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A method to improve corner detectors (Harris, Shi-Tomasi & FAST) using adaptive contrast enhancement filter

Haydar Abdulameer Kadhim[1], Waleed Abdullah Araheemah[2]
[1,2] Middle Technical University, Technical College of Management

ABSTRACT

A method to improve interested-points detectors in an image that suffers from the problem of illumination was conducted in this paper. Three algorithms are adopted based on Harris, Shi-Tomasi, and FAST algorithms to identify the interested-points in images that are required to match, recognize and track objects in the digital images.

Detecting the interested-points in images with bad illumination is one of the most challenging tasks in the field of image processing. The illumination is considered as one of the main causes of damage of the natural images during the acquisition and transition. Detecting the interested-points of these images doesn't give the desired results, which is why handling this problem for those images is very important. The Adaptive Contrast Enhancement Filter approach is applied for solving this problem.

Keywords: Harris Detector, Shi-Tomasi Detector, FAST Detector, Adaptive Contrast Enhancement Filter, Illumination

Corresponding Author:

Haydar Abdulameer Kadhim,
Middle Technical University, Technical College of Management, Baghdad, Iraq
Phone: +9647831156716
E-mail: diwani19842015@gmail.com

1. Introduction

Corners or Interest-Point is a point which consists of the intersection of two or more edges in a local area in the image, also can be defined as two directions of dominant and different edge. An edge represents a significant change in image contrast. Interest-Points detection is a methodology that is used in systems of computer vision like pattern recognition such as object recognition, motion detection through matching points' advantages and 3D reconstruction to get specific features from a certain image [1-3].

The concept of the first algorithm for Interest-Points Detection in an image can be used to find a matching region in two images or more, produced by Chris Harris and Mike Stephens in 1988 when improving Moravec detector. The second algorithm is Detector of Shi-Tomasi, which has been produced by Jianbo Shi and Carlo Tomasi in 1994, with a minor modification to the algorithm of Harris. The third algorithm is FAST Detector. This detector is used to identify specific interest points and using them to track objects in many tasks of Machine vision, produced by Rosten and Drummond in 2006. The most optimistic feature of the FAST detector is its computational efficiency.

One of the most popular ways to handle the problem of illumination is Histogram Equalization. This method is considered to be one of the least efficient methods in the treatment of the problem of contrast because the resulting image appears with dimmer colors. Contrast Enhancement Filter approach provides the solution and good result [4].

Several studies for corner detection can be found in the literature. The publication of [5] can be considered as the widely used reference for the detection of the corners. It depends on the eigenvalues of the matrix of the second moment [5].

Lindeberg in 1998, proposed the concept of selection of the automatic scale. This will lead to the detection of interest points in an image, for each of them has its own characteristic scale. He experimented with both the determinant of the Laplacian matrix as well as the Hessian matrix (that corresponds to the trace of the Laplacian matrix) to identify blob-like structures [6].

Mikolajczyk and Schmid in 2001, refined the method of Lindeberg, while creating interested-points detectors with more powerful, scale-invariant and high repeatability, which crafted Hessian-Laplace & Harris-Laplace. They used a scale-adapted Hessian matrix determinant or Harris to select the location, and the Laplacian to determine the scale [7].

in this study, the filter of the adaptive contrast enhancement has adopted to deal with the problem of the illumination in all images. The enhanced algorithms show good results compared with the original algorithms.

2. Harris detector

This detector is considered a good detector of the interest-points because has strong stability in noisy images. It identifies small image corrections (windows) that produce significant differences in the density when the window moves in both directions (a) and (b). The auto-correlation function measures the variance of the intensity with the window moving slightly in more than one direction with a shift (Δm, Δn) and a point (a, b). it is possible to define the Auto-correlation function as [8]:

$$X(u,v) = \sum a,b\, z(a,b)[I(a+u\,,b+v\,) - I\,(a\,,b\,)]^2 \qquad (1)$$

Where,

z (a , b) is window function .

I (a, b) stands for original intensity.

$I(a+u, b+v\,)$ is intensity for shifted window.

Harris algorithm depends on the intensity when the window is shifted in order to identify the interest-points. This is done by expanding the equation (1):

$[I(a+u, b+v\,) - I\,(a\,,b\,)]^2$

Using Taylor series:

Taylor Series $T\,(a,b) \cong \mathrm{X}(\,\mathrm{u}\,,\mathrm{v}\,) + \,(\,\mathrm{a}-\mathrm{u}\,)\mathrm{h_a}\,(\mathrm{a}\,,\mathrm{b}\,) + \,(\,\mathrm{b}-\mathrm{v}\,)\mathrm{h_b}\,(\,\mathrm{u},\ \mathrm{v}\,) + \,...$

To get good score of (X) [9] :

$$\mathrm{X}\ (\mathrm{a},\mathrm{b}) = \sum a,b\, [I(a,b)\, + uIa + vIb - \,I\,(a\,,b)]^2 \qquad (2)$$

We can write the formula in array form:

$$X\,(\,u,v\,) = [\,u\ v\,]\left(\sum\nolimits_{x,y} H(a,b)\begin{bmatrix} I_a^2 & I_a\ I_b \\ I_a\ I_b & I_b^2 \end{bmatrix}\right)\begin{pmatrix} u \\ v \end{pmatrix} \qquad (3)$$

Shortening the array to be (W):

$$\mathrm{W} = \sum\nolimits_{a,b} H(a,b)\begin{bmatrix} I_a^2 & I_a\ I_b \\ I_a\ I_b & I_b^2 \end{bmatrix} \qquad (4)$$

The formula can be expressed as:

$$X(u, v) = [u\ v]\ W \begin{pmatrix} u \\ v \end{pmatrix} \quad (5)$$

By the following equation, it is possible to compute the measured response of the interest-points [10] :

$$R = \text{Det}(W) - K\ (\text{Trace}(W))^2 \quad (6)$$

Where,

Det (W) = $\lambda1*\lambda2$, Trace (W) = $\lambda1 + \lambda2$

$\lambda1$ and $\lambda2$ are eigenvalues of (W), and (K) is a constant between (0.04 – 0.06)

Based on the value of R, the window can be classified as flat, edge, corner, or others. A big value of (R) indicates a corner ($\lambda1$ and $\lambda2$ are top), while a small value of (R) indicates an edge ($\lambda1$ is top and $\lambda2$ is a button) [11].

3. Shi-Tomasi Corner detector

A detector of Shi-Tomasi is entirely based on the Harris detector. There is only one difference in a "selection criteria" which recognizes the (Shi-Tomasi) detector on the Harris detector. This detector works well even where the detector of Harris is not successful [12].

Harris detector has the criteria for identifying the Interest-points. It computes the degree for all pixels, and then compares the degree with a certain value, if the degree is above the value, then the point is a corner. (R) Value is computed by two eigenvalues. That is, two eigenvalues are given to a function. The function handled them and returned the result.

Developers of this detector suggested that the function should be disposed of. The eigenvalues are only used to test the candidate pixel of whether or not it is an interest-point.

The score of R in the Harris detector was computed as:

$$R = \lambda1 * \lambda2 - (\lambda1 + \lambda\ )^2$$

For Shi-Tomasi, it's computed according to:

$$R = \text{Minimum}(\lambda1,\ \lambda2) \quad (7)$$

Shi- Tomasi practically proved that this criterion of the outcome was much better. Comparing (R) value with a certain value, if it is greater, then it can be classified as an interest-point. Therefore, the area of the effect for a point which might be an interest-point has been illustrated in the following figure:

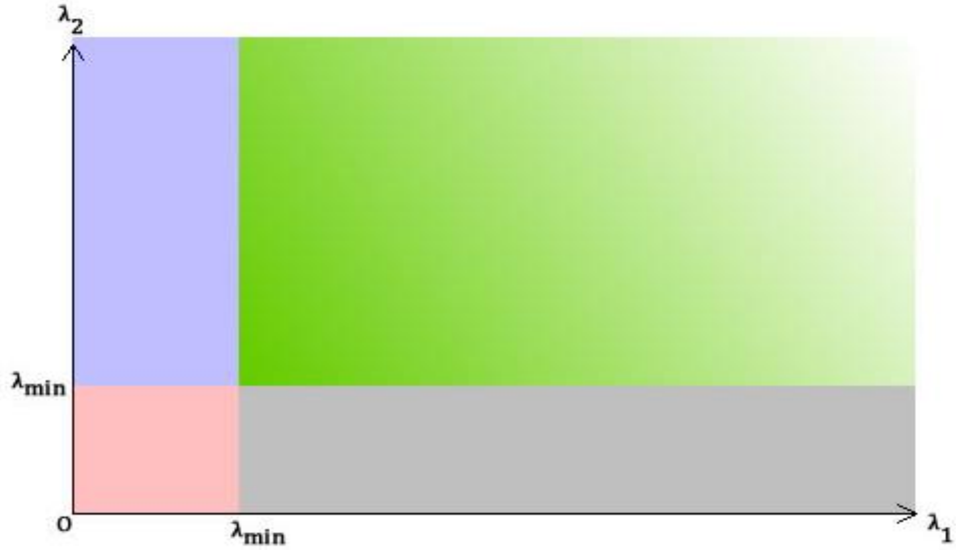

Figure 1. Effect area for any point to be interested-point

- Green: λ_1 and λ_2 are greater than a certain value. So, this region of pixels is "selected" as an interest-point.
- Blue and gray: One of the eigenvalues is less than its certain predefined value.
- In the area of the red: both eigenvalues are less than a certain predefined value.
  By Comparing this figure with the Harris detector algorithm. Blue and gray areas are equal to the edges area, the red area is for the "flat". And the green area is for the interest-point [12].

4. FAST detector

A detector for the interest-point detection was produced by Rosten and Drummond in 2006. In the field of real videos such as SLAM on a mobile robot, FAST detector gives good results in detecting the Interest-points. The standard test segment of the image by Bresenham circle stands for a circle of 16 pixels around the candidate pixel (p) [13].

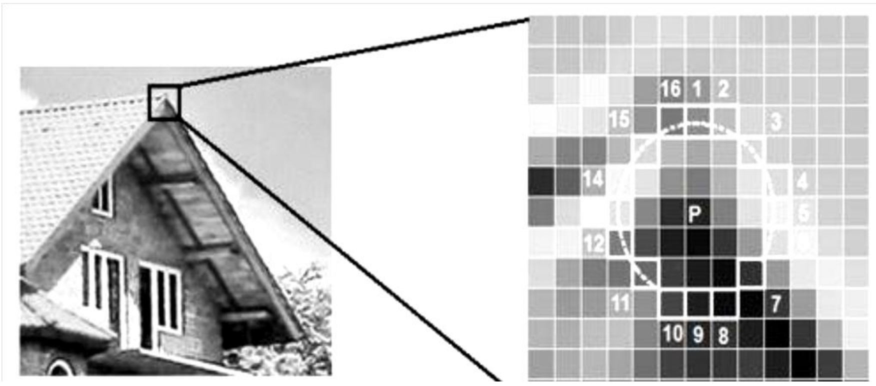

Figure 2. Circle of the 16 pixels around Candidate pixel

The algorithm steps can be described by the following:

1. Select any pixel-point (p) in an image. Assume the intensity (I) for the pixel-point (p), which is to be a candidate as an interest-point or otherwise.
2. Set the threshold intensity value (T), (make it 25% of the pixel value)
3. Draw a Bresenham Circle around the candidate pixel which is a circle of 16 pixels (with radius = 3).
4. The N adjacent pixel-points out of the circle must be brighter than (threshold + I) or darker than (I – Threshold), to be selected as an interest-point. (Frequently used N = 12) .
5. Initially, test the intensity of pixels (I1, I5, I9, and I13) of the circle (clockwise) and compare them with (I). As shown in Figure 2, to be the detector faster, it must be at least three of four pixels to satisfy the criterion of threshold (T). Consequently, the interest-point will be detected.
6. First, test (I1 and I9) pixels if they are darker or brighter. If so then test (I5 and I13). To be pixel point (p) an interest-point, it must be a minimum (3) of (4) pixels which are brighter than (I+ threshold) or darker than (I – threshold). If neither of those, the pixel point (p) isn’t an interested-point.
7. Repeat the steps for each pixel point [14].

There is a tow disadvantages with this algorithm. First, when (N) is less than 12, the algorithm does not work well because the results of the detected interest-points will be too many. Secondly, the arranging, in which the 16 pixels are queried and this limits the speed of the algorithm.

To handle these challenges, an approach of machine learning has been additive to the (FAST) detector [15].

5. Adaptive contrast enhancement filter (ACEF)

This filter is considered one of the most widely used methods in image processing, where the filter is applied on all elements of the image. For instance, the image is a one unit, and this method is called as the (Global Enhancement). Nevertheless, some applications doesn't meet the global treatment of the required results, so they are resorted to the local processing, where the image is divided into small parts (Sub Images) and then the filter is applied to each window. This is called the local enhancement, and in general, the image is improved in this way based on public and private variables and are applied to the image, Where the image rate is calculated by adding the value of each element in the image and then dividing the result by the total number of elements, then finding the standard deviation of the image and calculating the sum of the difference between the value of the element and the image rate and then dividing it by the number of elements minus one and taking the square root of the result. The enhancement equation is based on two variables (a1, a2) and its value ranges from (0 to 1), and then, the enhancement equation is applied to all points of the image to get the new image.

The difference between the general and the local enhancement is that the local enhancement is done by selecting a window size that represents the size of a specific segment in the original image and treating each segment as a separate image, then the window is crawled. The image is divided into equal parts. Each part is a window of any size and the windows are processed sequentially. This is done by cropping each window by one pixel, and the cropping is from left to right and from top to bottom, and then the processing result is placed in the middle pixel in the window and so on until the entire image is processed [15].

6. Proposed Method

The projected method includes applying the adaptive contrast enhancement filter on the images based on Figure 3. Then, applying one of the algorithms is done to detect corners, computing the number of corners and time consumption for each algorithm and comparing the results with the original algorithms.

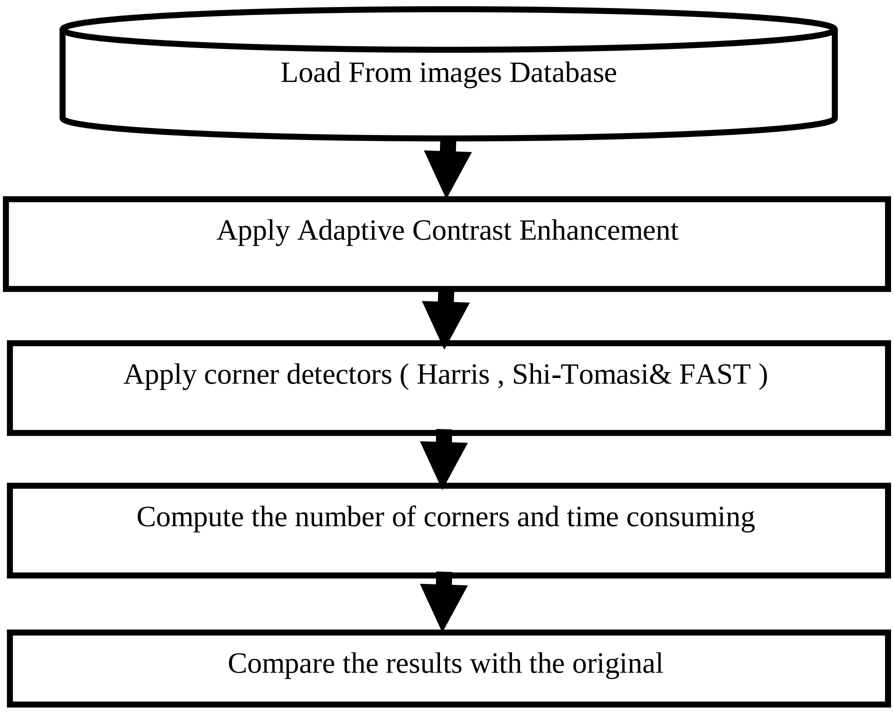

Figure 3. The diagram for the proposed method

7. Results

As shown in Figure 4, four types of images (Lena, Peppers, Cameraman and Baboon) have been used. Applying the algorithms of Harris, Shi-Tomasi and FAST on original Images and applying this algorithm on images after enhancing it by the Adaptive Contrast Enhancement filter, the enhancement of Harris, Shi-Tomasi and FAST methods show good results compared with the original algorithms. The results are shown in the table below.

Table 1. The detection of the corners by three detectors in the original image, and after enhancement by the adaptive contrast enhancement

Type of filter		Adaptive contrast Enhancement					
Type of detector		Harris		Shi-Tomasi		FAST	
		No.	Time	No.	Time	No.	Time
Lena	Original	221	0.99s	641	0.67s	149	0.55s
	Enhanced	252	0.29s	1089	0.27s	450	0.25s
Peppers	Original	173	0.38s	1461	0.83s	155	0.29s
	Enhanced	218	0.35s	4475	0.40s	460	0.31s
Cameraman	Original	376	0.43s	1890	0.47s	309	0.41s
	Enhanced	1265	0.34s	2748	0.35s	1562	0.30s
Baboon	Original	2304	0.85s	5565	0.77s	1778	0.53s
	Enhanced	3292	0.35s	6689	0.35s	7265	0.31s

where, No.: The number of corners that have been extracted by the algorithms.

Time: The time consumption of the process of extracting the corners.

The used execution algorithms are based on MatlabR2019a by using a laptop (HP model) with a system type of 64 bit, processor of 2600 corei5, and random access memory of 4 GB.

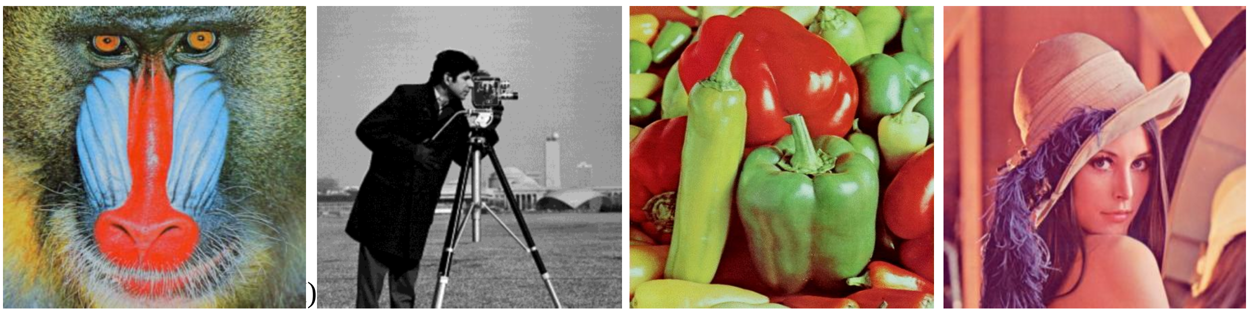

Figure 4. (I) Lena Image. (II) peppers image (III) cameraman image(IV) Baboon image

Then enhancing the images which suffer from the problem of the contrast by using the filter of (Adaptive contrast enhancement), as shown in figure (4).

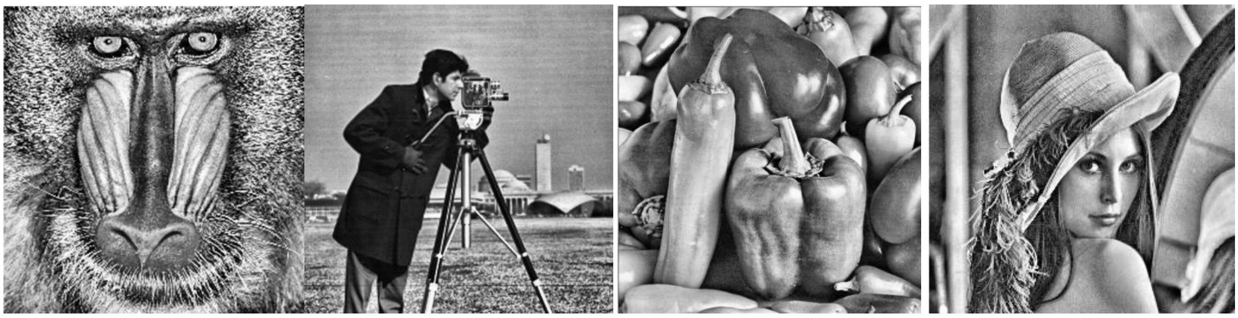

Figure 5. (V) enhanced Lena. (VI) enhanced Peppers(VII) enhanced Cameraman (VIII) enhanced Baboon

Harris, Shi-Tomasi and FAST corner detection is done in order to get the conclusive results of the study. Corners that have been detected by all detectors are shown in Table (1), where the corners (i.e., the interest-points) are obtained from the original images and after handling the problem of the contrast of this image. The proposed method showed good results compared with the original-algorithms.

Based on the results obtained from Table 1, the original Harris detected (221) corners in Lena-image with time consumption of (0.99s), while the enhanced Harris with the same image has detected (252) corner with time consumption of (0.30s). The original Shi-Tomasi detected (641) corners in Lena image with a time consumption of (0.67s), while the enhanced Shi-Tomasi detected (1,089) corners in the same image with a time of (0.27s). The original FAST detected (149) corners with time of (0.55s) and enhanced FAST detected (450) corners with time consumption of (0.25s), and so on. With number of corners more than original and lees time consumption in enhanced algorithms, the Shi-Tomasi detected the highest number of the corners with (6,689) in Baboon image, while the enhanced FAST recorded the lowest time of (0.25s) in Lena image.

8. Conclusions

Via this study, the filter of the adaptive contrast enhancement is considered one of the most commonly applied filters which play a valuable role to deal with the problem of the illumination in all images. The enhanced algorithms show good results compared with the original algorithms.

The enhanced Shi-Tomasi detector has provided better results than the enhanced (FAST & Harris) in detecting the corners. The enhanced FAST detector has provided better results than the enhanced (Harris & Shi-Tomasi) detectors in the criteria of time consumption.Accordingly, it is good to be used in real-time applications).

All enhanced algorithms in all used images were better than the original images through the number of the corner and time consumption for the implementation.

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