Optical Flow

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I. Introduction

This project implements two optical flow methods: the neighborhood-based Lucas-Kanade (LK) and the global Horn-Schunck (HS) methods. Since they differ in their optimization techniques and assumptions for estimating optical flow, a detailed analysis and comparison of both approaches is provided.

II. Experiments

A. Testing Lucas-Kanade and Horn-Schunck optical flow methods on synthetic data

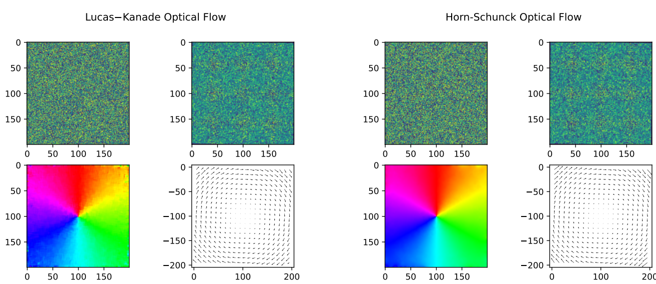

Figure 1: Comparison of both methods on rotated random noise images.

From Figure 1, we can see that both methods provide a good estimate of the optical flow for this example. However, Lucas-Kanade method is less precise in the edge regions, which is clearly visible in the color map representation.

B. Testing on different real-world images

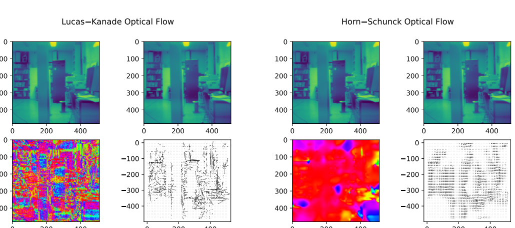

Figure 2: Comparison of LK and HS Optical Flows on Lab2 Data.

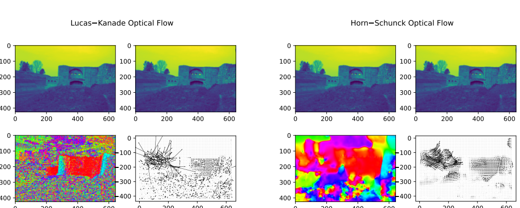

Figure 3: Comparison of LK and HS Optical Flow on Disparity Data.

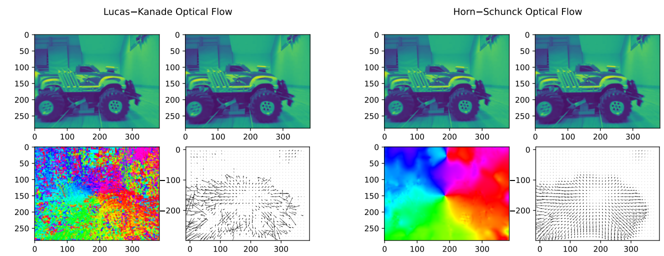

Figure 4: Comparison of LK and HS Optical Flow on Collision Data.

From Figures 2, 3, and 4, we can see that Lucas-Kanade results in a noisier flow estimation, while Horn-Schunck produces a more uniform flow. Both, the vector field and the color map for Lucas-Kanade show high variations, which means that more noise and fluctuations are captured.

C. Improvement in Lucas-Kanade Optical flow Method

In order to filter out flow vectors that cannot be reliably computed due to high self-similarity, we can evaluate the response of the Harris corner detector and threshold the results.

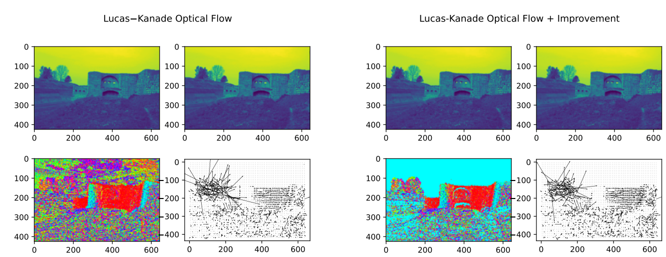

Figure 5: Comparison of the standard LK method and the improved version.

From figure 5, we can see that in the improved version, certain estimations are filtered out. In this specific example, the filtered regions correspond to the cloud areas with similar texture.

D. Methods Parameters

All previous resutls were obtained using fixed parameters (as provided in the instructions). However, by tuning the parameters of both methods, we can achieve different performance results.

Lucas-Kanade method depends on two key parameters [1]:

1) Sigma (σ): Defines the kernel size for smoothing before estimating the flow. A smaller σ captures finer motion details, as seen in Figure 6, which highlights movements on the edges and small details on the vehicle. However, increasing σ results with smoother field, but with loss of these details.

[1]For both parameters, are shown only the vector field representations, as they provided more relevant information.

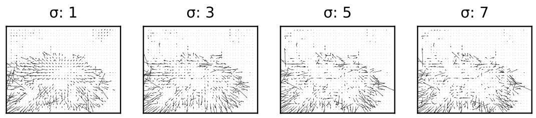

Figure 6: Lucas-Kanade performance with different sigma paramter for the kernel construction, shown on the same Collision data example as in Figure 4.

2) Neighborhood size (N):Determines how many pixels contribute to the flow estimation at a given pixel. A 3×3 neighborhood provides a more detailed but noisier flow, while larger neighborhoods smooth the motion. However, beyond 7×7, the effect on smoothness is minimal, as shown in Figure 7.

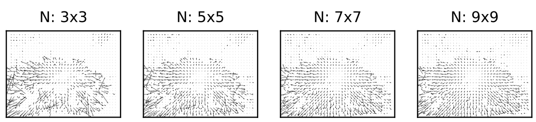

Figure 7: Lucas-Kanade performance with different neighborhood sizes, shown on the same Collision data example as in Figure 4.

The Horn-Schunck method depends on three key parameters:

1) λ: Controls the trade-off between capturing small motion details and making the flow smoother. As shown in Figure 8, increasing λ results in a smoother flow, but beyond a value of 3, the effect is minimal. With smaller λ values, the flow is less smooth, with some uneven regions, though the overall motion remains clear.

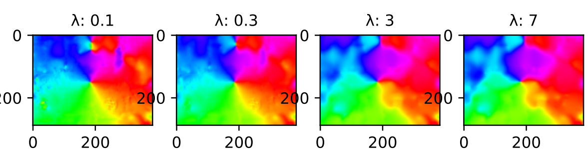

Figure 8: Horn-Shucnk performance with different λ values, shown on the same Collision data example as in Figure 4.

2) Iterations: Testing with more iterations showed that the flow stabilizes around 1000 iterations, meaning further computations do not significantly improve the result, as we can see from Figure 9.

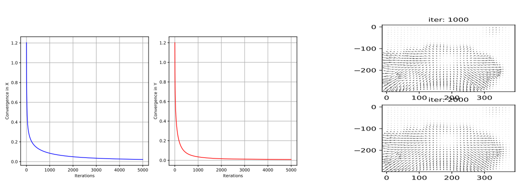

Figure 9: Convergence of the Horn-Schunck method measured as the change in optical flow vectors between consecutive images using the L2 norm.

3) Sigma (σ) has the same effect as in the Lucas-Kanade method.

E. Execution Time Comparison

To estimate the average time required for each method to compute the optical flow, we tested on 30 samples from the Collision and Lab2 datasets, calculating the sample average and standard error for each. The execution time varies slightly depending on the dataset, but Lucas-Kanade converges faster than both the Horn-Schunck and Horn-Schunck-accelerated methods. Additionally, initializing Horn-Schunck with the Lucas-Kanade estimate did not speed up convergence or significantly change the flow estimation, as shown in Figure 10.

Table I: *Average execution time for optical flow estimation on two consecutive images.*

Method / Data	LK	HS	HS-accelerated
collision	0.0043 ± 0.0002	0.9020 ± 0.1356	0.8695 ± 0.0823
lab2	0.0107 ± 0.0009	1.5432 ± 0.4612	1.3450 ± 0.2613

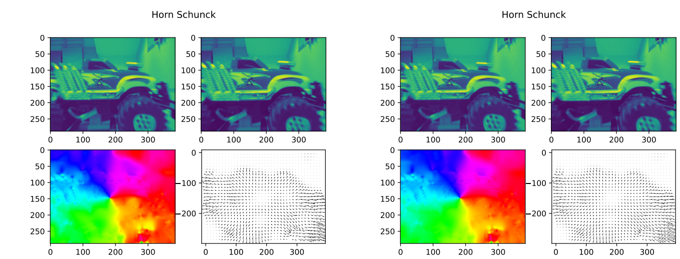

Figure 10: Comparison of Horn-Schunck and Horn-Schunck accelerated methods.

F. Pyramidial Lucas Kanade

Using the Pyramidal Lucas-Kanade method, from Figure 11 we can observe an improvement in flow estimation. By downsampling the image, the assumption of small motion becomes more consistent, leading to better results. This improvement achieves similar performance to the Horn-Schunck method.

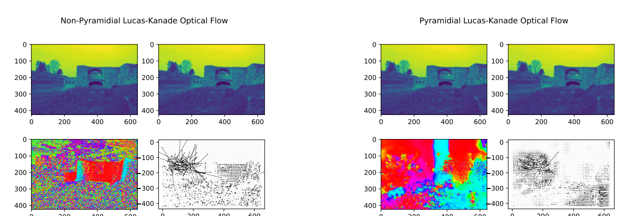

Figure 11: Comparison of Non-Pyramidial and Pyramidial implementaion of Lucas Kanade method.

Additionally, running the method at a single scale multiple times results in smoother flow.

III. Conclusion

In this project, we explored two optical flow methods: Lucas-Kanade, which is faster but less reliable, and Horn-Schunck, which produces more stable results at the cost of speed. Additionally, the pyramidal approach for Lucas-Kanade enhances performance, making it comparable to Horn-Schunck.