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Confusion Matrix as Performance Measure for Corner Detectors

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ABSTRACT

Nowadays, corner detection algorithms have been proposed by several researchers who described them contrarily, depending on their respective viewpoints to obtain the data and information as a human eye does. Basically, no researchers have come up with a technique to compare corner detectors with another's. Thus, this study proposed to adapt the confusion matrix technique as a performance measure for corner detectors. The judgement accuracy of every corner detector will only be pleased if the actual corner points are already known. Therefore, this study is attracted to explore the accuracy of corner detectors, namely the Global and Local Curvature Scale space (GLCSS), Affine Resilient Curvature Scale Space (ARCSS), and Harris. These corner detectors were analysed using the nine characters selected from Jawi, Chinese, and Tamil characters, three characters each, respectively. This study specifically detected the true corners for these characters using the determined corner detectors. The actual corner of all these characters was confirmed through a survey of twenty respondents. The majority of marked corners by respondents were considered actual corner points. Then, the input image for all characters was converted into a grayscale image. Every image will undergo pre-processing step, the process of boundary extraction using Canny edge detector. Thus, the edge image was extracted to get the corner point by applying the corner detectors, and the corner point detected was marked on that image. Above and beyond, the study aims to introduce a confusion matrix approach as a performance measure to carry out the most outstanding algorithm in detecting the true corner points for all the tested characters. From the evaluation, GLCSS and Harris algorithms have shown good accuracy. Henceforth, the study is not trying to judge the goodness of each corner detector but only to introduce confusion matrix as a tool that can be considered to measure the performance of the corner detector.

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1. Introduction

A corner is a crucial component of the human form recognition [1]. It has been extensively utilised for form description, identification, and matching. In the literature, the terms 'point feature,' 'dominant point,' 'important point,' and 'corner' are considered as synonymous. Current corner detection approaches may be categorised into three broad groups: contour-based, intensity-based, and model-based methods [2]. Each group has its own efficacy, weakness, and a number of revealing errors in practical application, which has sparked research interest in corner detection within the field of character recognition.

Extraction of boundaries and identification of corner points are fundamental steps in many image processing applications. A method of image processing known as edge detection is utilised to get the image's borders. Image processing is utilised for picture segmentation and data extraction by finding brightness discontinuities. In the medical area, image segmentation of pap smear images has become a more crucial area of research because the segmentation must be accurate since accuracy is frequently the primary concern when evaluating these systems' performance [3]. Edge detectors consist of Sobel, Roberts, Laplacian of Gaussian, Canny, Prewitt, and fuzzy logic techniques [4-5]. The Canny operator has been widely used due to its fast-operating time and relatively straightforward computation procedure [6]. It can reduce noise more efficiently and preserve more of the original image's information [7-8]. Thus, in this study, the Canny edge detector was applied as the boundary extraction tool to all corner detection algorithms since it is a better method for extracting the features in an image without disturbing its features.

A wide range of research can be found in the corner detection technique [9]. The fundamental issue with these algorithms is that their performance is typically impulsive with human explanation, particularly on complicated images with deformed and distorted corners. Finding the best and most accurate method for corner detection pleases the attention of researchers in the field of computer vision, particularly in character recognition. Thus, three methods were utilised and tested in this study: the Harris corner detector, the corner detection based on global and local curvature characteristics [10], and the affine-resilient curvature scale space corner detection algorithm [11]. Corner detection is a text detection and character identification technique that has played a vital role in the development of computer vision. Numerous research on corner detection exists now, concentrating on existing characters but primarily on Roman characters. In addition, there are several projections and requirements in other characters, such as Jawi, Chinese, and Tamil characters, that match the demands on character identification for non-Roman characters.

The performance of corner detectors must be evaluated because majority of corner detection algorithms have been developed by several researchers, each of whom has described them differently based on their own perspective. The accuracy of each algorithm for corner detection can only be satisfied if the real corner locations are previously known. There are several techniques for evaluating the performance of corner detectors. Most published corner detectors lack a standard evaluation approach for evaluating these requirements, and the way these criteria are measured varies depending on the corner detector. Their results were only validated in contrast to other test corner detectors using various images. Corner detectors' application potential is determined mainly by their detection precision, computational cost, and repeatability. Hence, the corner detector's performance is evaluated based on these three variables [12]. Consistency and accuracy are the two criteria provided by [13] for evaluating the performance of corner detectors. The current evaluation methods, which include ground-truth verification, localisation accuracy, visual inspection, repeatability, theoretical analysis, consistency, accuracy, information rate, and specific tasks, are reviewed in [14].

The effectiveness of a classification algorithm may be analysed, represented graphically and summed up through a table called confusion matrix. Hence, in this study, the performance of all corner detectors was testified and measured using the confusion matrix approach. The method of calculating accuracy adopted the confusion matrix approach. Accuracy requires the detected corner to be close to the true place as feasible. The confusion matrix provides information on how frequently a specific activity is successfully recognised and how frequently it is labelled as another behaviour [15]. Various performance metrics, such as precision, sensitivity, and specificity, are often used to determine classification accuracy.

Therefore, this work investigates the corner detection methods of the Global and Local Curvature Scale space (GLCSS), Affine Resilient Curvature Scale Space (ARCSS), and Harris. These algorithms analysed Jawi, Chinese, and Tamil characters, a selection based on three primary ethnic groups in Malaysia. Only the detection of the true corners of these characters using these corner detection techniques is described. The analysis was later conducted using a confusion matrix to determine the accuracy of the corner detection methods considered for this study. In addition, the study aims to introduce a confusion matrix approach as a performance measure to execute the most outstanding algorithm that detects the true corner points for all tested characters.

2. Methodology

The methodology process started by studying the three characters: Jawi, Chinese, and Tamil, to get a sense of the technique. The last nine characters, three of each character, were tested in the algorithm afterwards. The real corner position for each character must be identified since recognising the corner is a difficult task that relies heavily on perception. As a result, a simple survey form was distributed to a random sample of twenty persons, each of whom was asked to mark and clarify the exact corner point of each character applied in this study. In accordance with the findings of this research, all nine characters marked with corner points were considered to have actual corner points.

Then, following the determination of the true corner for each character, the input images for each character were converted to grayscale images. The images were subjected to a pre-processing stage that comprised the extraction of boundaries using Canny edge detector. Consequently, the edge images were extracted to obtain the corner point using corner detectors, and the detected corner points were indicated in the picture. In this stage, three different algorithms were inferred. The algorithm's determined corner points were then analysed and evaluated using confusion matrix.

2.1 Actual Corner Determination

Corner points are crucial for character representation and analysis. If the corner points are appropriately acknowledged, a character can be denoted efficiently and compactly with necessary accuracy. A good corner recognition algorithm must be capable of distinguishing between actual and unintended corners, detecting corners consistently, and detecting the locations of corners accurately and correctly. Numerous techniques for finding corners have been proposed, often enhancing the fundamental concept. The accuracy of any corner detector can only be identified if the true corner points are already known.

As illustrated in Figure 1, a panel of twenty respondents was utilised to evaluate the position of corner points for nine test characters represented by J1, J2, J3, C1, C2, C3, T1, T2, and T3, respectively. These characters, selected from each type of character, illustrate the complexity of the character's form, which varies from simple (J1, C1, and T1) to moderate (J2, C2, and T2) to complicated (J3, C3, and T2) (J3, C3 and T3). The corner points marked by most respondents were taken as actual corner positions and were then considered and used to evaluate the accuracy of various corner detectors. Figure 2 shows the characters marked with actual corner points and their counts.

Fig. 1. Characters used in the tests.

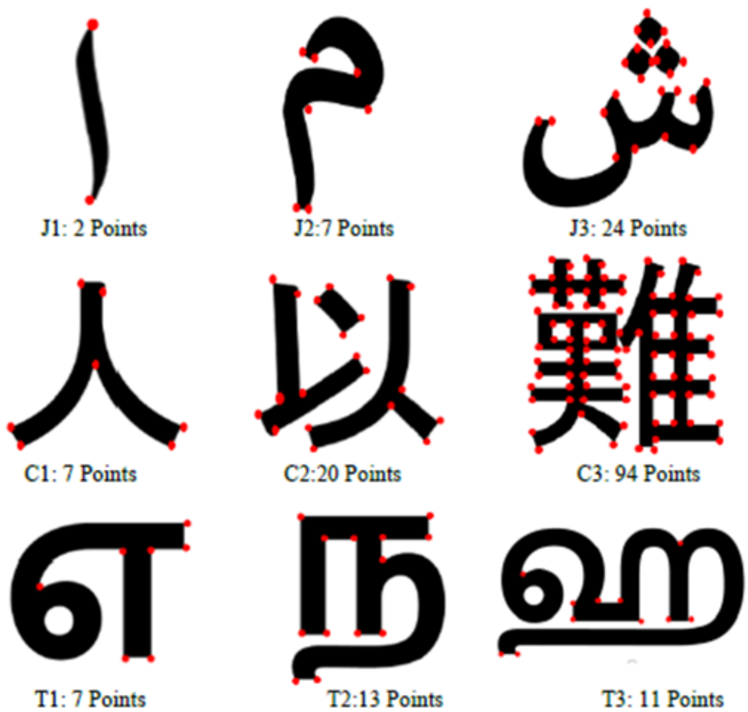

Fig. 2. Characters marked with actual corner points.

2.2 Boundary Extraction by using Canny Edge Detection

The Canny edge detector is one of the most clearly defined edge detection technique that provide excellent and consistent detection among the known edge detection techniques. The Canny edge detection algorithm was proposed to enhance the edge detection process. Three important criteria were taken into consideration for this purpose. The first and most important criterion was detecting all of the source images' critical edges. The goal of this process was to lower the error rate. The second criterion was that the edge points be seen as close as possible to the true edge, also called localisation. A third criterion was not to have more than one response to a single edge. Since the edge detector is not the primary focus of this study, the detailed explanation is not discussed in this study.

In this study, the Canny edge detector was used as an image processing method to extract edges in an image. Due to its minimalism of process for execution, it is one of the most extensive algorithms for edge detection. Figure 3 shows the edge map image of all characters. The result indicates that Canny edge detector offers good localisation and provides one-pixel wide edges (thin). It is less sensitive to noise and removes streaking by using double thresholding. Finally, the strong edge was included in the edge map, and the weaker edge was included in the edge map if and only if they were connected to the strong edges.

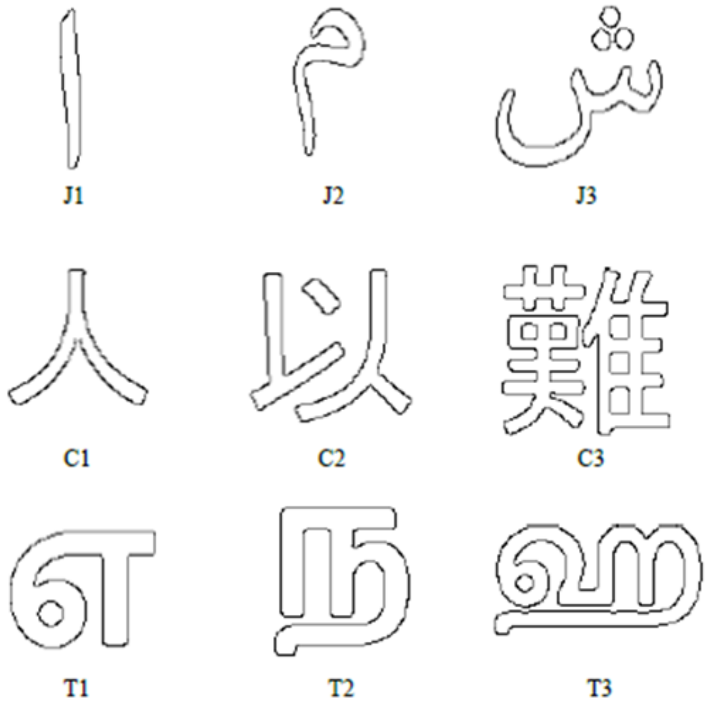

Fig. 3. Edge image of the J2 character

2.3 Corner Detection Algorithm

Since corners in the image signify critical data in defining object features crucial for pattern recognition and identification, several corner detection approaches have been studied previously by different researchers. Therefore, this subsection is dedicated to the enlightenment of three corner detection algorithms proposed by various researchers. Each algorithm has its principles and ideas for finding the corner point. The algorithms used were the Global and Local Curvature Scale Space Corner Detector (GLCSS), Affine Resilient Curvature Scale Space Corner Detector (ARCSS) and Harris Corner Detector (Harris). All algorithms are based on their default parameters. The result of the three algorithms was put together for each character to have a more apparent comparison, as shown in Figure 4.

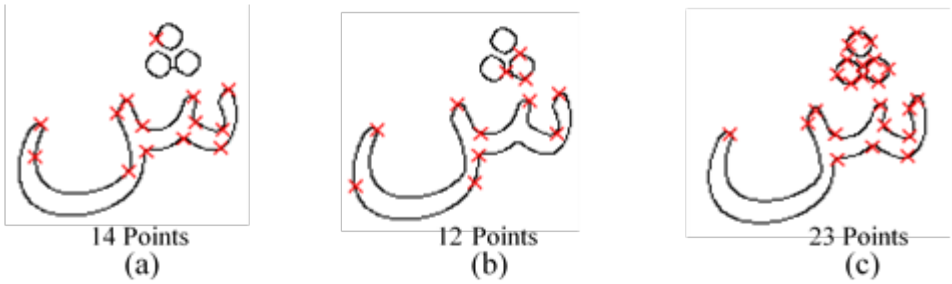

Fig. 4. Detected corner points for J3 using three algorithms (a) GLCSS, (b) ARCSS, (c) Harris

2.3 Confusion Matrix

Confusion matrix is a method practically used to determine the set of test data grouping model performance with known true values. It is relatively simple, but the related terminology can be baffling. Table 1 shows the terms used in this confusion matrix table.

Table 1
Confusion matrix table

		Algorithm Detected Corner Point?		
		NO	YES	
Actual Corner Point	NO	True Negative	False Positive	True Positive + False Negative
	YES	False Negative	True Positive	False Negative + True Positive
		True Negative + False Negative	False Negative + True Positive	TOTAL

Note:
Algorithm Detected Corner Point
(NO – Undetected; YES – Detected)
Actual Corner Point
(NO – Not an actual corner; YES – Actual corner

The elementary terms used in the confusion matrix table are explained in Table 1, which is the whole number.

i. True Positive (TP): The algorithm detects the point as a corner point when it is a corner point
ii. True Negative (TN): A corner point is undetected by the algorithm. Despite not being a corner, this value will always be zero in this practice because one needs to compare the actual point with the detected point using an algorithm.
iii. False Positive (FP): The algorithm detects a corner point, but it is not a corner point in nature. However, it is known as a “Type I error”.
iv. False Negative (FN): A corner point is undetected by the algorithm, but it is a true corner point, which is also known as a “Type II error”.

Figure 5 shows J2 marked with the actual corner point and corner point detected by algorithm GLCSS, while Table 2 shows the confusion matrix table for J2 using the GLCSS algorithm. Based on this confusion matrix table, then, the accuracy of the algorithm to detect the correct corner point was calculated using equation (1).

$$Accuracy = \frac{(TP+TN)}{TOTAL}\ x\ 100\% \quad (1)$$

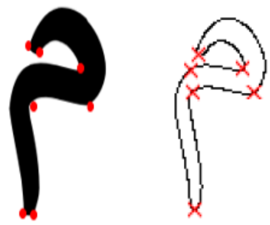

Fig. 5. (a) Character J2 marked with an actual corner (b) Character J2 corner points detected using algorithm GLCSS

Table 2
Confusion matrix table for J2 using algorithm GLCSS

		Algorithm Detected Corner Point?		
		NO	YES	
Actual Corner Point	NO	0	1	1
	YES	2	5	7
		2	6	8

3. Results & Discussion
3.1 Corner Point Detected by Algorithm

The number of corner points that were correctly, incorrectly, and missed for each algorithm is summarized in Table 3. The number of correctly detected corner points as actual corner points by algorithms was counted as correct. In contrast, the algorithm calculated the number of wrongly seen corner points as incorrect. The actual corner point that did not detect by the algorithm was notified as missed. The inaccurate and missed corner point detected by the algorithm was known as Type 1 error and Type 2 errors, respectively, which may lead to less accuracy. Each test parameters were assigned based on the algorithm's default values.

According to Table 3, the data clearly shows that all algorithms tend to have Type 1 and Type 2 errors (incorrectly and missed detecting the corner points). The complexity of the character shape moves from simplest, moderate, and complex shapes, except the Harris algorithm, tested on Chinese characters. The Harris algorithm outperformed all other algorithms in Chinese characters because the number of incorrectly and missed detected corner points is zero for all tested characters (C1, C2, and C3), which is no error in either Type 1 or Type 2 error. Apparently, in all results of Harris, the probability of selecting the wrong corners is almost nil in all Chinese characters. Still, it detected some bad corners on Jawi characters (J1, J2, and J3) and Tamil characters (T1, T2, and T3).

The data shows the missed detected corner points (Type 2 error) by the ARCSS algorithm were very high compared to other algorithms that will give the lowest accuracy in calculation later on. However, GLCSS seems to provide an almost similar result to Harris, except on Tamil characters, in which GLCSS detected fewer incorrectly corner points than Harris. The implemented variation results in difficulty to compare the accuracy between different algorithms.

Table 3
Confusion matrix table for J2 using algorithm GLCSS

Characters	Correct			Incorrect			Missed		
	GLCSS	ARCSS	Harris	GLCSS	ARCSS	Harris	GLCSS	ARCSS	Harris
JI	2	2	2	0	0	0	0	0	0
J2	5	5	5	1	1	1	2	2	2
J3	10	8	20	4	4	3	14	16	3
C1	7	4	7	0	0	0	0	3	0
C2	20	12	20	0	1	0	0	8	0
C3	77	32	94	2	0	1	17	63	0
T1	7	3	7	0	2	4	0	4	0
T2	13	5	13	1	3	1	0	8	0
T3	6	5	10	5	7	9	5	6	1

3.2 Performance Evaluation using Confusion Matrix

Accuracy is the most important criterion for all other values of any corner detectors. The detected corners' accuracy can be measured by the percentage of the correctly determined corners of the algorithm. This study evaluates the accuracy by considering the confusion matrix. All the results are then summarized in a single table shown in Table 4.

According to Table 4, for Jawi characters (J1, J2, and J3), the average accuracy for Harris algorithm correctly detected corners is the highest, 79.8%, followed with GLCSS algorithm which is 65.6% and ARCSS algorithm with 63.7%. The accuracy of correctly detected corners for J1 and J2 are identical for all algorithm which are 100% and 62.5%, respectively. The GLCSS and ARCSS algorithm accuracy for J3 are 34.5% and 28.6%, respectively, the lowest compared to Harris algorithm which is 76.9%. The reason for the higher percentage in Harris algorithm is due to the specific corner known as the obtuse corner. Intensity-based corner detectors, such as the Harris, can discern corners in noisy situations, however, their corner placements are imprecise and obtuse angles are missed [16]. However, it is deemed as good in this case as it is parallel to the human perception corner.

Besides, for Chinese characters, the Harris algorithm shows excellent performance by giving almost 100% accuracy for each character. The GLCSS algorithm gives 100% accuracy for characters C1 and C2 but not C3. The algorithm misses some important corner points on C3 with only 80.2% accuracy. The ARCSS algorithm gives the worst result compared to others since the overall accuracy at only 49.3%. This algorithm tends to miss many essential corners.

Next, the result for the Tamil character is quite interesting to discuss because the GLCSS algorithm gives the highest average accuracy with a figure of 76.8%. This is followed by the Harris and ARCSS algorithm at 68.8% and 30.8%, respectively. Tamil characters have rounder corners that may lead to false corners detection on the Harris algorithm, resulting for lesser accuracy. This occurs may be due to the default value of the parameters.

Overall, the ARCSS algorithm shows the lowest correctly detected corners which is 47.9% for the presented test characters. The ARCSS algorithm detected the highest number of wrong corners compared to other algorithms. For the GLCSS algorithm, the overall accuracy of correctly detected corners is 78.6%, much better than the ARCSS algorithm. Then, the overall accuracy of correctly detected corners by the Harris algorithm is the highest, 82.7%.

Table 4
Corner point accuracy (%)

	Jawi		Chinese			Tamil			
	J2	J3	C1	C3	C3	T1	T2	T3	J2
GLCSS	100	62.5	34.5	100	100	80.2	100	92.9	37.5
		65.7			93.4			76.8	
					78.6				
ARCSS	100	62.5	28.6	57.1	57.1	33.7	33.3	31.3	27.8
		63.7			49.3			30.8	
					47.9				
Harris	100	62.5	76.9	100	100	98.9	63.6	92.9	50.0
		79.8			99.6			68.8	
					82.7				

4. Conclusions

Corners are not simply the point of dominant, high curve or the local maxima. The true corners are defined as the abruptly changed points where the segmented shape can be and have meaningful points from a human being perceptive. Three corner detection algorithms; GLCSS, ARCSS, and Harris have been tested, analysed and further discussed. GLCSS and Harris algorithm have shown to have the highest accuracy and efficacy to be used for any type of character. A comparative study, based on the default value of parameters evaluation using confusion matrix analysis shows that both algorithms got shallow false detection ratio and are the most consistent with the human judgement of corners, and they are very suitable for natural character. In conclusion, the confusion matrix technique is suggested to be used as a tool to measure corner detectors performance.

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