Optical Flow

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I. INTRODUCTION

As part of the first exercise we implemented 2 methods of estimating optical flow: Lucas-Kanade, which is a local neighborhood based algorithm and Horn-Schunck, a global method. In this report we present the differences between the two methods, improvements applied, how the choice of parameters impacts their performance and how these methods perform in terms of speed.

II. EXPERIMENTS

A. Comparisons of the Lucas-Kanade nad Horn-Schunck methods
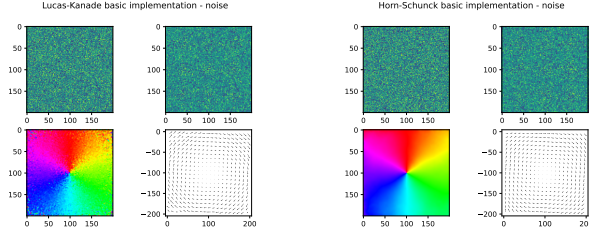

Figure 1. Lucas-Kanade (left) and Horn-Schunck (right) applied to a rotated image of noise.

In Figure 1 the optical flow is presented in terms of colors and arrows for both methods. We can observe that both methods estimate optical flow well, however the Lucas-Kanade method struggles slightly at the corners, while the Horn-Schunck method doesn't, and generally outputs a smoother estimation.

In Figures 2, 3 and 4 we present a couple of examples of both methods. We can observe mostly smooth optical flow estimation when using the Horn-Schunck method (failing on Figure 4), whereas the Lucas-Kanade fails to estimate the flow when it's basic assumptions are violated.
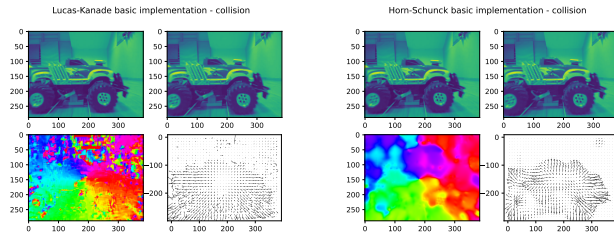

Figure 2. Lucas-Kanade (left) and Horn-Schunck (right) applied to an image from the "collision" dataset.

B. Lucas-Kanade deficiencies

As mentioned in Section II-A, the Lucas-Kanade method fails when the basic assumptions of brightness constancy, small displacement and spatial coherence are violated. To counter
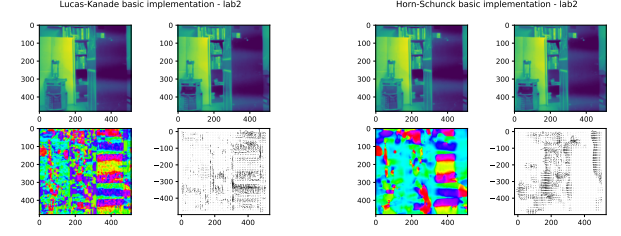

Figure 3. Lucas-Kanade (left) and Horn-Schunck (right) applied to an image from the "lab2" dataset.
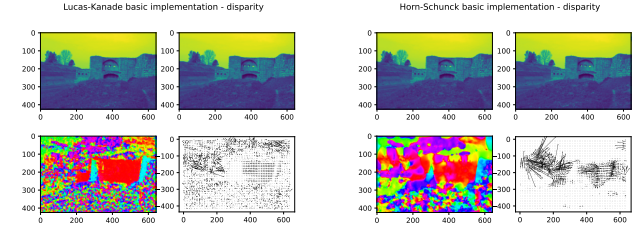

Figure 4. Lucas-Kanade (left) and Horn-Schunck (right) applied to an image from the "disparity" dataset.

that, we used the Harris response to determine where the optical flow can be estimated properly. The Harris response allows us to set a threshold with which we can choose only those vectors, where we think the optical flow estimation will succeed. The threshold chosen in our implementation is $0.01 \times max(R)$, where R represents the Harris response.

In Figure 5 we can observe the results of the Lucas-Kanade method with Harris response. We can observe that the results are still flawed, but more accurate since we removed the failed results of the calculations. Arguably, the threshold used is too strict.
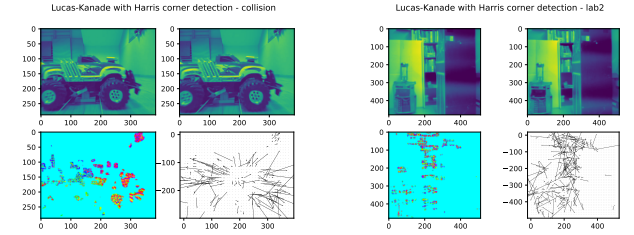

Figure 5. Lucas-Kanade with Harris response applied images from the "collision" and "lab2" datasets.

C. Method parameters

1) Lucas-Kanade: When implementing the Lucas-Kanade method, we had to consider 2 parameters: σ, which is used when computing the Gaussian derivatives and performing Gaussian

smoothing and N, which determines the size of the kernel used in convolution. For all previous sections, parameter values of $\sigma = 1$ and $N = 10$ were used. Here, we experimented with parameter combinations of $\sigma \in \{0.5, 1, 1.5\}$ and $N \in \{5, 10, 15\}$. In Figures 6 and 7, we can observe that the size of the kernel impacts performance the most.
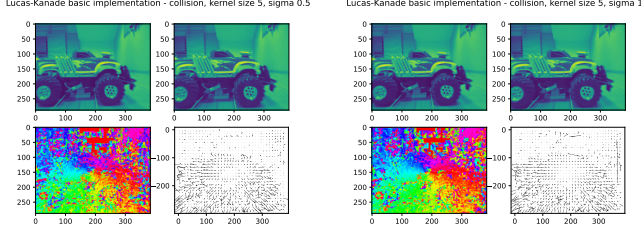

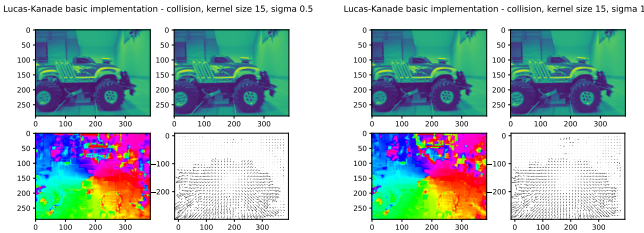Figure 6. Lucas-Kanade with parameters $\sigma = 0.5, 1$ and $N = 5$.

Figure 7. Lucas-Kanade with parameters $\sigma = 0.5, 1$ and $N = 10$.

2) Horn-Schunck: When implementing the Horn-Schunck method, we again had to consider 2 parameters: σ, which is used when computing the Gaussian derivatives and performing Gaussian smoothing and λ, which is a regularization constant which controls the smoothnes of the flow. In all previous sections, parameter values of $\sigma = 1$ and $\lambda = 0.5$ were used. Here, we experimented with parameter combinations of $\sigma \in \{0.5, 1, 1.5\}$ and $\lambda \in \{0.1, 0.5, 1\}$. In Figures 8 and 9 we can observe that the λ parameter impacts performance the most, but a too high value of λ can also worsen the performance of the estimator.
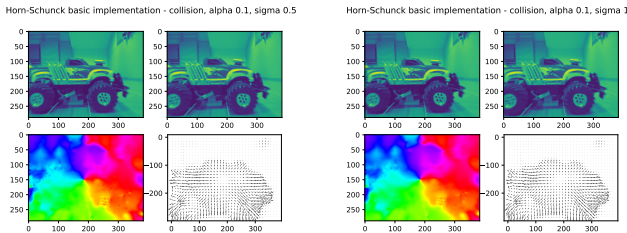

Figure 8. Horn-Schunck with parameters $\sigma = 0.5, 1$ and $\lambda = 0.1$.

D. Measurements

To finalize our project, we conducted an evaluation of both methods, including their respective enhancements, focusing on elapsed time and, particularly for the Horn-Schunck method, the number of iterations required for convergence. In an attempt to speed-up the Horn-Schunck method, we investigated
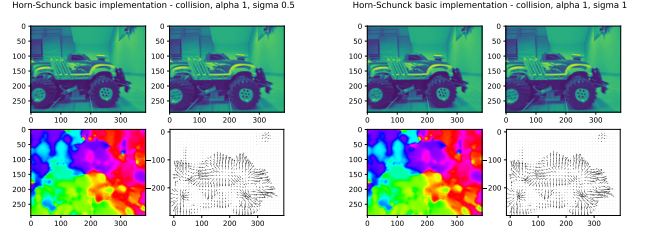

Figure 9. Horn-Schunck with parameters $\sigma = 0.5, 1$ and $\lambda = 1$.

initializing it with results from the basic Lucas-Kanade approach. The findings from our evaluation are presented in Tables I, II, and III.

Method	Time (ms)	Iterations
Lucas-Kanade	91.92	n/a
Horn-Schunck	2454.80	384
Lucas-Kanade Harris	49.43	n/a
Horn-Schunck Lucas-Kanade	2045.27	313

Table I

PERFORMANCE OF METHODS THE "COLLISION" DATASET.

Method	Time (ms)	Iterations
Lucas-Kanade	204.94	n/a
Horn-Schunck	6616.19	325
Lucas-Kanade Harris	108.41	n/a
Horn-Schunck Lucas-Kanade	32153.23	1838

Table II

PERFORMANCE OF METHODS THE "LAB2" DATASET.

Method	Time (ms)	Iterations
Lucas-Kanade	226.73	n/a
Horn-Schunck	4972.27	258
Lucas-Kanade Harris	118.79	n/a
Horn-Schunck Lucas-Kanade	8941.31	454

Table III

PERFORMANCE OF METHODS THE "DISPARITY" DATASET.

We can observe that Lucas-Kanade is generally a much faster method compared to Horn-Schunck, while Horn-Schunck results in smoother flow, as seen in previous chapters. Additionally, we can observe that when incorporating the Harris response in Lucas-Kanade, it performs almost twice as fast. Another interesting observation we can make is that when Horn-Schunck is initialized using Lucas-Kanade, it sometimes performs better (Table I) and sometimes much worse (Tables II, III). Such performance differences result from the quality of the Lucas-Kanade computation. In the 'collision' dataset (Table I), Lucas-Kanade generally performs quite well, which in turn reduces the number of iterations Horn-Schunck needs until convergence.

III. CONCLUSION

In conclusion, our implementation and evaluation of Lucas-Kanade and Horn-Schunck methods highlight Lucas-Kanade's speed advantage, especially with the Harris response, while Horn-Schunck provides smoother flow but may require more iterations. Initializing Horn-Schunck with Lucas-Kanade occasionally improves performance but not consistently. These insights emphasize the trade-offs between speed and accuracy in optical flow estimation.