Computer Vision Assignment 3: Optical Flow, Motion Analysis and Stabilization

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***Abstract*—This report presents the implementation and results of four computer vision tasks: ROI-based motion analysis, slow-motion frame synthesis, video stabilization, and vanishing point detection. All were implemented in Python using OpenCV without GUI dependencies. Each task explores a practical application of optical flow and motion geometry.**

***Index Terms*—Optical Flow, Lucas-Kanade, Stabilization, Vanishing Point, Motion Estimation, ROI.**

I. Introduction

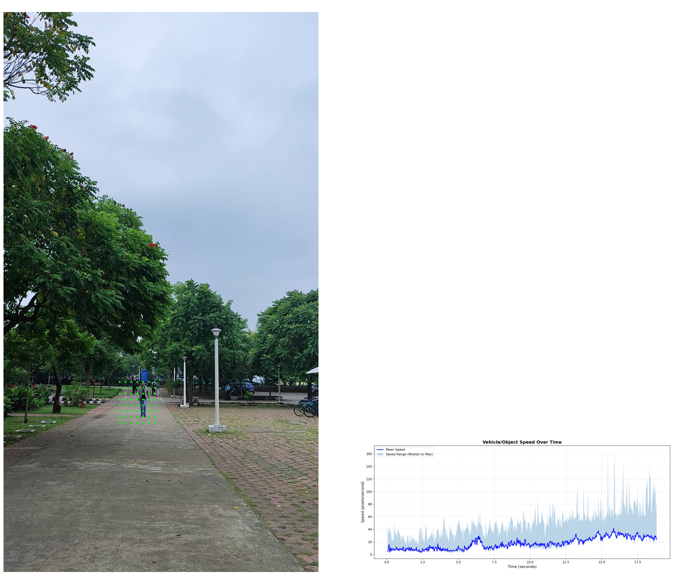
Optical flow describes the apparent motion of features between consecutive frames in a video sequence. It forms the basis for tasks such as tracking, motion estimation, and structure analysis. This report explores different applications of optical flow — including slow-motion interpolation, ROI-based analysis, stabilization, and vanishing point estimation.

II. Q1: ROI-Based Motion Estimation

The Lucas–Kanade optical flow was computed within a fixed region of interest (ROI):

$$x_1 = 0.35W,\ x_2 = 0.50W,\ y_1 = 0.65H,\ y_2 = 0.75H$$

This focuses on the main moving subject (a walking person). Displacement magnitudes were converted into approximate speed (pixels/sec) to analyze motion trends.



(a) ROI optical flow. **(b)** Speed vs. time.

Fig. 1: ROI-based motion estimation and speed analysis.

III. Q2: Slow-Motion Frame Interpolation

Intermediate frames were generated using bidirectional dense optical flow:

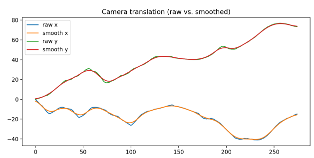
$$I_{mid} = \frac{1}{2}\big(W(I_t, \tfrac{fwd}{2}) + W(I_{t+1}, \tfrac{bwd}{2})\big)$$

where $W(I, F)$ warps image I using flow F. Limiting computation to the ROI improved clarity by avoiding background noise.

Fig. 2: Generated middle frame using bidirectional optical flow inside ROI.

IV. Q3: Video Stabilization

Stabilization was achieved using sparse optical flow within the ROI. Median displacement across feature points defined the frame translation path, which was then smoothed with a moving average.

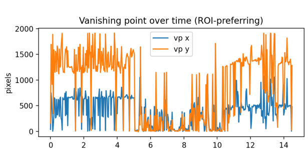


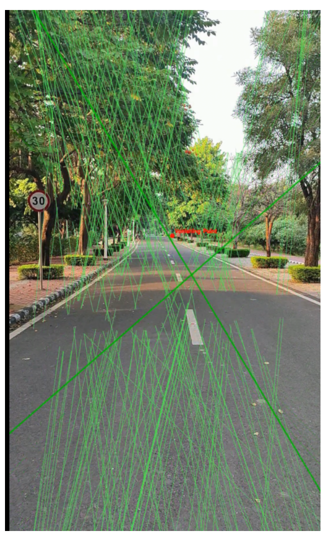
(a) Sparse tracked points. **(b)** Smoothed motion path.

Fig. 3: Sparse flow-based video stabilization results.

V. Q4: Vanishing Point Estimation

Edges were detected using the Canny operator, and line segments were extracted via the Probabilistic Hough Transform. Intersections of random line pairs were used to estimate the vanishing point using a RANSAC-based filter. ROI selection ensured the dominance of road-region lines.





(a) Detected VP. **(b)** VP stability plot.

Fig. 4: Vanishing point detection and temporal consistency.

VI. Results and Discussion

The ROI-focused analysis produced reliable motion insights:

- **Q1:** The pedestrian's motion showed consistent velocity patterns.
- **Q2:** Interpolated frames were smooth and visually stable.
- **Q3:** Stabilization reduced camera shake and jitter.
- **Q4:** The vanishing point remained stable across time, confirming consistent perspective.

VII. Conclusion

This assignment demonstrates that ROI-based optical flow significantly improves precision and stability in motion analysis. Lucas–Kanade and geometric approaches together enable accurate understanding of real-world scene dynamics with minimal computation.

References

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