Exercise 1: Optical Flow

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I. Introduction

Optical flow is a velocity field in the image which transforms one image into the next in a sequence. Multiple different methods for estimating optical flow are known, however, two such methods, one taking into account selected neighborhood and one the whole image, are to be studied – Lucak-Kanade and Horn-Schunck.

II. Experiments

After implementing both algorithms, we first show the results on a random noise image and its rotation. Observing the results shown on the Figure 1, we can see that both methods estimate the optical flow correctly, however, the result from Lucas-Kanade method confirms the "locality" of the method, since the pixels on the edges are not estimated as well as those near the center. This follows from the fact that the pixels near the edges move much more during the rotation process.

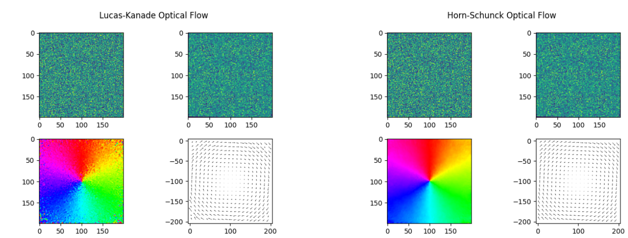

Figure 1. Optical flow on a random noise image and its rotation.

Next, we will take a look at results based on three pairs of real world images. But before rushing into the analysis, let us first compare the optical flow results obtained with method Horn-Schunck of the *Image1* without and with normalization (scaling the pixel values from $[0, 255]$ to $[0, 1]$). The results are shown on the Figure 2.

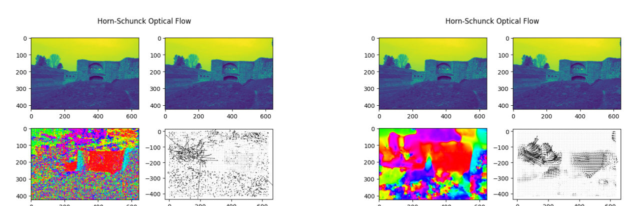

Figure 2. Optical flow of method Horn-Schunck on *Image1*. On the left without and on the right with normalization.

We can quickly see that normalization does improve the optical flow estimation. The improvement is most visible in the upper part of the image, which represents the "static" part, i. e. the background, thus not detecting any movement there seems more right. Since we recognized some major improvement in normalizing the pixels, the images in the following discussion are always normalized before inputed into algorithms.

The optical flows of both methods on real world images are shown on Figures 3, 4 and 5. The parameters are set as proposed in the given testing script ($N = 3$ for Lucas-Kanade and $n\_iter = 1000$, $\lambda = 0.5$ for Horn-Schunck) and σ is set to 1.

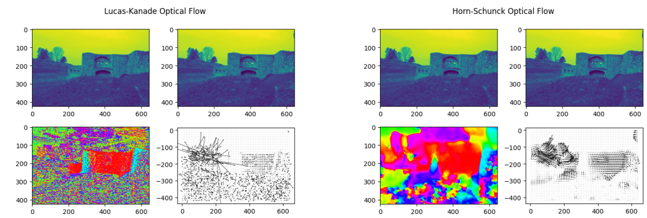

Figure 3. Optical flow of both methods tested on *Image1*.

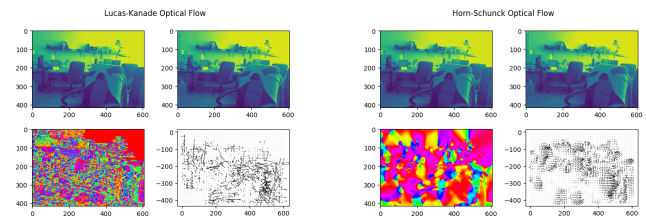

Figure 4. Optical flow of both methods tested on *Image2*.

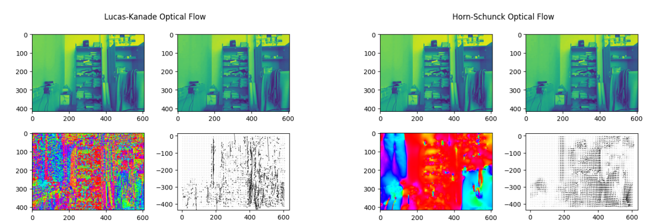

Figure 5. Optical flow of both methods tested on *Image3*.

We notice that Horn-Schunck estimations are much more aligned and mostly also correct (i. e. the fields make sense), while Lucas-Kanade looks more like random noise than a real estimation.

From the examples above it is obvious that Lucas-Kanade method does not work well in all cases (i. e. in all parts of the image). Actually, Lucas-Kanade method works well only for small motions (small motion assumption). This means that when small motion assumption is violated, the optical flow estimation is poor in the areas of large motion. However, we can easily determine where the Lucas-Kanade optical flow can not be well estimated, only by looking at eigenvalues of the matrix $A^T A$, which represents a covariance matrix of local gradients (as defined on lectures). Both eigenvalues should be of the same size, meaning that the gradients in horizontal and vertical direction can be properly estimated. If one eigenvalue is large and the other is small, we can not estimate the optical flow well in one direction (i. e. the gradient is large only in one direction) and if both eigenvalues are small, the gradient magnitudes are small.

When running the algorithms of both methods, we need to set some parameters, affecting both results and speed of the algorithms. In Lucas-Kanade methode, we need to determine the size of the kernel to concolve an image. The results of calibrating the parameter on all three selected images can be seen on Figures 6, 7 and 8.

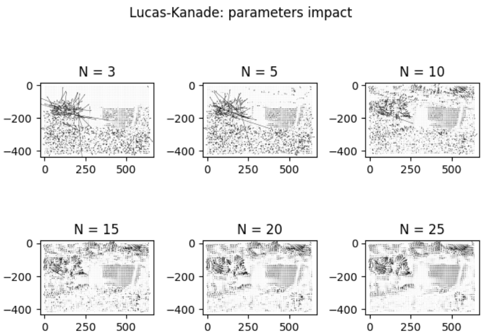

Figure 6. Calibrating N to change the size of the kernel on *Image1*.

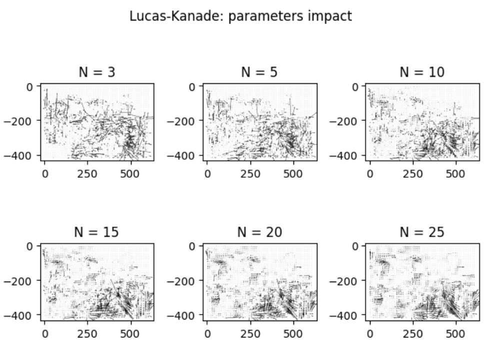

Figure 7. Calibrating N to change the size of the kernel on *Image2*.

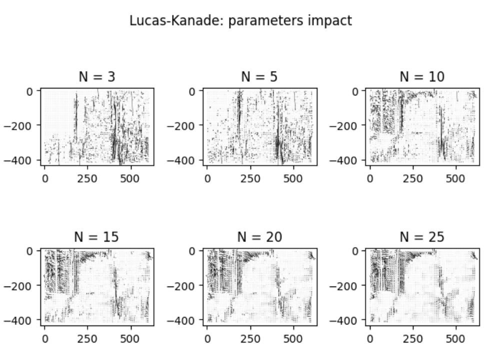

Figure 8. Calibrating N to change the size of the kernel on *Image3*.

We can see that with increasing parameter N, the results are starting to seem more smooth, however, we also notice some motion in the background, not detected with smaller N (can be clearly seen on Figures 6 and 8). Thus, empirically calibrating the parameter N and visualizing the result is, clearly, the sensible approach. The most ideal choices for N for selected images would be 3 or 5.

In Horn-Schunck method, we can tune two parameters: number of iteratioons and a flow smoothness regularizartion constant λ. The results of parameter calibration on all three selected images can be seen on Figures 9, 10 and 11.

We can easily notice that quite some number of iterations is required that the method results well in all three cases. Increasing λ makes the flow smoother, however, calibrating λ does not have a lot of impact on flow result. In all cases we would choose the number of iteration to be 1000 and λ to be 0.5 as proposed, since tunning it does not change the results.

From the previous analysis it is obvious that Horn-Schunck

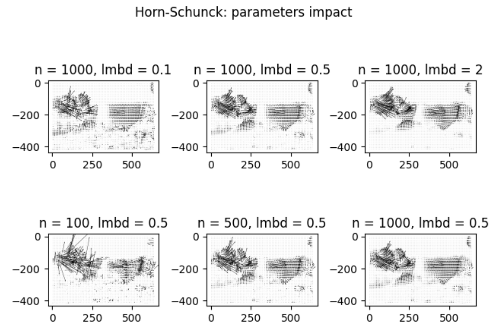

Figure 9. Calibrating parameters n and λ on *Image1*.

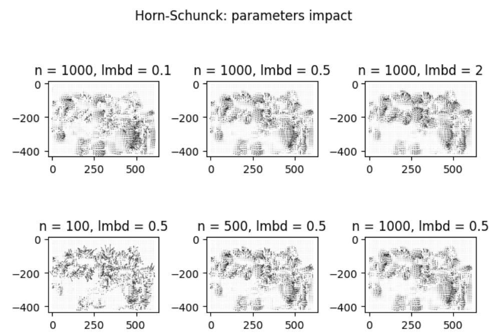

Figure 10. Calibrating parameters n and λ on *Image2*.

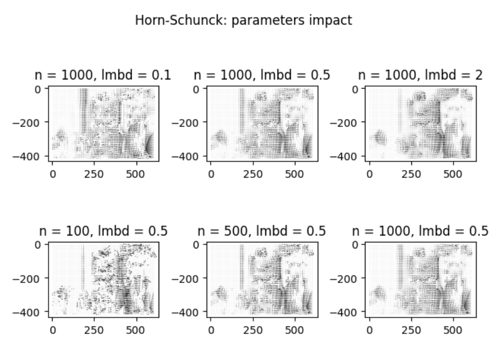

Figure 11. Calibrating parameters n and λ on *Image3*.

algorithm yields much better results. However, it is more time wasting than the Lucas-Kanade, which we confirm also empirically. We can speed up the Horn-Schunck algorithm to initialize values with the help of Lucas-Kanade algorithm output values. This discussion is more explicitly shown in the Table II.

	Lucas-Kanade	Horn-Schunck	Improved Horn-Schunck
Image1	0.01824	5.81270	1.67755
Image2	0.01512	3.27449	1.55561
Image3	0.01402	3.17873	1.36632

III. Conclusion

As a part of the exercise, we implemented two optical flow estimation methods, known as Lucas-Kanade and Horn-Schunck along with some basic analysis. Even though, in general, Horn-Schunck method performs better, both methods can lead to poor results if the parameters are not chosen properly. Thus, testing and calibrating parameters first and doing analysis later can, indeed, make a lot of positive impact on the final results.