Assignment 3: Computer Vision 1 - Harris Corner Detector and Optical Flow

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Section 1

In figure 1 you can see the original image of the figure toy with its corners. In order to have a closer look at the corners, the image is added to the zip file under the name `figure_toy_3`.

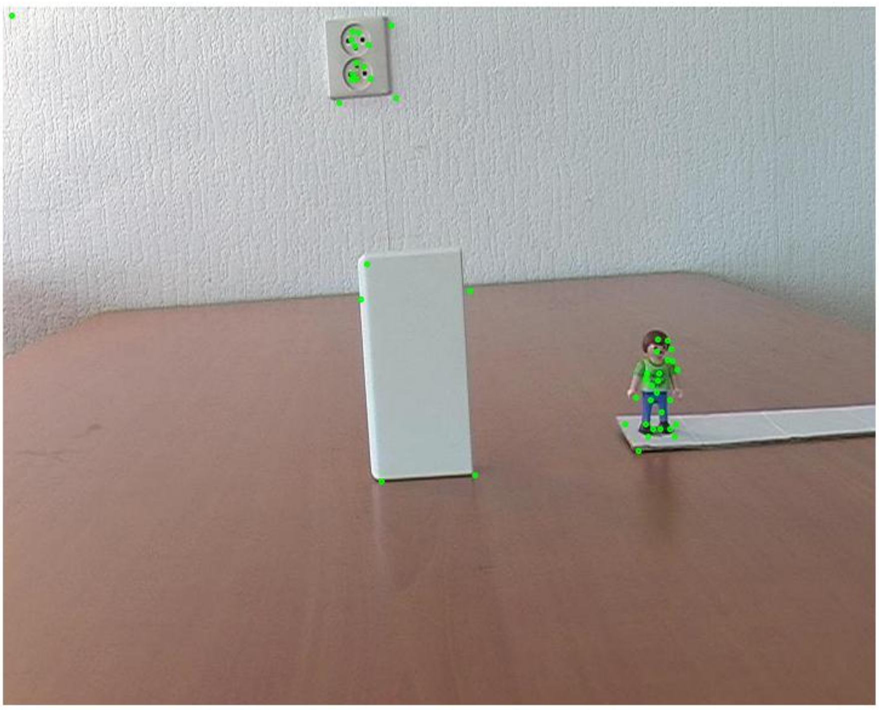

Figure 1: Original figure toy image with corners

In figure 2 you can find the derivative in X direction of the figure toy image.

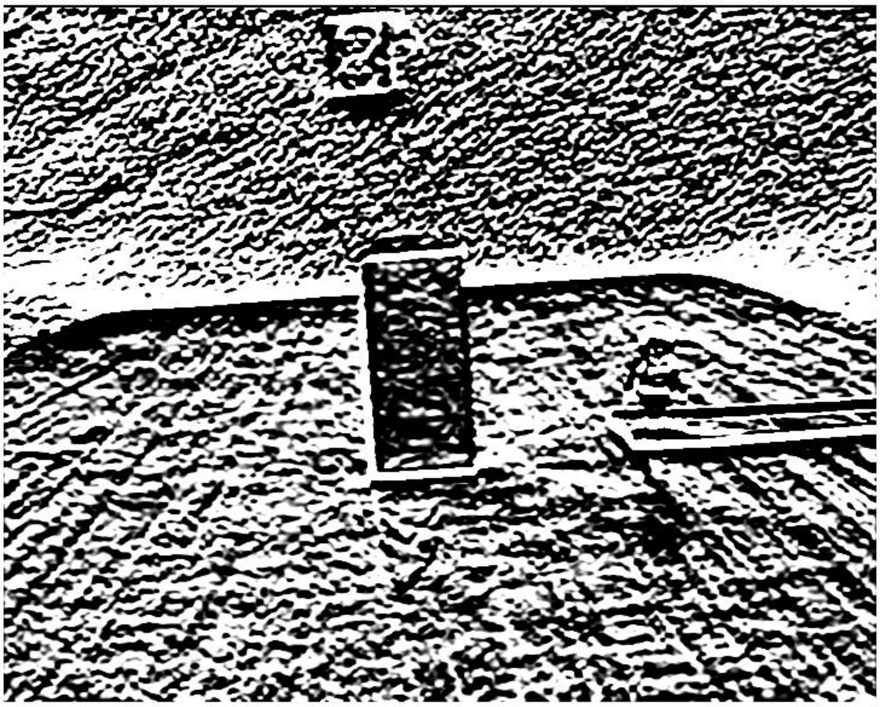

Figure 2: Derivative in X direction

In figure 2 you can find the derivative in Y direction of the figure toy image.

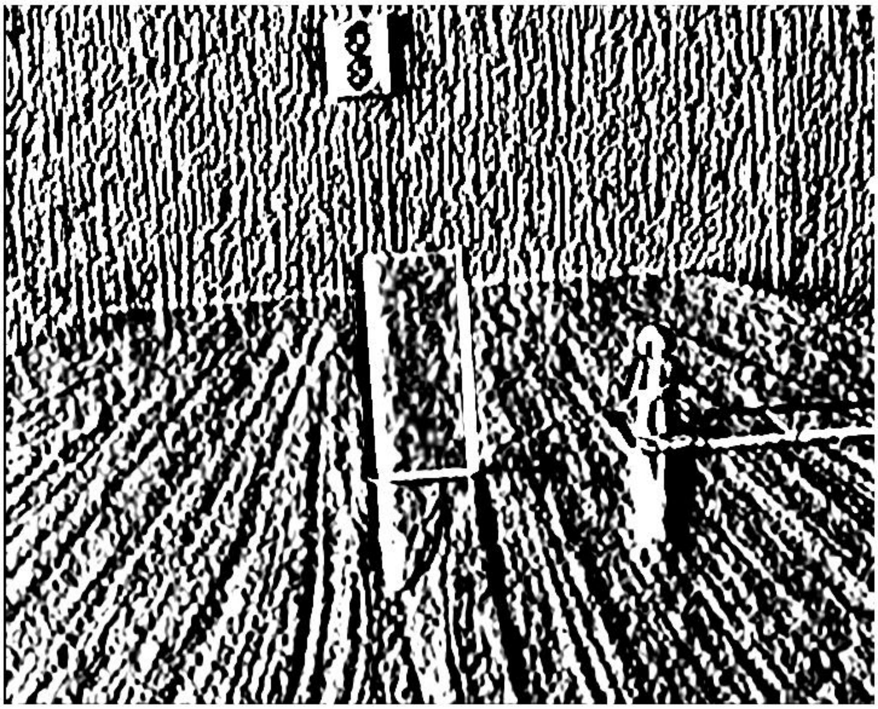

Figure 3: Derivative in Y direction

In figure 4 you can see the original image of the pingpong with its corners. In order to have a closer look at the corners, the image is added to the zip file under the name `figure_pingpong_4`.

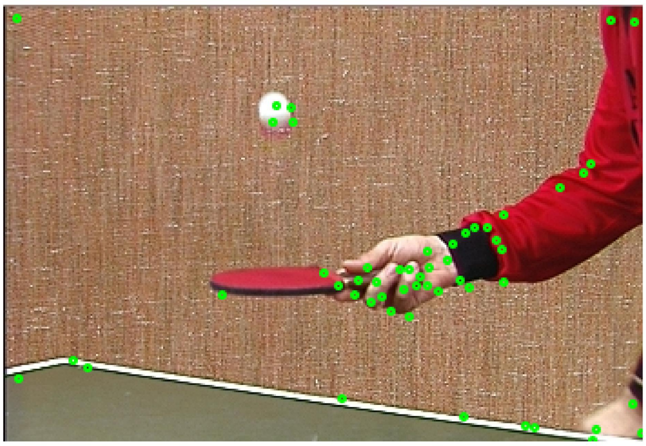

Figure 4: Original pingpong image with corners

In figure 5 you can find the derivative in X direction of the pingpong image.

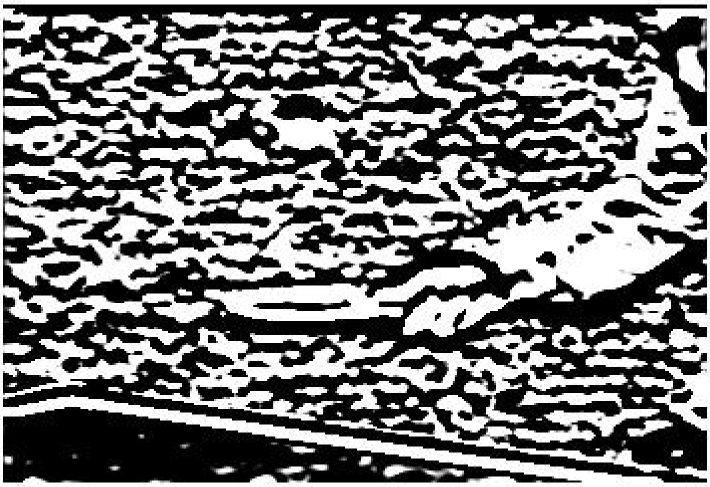

Figure 5: Derivative in X direction

In figure 6 you can find the derivative in Y direction of the pingpong image.

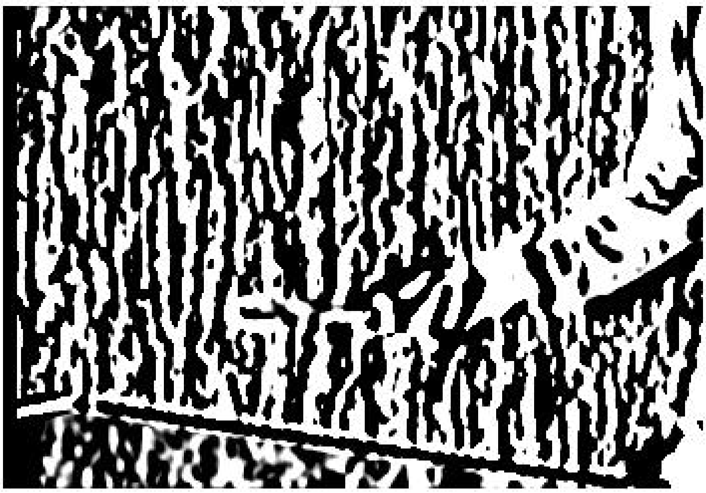

Figure 6: Derivative in Y direction

Visualization of three figures. The computed image derivative Ix The computed image derivative Iy The original image with the corner points plotted on it

(a) How do they define cornerness? Write down their definition using the notations of equation 10.

Shi-Tomasi Corner Detector is to a large extent similar to the Harris Corner Detector, however Shi and Tomasi decided to adapt a small element from the Harris Corner Detector, they only use the minimum of the eigenvalues, making the new approach work better than the old one. As we can see in the 10th equation, the Harris Corner Detector 'cornerness' *H(x,y)* is defined by the two eigenvalues of *Q(x,y*, λ_1 and λ_2:

$H = \lambda_1\ \lambda_2$ - $0.04(\lambda_1 + \lambda_2)^2$

Shi and Tomasi proposed their approach in this new version:

$H = \min(\lambda_1,\lambda_2)$

With this new version, Shi and Tomasi only consider the eigenvalues and decided that the manipulation of the eigenvalues done by the function of the Harris Corner Detector should be left out.

(b) Do we need to calculate the eigen decomposition of the image or patches? Explain your answer.

We do not need to calculate the eigen decomposition for the image, only for the patches. In the Shi and Tomasi method you need to calculate the eigenvalues.

(c) In the following scenarios, what could be the relative cornerness values assigned by Shi and Tomasi? Explain your reasoning.

The approach proposed by Shi and Tomasi in their paper Good Features to Track [1] requires a symmetric matrix Z of 2x2, which has to be above the level of noise of the image and has to be well-conditioned as well. When you consider the eigenvalues in these requirements they need to be large for the noise level and there cannot be different eigenvalues in order to meet the requirements.

1. Both eigenvalues are near 0.

When you have two small eigenvalues that means the profile within a window has an almost constant intensity, a pixel will be [1].

2. One eigenvalue is big and the other is near zero.

When you have two different eigenvalues, a small and a large one, that means there is a unidirectional texture pattern, a pixel might not be considered as a corner, or it might be considered as a corner. The decision depends on the threshold. [1].

3. Both eigenvalues are big

When you have two large eigenvalues that might indicate corners or salt-pepper textures. It may also indicate any pattern which can be tracked in a reliable way [1].

Section 3

In figure 7 you can see the result of the optical flow for the sphere images. In figure 8 you can see the result of the optical flow for the synth images.

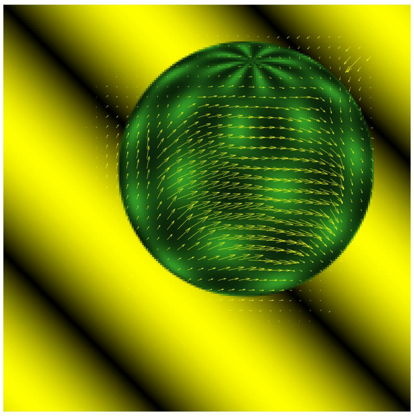

Figure 7: Optical flow sphere

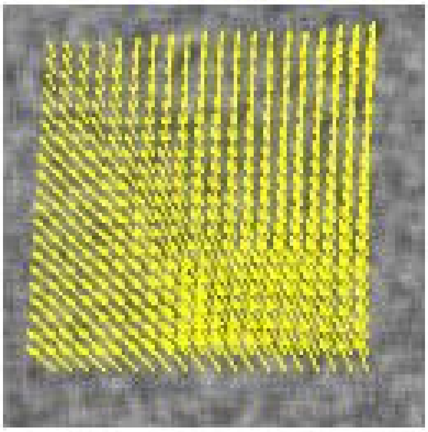

Figure 8: Optical flow synth

(a) At what scale those algorithms operate; i.e. local or global?

The Lucas-Kanade algorithm is a method that operates on local scale, these methods are more robust under noise. The Horn-Schunck algorithm operates on global scale, these methods yield dense flow fields [2].

(b) How do they behave on flat regions?

The Lucas-Kanade algorithm might be more precise and faster than the Horn-Schunck algorithm, on flat regions it does not regularize the flow.

Section 4

In figure 9 you can see two screen shots of of the pingpong and person toy videos. In the zip file the two videos can be found of the implemented trackers for *pingpong* (`pingpong.avi`) and *person toy* (`person_toy.avi`).

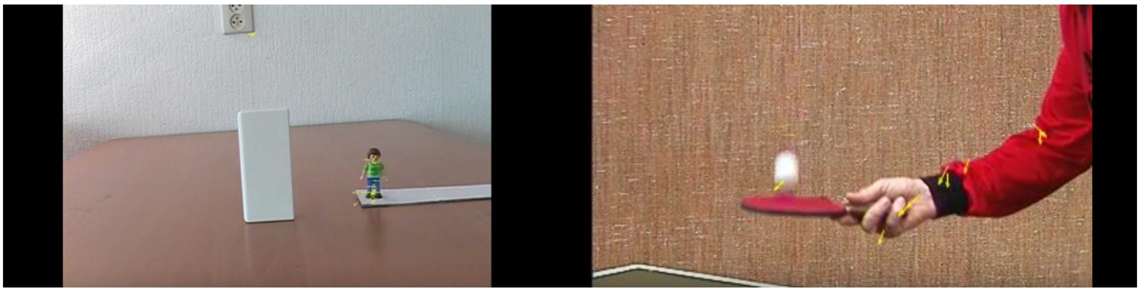

Figure 9: Screen shots of pingpong and person toy videos

References

[1] Jianbo Shi and Carlo Tomasi. *Good Features to Track.* 1994.

[2] Andres Bruhn and Joachim Weickert. *Lucas/Kanade Meets Horn/Schunck: Combining Local and Global Optic Flow Methods.* 2004.