Optical flow

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I. Introduction

In this exercise, we have implemented two methods for computing the optical flow, the Lucas-Kanade and Horn-Schunck methods. Both are evaluated on multiple images and for multiple values of their parameters. To make the Lucas-Kanade more robust we implement an improvement using the Harris response, as well as the pyramidal version of it for better detection of motion of different sizes.

II. Experiments

A. Rotated random noise

Both methods are first evaluated using a toy example, i.e., a random noise image and 1 degree rotation. In Figure 1 we can see that the Horn-Schunck method produces a smoother field, especially near the border. Lucas-Kanade orientations are not as uniform and contain artefacts close to the border, where the motion is larger. Both methods manage to detect the correct motion overall.

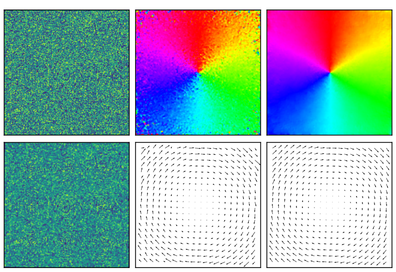

Figure 1: Results of both methods on a rotated random noise image. Top left image is the original one, Lucas-Kanade results are in the middle and Horn-Schunck on the right.

B. Evaluation on other images

Similar results are shown in Figure 2. In the first example, Horn-Schunck detects the correct flow, where all vectors are rotated from the centre out and the RC car is moving more, due to being closer to the camera. Similar orientations (hue) can be seen from Lucas-Kanade, but there is a lot of noise and artefacts with vectors of large magnitude. This is expected because Lucas-Kanade assumes small motions.

In the second example, Horn-Schunck returns a smooth field with the main part of the building being detected correctly, but there are also some parts which look smooth but seem to include some artefacts (grass hill). Lucas-Kanade also detects the same motion on a small part of the building, but the result contains even more noise and is not smooth anywhere else.

In the last example, Horn-Schunck performs much better than Lucas-Kanade. In the hue image, we can see outlines of a few objects in the vector field and the difference between floor and ceiling. In Lucas-Kanade results, there is a lot of noise and we can only observe a weak outline of the centre object, the floor and the ceiling.

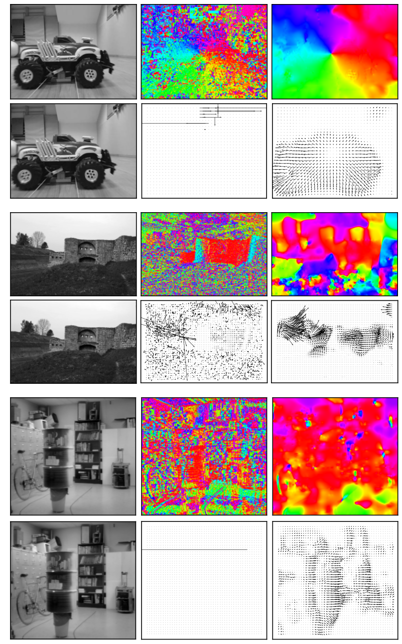

Figure 2: Evaluation of three more pairs of images. In all cases Horn-Schunck produced smoother optical flows with less spurious vectors of large magnitude and less noise. Images are organised the same as in Figure 1.

C. Lucas-Kanade with Harris response

The Lucas-Kanade method solves a matrix system, which cannot be reliably solved when eigenvalues are small or their ratio is big. These are flat regions and edges, which are not detected by the Harris corner detector. We set optical flow, where the Harris response is small, to zero. Results of the improvement method are shown in Figure 3. Optical flow on the main building remains, but the noisy parts which include most of the image are removed. These regions are problematic because they are very uniform (grass, sky). Some incorrectly computed vectors remain in the grass area and on the tree line on the left.

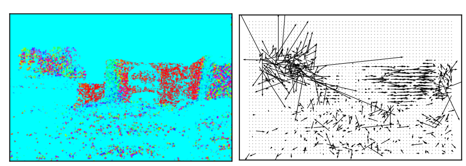

Figure 3: Results of the Lucas-Kanade method with the Harris improvement on the second example from Figure 2.

D. Parameters

In the Lucas-Kanade method, there is one parameter - the size of the neighbourhood. As it can be seen in Figure 4, using a larger neighbourhood smooths out the flow field. This decreases the amount of noise and vectors with large magnitude. In this case, a value of around 9 or even higher seems to work best,

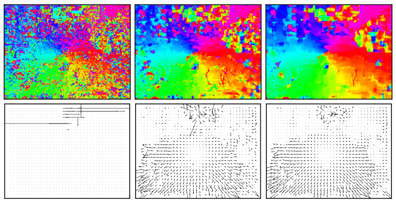

Figure 4: Lucas-Kanade results of the first image from Figure 2 with three different sizes of neighbourhoods, 3 (left), 9 (middle) and 15 (right).

but we may want to keep it lower if we want to obtain small details.

In the Horn-Schunck method, there are two parameters - the number of iterations and a trade-off between the two constraints λ. The number of iterations needs to be high enough for the method to converge. If so, the results of the method are the same. We can automatically detect convergence by looking at the sum of squared differences between the current and the new flow field approximations in each iteration. The results of this approach are shown in the next subsection. With λ, we can determine the smoothness of the flow field, see Figure 5. If the value is too small, the smoothness constraint is not satisfied and the flow contains many vectors with incorrect orientation. On the other hand, too high a value prioritises smoothness constraint too much, producing a flow field with no noise, but incorrect orientations due to oversmoothing. Value around 1 seems to work best.

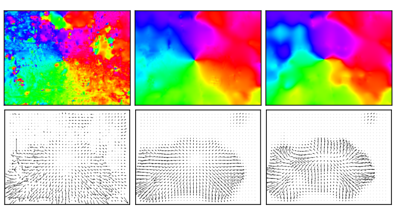

Figure 5: Horn-Schunck results of the first image from Figure 2 with three different values for λ, 0.001 (left), 1 (middle) and 100 (right).

E. *Time measurements*

Because the Horn-Schunck method is an iterative method, it is expected to run slower than Lucas-Kanade. Results of time measurements are shown in Table I. For more robust measurements, we run algorithms multiple times and take an average. Because Horn-Schunck takes more time, we run it fewer times than Lucas-Kanade.

Method	Time	Iterations
Lucas-Kanade	7.17 ms	/
Horn-Schunck	5.26 s	7087
Horn-Schunck (with LK)	3.75 s	5028

Table I: Average times of running the Lucas-Kanade method 500 times and Horn-Schunck method 3 times on the first example from Figure 2. We improve the Horn-Schunck method by initialising it with the output of the Lucas-Kanade (LK) method. To utilise this, we automatically detect convergence in the Horn-Schunck method using tolerance 1e−4.

We can see that Lucas-Kanade is a few magnitudes faster, which is expected. We only need to compute a few convolutions and matrix multiplications. Many of these are also computed in the Horn-Schunck method, but there is a lot of additional computation that needs to run in every iteration.

To speed up the Horn-Schunck method, we can try initialising it with the output of the Lucas-Kanade method. We can see in the table that convergence in this case is faster and consequently, the method takes less time. The main reason for this is the number of needed iterations. Even though both methods converge by the same criteria, the results are not exactly the same, but they are very similar, see Figure 6. The difference probably comes from the fact that the Lucas-Kanade solution is not the same and it contains a lot of noise that needs to be removed. To minimise this effect, we use the Harris improvement, remove large flows and smooth the field. The amount of noise also affects the speed up. In some cases, this improvement does not yield an improvement at all.

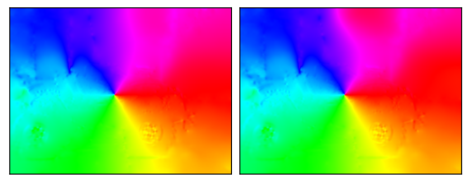

Figure 6: Results of the Horn-Schunck method after convergence without (left) and with (right) Lucas-Kanade initialisation. Flow fields are similar, but there are a few subtle differences.

F. *Pyramidal Lucas-Kanade*

This improvement enables the Lucas-Kanade method to detect motions of different sizes. We compute the flow using lower-resolution images and warp the second image with the negative result. We repeat this for all levels in the Gaussian pyramid, upsampling the optical flow in between. Results can be seen in Figure 7. As we can see, this improvement does produce a smoother flow field, but the results are still not as good as Horn-Schunck. We also tried running the method multiple times on each pyramid level, but this did not yield an improvement over running it only once.

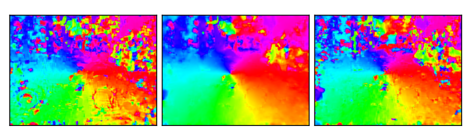

Figure 7: Results of ordinary Lucas-Kanade method (left) and pyramidal Lucas-Kanade with 1 (middle) and 5 (right) repetitions on each level. We use pyramids down to size 4×4.

III. Conclusion

In most cases, the Horn-Schunck method works better. The results are smoother fields, but the computation takes longer than the Lucas-Kanade method. The latter produces fields with more noise but can be further improved, even though the results are still not as good as with Horn-Schunck.