Exercise 1: Optical flow

Matej Miočić, 63180206, mm9520@student.uni-lj.si

I. Introduction

In this exercise we look into 2 methods to estimate optical flow. A local neighbourhood based algorithm named Lucas-Kanade and a global Horn-Schunck method. We show their differences, how they are impacted by parameter choice, where do these methods fail and improvements.

II. Experiments

A. Examples of Lucas-Kanade and Horn-Schunck methods

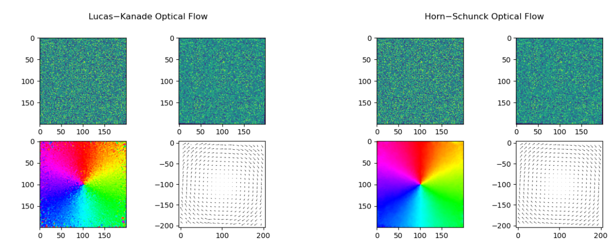

Figure 1: Both methods applied to a rotated image of noise.

In Figure 1 we show angles of displacement vectors of optical flow (with color and arrows) for both methods. We can see that both methods perform a good estimation of optical flow, but Horn-Schunck method (right) outputs a smoother estimation.

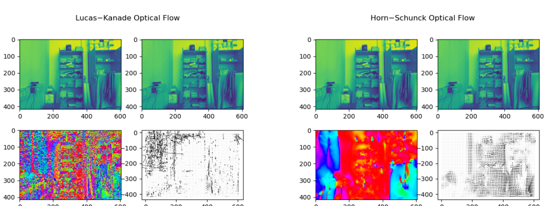

Figure 2: Both methods applied to disparity images.

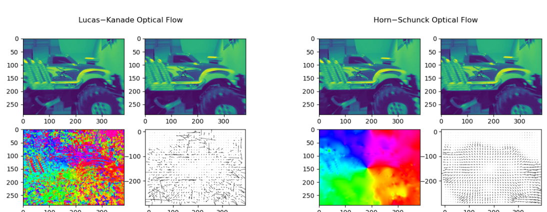

Figure 3: Both methods applied to collision images.

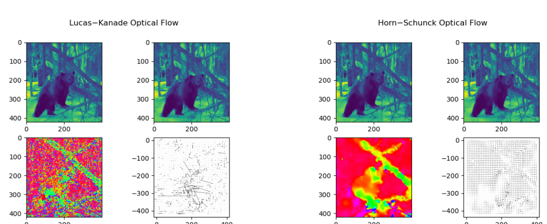

Figure 4: Both methods applied to images of a bear.

We show a few comparisons between Lucas-Kanade and Horn-Schunck estimation. In Figures 2, 3 and 4 we show a smooth flow estimation with Horn-Schunck (right), whereas we show that with Lucas-Kanade method (left), flow estimation fails where we violate our assumptions (most visible in Figure 2). Lucas-Kanade method assumes that the optical flow is very similar in the local neighborhood.

B. Method optimizations

1) Lucas-Kanade: We have shown that Lucas-Kanade method fails to estimate optical flow in areas where we violate our assumptions. We can approximately determine where optical flow can be estimated properly by using Harris response. By setting a threshold, we can pick only displacement vectors where we think optical flow estimate will succeed. For a more general use, we decide to pick the threshold as 75th quantile of Harris response.

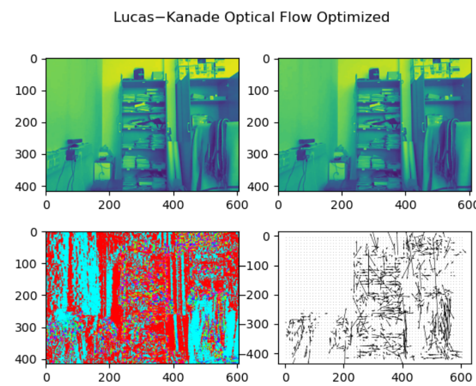

Figure 5: Lucas-Kanade method optimized example.

In Figure 5 we can see still flawed, but much more accurate flow estimation than in Figure 2, since we removed assumed failed calculated displacement vectors.

2) Horn-Schunck: Since Horn-Schunck method already performs really good we will not try to optimize its flow estimation but its speed performance. The idea is to initialize displacement vectors with Lucas-Kanade method. Since Horn-Schunck is an iterative method its speed is correlated to number of iterations. If initialized vectors are better we can lower the number of iterations and improve speed performance.

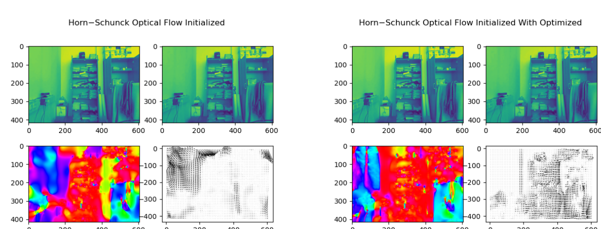

Figure 6: Horn-Schunck initialized with normal Lucas-Kanade (left) and optimized Lucas-Kanade (right).

So far for every plot we have used 1000 iterations for Horn-Schunck, but we show that we can achieve the same results as in Figure 2 with 500 iterations using the right initialization. Estimated time for Lucas-Kanade method is about 0.25 seconds. Estimated time for Horn-Schunck with 1000 iterations is about 2.5 seconds. With initialization and 500 iteration estimated time is about 1.3 seconds which is almost half the time without initialization. There is a downside, in Figure 6 we can see that the output of initialized Horn-Schunck is heavily influenced by the performace of Lucas-Kanade. If we use wrong estimation of optical flow, Horn-Schunck method might not be able to repair it.

C. Method parameters

For Lucas-Kanade method we have 2 parameters. σ parameter used in image derivatives computation and image smoothing. The other parameter $\mathbf{N}$ decides the size of neighbourhood region. For all plots above we used $\sigma = 1$ and $\mathbf{N} = 3$. We now show experiments with $\sigma = 3$ and $\sigma = 5$ and $\mathbf{N} = 5$ and $\mathbf{N} = 9$. Meanwhile for Horn-Schunck method we have σ and λ parameters. λ parameter is a regularization constant, where bigger values lead to a smoother flow. For all plots above we used $\sigma = 1$ and $\lambda = 0.5$. We show experiments with same σ values as with Lucas-Kanade method, while for λ we show results with $\lambda = 3$ and $\lambda = 5$. We used images from Figure 4.

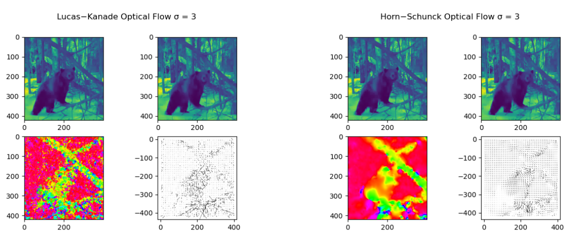

Figure 7: Both methods with $\sigma = 3$.

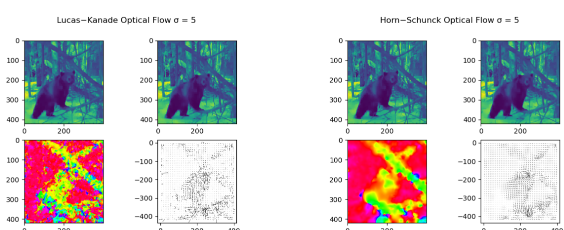

Figure 8: Both methods with $\sigma = 5$.

We observe some improvements with increasing the σ parameter with Lucas-Kanade method. Since we're increasing smoothness, we're violating our assumptions less. Neighbourhood regions change less the more we smooth the image. We don't really see much of a difference for Horn-Schunck method. That's why we decided to show *angle magnitude* plots of sigma parameters, to get more intuition.

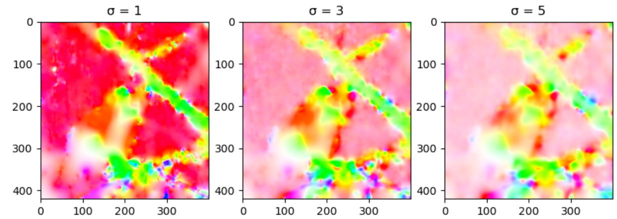

Figure 9: *Angle magnitude* plots with different σ parameters with Horn-Schunck method.

In Figure 9 we observe a lower magnitude in the background with increasing σ. Optical flow estimation is now focused more on actual moving object, but we observe more inacurate estimations.

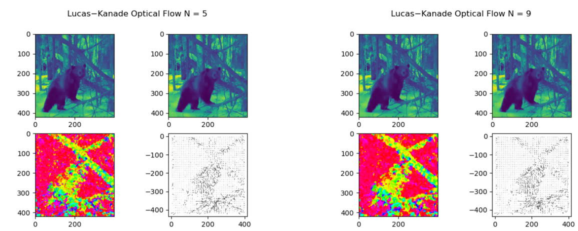

Figure 10: Lucas-Kanade method with changing the N paramater.

Since we have shown that larger σ parameter for this estimation is better we used $\sigma = 3$ in Figure 10. If we compare these 2 estimations to Figure 7, we can see estimations are smoother since we take into account a bigger neighbourhood for every estimation.

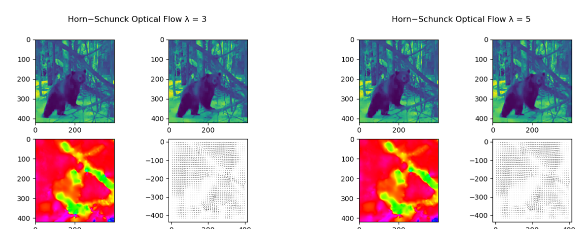

Figure 11: Horn-Schunck method with changing the λ paramater.

We decided to use $\sigma = 1$ for Figure 11. Increasing the λ parameter affects smoothness of the estimation. We see little change in estimations. With increasing λ we see a bit of information loss.

III. Conclusion

We have explored 2 optical flow estimation methods. We have shown optimization and differences for both. Lucas-Kanade method works better where our assumptions are not violated. Horn-Schunck method worked on every testing image with the cost of perfomance speed.