in testing using sasirangan fabric images obtained lower error results with the compact watershed method. From the segmentation results, fewer errors are obtained from the canny way.
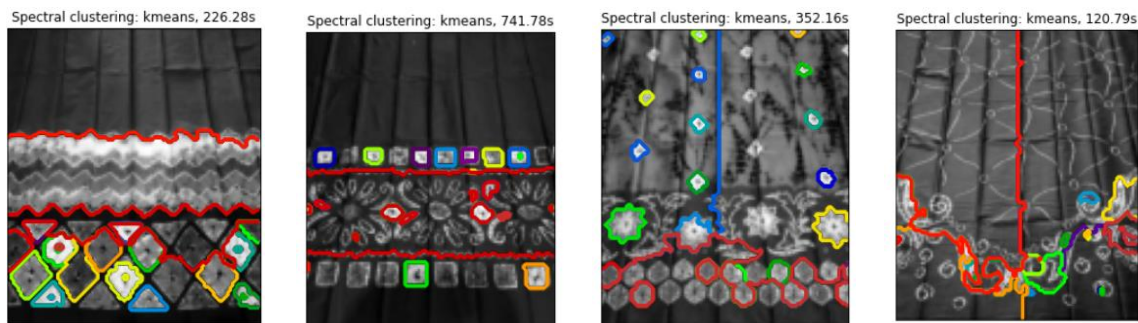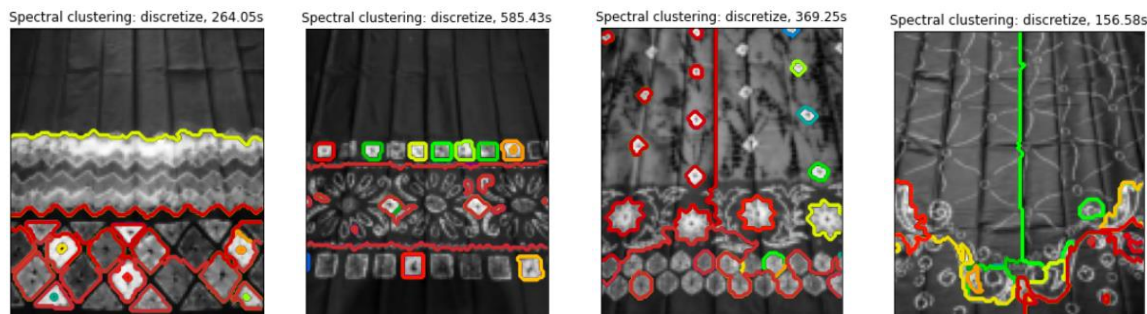
Fig. 7 Grouping results with the k-means method

Figure seven shows a cluster of fabric patterns divided into colour clusters from the test results using different fabric pattern motifs. The results of the runtimes process with pattern number two get more time than other images. Irregular patterns can be clusters captured by the k-means method.

Tabel 2
discretize Comparison of runtimes on spectral clustering K-means and discretize

No	kmeans	discretize
1	226.28s	264.05s
2	741.78s	585.43s
3	352.16s	369.25s
4	120.79s	156.58s

Table 2 shows the results of the Comparison of computational time with the processing of test results on the k-means algorithm. From the results above, the segmentation with sasirangan fabric with a full motif or data number four 741.78s has the results of processing the fastest and the longest computational time on data number two 120.79s.

CONCLUSION

The results obtained from the Comparison of evaluation of image segmentation metrics using the Compact watershed method, Canny Filter, and Geodesic active contour Morphology have a less significant difference in numbers. In Comparison, the evaluation of metrics on subtle motif patterns with the Canny filter method is more recommended. Fabric patterns with different motifs have different results as well. Sasirangan fabric patterns grouped using the K-means algorithm as different labelling strategies have other processing times when tested. Labelling processes that use the K-means algorithm to better match details to balance unstable labelling processes using the k-means algorithm can use discretization. The addition of the K-means method with discretization can make motifs with geometric shapes that are flat enough so that more irregular fabric patterns can be clustered well by the k-means method.

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