Comparison Report: Optical Flow Evaluation on KITTI Dataset

1. **Introduction**

This report presents the evaluation of two optical flow methods Lucas-Kanade (sparse) and Horn-Schunck (dense) on the KITTI dataset. Optical flow is essential in autonomous vehicle navigation for tasks such as object identification, motion tracking, and path planning. Accurate motion vector estimation enables cars to perceive their environment and make real-time judgments.

2. **Methodology**

1. Lucas-Kanade Method

The Lucas-Kanade method is a sparse optical flow technique that follows a set of feature points across multiple frames. It presupposes that the motion of small patches in the image may be approximated with a constant velocity. This approach is computationally efficient and ideal for tracking salient visual features like edges and corners.

2. Horn-Schunck Method

The Horn-Schunck method is a dense optical flow approach that determines motion vectors for each pixel in a picture. It minimizes a global energy function that incorporates data accuracy and smoothness restrictions. This approach is great for catching minute details of motion over a whole image, making it useful in applications requiring dense motion fields.

3. **Evaluation Metrics**

Both techniques are evaluated using the Endpoint Error (EPE), which calculates the Euclidean distance between the estimated flow and the ground truth flow provided by the KITTI dataset. EPEs are calculated for both sparse (Lucas-Kanade) and dense (Horn-Schunck) flows.

4. **Results**

1. Quantitative Evaluation

The below data summarizes the average EPE for both methods over evaluated image pairs:

Average EPE for Lucas-Kanade: 188.1249

Average EPE for Horn-Schunck: 188.0186

Horn-Schunck exceeds Lucas-Kanade in terms of average EPE, indicating that it gives a more accurate estimate of the motion field than the sparse method.

2. Visualizations

Figures 1-3 present a visual comparison of the motion vectors estimated by both approaches and the ground truth.


Figure 1: Lucas-Kanade Optical Flow

This figure depicts the sparse motion vectors superimposed on the first frame of the visual sequence. The green lines depict the movement of monitored feature points from their original positions in the first frame to their new positions in the second frame.

Figure 2: Horn-Schunck Optical Flow

This diagram displays the dense motion vectors using a color-coded format. The hue shows the direction of motion, while the brightness represents the amplitude of the flow.

Figure 3: Ground Truth Optical Flow

This graphic depicts the ground truth motion field provided by the KITTI dataset. The motion vectors across the image are shown using color coding, similar to the Horn-Schunck depiction.

3. Qualitative Analysis

Visually, the Lucas-Kanade approach captures the motion of conspicuous features well, but it struggles in spaces with no obvious corners or edges. This issue causes incomplete motion estimates, particularly in places with smooth surfaces.

On the other hand, the Horn-Schunck approach generates a dense flow field that captures motion across the image. However, the approach is more sensitive to noise, which can cause over-smoothing in specific locations, resulting in less accurate flow vectors in places with quick changes in motion.

5. **Discussion: Strengths and Weaknesses**

1. Lucas-Kanade Method

   Strengths:

   - Efficiency: Lucas-Kanade's sparse nature ensures computational efficiency, making it ideal for real-time autonomous driving applications.
   - Accuracy in Features: The approach accurately detects object boundaries by tracking defined features such as edges and corners.

   Weaknesses:

   - Limited Coverage: Lucas-Kanade is a sparse approach that only provides motion estimates at certain places, potentially missing vital information in areas with less conspicuous characteristics.
   - Sensitivity to Noise: The approach may struggle with noisy inputs, especially in low-texture areas, resulting in erroneous flow estimations.
2. Horn-Schunck Method

   Strengths:

   - Dense Flow Estimation: Horn-Schunck's dense flow estimation provides a comprehensive perspective of the scene's dynamics, making it ideal for applications requiring deep investigation.
   - Smoothness Constraint: The method's smoothness constraint enhances its effectiveness in capturing background flow in circumstances with gradual motion.

   Weaknesses:

   - Computational Cost: The method's dense nature may limit its real-time use in autonomous cars.
   - Over-Smoothing: The assumption of global smoothness can cause inaccuracies in places with quick motion changes, like object boundaries or sudden moves.

6. **Conclusion**

Both optical flow systems offer advantages and disadvantages in the context of autonomous vehicle navigation. Lucas-Kanade tracks important features efficiently and accurately, however it may not capture all of the scene information. Horn-Schunck, while giving a more comprehensive motion field, necessitates more computer power and may obscure crucial details in dynamic settings..

For real-time autonomous driving applications, a combination of both technologies could be used. Lucas-Kanade can be utilized for quick feature tracking, but Horn-Schunck can be used selectively in areas where dense motion information is required.