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Improvement of Harris Algorithm Based on Gaussian Scale Space

Abstract- *Features is the description of the image contents which could be corner, blob or edge. Corners are one of the most important feature to describe image, therefore there are many algorithms to detect corners such as Harris, FAST, SUSAN, etc. Harris is a method for corner detection and it is an efficient and accurate feature detection method. Harris corner detection is rotation invariant but it isn't scale invariant. This paper presents an efficient harris corner detector invariant to scale, this improvement done by using gaussian function with different scales. The experimental results illustrate that it is very useful to use Gaussian linear equation to deal with harris weakness.*

Keywords: Difference of Gaussian, Harris corner detection.

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1. Introduction

An edge is determined by an abruption in values of gray level. Edges are set by considering the ratio of brightness variation (or gradient) in a specific trend. Corners are local points of where there is a high rate of change in more than one direction or the intersection pixels of object edges. Corners described as robust features because they can be found accurately with existing noise or change the condition of image acquisition, e.g. varying light. Detection of corner useful for many applications, e.g. objects tracking. Other properties of corners are the orientation can keep track of simply and useful for matching multiple images [1].

Corners retain the important feature information of objects; at the same time it effectively reduces the amount of data information; therefore corner detection plays a very important role in image processing and pattern recognition. Corner detection methods can be essentially divided into two class: corner detection methods depend on the edge and corner detection methods depend on the gray variety. The first one, get the image edge chain code, according to the difference between adjacent code values to determine whether it is a corner, the abuse of method is a large amount of calculation and process unsteadiness. The second one, calculate the curvature and gradient, the most representative algorithms for corner detection are Moravec, Harris, SUSAN [2].

The most popular interest point operators are the Harris corner detector. the Harris corner detector is a suitable starting point for the computation of positions of scale and affine invariant features [3].

Harris detector, proposed by Harris and Stephens, is based on the second-moment matrix (the auto-correlation matrix), which is used for feature detection of local image structures. The Harris corner proved to be the most repeatable and most informative algorithm. In addition, sub-pixel precision can be achieved through a quadratic approximation of the function of the corner in the neighborhood of a local maximum [4].

In this paper section, 2 presents some works that have similar objectives for this work. In section 3 traditional Harris corner detection method has been discussed briefly. Section 4 present Harris as scale-invariant corner detection. Section 5 discusses and presents some of the experimental images.

2. Related Work

Various survey for Harris corner detector can be found, in literature below some of those which are most related to the present work:

In **2009**, Pedram Azad, Tamim Asfour, and Rüdiger Dillmann present a combination of the Harris corner detector and the SIFT descriptor, which computes features with high repeatability and very good matching properties. Scale-invariance can be achieved without a time-consuming scale space analysis [3]. In **2009**, Yu et al. extend Harris and use hessian matrix which is more stable in scale space than Harris matrix. The detector has high precision, and less wrong points can be detected [5]. In **2012**, Wang et al. created three scales of the image using Gaussian function and use the Harris algorithm to get a corner from each scale. The method could remove the noised corners and most of the unstable corners effectively, and extracted the

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corners with the characteristic of scale invariance [6]. In **2012**, Mahesh, and M.V.Subramanyam compare the performance of SUSAN, Harris, and propose an invariant corner detection algorithm using steerable filters and Harris corner detection. Experimental results show that the proposed method is robust to rotation and scaling invariant [7]. In **2016**, Peng et al. present a significant region detection algorithm to improve corner detection performance. Experimental results show that the detection algorithm is more quickly and reasonable [2].

3. Gaussian Scale Space

Gaussian linear filter can be used as blurring the image and sharping the image. The Gaussian smoothing operator is used to blur images and remove unwanted detail and noise that created using a Gaussian function. Gaussian function depends on mean value and variance. Gaussian function requires an infinite window length since it decays rapidly [8].

Difference of Gaussian (DoG) is a common approximation to Laplacian of Gaussian (LoG) operator and they are very important basic image transforms. Equation (1) defined a centred Gaussian function G_σ (i.e. with zero-mean $\mu_x = \mu_y = 0$):

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (1)$$

Where,
$\pi = 3.14$, σ = sigma = 0.8,
x and y represent scale of Gaussian window.

For a scaling factor $k > 1$, we can step from the smoothed image $L(x, y, \sigma)$ to $L(x, y, k\sigma)$. By using repeatedly scales $k^n * \sigma$, for an initial scale σ and $n = 0, 1, \ldots, m$, we create a set of subsequent layers of a Gaussian scale space. The DoG is defined by an initial scale σ and a scaling factor $k > 1$ as follows:

$$D_{\sigma,k}(x, y) = L(x, y, \sigma) - L(x, y, k\sigma) \quad (2)$$

where
$L(x, y, \sigma)$ is blured image comes from the convolution of the image with Gaussian filter at scale σ,
$L(x, y, k\sigma)$ is blured image comes from the convolution of the image with Gaussian filter at scale $k*\sigma$.

It is the difference between a blurred copy of the image I and an even more blurred copy of I. with $k = 1.6$ as a recommended parameter for approximation. Due to this approximate identity, DoGs are used in general as time-efficient approximations of LoGs. Different scales σ produce layers $D_{\sigma,k}$ in the DoG scale space [9].

4. Harris Corner Detector

Harris Corners Detector is one of the most commonly used feature-based algorithms, it is used to detect the common points (Interest Points) in the image, these points (Corners) have a large intensity variation between the directions around [10]. Harris algorithm can be recognized by calculating the gradient of each pixel. The pixel can be taken as a corner if the absolute gradient values in two directions are both mighty [11].

Harris corner detection detects corners by essentially employing gray information. Harris is widely used due to easy calculation, corners extraction ideal and high steadily, although there are restrictions, such as it is suffering from a loss in accuracy of localization [2].

The Harris corner detector method supposes that maxima of the local function represent corner. The calculation depends on first derivatives, therefore, Harris is less sensitive to noise. Harris corner detector calculates the value of each pixel in the image *I(x, y)*. Harris calculates R (the corner value) from the intensity gradient in the two direction x and y, M matrix describes the autocorrelation measure:

$$M = \sum_{x,y} W(x, y) \begin{bmatrix} \mathrm{Ix}^2(x) & \mathrm{IxIy}(x) \\ \mathrm{IxIy}(x) & \mathrm{Iy}^2(x) \end{bmatrix} \quad (3)$$

Where I_x and I_y denote the first derivative of the point I(x, y) (pixel intensity) in the image according to x and y trends. The derivatives are defined by convolving the image by a kernel of the correspondent derivative of a Gaussian [7].

The anti-diagonal entity (I_x $I_y(x)$) is the multiplication of I_x and I_y, the diagonal entries (I_x^2 (x), I_y^2 (x)) are squares of the corresponding derivatives. W(x,y) is the weighting equation, typically circular Gaussian, equation (1) [12].

Harris detector depends on computing the matrix of auto-correlation and the change in gray value response (R) to define the corners:

$$R = \det(A) - \alpha\, \mathrm{trace}^2(A) = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2 \quad \ldots(4)$$

Where,
det(A) is the matrix determinant, trace(A) is the matrix trace, α is the constant which takes value between [0.04 - 0.06], λ_1 and λ_2, are the Eigen values, the characteristic values of the matrix, they are rotationally invariant description, they reflect the surface curvature of two principal axes in the image, diagonalizable processing obtains. When both Eigen values λ_1 λ_2, are large, this means that the local autocorrelation function has

a peak, pixel curvature variation in any direction is large. Harris detector defines a corner in the local region when the window detects a change in intensity in all directions and is larger than the threshold [2].

Harris corner detection Algorithm can be abbreviated in the following steps [1]:

1. Create a grayscale image from a colored image.
2. Compute horizontal and vertical derivatives of the grayscale image at each pixel I_x and I_y, get the image gradient in x and y directions, for example, use the two Prewitt or Sobel masks.
3. Define matrix M at each pixel (x,y) as in equation (1).
4. Compute the response (R) at each pixel using corner response function as in equation (3).
5. Shift window in all directions and define new M and compute R,
6. Threshold on the value of R (R > threshold),
7. The points of local maxima of R in the min image are the corners.

4. Improved Scale Invariant Harris Corner Detector

Harris is invariant to the rotation but not invariant to scale. This paper present improvement to the Harris corner detector by using the differences of grayscale images convolved Gaussian windows with a different scale. The improved scale invariant Harris corner detector can be presented as in the following algorithm:

Scale Invariant Harris Corner Detector Algorithm

Input: Color image, sigma ($\sigma = 0.8$), scaling factor ($k = \sqrt{2}$), α constant ($\alpha = 0.06$), Corner threshold, λ_1 threshold ($\lambda_1 = 255$), λ_2 threshold ($\lambda_2 > \lambda_1 * 11$).

Output: Image corner for different scale image.

1. The color image converted to a grayscale image.
2. Create four Gaussian windows with different scales using equation (1).
3. Console each Gaussian window with the original gray image as in equation (5):

$$L(x, y, \delta) = G(x, y, \delta) * I(x, y) \quad \dots (5)$$

4. Take the differencing of the resulting four smoothed images to create three differenced images as in equation (2).
5. Select any image (one image) from the previous stage and apply the Harris corner detection method
6. End.

Experimental Result

The scale-invariant Harris corner detection implemented on 18 images 2 of them only will be shown with two image size:

Image size (256×256) Image size (200×200)
(a) Original Harris algorithm

Image size (256×256) Image size (200×200)
(b) Scale Invariant Harris algorithm

Figure 1: Missing Corner(s) in House image

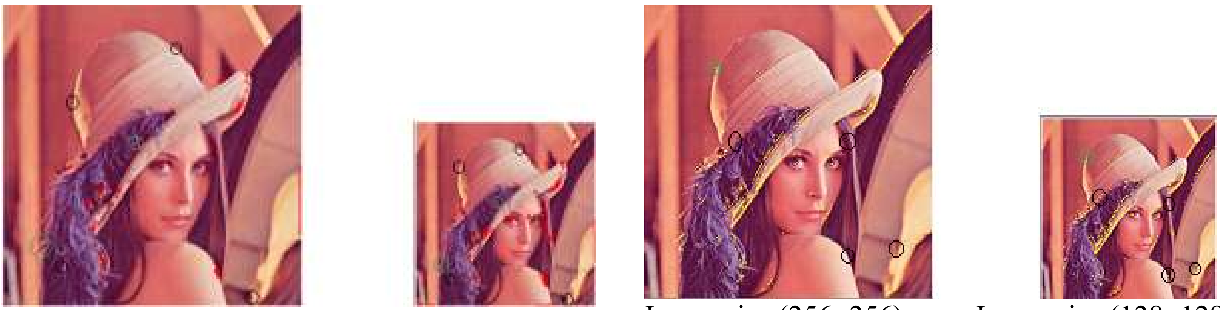

Image size (256×256) Image size (128×128)
(a)Original Harris algorithm

Image size (256×256) Image size (128×128)
(c) Scale Invariant Harris algorithm

Figure 2: Missing Corner(s) in Lena image

Table 1: Original Harris corner detector

Image\ corners	Number of true corners	Number of detected corner	Missed corner(s)	Position set as a corner in large image not set in small (Missed corners)
House (Large image) Fig. (1-a) left image	53	42	11	3
Lina (Large image) Fig. (2-a) left image	57	52	5	4
House (Small image) Fig. (1-a) right image	44	34	10	5
Lina (Small image) Fig. (2-a) right image	45	39	6	6

Table 2: Scale-invariant Harris corner detector

Image\ corners	Number of true corners	Number of detected corner	Missed corner(s)	Position set as a corner in large image not set in small (Missed corners)
House *(Large image)* Fig.(1-b) left image	53	44	9	1
Lina *(Large image)* Fig.(2-b) left image	57	53	4	1
House *(Small image)* Fig.(1-b) right image	44	39	5	3
Lina *(Small image)* Fig.(2-b) right image	45	40	5	4

Good corner detector must detect all the right corners with good localization. As seen in the previous experimental images scale invariant harris detected the same important corners in different size of the same image this will give the algorithm more power. Successful of the algorithm can be seen by comparing not only the number of detected corners but also the position of corners.

In the previous experimented image of hours the black circle represent missing corners in *Image size (256×256)* but exist in *Image size (200×200)* while the red circle represent missing corners in *Image size (200×200)* but exist in *Image size (256×256)*. The second image (Lina) have the same meaning with black and green color.

The number of missed corners are resulted from changing in scale that was very small. Original Harris corner detection for the image of the house with size (256×256) have 53 true corners, 42 of them are truly detected while 11 of them are falsely detected (missing corners). Original Harris corner detection for house image with size (200×200) have 44 corners 34 of them are true detected while 10 of them are false detected, missing corners are 10, and so on.

The position and number of corner detected for scale-invariant Harris corner detection can be observed clearly in the image results that the proposed Harris corner detector is more efficient.
The threshold of R Harris equation and the threshold for λ_1 and λ_2 must be established well, in this work the threshold of R set to (40000) and threshold of λ_1 set to 225 and threshold of λ_2 set to value that is larger than (λ_1*11).
The experimental parameter used to create Gaussian window in this work are as follows:
$\text{Sigma}_1 = 0.8$, $\text{sigma}_2 = k \times 0.8$, $\text{sigma}_3 = k^2 \times 0.8$, $\text{sigma}_4 = k^3 \times 0.8$, Where $k = \sqrt{2}$.
Gaussian window created with two dimensions with size (5 × 5).

Conclusions

Corners are one of the most important images features. There are various algorithms to detect corners but the most widely used method is the Harris corner detection method. The disadvantage of the Harris corner detection algorithm is scaled invariant. In this paper a suggestion to improve Harris detector according to scale done by applying the Harris corner detection algorithm on the difference of grayscale image convolved with four Gaussian windows with different scales. The experimental results show that the difference of Gaussian gives the algorithm more power to produce Harris as scale-invariant method.

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