Exercise 1: Optical Flow
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I. Introduction

In this report, we discuss our implementation of two of the most fundamental methods for optical flow calculation - Lucas-Kanade [1] and Horn-Schunck [2] algorithms. To test their functioning, we computed the motion flow in complicated scenes. The goal was to identify certain pitfalls of these techniques and provide solutions for such situations. In that manner, an extensive number of measurements were performed in order to establish the most suitable values for the input parameters of the algorithms.

II. Experiments

A. Optical flow estimation on random noise images

To begin with, we tried to compute the optical flow for a Gaussian noise image rotated by 1°. The results of the performance of the algorithms on this task can be observed in Figure 1. It can be easily noticed that the Horn-Schunck algorithm estimates the motion flow slightly better. The reason for this lies in the fact that it emphasizes global smoothness whereas Lucas-Kanade is focused on local regions. Nevertheless, both methods perform satisfactory as the gradients in every pixel in the images are big. Yet, there exist certain inaccuracies near the edges of the image, because pixels in those regions of the image are further from the image center, and as such exhibit larger movement during the rotation. Consequently, the small movement condition of the techniques is violated.

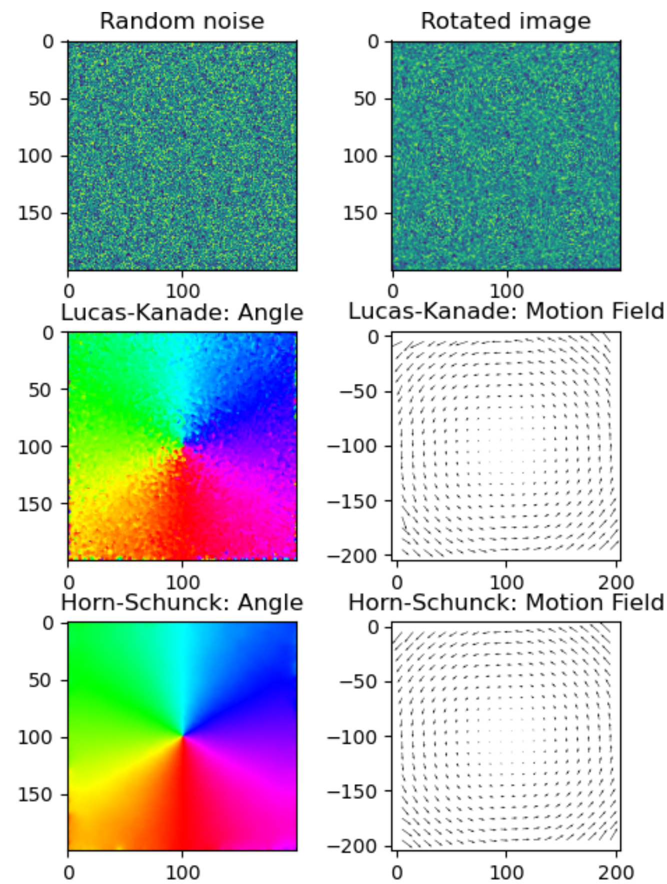

Figure 1: The Horn-Schunck algorithm is superior to the Lucas-Kanade method, because it assures smooth flow along the whole image. Yet, both techniques tend to under-perform close to the edges of an image where is bigger movement.

B. Testing algorithms in more difficult image scenes

In order to get a better understanding of the capabilities of our methods, we tested them on a number of more detailed images. The first pair of images is shown in the first row in Figure 2. As drawn on the images, there is a shift in the horizontal direction of around 25 pixels which immediately tells us our small movement assumption doesn't hold in this case. As a proof of this, we can see a great deal of long vectors in the pictures of the optical flow in the next row. In addition, in the optical flow image on the left-hand side (Lucas-Kanade method) these vectors are pointing in all directions. The explanation for this is that sky regions are inherently difficult for flow estimation due to having gradients of small magnitude. Same can be said for the areas of grass in the pictures where we almost fail to detect the motion field. We elaborate more deeply on this problem in section *C.* of our report.

The second and third row in Figure 2 represent optical flow estimation done with the Horn-Schunck algorithm. The performance is rather satisfactory owing to the fact that this technique does not require local constancy, but smoothness which allows for capturing properly the movement of the small object present in these pictures.

C. Identification of failure cases for the Lucas-Kanade method

As already mentioned above, it is not always possible to estimate the optical flow correctly with the Lucas-Kanade technique. In order for our system of equations for the motion flow to be solvable, this matrix **M** or more precisely its eigenvalues need to have certain properties. A good measure of them can be the response value **R** from the Harris corner detector computed for every image pixel by the following equation:

$$R = \det(M) - k \cdot \operatorname{tr}(M)^2$$

where k is a value in the range 0.04-0.15 [3]. Once having the response, we were able to tell where the optical flow was reliable as depicted in Figure 3. The dark pixels represent points where derivation of the optical was possible, and seeing how few they are, the results in Figure 2 should come as no surprise. Lastly, it is worth mentioning that other parameters like the determinant

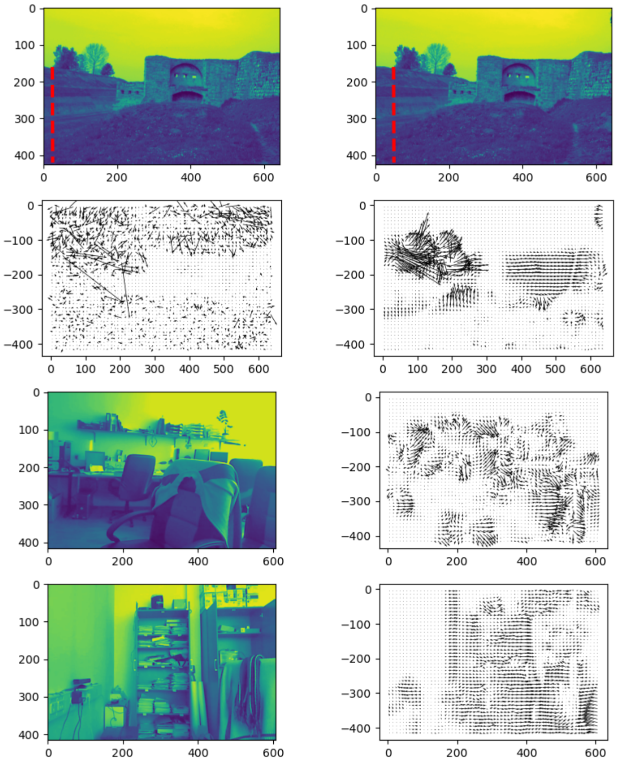

Figure 2: Both algorithms are unable to correctly estimate the optical flow when the motion is not negligible. Additionally, in image regions with small gradients our computations might also be unreliable. These issues are characteristic for both methods, however the Horn-Schunck method has one advantage over the Lucas-Kanade method - is able to capture the motion of tinier objects or details in images.

of **M** or the autocorrelation of the image are also sufficient for estimation of optical flow reliability in many situations.

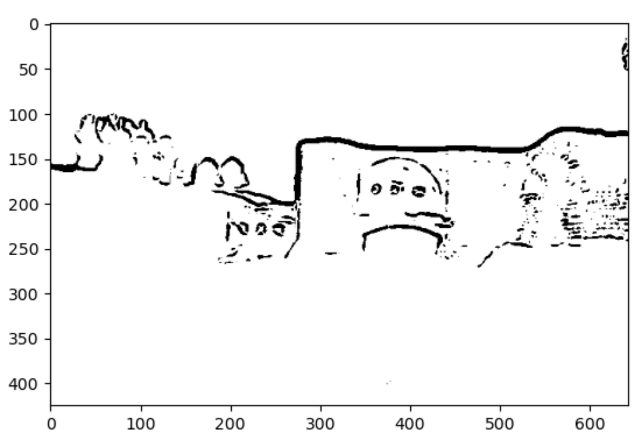

Figure 3: The application of the Harris Corner Detector to one of our images allowed us to identify where the motion field computed with the Lucas-Kanade technique was correct or reliable enough.

D. Analysis of the impact of parameters on time complexity of algorithms and optical flow performance

Algorithm parameters play a crucial role in the optical flow estimation. In the case of the Lucas-Kanade algortihm, the optimization is focused onto the size of the kernel of the applied Gaussian filer and the neighbourhood size. The most adequate values for these settings depend on the image resolution and the size of the objects in it. However, what is always true and can be concluded from Table I is that the larger one of the two or both values at the same time, the longer it will take for the algorithm to generate the motion flow.

Table I: Measurements of Lucas-Kanade algorithm execution time for different values of the Gaussian kernel and the neighbourhood.

Images\Parameters	N = 3		N = 5	
	$\sigma = 1$	$\sigma = 3$	$\sigma = 1$	$\sigma = 3$
sec. B, 1st pair	203 ms	244 ms	329 ms	379 ms
sec. B, 2nd pair	188 ms	222 ms	290 ms	331 ms
sec. B, 3rd pair	186 ms	217 ms	286 ms	330 ms

For the Horn-Schunck method, the analysis is done in a slightly different manner. The only convolution here happens when we convolve the residual Laplacian kernel with the displacement vectors, however this is an iterative process, so we end up performing significantly more convolutions than in the Lucas-Kanade algorithm. As a result, the execution of the former method is noticeably lengthier.

III. Conclusion

All in all, it is safe to say that the methods analyzed in this report might serve well in simpler applications which do not impose very precise optical flow calculation. On the other hand, if we were to encounter complex image patterns with lots of or very few details (sky or grass regions as mentioned above), we better opt for some more sophisticated technique. Another idea would be to try to optimize the algorithm parameters which might sometimes come at the cost of higher time complexity.

References

[1] B.D. Lucas and T. Kanade, "An Iterative Image Registration Technique with an Application to Stereo Vision", IJCAI '81.
[2] B. K. P. Horn and B. Schunck, "Determining Optical Flow", Artificial Intelligence, 17 (1981), pp. 185-203.
[3] S. J. D. Prince, "Computer Vision: models, learning and inference", Cambridge University Press 2012.