Data Driven Tracking with Event Cameras

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Github: https://github.com/xxender13/DL_Final_Project_Team6/tree/main

1. Event Representation with MultiFlow Data

We initiated the project by generating event representations using the MultiFlow dataset. This process involved:

- Parsing and processing raw MultiFlow data.
- Transforming the data into structured event representations suitable for downstream tasks.

2. Track Generation with MultiFlow Data

Tracks were generated using the MultiFlow data to establish temporal consistency and sequence continuity. Key steps included:

- Identifying event sequences across time.
- Generating and refining tracks to represent object motion and interactions effectively.

3. Model Training with MultiFlow Tracks

We utilized the generated MultiFlow tracks to train a deep learning model. This training phase focused on:

- Inputting the generated tracks as training data.
- Optimizing the model to extract relevant spatio-temporal features.

4. Pose Data Preparation Using EDS Dataset

To fine-tune the model for pose estimation, we leveraged the EDS dataset. Steps included:

- Preprocessing EDS data to extract pose-related features.
- Aligning and formatting the data to integrate seamlessly into the fine-tuning pipeline.

5. Pose Refinement Using COLMAP

COLMAP was employed to refine the pose data, ensuring higher accuracy and reliability. The procedure involved:

- Utilizing COLMAP's capabilities for pose optimization.
- Incorporating refined pose data into the model for enhanced performance.

6. Model Testing Using Pretrained Models on EDS Dataset

We tested the pretrained model using the EDS dataset to validate its performance. This phase involved:

- Evaluating model predictions against ground truth data.
- Analyzing the accuracy and robustness of the model.

7. Augmented Lab Dataset Testing

The lab dataset was augmented with noise to test the model's robustness under varying conditions. This included:

- Introducing controlled noise variations into the lab dataset.
- Analyzing the model's predictions to assess sensitivity to noise.

Observations and Results

- The MultiFlow dataset provided a strong foundation for generating meaningful event representations and tracks.
- Fine-tuning with EDS data and COLMAP refinement significantly improved pose estimation accuracy.
- Testing with augmented lab data highlighted the model's resilience to noise, revealing areas for further optimization.