Optical flow

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I. Introduction

In this assignment, we implemented the Lucas-Kanade and Horn-Schunck methods to estimate optical flow, which describes motion between video frames. We tested different parameters to determine the best settings for various scenarios. To improve the Lucas-Kanade method, we introduced a reliability criterion and implemented a pyramidal structure.

II. Experiments

To begin, we present some implementation details that differ slightly from the explicit instructions for both methods. Gaussian smoothing was applied when calculating the time derivative in both methods. In the Lucas-Kanade method, if the matrix used to compute flow at a given pixel was singular, the calculation was omitted, and a flow of 0 was assigned. For the Horn-Schunck method, convergence was determined using the following equation:

$$\frac{\sum_{\text{All pixels}} \left((u - u_{\text{previous}})^2 + (v - v_{\text{previous}})^2\right)}{\text{height} \times \text{width}}$$

where the u and v represent the flow in each pixel. The threshold of convergence is set to 1e-7.

A. Random noise evaluation

First, the two methods were evaluated on random noise images, with the second image rotated by 1 degree to simulate motion. As shown in Figure 1, the Horn-Schunck method outperforms Lucas-Kanade, particularly along the edges where motion is faster. This result is expected since the Lucas-Kanade method assumes small motions.

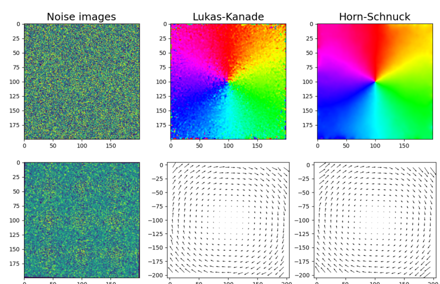

Figure 1. Comparison of Lukas-Kanade and Horn-Schnuck methods on real world examples.

B. Testing the methods on real world examples.

After testing on synthetic images, the methods were evaluated on real-world examples. As seen in Figure 2, the Horn-Schunck method generally produces a smooth flow field, with direction errors mainly occurring in areas with fine details, such as the trees in example 2.

The Lucas-Kanade method, however, struggles to capture motion direction in certain areas across all three examples. This is expected, as it tends to fail when the eigenvalues of the flow calculation matrix are both small or when their ratio is too large. The first issue arises when gradients in a region have small magnitudes, as seen in example 2 (background sky) and example 3 (background wall). The second issue occurs in edge-like structures, where the gradient is strong in only one direction. An instance of this is in the third image, where the flow along the edges of the wardrobes appears entirely vertical.

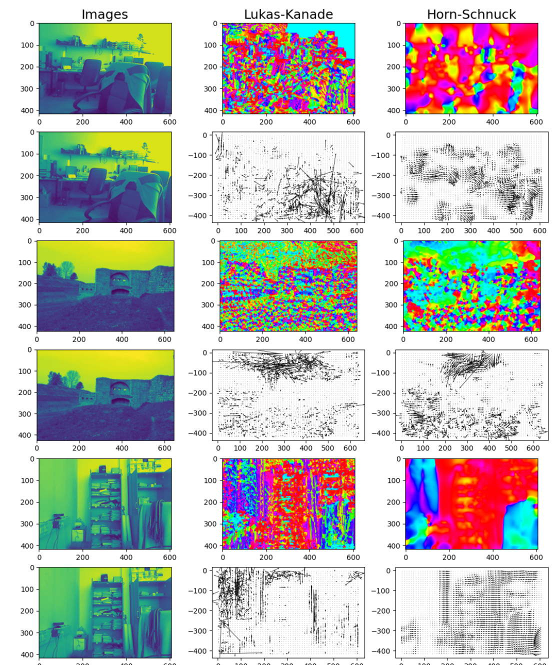

Figure 2. Comparison of Lukas-Kanade and Horn-Schnuck methods on real world examples.

C. Lukas-Kanade method reliability

To address some of the previously mentioned issues with the Lucas-Kanade method, we utilized a technique to estimate the reliability of the optical flow at each pixel. While reliability could be assessed by computing eigenvalues, this approach is computationally expensive. Instead, we used the more efficient Harris corner detection method, which identifies regions where eigenvalues are strong in both directions.

As shown in Figure 3, this enhancement effectively reduces noise in uniform areas, such as the top-left wall in the image, and improves the flow direction near edges.

D. Parameter tuning

Both methods use the sigma parameter, which controls the Gaussian filters applied for computing image derivatives and

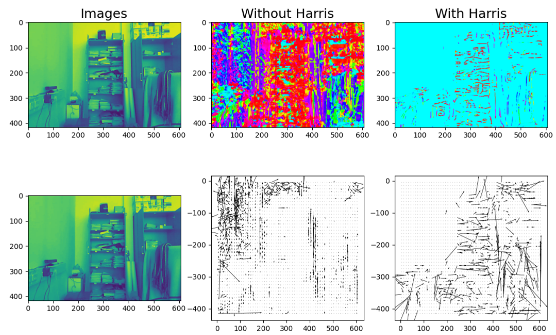

Figure 3. Comparison of optical flow with and without the addition of Harris corner detection.

smoothing. This parameter was set to 1/170 of the image width to ensure it scales with image size.

The Lucas-Kanade method also relies on the N parameter, which defines the neighborhood size. As shown in Figure 4, a larger neighborhood results in a smoother flow field. However, increasing the neighborhood size reduces the ability to detect movement in smaller or more distant objects.

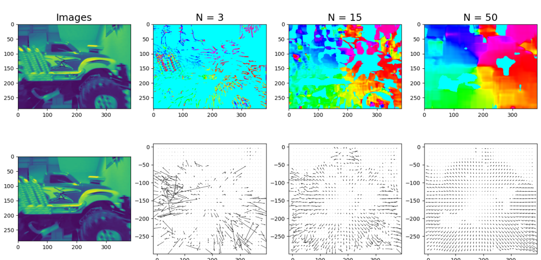

Figure 4. Comparison of optical flow using Lukas-Kanade with different sizes of neighbourhoods.

The Horn-Schunck method includes a lambda parameter, which controls the importance of the flow smoothness term, as well as the number of iterations, which only needs to be set high enough for the method to converge. As shown in Figure 5, a smaller lambda results in a less smooth flow field. However, if lambda is too large, some regions may lack a flow field entirely because too little emphasis is placed on color constancy and small motion errors. Therefore, in most cases, choosing a lambda between 0.1 and 1 provides a good balance.

E. Time measurement

While the Horn-Schunck method generally produces better results, it is significantly more time-consuming. We tested both methods on three different pairs of images and calculated their average runtime, as shown in Table I. The measurements were performed 10 times and then averaged.

We also evaluated the Horn-Schunck method with Lucas-Kanade initialization. When the Lucas-Kanade neighborhood size was set to a large value (e.g., 50), there was a notable improvement in time efficiency, as shown in Table I. However,

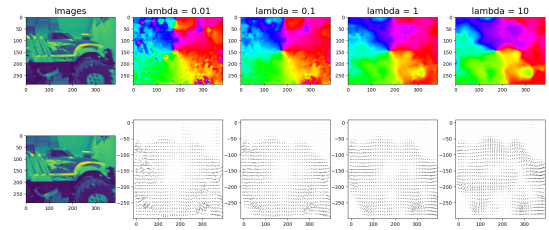

Figure 5. Comparison of optical flow using Horn-Schnuck with different weights on the smoothness error.

using a smaller neighborhood (e.g., 3) resulted in slower convergence than the base Horn-Schunck method.

Method	**Average time[s]**
Lukas-Kanade	0.0310 ± 0.0001
Horn-Schnuck	6.55 ± 0.02
Horn-Schnuck (Lukas-Kanade initialization)	4.27 ± 0.01

Table I
Comparison of time-consumption for different methods

F. Pyramidal Lucas-Kanade

We implemented the pyramidal version of the Lucas-Kanade method. Images that were at least 4 times the size of the neighborhood (we used a neighborhood size of 15) were input into the pyramid. As shown in Figure 6, the pyramidal structure produces a smooth optical flow, even when the image has a highly diverse background, as in this example. The advantage of the pyramidal structure is that it can capture both small and large movements. Additionally, we observed that applying the method multiple times at each level slightly improved the flow direction in the bottom-right area

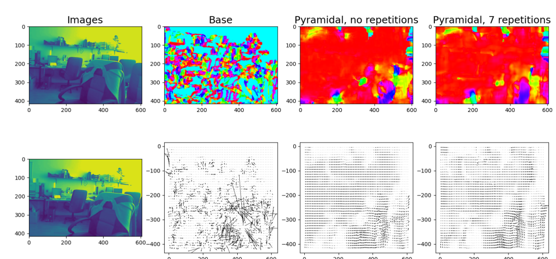

Figure 6. Comparison of the base Lukas-Kanade method with its pyramidal alternative, without and with 7 repetitions at each resolution.

III. Conclusion

The experimentation showed that the Horn-Schunck method generally performs better than the Lucas-Kanade method. However, it is significantly slower, which is a critical factor for many motion tracking applications. We demonstrated that the Lucas-Kanade method can be improved by introducing a reliability criterion for flow estimation and incorporating a pyramidal structure.