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IDENTIFYING COMPLEMENTARY CORNER DETECTORS FOR CORRECT IMAGE PIXELS CLASSIFICATION

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ABSTRACT: Classification of digital image content is mainly done by identifying low level image features such as corners and edges. The literature shows variety of algorithms for the identification of corner and non-corner pixels, important for objects' identification and image segmentation. However, all of these algorithms produce different results for same data and therefore, suitable for limited applications. This paper proposes a hybrid solution of combining complementary corner detection algorithms to improve image pixels' classification. This has been done by identifying the best detection algorithm for corner points with small and large angles and producing a hybrid algorithm by combining the latter two. Results have shown that Harris detector combined with Global and Local Curvature Points (GLC) improved the detection rate by 28% in synthetic images, but 50% in real images whereas, the combination of Shi's detection algorithm with GLC enhanced the detection rate by 25.9% in synthetic images and 123% in real images, showing a significant improvement.

Keywords: Corner Detectors, Complementary, Statistical tests, Performance Analysis, McNemar's Test

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INTRODUCTION

For the last two decades or so local distinctive image features such as corners, edges, salient regions *etc*. have been used for matching images or video frames for detection, recognition, tracking, stitching panoramic images and other image processing tasks. For these vision applications corer points appear to be more appropriate because of their defining property. A corner point is defined to be the intersection of two more edges and therefore, can easily be used to find regions of interests in digital image content (Sonka*et.al*. 2014).

There area number of performance evaluation studies to characterize the performance of corner detection algorithms using different metrics such as detection accuracy (Mohanna and Mokhtarian, 20001, Mokhtarian and Mohanna, 2006), repeatability (Schmid*et al*., 2000, Rosten and Drummond, 2006), stability which is consistent appearance of corner points in video frames over a period of time, (Rockett, 2003,Tissainayagam and Suter, 2004) and accurate localization (Wang and Dony, 2004,He and Yung, 2004, Martinez-Fonte *et al*., 2005, Rodehorst and Koschan, 2006). A statistical measure, variance has also been used in identifying polyhedral objects (Heyden and Rohr, 1996), moreover, (Zheng *et al*., 1999) have used gradient direction to assess the performance of corner detection algorithm in grayscale images, a criterion specific for algorithms using gradient information for corner detection. Similarly, (Martinez-Fonte *et al*., 2005; 1999; Gil *et al*., 2010) have developed application specific evaluation criteria for performance assessment. All of these studies show that if one corner detection algorithmis able to find a corner in an image, some other detector fails to find the same. This is mainly because of their different underlying working principlesas has been reported by (Harris and Stephens, 1988 and Shi and Tomasi, 1994), both of them use *eign* values to calculate the change in pixels' intensities whereas SUSAN and FAST use circular masks to compare intensity differences for corner detection. This variation in detection results can be used as performance evaluation criteria and therefore, has been employed in this study to characterized detection algorithms. Furthermore, large numbers of images have been used for statistical analysis, which made the presented results more reliable and statistically significant (Eliasziw and Donner 1991).

Literature shows a number of corner detectors, some of which are still considered state of-the-art as the one reported by(Harris and Stephens, 1988). A complete survey of corner detection algorithms could be found in (Zheng *et al*., 1999; Smith and Brady, 1997); here, a subset of these detection algorithms isanalyzed which includes Harris corner detector(Harris and Stephens, 1988), Smallest Univalue Segment Assimilating Nucleus (SUSAN) (Smith and Brady, 1997), Shi's detection algorithm(Shi and Tomasi, 1994); and some latest ones: Features from Accelerated Segment Test (FAST) (Rosten and Drummond, 2006) and Global and Local Curvature Points (GLC) (He and Yung, 2008).

In addition to find good detection algorithms, this paper also proposes hybrid corner detection algorithms based on the performance of individual detectors. These hybrid algorithms are assessed using same synthetic and digital image data that proves to be more powerful than working independently as is shown in the results section.

MATERIALS AND METHODS

In-order to collect detection results of corner detectors their responses were gathered individually on sufficiently large amount of synthetic and real image data. These images contained geometric shapes such as rectangle, triangle, pentagon, hexagon, star shaped polygons with different number of arms. The data was originally developed to identify the angular sensitivity of corner detectors and is publically available for research purpose (kanwal *et al.*, 2011a and kanwal *et al*. 2011b).

For performance evaluation, a detector's response was calculated for every corner point in each image; there were a total 2234 corner points in different images which were expected to be correctly detected by corner detectors along with non-corner pixels. Since actual locations of corner points in each image was available, corner detectors' responses were calculated and assessed by calculating the Euclidean distance of detected corner from its actual location. Responses from all detection algorithms under study were recorded and compared using McNemar's test (McNemar, 1947). It was used here because of its non-parametric nature, simplicity and reliability. The test was used in null hypothesis testing framework to find similarity in corner detection algorithms.

McNemar's test statistics involved recording two algorithms' classification results as corner or non-corner point for each image pixel. In order to apply the test using Eq: 2***sf*** and ***fs*** was counted as the number of times an algorithm's result was true or false such as

***sf*:** algorithm A's classification is correct while algorithm B's classification is wrong.

***fs*:** algorithm A's classification is false while algorithm B's classification is correct.

ss and ***ff*:** counts of the results where both algorithms either succeed or failed respectively.

Then Z is calculated as Eq. 2

$$Z = \frac{|sf - fs| - 1}{\sqrt{sf + fs}} \quad (2)$$

where the -1 is a continuity correction. According to the central limit theorem, Z should be reliable if *sf* + *fs*20 (Abdi, 2007). If algorithm A and algorithm B produce similar results, t $\gtrsim$ Z ≈ 0; as they differ, the value of Z increased and cross the significance level α. The beauty of this test was that it focused on the outcome where one detector passed and the other failed, contrary to other performance measures which consider only the outcomes where detectors succeed such as Accuracy, Precision *etc*.

For instance, if the detection responses of Algorithm A and Algorithm B on some images were counted as ***sf***= 162 and***fs***= 61 and used to determine the Z-score and hence the relative performances of the algorithms. Then the Z-score computed using Eq. 2 will be 6.69 $> Z_{crit}$ (Where Z_{crit}=1.96 for α = 0.05), giving 99.9%confidence that Algorithm A performed better than Algorithm B.

It was a well-known fact that performing multiple binary comparisons were likely to increase the family-wise error rate also known as Type - I error. This was the probability of falsely rejecting Null Hypothesis. One way to handle this problem was to adjust the level of significance based on a number of algorithms under study. A number of adjustments were suggested in the literature, one such correction was known as a Bonferroni correction (Abdi, 2007). According to this if α is the significance level for a family of tests, then each test should have been carried out with *α/m* level of significance. The Bonferroni correction adjusts alpha by dividing it by number of algorithms under study as shown in Eq. 3

α/m(3)

To reduce this Type -1 error while comparing the six corner detection algorithms here, α was adjusted as follows:

$$\frac{0.05}{6} = 0.008$$

For α = 0.008, Z_{crit} = 2.4; hence, a Z-score less than this value was considered insignificant; for example, a Z = 0.75 showed similar performance of algorithms being compared. Similarly, all six algorithms were compared in a similar way.

RESULTS AND DISCUSSION

McNemar's test not only focused on correctly classifying image pixels, but taken into account the total number of corners correctly identified in the imagery (Eliasziw and Donner, 1991). However, the best detector should also identify the maximum number of corners in an image, so the last column of Table-1 and Table-2showed the percentage of correct corners identified by each detector.

Figure-1 should be referred to visualize the detectors' results for both synthetic and real images. A low Z-score and high percentage of TP corners identified the best detector when compared with ground truth (Kanwal *et al*., 2011a; Kanwal *et al*., 2011b). From Table-1 and Table-2, Harris detector (Harris and Stephens, 1988) worked very well for synthetic images similar to (Mokhtarian and Mohanna, 2006) but for real, noisy images SUSAN (Smith and Brady, 1997) and FAST-12 (Rosten and Drummond, 2006) performed better than Harris detector (Harris and Stephens, 1988). Similarly, the same principle was applied to pair-wise comparisons of detectors. If both detectors detect a pixel as corner for which the ground truth image pixel is also a corner point, then both detectors pass, otherwise only one of them could pass; or both could fail if the ground truth image pixel is a non-corner pixel.

These pair-wise comparisons among detectors revealed similar results as generated while comparing detectors with ground truth, given in Table-3 and 4.

Table-1. Comparison of corner detectors with ground truth synthetic images of size 200 x 200. Algorithms are sorted by minimum Z-score and high % of TP corners.

Detector	***ss***	***ff***	***Sf***	***Fs***	**Z-score**	**% TP Corners**
Harris and Stephens	1793702	0	452	0	21.21	46.76%
FAST - 12	1791102	0	496	0	22.23	14.76%
SUSAN	1788947	0	504	0	22.41	51.20%
FAST-9	1791096	0	517	0	22.69	19.73%
GLC	1789622	0	556	0	23.54	48.89%
Shi and Tomasi	1792747	0	629	0	25.04	59.91%

Table-2. Comparison of corner detectors with ground truth real images. Algorithms are sorted by minimum Z-score and high percentage of TP corners.

Detector	***ss***	***ff***	***sf***	***fs***	**Z-score**	**% TP Corners**
FAST - 12	401214659	0	917	0	30.25	7.02%
SUSAN	401210830	0	974	0	31.18	7.56%
Harris and Stephens	401211691	0	1122	0	33.47	11.29%
FAST-9	401172872	0	1740	0	41.69	14.04%
GLC	401169192	0	2047	0	45.22	9.51%
Shi and Tomasi	401091955	0	3285	0	57.30	16.36%

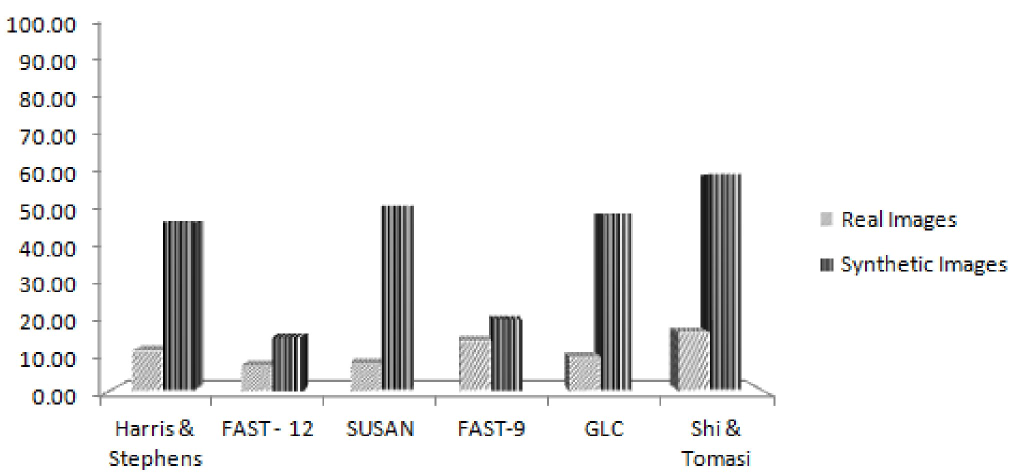

Figure-1: Percentage of corners detected in both synthetic and real images

Table 3. Pair-wise comparison of corner detectors for synthetic images using ground truth images. Z-score less than 2.4 was considered non-significant.

	SUSAN	**Shi and Tomasi**	**FAST-9**	**FAST-12**	**GLC**	**Score**
Harris and Stephens	←7.04	←6.90	←14.96	←18.74	←2.65	6
SUSAN		↑4.46	←14.77	←17.52	←2.61	4
Shi and Tomasi			←11.94	←14.80	1.71	4
FAST-9				←18.89	↑5.64	2
FAST-12					↑8.04	1
GLC					__	3

Table 4. Pair-wise comparison of corner detectors for real images using ground truth images. Z-score less than 2.4 was considered non-significant.

	SUSAN	Shi and Tomasi	FAST-9	FAST-12	GLC	Score
Harris and Stephens	1.51	←42.85	←17.48	0.74	←17.11	4
SUSAN		←33.85	←15.68	2.21	←18.67	4
Shi and Tomasi			↑14.85	↑32.35	↑14.81	1
FAST-9				↑4.99	←6.44	3
FAST-12					←19.81	4
GLC					__	2

For paired comparisons Harris detector(Harris and Stephens, 1988) worked very well for synthetic images but for real and noisy images SUSAN and FAST-12 performed better than Harris detector (Harris and Stephens, 1988) as indicated by the rankings presented inTable-3 and Table-4. Therefore, the applications where false responses could make a critical impact on the results FAST (Rosten and Drummond, 2006); and GLC (He and Yung, 2008) detectors should be avoided. These results suggested that some detectors were more powerful for noisy images than others; so combining them might give better results. The following tests were employed to explore this.

Different detectors have different principles of operation, and hence performed differently on the same images. Harris detector (Harris and Stephens, 1988); and Shi's detection algorithm (Shi and Tomasi, 1994) usedeign values to find corner and edge pixels, which appeared to be a more effective approach than mask-based methods like SUSAN (Smith and Brady, 1997); FAST (Rosten and Drummond, 2006). However, for real images, SUSAN (Smith and Brady, 1997); FAST (Rosten and Drummond, 2006) gave better performance, so it was logical to combine two detectors that worked differently to see whether overall performance on all kinds of images was improved. Based on individual performances on synthetic and real images, Harris detector (Harris and Stephens, 1988); and Shi's detection algorithm (Shi and Tomasi, 1994) were combined with other detectors and their combined performances were evaluated. The results are presented in Tables-5 and Table-6. These results indicated that combining either of these two detectors with GLC (He and Yung, 2008) lead to the detection of more corner points with fewer negative results, in both noisy real and noise-free synthetic images. The improvement in results using GLC (He and Yung, 2008) has come as a surprise because individually its performance was not even considerable as compared to others.

It was also interesting to see that combining Shi's algorithm (Shi and Tomasi, 1994) with GLC (He and Yung, 2008); or FAST (Rosten and Drummond, 2006) detected more corner points as compared to Harris detector(Harris and Stephens, 1988) even on synthetic images.

This analysis showed two important results; one was that hybrid detectors could produce algorithms which in turn could give better general performance in various applications; secondly the combination of detectors could not be predicted from individual performance analysis results.

As we have seen from Table-1 and Table-2 that highest corner detection rate was achieved using Harris detector(Harris and Stephens, 1988) and FAST-12 (Rosten and Drummond, 2006), however, the complementarity results revealed that the combination of Shi's algorithm with GLC worked best as shown in Figure-2.

Table 5. Combining Harris and Stephens with FAST, SUSAN and GLC Results are sorted according to minimum Z- score and high percentage of corners detected.

Detectors	Z-score for Synthetic Images vs GT	% of Corners Detected (Synthetic Images)	Z-Score for Real Images vs GT	% of Corners Detected (Real Images)
Harris and Stephens + GLC	21.19	59.91%	30.53	16.98%
Harris and Stephens + FAST-9	22.16	56.18%	30.71	16%
Harris and Stephens + SUSAN	23.11	52.36%	30.66	16.27%
Harris and Stephens + FAST-12	24.12	48.09%	31.03	14.22%

Table 6. Combining Shi and Tomasi with FAST, SUSAN and GLC; Results are sorted on minimum Z-score and high percentage of corners detected.

Detectors	Z-score for Synthetic Images vs GT	% of Corners Detected (Synthetic Images)	Z-Score for Real Images vs GT	% of Corners Detected (Real Images)
Shi and Tomasi+ GLC	20.74	61.6%	29.73	21.24%
Shi and Tomasi+ FAST-12	20.86	61.12%	30.22	18.67%
Shi and Tomasi+ FAST-9	20.98	60.71%	29.93	20.18%
Shi and Tomasi+ SUSAN	21.09	60.27%	29.79	20.98%

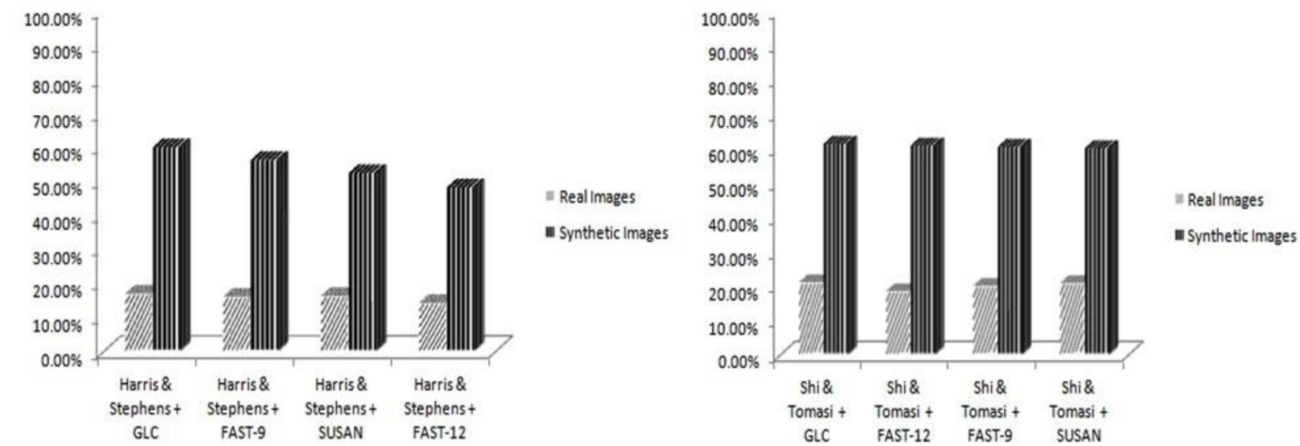

Figure-2. Improved percentage of corner detection using complementary detectors

Conclusion: The statistically valid performance evaluation of corner detection algorithms was presented in this study where the focus was to assess an algorithm for its failures as well as its success. The use of McNemar's test enabled to rank algorithms under study based on their corners' detection rate as well as for accurate categorization of non-corner image pixels. According to test results Harris detector, Shi's detection algorithm and SUSAN appeared to be the best detectors. The FASTdetector though could work very fast, but it should be classified as a feature detector but not agood corner detector. Likewise, combined detectors' results could be used to directresearch into hybrid corner detectors for more stable and reliable detection of corner points.

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