Optical Flow Estimation

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I. Introduction

In this project, two classical algorithms for optical flow estimation were implemented: Lucas-Kanade (LK) and Horn-Schunck (HK). Their performance was tested on different consecutive image pairs and with different combinations of parameters.

II. Experiments

A. Lucas-Kanade and Horn-Schunck optical flow on rotated random noise images

Implemented Lucas-Kanade(LK) and Horn-Schunck(HS) methods were tested on rotated random noise images and the results are shown in Fig. 1 and Fig. 2. The optical vector flow field in the bottom-right corner of the figures exhibits smaller values near the center and larger values near the edges of the image. This is because the pixels near the edges of the image undergo greater motion during rotation compared to the pixels located towards the center. As for the performance of the LK and HS methods, we can see that the vectors in the flow fields of both images are consistent with the motion of the objects in the scene, indicating good performance of both models on those images. From the bottom-left corner of the figures we see that angle plot of the HS is smoother, especially around the corners, indicating a somewhat better performance of the HS method compared to LK.

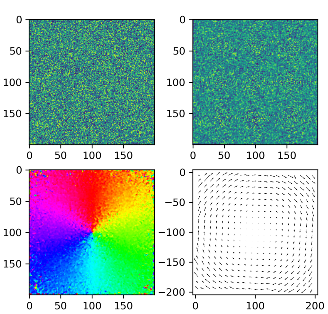

Fig. 1: Lucas-Kanade (N=3, σ=1) optical flow on rotated random noise image

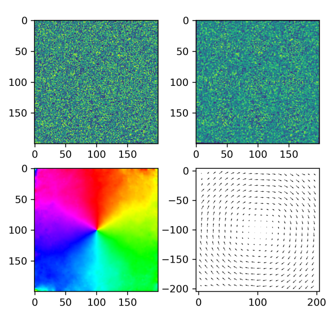

Fig. 2: HS(λ=0.5,n_iter=1000 σ=1) optical flow on rotated random noise image

B. Testing LK and HS methods on 3 pairs of images

Fig. 3 shows the results of testing LK and HS on 3 pairs of images. The reasons for the LK unsatisfactory performance in all 3 cases are that the assumptions of the method (brightness constancy, small motion assumption and local coherency assumption) are violated for the given examples of consecutive frames. For the first pair of frames, LK fails in the regions that are closer to the camera, as objects in these regions appear to move faster than objects that are further away, thus violating the small motion assumption. On the second pair of frames we see an obvious difference in lighting, which indicates a violation of the brightness constancy assumption. On the third pair of frames, local coherency assumption, that assumes that neighboring pixels have similar motion vectors, is violated. This is visible from the HS flow field in the bottom-right corner in Fig.4. HS outperforms LK, because it is a global method that considers the entire image simultaneously to estimate the motion fields, while the LK is a local method that only considers the small neighborhood around each pixel and estimates the flow for each individual feature point independently. This makes HS more robust to changes in brightness,large displacements and deformations in the motion field.

C. Parameters of LK and HS and their impact on performance

The most important Lucas-Kanade parameters that have to be defined are: σ parameter for Gaussian smoothing, window size(N) used to estimate the optical flow and threshold if we are incorporating Harris response in LK algorithm. A larger sigma value is useful for removing noise in the image, but it can also blur out small-scale features. Larger sigma values are suggested when we are computing optical flow on images that contain a significant amount of noise. When tracking small-scale features or when the motion in the image is fast, a small window size is suggested. This is because a smaller window can capture the finer details and local changes in the image more accurately. On the other hand, a large window size is used when tracking large-scale features or when the motion in the image is slow. The Fig. 4 shows the LK flow fields for the first pair of images with different parameters. For these frames, LK has the best performance with N=25 and σ=1, because the flow field (bottom-right corner) is more coherent compared to other parameter combinations. This is expected, as we are tracking a large object, so small N fails to estimate field flow, while increasing σ blurs out important features. However, it's important to keep in mind that a larger N increases the computational cost of the optical flow estimation algorithm.

Horn-Schunck parameters than need to be defined are: λ, that balances the influence of smoothness constraint and brightness&motion constraint, and number of iteratations, that determines the number of times the algorithm iteratively updates the optical flow vector field until convergence. Fig. 5 show HS vector flow fields of the first pair of images for different combinations of λ and n_iter. For large λ (top-right corner) we get a coarser estimate of the optical flow, as it puts more weight on the smoothness term and less weight on the gradient term. Low value of λ (top-left corner) results in more detailed and accurate flow field, as it puts more weight

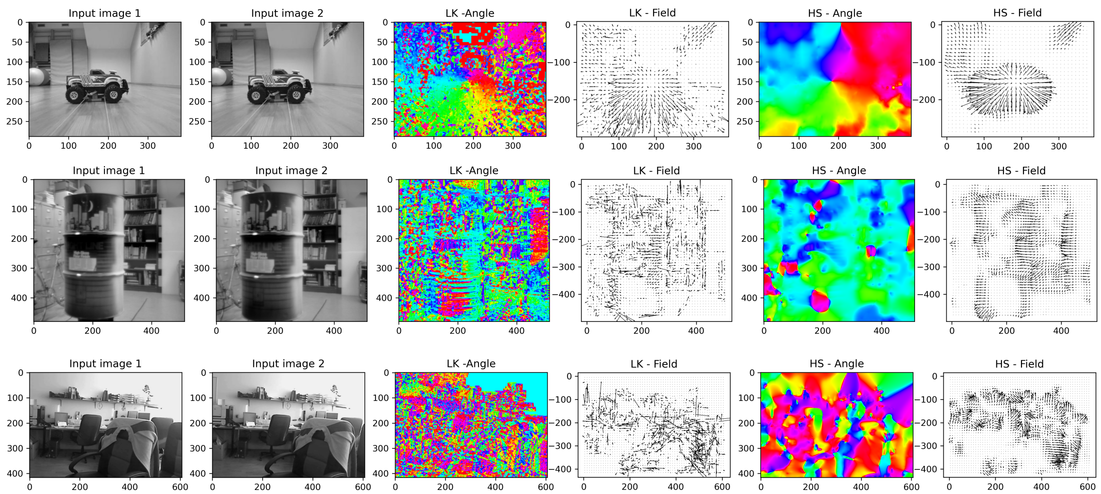

Fig. 3: Lucas-Kanade (N=5, σ=1) and Horn-Schunck (λ=0.5, n_iter=1000, σ=1) optical flow on 3 pairs of images.

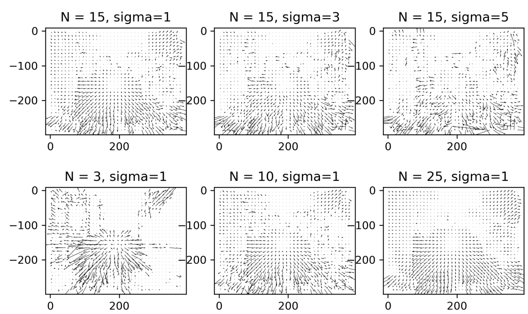

Fig. 4: Lucas-Kanade flow fields for different N and σ

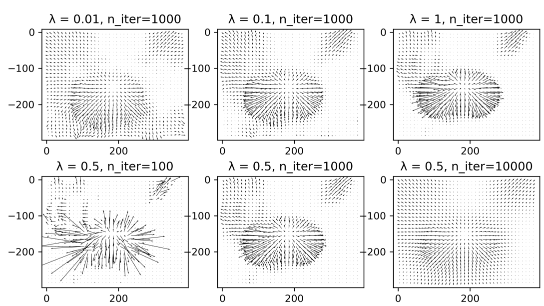

Fig. 5: HS flow fields for different λ and number of iterations

on the gradient term. In general, smaller values of λ are appropriate for scenes with more complex, rapidly varying motion, or when a more detailed estimate of the optical flow is required. Considering the n_iter parameter, increasing the number of iterations improves the accuracy and smoothness of the optical flow estimation, but also significantly increases the computational cost of the algorithm. In bottom-left corner of Fig. 5 we see that algorithms doesn't converge within 100 iterations, resulting in inaccurate flow field estimation. Identical bottom-middle and bottom-right subplots show that algorithm converges within 1000 iterations.

D. Initializing HS method with output of LK

The idea behind initializing HS with the output of LK is that by using the output of LK as an initial guess for HS, the algorithm can converge faster and produce better results. This is because the initial guess provided by LK can serve as a good approximation of the true optical flow, which can help HS to converge to a better solution. In this experiment we measured the time it takes for the algorithm to complete its execution for LK (N=5, σ=1), HS (λ=0.5, n_iter=10000, σ=1) and HS with same parameters, initialized with the output of LK (N=5, σ=1), for the rotated random noise images and the first pair of images from Fig. 3. The results are shown in Table 1. Optical flow fields for the first pair of images with HS and HS initialized with LK output are shown in Fig.6.

TABLE I: Runtime in seconds of the LK, HS and HS initialized with the output of LK algorithms.

Frames	LK	HS	HS initialized with LK
Rotated random noise	0.0s	$\approx$ 0.3s	$\approx$ 0.2s
First pair of images	$\approx$ 0.01s	$\approx$ 5.3s	$\approx$ 6.7s

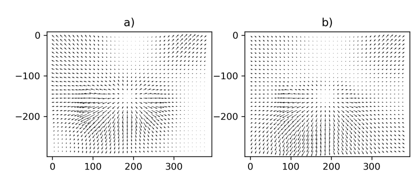

Fig. 6: Flow fields of: a) HS; b) HS initialized with LK output

We can conclude that HS initialized with LK output will converge faster only if the LK flow estimation is good enough, which is the case for rotated random carrier images, but not the case for the first pair of images. However, even though the runtime for the first pair of images is longer, from Fig. 6.b) we can see that that HS initialized with LK gives better results, in terms of a more accurate and detailed flow field compared to 6.a).