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A Comparison between Harris and FAST - Corner Detection of Noisy Images Using Adaptive Non-Local Means

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Abstract

In this paper a comparison between Harris and FAST (Features from Accelerated Segment Test) corner detection has been presented that is track features within a noisy images where it is a challenging task in the field of image processing. As long as noisy image does not give the desired results in corner detection, de-noising is required. Adaptive non-local means are applied for salt and pepper, Gaussian and speckle noise before applying corner detection. FAST corner detection outperformed Harris in detecting actual and exact number of corners and more robust to noise than Harris, the obtained results shown a good satisfaction in this study especially in the numbers of real detected corners.

Key words: Harris corner detection, FAST corner detection, non-local means, weight function.

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مقارنة بين هاريس و فاست للكشف عن الزاوية للصور التي تحتوي على الضوضاء باستخدام وسائل التكيف غير المحلية

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الخلاصة الم

في هذه الدراسة تم عرض مقارنة بين هاريس و فاست (مميزات من الاختبار الجزئي المعجل) للكشف عن الزاويا لتتبع الخصائص ضمن الصور التي تحتوي على الضوضاء حيث انها مهمة ليست باليسيرة في مجال معالجة الصور، حيث ان الضوضاء مشكلة شائعة في مجال معالجة الاشارة او معالجة الصور. طالما ان الصورة التي تحتوي على الضوضاء لا تعطي النتائج المرجوة او المتوقعة في كشف الزوايا ، لذلك فان عملية از الة الضوضاء من الصورة مطلوبة قبل الشروع بأي اجراء لكشف الزوايا. في هذا البحث المقترح تم تطبيق وسائل غير محلية تعالج ضوضاء الملح والفلفل و الضوضاء الغاوسي وضوضاء البقع قبل تطبيق الكشف عن الزاوية للحصول على صورة مقاربة للصورة الاصلية. النتائج التي تم الحصول عليها أظهرت رضى من ناحية تقارب اعداد الزوايا الحقيقية التي تم الكشف عنها بين الصورة الاصلية و الصور المعالجة بعد از الة الضوضاء منها كذلك بينت النتائج ان خوارزمية فاست تقوقت على خوارزمية هاريس من ناحية الكشف عن الزوايا الحقيقية و ايضاً تعمل بشكل افضل في البيئة التي تحتوي نسبة من الضوضاء.

الكلمات المفتاحية : هاريس للكشف عن الزوايا ، فاست للكشف عن الزوايا ، وسائل غير محلية ، دالة الوزن

Introduction

In human visual system, a corner nothing but another feature in the scene can be identified easily without any efforts. A corner is an intersection of two edges, the edge is the change in image brightness sharply. Also, a corner can be defined as an interest point and it can strongly detected. Interest point detection could be a recent nomenclature in computer vision that refers to the detection of interest points for future processing. Corner detection is important and used in many fields such as computer vision and pattern recognition like face recognition, in and motion detection by exploiting the advantages of matching points and in 3D reconstruction such as piecewise-planar [1] [2] [3].





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Many algorithms have been developed for corner detection and attracted many researchers for this issue. Corner detection is used in many application in real life like unmanned underwater vehicle (UUV), event-driven cameras and so on [4][5], so the need for such a technique is required. Mathematically, it is required an algorithms to successfully detect a corner. In 1977, Moravec presented one of the premature corner detection algorithms and defined a point with low self-similarity as a corner [6]. However, Moravec detector suffers from many problems, these problems are solved by Harris, 1988 with an algorithm based on Moravec's one [7]. Later, Edward Rosten and Tom Drummond proposed another algorithm named FAST for corner detection which is applied in real time applications [8]. The key point for any corner detection is the ability to detect the same corner in many images in different circumstances. One of the problems facing the corner recognition or detection is noise. Whereas noise is undesirable information in image or changing in image brightness or color or both. Image denoising is often used as a solution for degraded scene. Many types of noise exists in the field of image processing such as salt & pepper, Gaussian and speckle and these are the subjects in this paper. Non-local means for image de-noising will address noise issue with a cosine function acts as a weight function to improve the algorithm's efficiency and robustness. In this paper, a study Harris and FAST corner detectors will be present and provide an adaptive algorithm for noise problems that stand up to corner detection in noisy images and observe corners numbers before and after de-noising. Section 2 describes Harris corner detection. Whereas section 3 describes Fast corner detection. Concerning section 4, Non-local means for image de-noising are explained with an adaptivity by computing a cosine function (section 4.2) as a new weight function. Finally, section 6 gives the results of the images and tables obtained from the experiments.

Harris Corner Detection

Harris corner detection algorithm was proposed by Harris C and Stephens MJ 1988 [9]. Harris's detector is a well-known corner detector due its robust stability in image noise. The local autocorrelation function measures the variation of the intensity with window moved by a small amount in different directions given a shift (Δx , Δy) and a point(i, j) [10]. The auto-correlation function is defined as [9]:

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$$H(x,y) = \sum i, j w(i,j) [I(i+x, j+y) - I(i,j)]^2 \qquad ... (1)$$

where:

- w(i, j) is the window function.
- I(i,j) is the original intensity at (i,j).
- I(i + x, j + y) is the intensity at shifted window.

Harris coroner operator depends on high intensity for shifted window in order to detect the

corner. To do that, expanding the term form (1):

$$[I(i + x, j + y) - I(i, j)]^2$$

using Taylor series to have high result of H [10] :

$$H(x,y) = \sum i, j [I(i,j) + xIi + yIj - I(i,j)]^2 \qquad ... (2)$$

Simplifying the equation which can be expressed in matrix form:

$$H(x,y) = [xy] \left(\sum_{i,j} w(i,j) \begin{bmatrix} I_i^2 & I_i & I_j \\ I_i & I_j & I_j^2 \end{bmatrix} \right) \begin{pmatrix} x \\ y \end{pmatrix} \dots (3)$$

Then shortening the matrix and denote it to be M:

$$M = \sum_{i,j} w(i,j) \begin{bmatrix} I_i^2 & I_i & I_j \\ I_i & I_j & I_j^2 \end{bmatrix} \dots (4)$$

To be the equation:

$$H(\mathbf{x},\mathbf{y}) = [\mathbf{x}\,\mathbf{y}]\,M\begin{pmatrix}\mathbf{x}\\\mathbf{y}\end{pmatrix}\qquad\dots(5)$$

Calculation of measure of corner response by the following formula [11]:

$$R = \text{Det}(M) - k * \text{Trace}(M)^2$$
 ... (6)

where:

• Det $(M) = \lambda 1 \lambda 2$...(7)

• Trace
$$(M) = \lambda 1 + \lambda 2$$
 ...(8)

• *K* is empirical constant which is (0.04 - 0.06)

Note that H is closely related to the local autocorrelation function, let $\lambda 1 \lambda 2$ be the eigenvalues of H(x, y). As before, there are three cases to be considered, if both $\lambda 1$ and $\lambda 2$ are small, flat



...(7)



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area will occur, if λI is high and $\lambda 2$ is low or vice versa, an edge will appear and if both λI and $\lambda 2$ are high, a corner will be detected [7].

Fast Corner Detection

FAST (Features from Accelerated Segment Test) is a corner detector developed by Rosten and Drummondn in (2006) [12]. In real video application, FAST algorithm shows a good results in detection corners. The segment test standard run by taking into account a circle of sixteen pixels (Bresenham circle) around the corner candidate p [8].

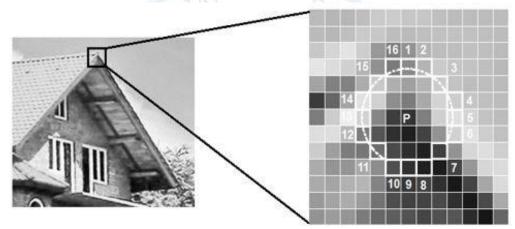


Figure1: Feature detection in an image patch using FAST detector

The algorithm nominates p is a corner whether or not a corner with the intensity of the candidate pixel Ip and a suitable threshold t. Now p is a corner if there is a set of contiguous pixels n of the 16 pixels of the circle as shown in figure (1) which are all brighter than Ip+t or all darker than Ip-t. Where n was chosen to be twelve (12 pixels seem as white dash line within the Figure (1)) as a result of it admits a high-speed take a look at which might be accustomed exclude a really sizable amount of non-corners [13].

The test checks only four pixels at 1, 5, 9 and 13 (at clockwise direction) where it checks first 1 and 9 if they are too brighter or darker, if so it checks 5 and 13. If p could be a corner, then a minimum of 3 of those should all be brighter than Ip+t or darker than Ip-t. If neither of those is that the case, then p can't be a corner. Although, the algorithm demonstrate a high effectiveness but there are several weaknesses. The high-speed test don't reject as several candidates for n < 12. The choice of pixels isn't best as a result of its potency rely on ordering of the queries and



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distribution of feature (corner) appearances. Results obtained the tests are forsake. Many features are observed contiguous one to another [13]. Machine learning approach is given to handle initial 3 points whereas the last one is handled by non-maximal suppression. For each pixels $(p \rightarrow x)$ of the 16 pixels can have on of the following states:

$$S_{p \to i} = \begin{cases} d, & I_{p \to i} \leq I_p - t & (darker) \\ s, & I_p - t < I_{p \to i} < I_p + t & (similar) \\ b, & I_p + t \leq I_{p \to i} & (brighter) \end{cases}$$

Using the ID3 algorithm (decision tree classifier) to question every 16 pixels using the variable K_p for the most information concerning verity pixel [13]. A score function *C* has been computed, where *C* is the sum of absolute difference between *p* and 16 surrounding pixels values. *C* is generated by [14]:

$$C = max \left(\sum_{i \in S_{bright}} \left| I_{p \to i} - I_{p} \right| - t, \sum_{i \in S_{dark}} \left| I_{p} - I_{p \to i} \right| - t \right) \qquad \dots (9)$$

Non-local means

Non-local means presented by Antoni Buades in (2005) [15].Unlike other methods which attempts to isolate the image into smooth part (original image) and wavering part (noise) by excluding the higher frequencies from the normal frequencies, non-local means depend on the advantageous of self-similarity [16].

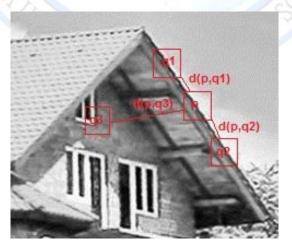


Figure2: scheme of non-local means.



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As shown in figure (2), the neighborhoods of patch P are similar to the patches q1 and q2 which will have a large weight d(p,q1) and d(p,q2) while patch q3 will have a small weight d(p,q3) because adjacent pixels inclined to have similar neighborhoods. Next a discrete description will be given for the algorithm since the image is considered as discrete grid *I*.

Description

Given a discrete noisy image $n = \{n(x) \mid x \in X\}$, each pixel *x* of the NL-means de-noised image in computed with [17]:

$$NL[n](i) = \sum_{y \in X} d(x, y)n(y)$$
 ... (10)

where *n* is the noisy image and the weight d(x, y) rely on the similarity between pixels *x* and *y*, and the weight fulfil the next stipulation $0 \le d(x, y) \le 1$ and $\sum_y d(x, y) = 1$ [18]. To compute the similarity between two neighborhoods and take the weighted Euclidean distance $||n(K_x) - n(K_y)||_{2,a}^2$ where a > 0 is the standard deviation of the Gaussian kernel. The weighted sum of square difference between the neighborhoods give us the following formula [19]:

$$E||n(K_x) - n(K_y)||_{2,a}^2 = ||u(K_x) - u(K_y)||_{2,a}^2 + 2\sigma^2 \qquad \dots (11)$$

The weights then can be defined by the following formula [18]:

$$d(x,y) = \frac{1}{G(x)} e^{-\frac{||n(K_x) - n(K_y)||_{2,a}^2}{h^2}} \dots (12)$$

where G(x) is the normalization constant and defined as:

$$G(x) = \sum_{y} e^{-\frac{||n(K_x) - n(K_y)||_{2,a}^2}{h^2}} \dots (13)$$

and h is the weight decay of exponential function control parameter.

Proposed Method

In the original non-local means algorithm, to make the neighborhoods with similar texture gets a larger weight, it uses the exponential function [17]. In this paper, cosine function is used and expressed as:



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$$f(x) = \begin{cases} \cos\left(\frac{\pi x}{2h}\right) & 0 < x \le h \\ 0 & else \end{cases}$$
... (14)

By analyzing the exponential function and the cosine function, a new weight function is achieved:

$$d(x,y) = \frac{1}{G(x)} e^{-\frac{||n(K_x) - n(K_y)||_{2,a}^2}{h^2}} f(x) \qquad \dots (15)$$

Where $G(x) = \sum_y e^{-\frac{||n(K_x) - n(K_y)||_{2,a}^2}{h^2}} f(x)$

Furthermore (C. Tomasi et al) proposed bilateral filtering, bilateral filtering change the intensity of each pixel with the closest neighbor pixel [20]. The size and contrast plays an important role in preserving features in the processed image which the filter rely on them .Also, the weights of this algorithm is depended on Euclidean distance. In this way, the edges, corners and some other details preserved efficiently. The bilateral filter is defined as [20]:

$$BF(i) = \frac{\sum_{(x,y)\in X} D_s(x,y) D_r(x,y) z(y)}{\sum_{(x,y)\in X} D_s(iC(x,y),y) D_r(x,y)} \dots (16)$$

$$D_{s} = \exp\left(-\frac{||n(K_{x}) - n(K_{y})||_{2,a}^{2}}{2h_{r}^{2}}\right) \qquad \dots (17)$$

$$D_r(x,y) = \exp\left(-\frac{|n(y) - n(x)|^2}{2h_r^2}\right) \qquad \dots (18)$$

where $|n(y) - n(x)|^2$ is the gray distance of pixels x and y which gives the effect of weighting function variation in pixels gray. The parameter h_s represent the size of the neighborhood pixels used to filter other pixels whereas h_r indicate how many an adjacent pixel is weighted because of the intensity variance. According to what is mentioned above, a proposition of new weighting function expressed as:

$$d(x,y) = \frac{1}{G(x)} e^{-\frac{\left|\left|n(K_x) - n(K_y)\right|\right|_{2,a}^2}{h^2} f(x) D_s(x,y) D_s(x,y)} \dots (19)$$

where $G(x) = \sum_{y} e^{-\frac{\|[n(K_x) - n(K_y)]\|_{2,a}^2}{h^2} f(x) D_s(x,y) D_s(x,y)}$



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The proposed method is sketched in figure (3) below depending on the new weight function in equation (19), the steps of the proposed method is briefed as:

Step1. Load noisy image.

Step2. Apply Adaptive Non-local means



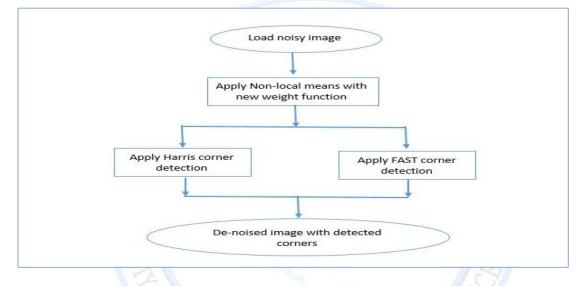


Figure3: Scheme for corner detection of De-noised images

Results

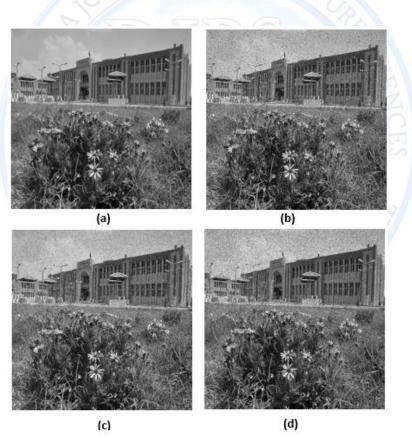
This section presents the results of the proposed method. The model shows a good result in the numbers of detected corners after eliminating the noise from them by using adaptive non-local means. Three types of noise are used salt & pepper with 0.05 noise density, Gaussian with zero mean noise with 0.01 variance and Speckle with default variance 0.04 and 0 mean to the original image of 512*512 sized grayscale image as shown in figure (4). In the original image, corner detected using Harris 475 corner whereas with FAST 4362 corners and then the detection of corners is carried out for the three types of noise, the results are shown in table (1).

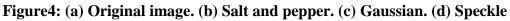


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Table (1): Number of corners detected in the original image, noised images and denoised images in the case of Harris detector and FAST detector.

Filter type		Non-local means with new weight function		
Corner method		Harris	FAST	
Original Image		475	4362	
Salt and peppers	Noised	1222	12570	
	De-noised	470	6434	
Gaussian	Noised	609	12090	
	De-noised	273	4721	
Speckle	Noised	660	9449	
	De-noised	259	4157	





The next step is to eliminate the noise form the images corrupted previously of the three types salt & pepper, Gaussian and speckle respectively, see figure (5).

f Noisy

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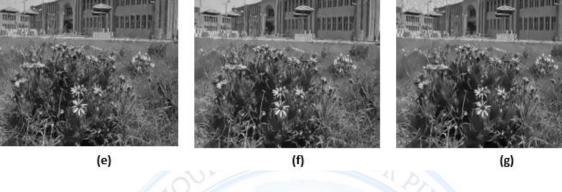


Figure5: (e) De-noised Salt and pepper. (f) De-noised Gaussian. (g) De-noised Speckle.

Harris and FAST corner detection is done in order to obtain the final results of the work, the numbers of corners detected for both cases is shown in table (1) and figure (6) and figure (7). As shown in table (1), the desired numbers of corners is obtained from the de-noised images and it is close to the numbers detected in the original image.

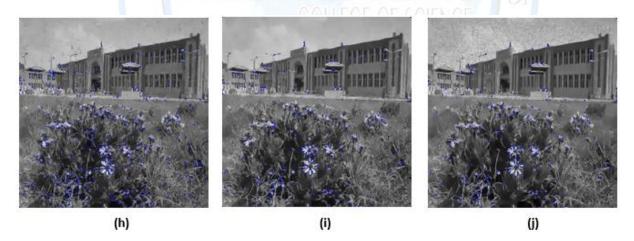


Figure6: (h) Harris Salt and pepper. (i) Harris Gaussian. (j) Harris Speckle.



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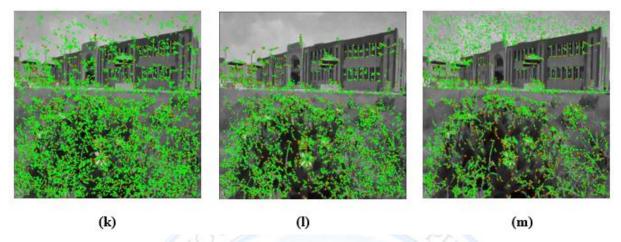


Figure7: (k) Fast Salt and pepper. (l) Fast Gaussian. (m) Fast Speckle.

To support the work, three measures are used in order to evaluate it, the measures are peak signal to noise ratio (PSNR), mean squared error (MSE) and the structural similarity index (SSIM) [21] [22]. MSE measures the <u>average</u> of the squares of the <u>errors</u>, that means the difference between the noisy image and the original image and it can be defined as [21]:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [u(i,j) - v(i,j)]^2 \qquad \dots (20)$$

PSNR is the ratio between power of a signal and the power of corrupting noise that affects the image. It can be defined as [21]:

$$PSNR = 10 * log_{10} \left(\frac{MAX_i^2}{MSE}\right) \qquad \dots (21)$$

where MAX_i^2 is the maximum value of pixel in image. Also SSIM is used for measuring the similarity between two images, it can give a ratio similarity between original image and any processed image and it can be expressed as [22]:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1) + (2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1) + (\sigma_x^2 + \sigma_y^2 + c_2)} \qquad \dots (22)$$

The results of MSE, PSNR and SSIM are shown in table (2).



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Table (2): MSE, PSNR and SSIM values of de-noised images of the three types on noise

Noise type	Proposed Non-local means		
	MSE	PSNR	SSIM
Salt and pepper	8.87	38.68dB	0.8162
Gaussian	10.91	37.78dB	0.8583
Speckle	13.11	36.98dB	0.8529

Based on the results obtained from table (1), FAST corner detection shows better results than Harris corner detection in finding the actual numbers of corners in Gaussian and speckle noise cases while Harris corner detection surpassed FAST in salt and pepper noise case. In addition, FAST corner detection performs in more flexible ways than Harris in noisy environments, in other words FAST is more robust to noise than Harris. In table (2), PSNR values compared to MSE values demonstrates that the new weight function for non-local means gives the desired results, also SSIM values shows a good matching between original image and de-noised image of the three types of noise subjected in this work.

Conclusion

In this paper, adaptive non-local means plays an important role in image de-noising for images including salt & pepper, Gaussian and speckle noise. FAST corner detection has superior over Harris in detecting actual and precise number of corners. FAST corner detection is more robust to noise than Harris. The proposed weight function shows a good results in number of corners detected by de-noised images is roughly equal to the same number of Harris and FAST corner detected for obtained corner from the original image especially in the case of Gaussian and speckle for FAST noise and salt & pepper noise for Harris using the new weight function in Non-local means algorithm. MSE and PSNR indicates relief values of high PSNR and low MSE for de-noised images and the similarity between original image and de-noised images estimated using SSIM after de-noising salt and pepper, Gaussian and speckle noise from corrupted images was 81%, 85% and 85% respectively. The plane for future work is to minimize computation burden of FAST and Harris algorithms in motion scene.



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