VISION: Practical work – Implementation of two optical flow methods

Maximilien Nowak, Matthieu de Castelbajac

January 2023

In this practical work, we compare and experiment with two methods for optical flow estimation, the Horn & Schunck scheme and the Lucas & Kanade method. We test the methods on the four pair of images for which the true optical flow is available, that is, `mysin.png`, `square.png`, `rubberwhale.png` and `yosemite.png`.

1 Horn & Schunck

As metrics, we use the angular error and the relative endpoint error, the number of iterations is fixed to two hundred and we try to optimize the alpha regularization parameter. We display the results below.

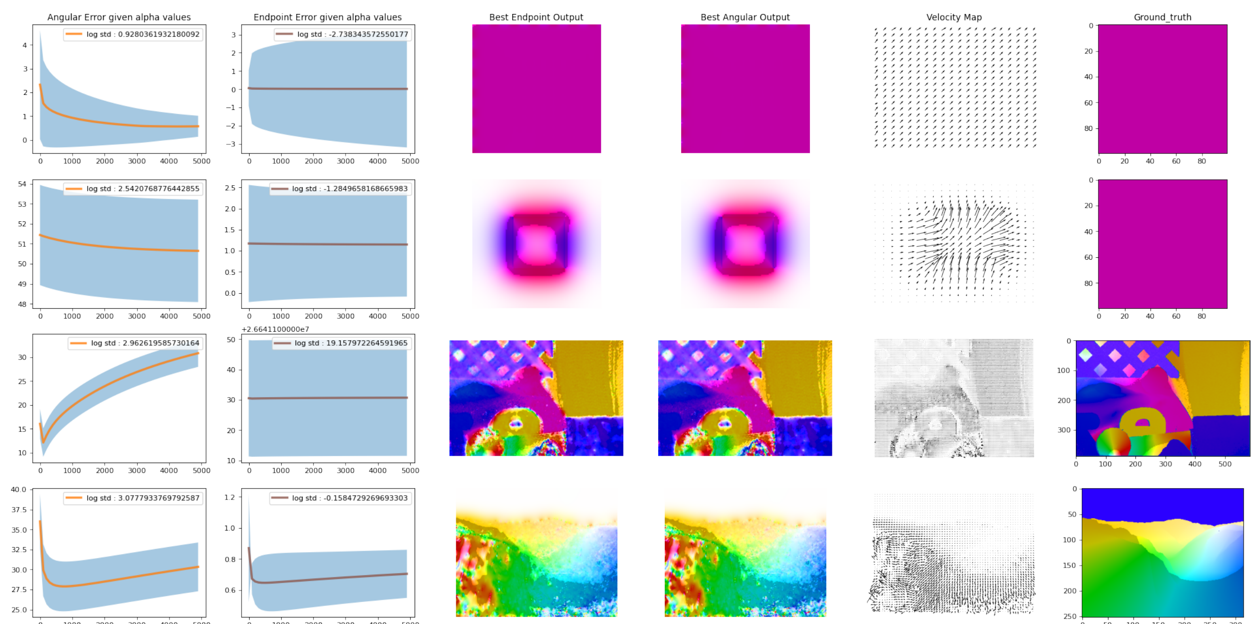

Figure 1: Error plots, outputs, vector map and ground truth for each pair of images

Immediately we see that the scheme accurately estimates the `mysin` optical flow. The loss metric converges, slowly but surely, and the result is convincing. As for the `square` optical flow, the method struggles to converge (even if we had up the number of iterations), and the result is not convincing as it gives the highest errors of the four images. It was to be expected, for the strength of this method relies in its global characteristics. But here, there is seldom information about the motion - although the movement is really easy to spot at local scale. Finally, for more complex scenes such as the last two ones, results are not great either. Note how we need lower regularization parameters to match the complexity.

2 Lucas & Kanade

We are going to use the same metrics used in Horn & Schunck, although here we try to optimise the window size rather than the alpha parameter.

2.1 Rectangular window

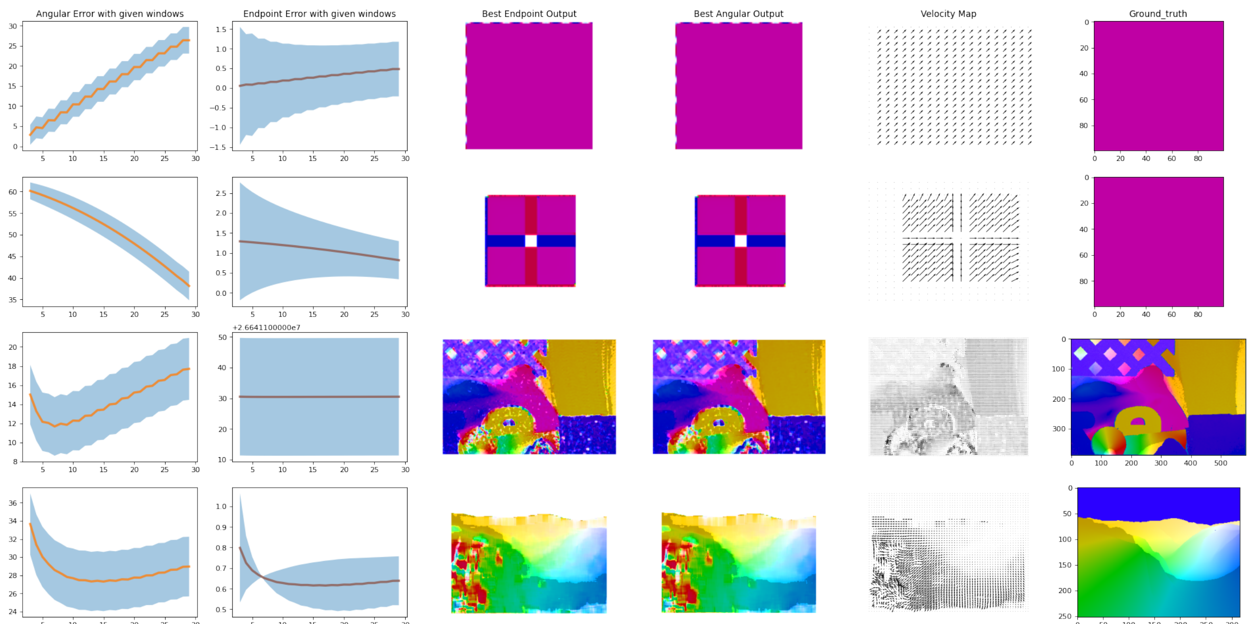

Figure 2: Lucas-kanade Algorithm with a rect window

The window is a key factor in the Lucas & Kanade algorithm, so to start, we use a rectangular window. This window, while simple, shows the locality of the algorithm. Therefore, a window that is too large will lead to an increasing error for both metrics. This applies also for small windows, as the algorithm will lack information and again result in a large error.
Another important aspect of the Lucas-Kanade algorithm is its robustness in the presence of noise. The result with the Yosemite data set is significantly smoother than the with Horn-Schunck estimation due to the algorithm's locality.

In addition the resulting data provided by Lucas & Kanade it more sparse than the data provided by Horn & Schunck. It is linked to the algorithm's fundamental operations, matrix inversion and the dot product of A and B. Even though it is mathematically correct, computers lack the precision needed to do such calculations for huge matrices. This error led to a more sparse output than the Horn & Schunck would have given us.

2.2 Bartlett window

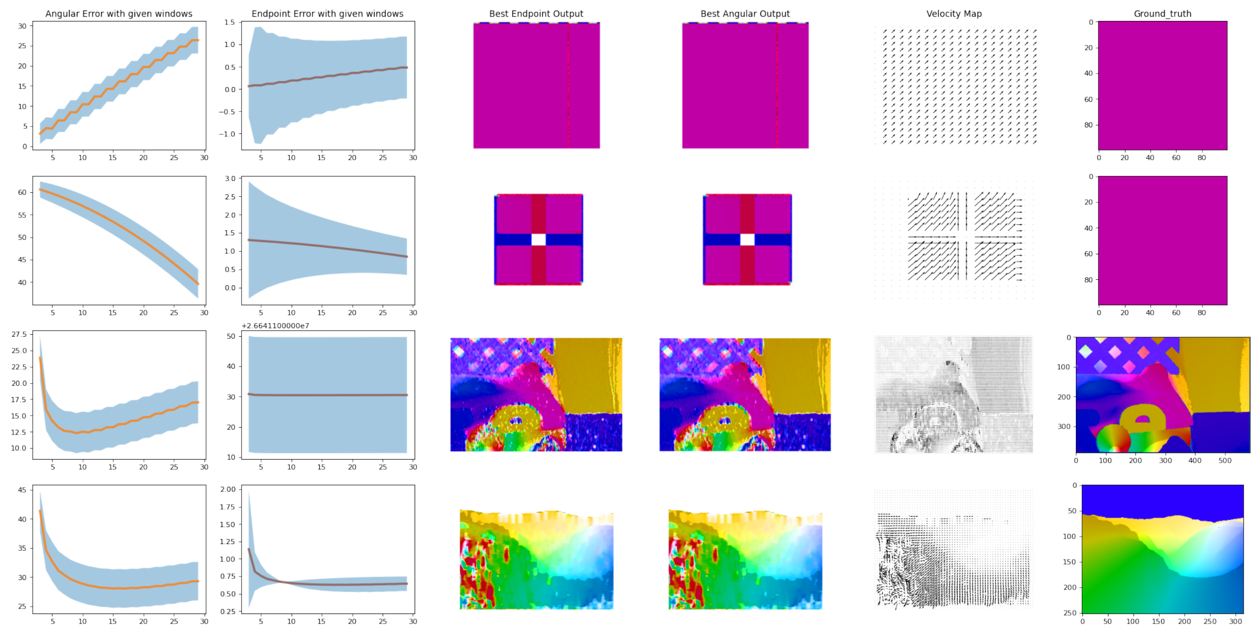

Figure 3: Lucas-kanade Algorithm with a Bartlett window

A Bartlett window prioritises the pixel closest to the centre of the window in a linear way. It helps by lowering the pixel's importance while still allowing it. Lucas-Kanade heavily depends on the way the pixels are pondered and can output different result with the same dataset (the rubberwhale for exemple).
Other windows, such as the Hamming window or the gaussian window, can be useful and help achieve better robustness.