Exercise 1: Optical flow

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I. Introduction

In this paper we present different implementations of Lucas-Kanade and Horn-Schunck optical flow algorithms. We also present results that were obtained by testing algorithms on different set of images and how the performance can be optimized. Best result were obtained using pyramidal implementation of LK.

II. Experiments

In Figure 1 we can see results from rotated random noise images. In the first row there are angle (left) and field (right) plots for Lucas-Kanade, in the second row same for Horn-Schunck. We get quite similar results from both methods and good optical flow estimation. For LK we used 5×5 neighborhood, for HS we used 200 iterations and $lambda = 0.5$.

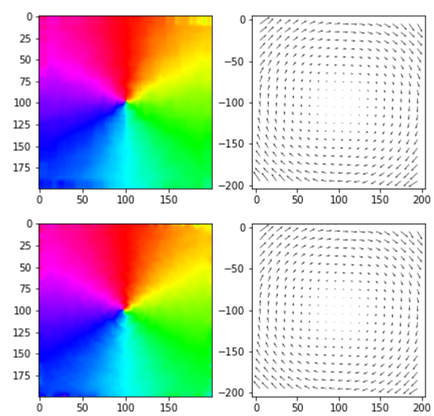

Figure 1. Angle and field flow plots for LK and HS.

On non-random noise images, differences began to emerge. We tested both methods on 3 different sets of images with same parameters. In Figure 2 is an example of a rotating sphere with moving background. We get better flow estimation from HS method (bottom-right), which clearly indicates sphere rotation and little background movement. LK (bottom-left) introduces a lot of noise (extreme vectors pointing out of the sphere, non-uniform background). Second example, the camera is approaching towards the car as shown in Figure 3. LK (bottom-left) is still noisier than HS (bottom-right), but overall estimation seems better - the floor annotates the biggest movement (because it is closest to the camera), while on HS the car is the main flow mark and the floor is almost ignored. In the last example (Figure 4), we can again see better performance with HS (bottom-right), mainly on the edges but also less overall noise than LK (bottom-left).

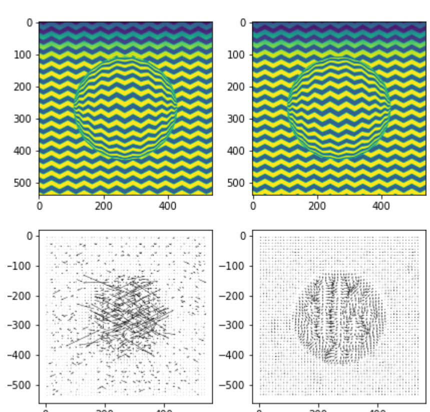

Figure 2. Field flow plots for LK and HS.

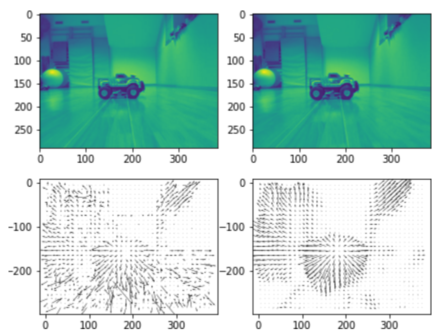

Figure 3. Field flow plots for LK and HS.

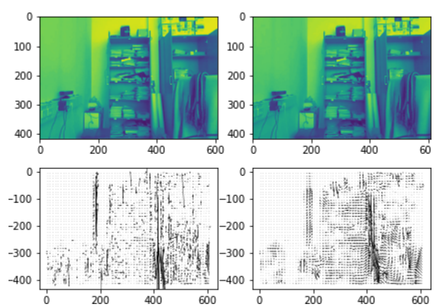

Figure 4. Field flow plots for LK and HS.

We can determine where the Lucas-Kanade optical flow can not be estimated reliably by looking at eigenvalues λ_1, λ_2 of the system $A^T A$. Eigenvalues should not be too small, ratio λ_1/λ_2 should not be great. Then the Lucas-Kanade optical flow can be estimated reliably.

Parameters for both methods have large impact on their performance. For LK we need to determine neighborhood size. This parameter can impact on performance when there are areas of large motion. We can see an example in Figure 5 when we used $N = 3$ (left) and $N = 25$ (right). With larger N, sphere flow is estimated better, because of 2 areas of large motions (background and sphere). For HS method we need

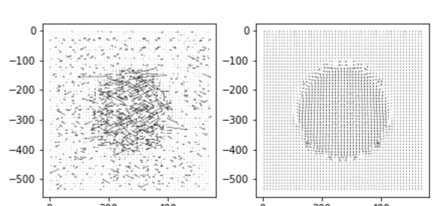

Figure 5. Field flow plots for LK with different parameters.

to determine number of iterations and lambda. We tried two different number of iterations $i \in \{10, 300\}$ and two different lambda values $\lambda \in \{0.5, 0.00005\}$ (four combinations in total). Result are shown in Figure 6, small i and large λ (top-left), large i and large λ (top-right), small i and small λ (bottom-left), large i and small λ (bottom-right). So with larger number of iterations the overall estimation is improved and the noise is minimized. Lambda value impacts on performance when there are areas of large motion. The best combination is large number of iterations and large lambda value (top-right).

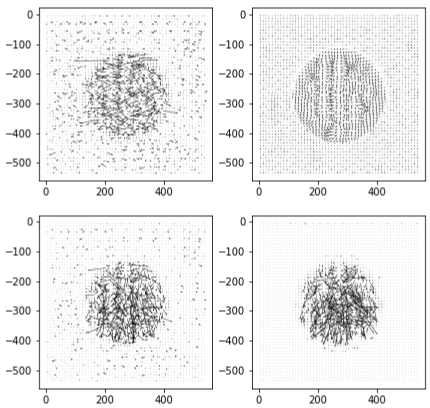

Figure 6. Field flow plots for HS with different parameters.

We timed LK, HS and HS initialized by output of LK (HS+LK), time results are shown in Table I and flow in Figure 7. Random noise images (top) and sphere rotating images (bottom) were used. We tried to get outputs as similar as possible. Final parameters for random noise image were $N = 10, lambda = 0.5, n\_iter(HS) = 1000, n\_iter(HS{+}LK) = 30$, and $N = 20, lambda = 0.5, n\_iter(HS) = 1000, n\_iter(HS + LK) = 200$ for sphere rotation image. Fastest method in both cases is LK, followed by HS+LK, the worse is HS. We can see quite big optimization with HS+LK compared to HS (22x in first case and 4x in second).

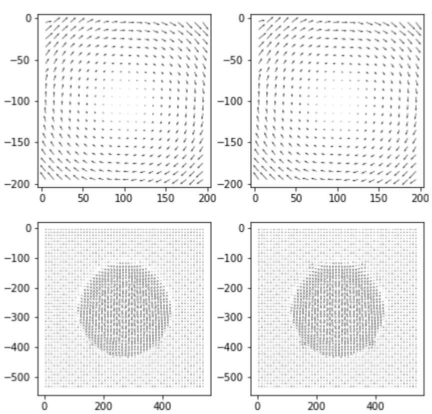

Figure 7. Field flow plots for LK and HS.

Table I

fig	LK	HS	HS+LK
random noise	$0.08s$	$3.61s$	$0.16s$
sphere	$1.42s$	$32.13s$	$7.97s$

Lastly, we implemented the pyramidal implementation of LK method. Comparison between LK (bottom-left) and pyramidal LK (bottom-right) can be seen in Figures 8, 9. In the first example we used sphere rotation images, and for the second one we used two dancers walking in a circular motion. In both cases, the pyramidal version returned better results than the regular. There is a lot less noise and better estimation in areas of large motion (the closest dancer and the sphere). We can clearly see the forward movement of the dancer, the sphere motion seems more uniform. In both cases we used a neighborhood of size 15x15 and 3 levels of pyramid subsampling. Running

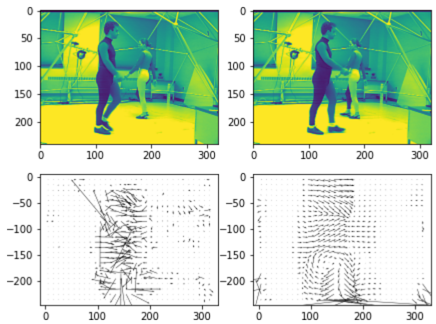

Figure 8. Field flow plots for LK and pyramidal LK.

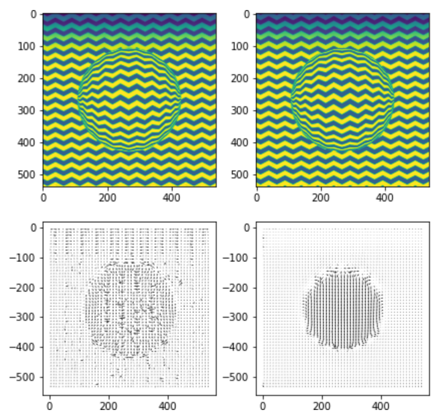

Figure 9. Field flow plots for LK and pyramidal LK.

LK iteration multiple times on the same scale only worsens the performance by taking more time and introducing more noise.

III. Conclusion

Both methods can be easily optimized, but we got the best performance from pyramidal implementation of LK method. Outputs from pyramidal LK and HS+LK may not differ a lot, but pyramidal is vastly faster.