

Master Thesis Presentation

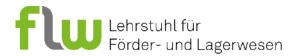
Motion Segmentation in Dynamic Environments using Event Cameras

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Examiners:

Prof.'in Dr.-Ing. Alice Kirchheim M.Sc. Shrutarv Awasthi



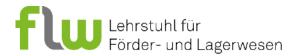


Agenda

- Introduction
- Motivation & Problem Definition
- Objectives
- Approach
- Experiments
- Results
- Challenges
- Conclusions
- Future Scope



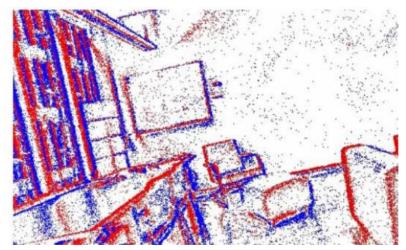




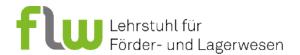
Introduction

- What is Motion Segmentation?
- What are Event Cameras?
- Why Event Cameras for Motion Segmentation?





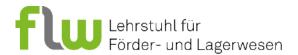




Motivation & Problem Definition

- Challenges with Standard cameras: Struggle with motion blur and low temporal resolution,
 limiting motion segmentation in complex environments.
- **Ego-Motion Problem**: Camera movement distorts image capture, complicating object segmentation and tracking.
- Research Focus: Investigating both classical and deep learning approaches for robust motion segmentation in dynamic environments.

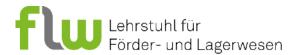




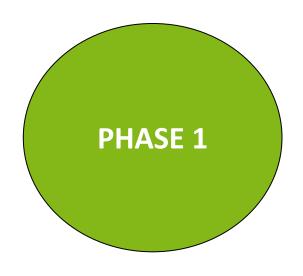
Objectives

- 1. Classical Approach: Implement and test spatio-temporal graph cuts
- 2. Dataset Collection: DVXplorer event data or EV-IMO dataset
- 3. **Neural Network Adaptation**: Modify "EV-IMO" model for the dataset
- 4. Training Pipeline: Develop a learning pipeline
- 5. Model Testing: On pre-recorded videos and images





Approach



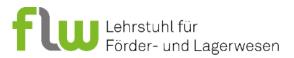


Implement and test traditional space-time graphs using energy minimization.

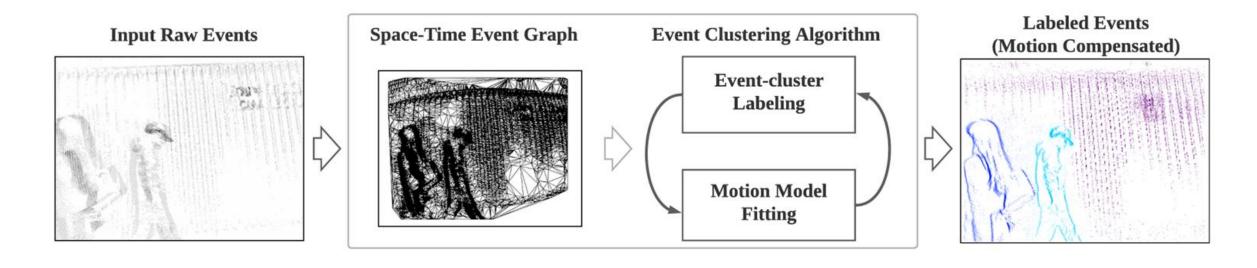
Develop and deploy data-driven models, evaluating three different structures on a dataset.



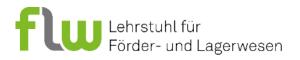




Classical Approach: Using Space-Time Graphs







Results: Classical Approach



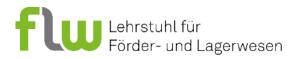




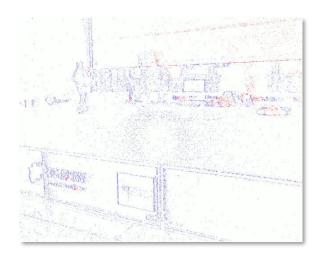
DVSMOTION20

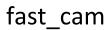
EED

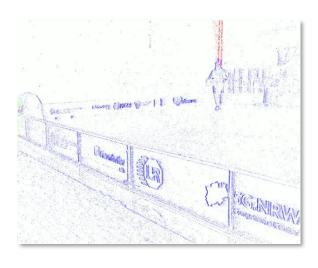
EVIMO



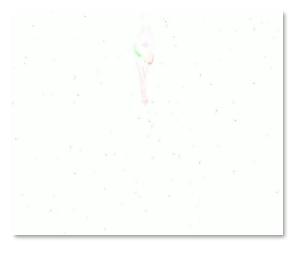
Results: Classical Approach



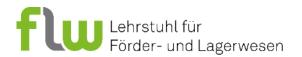




slow_cam



near_obj

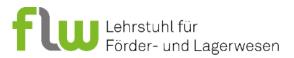


Limitations: Classical Approach

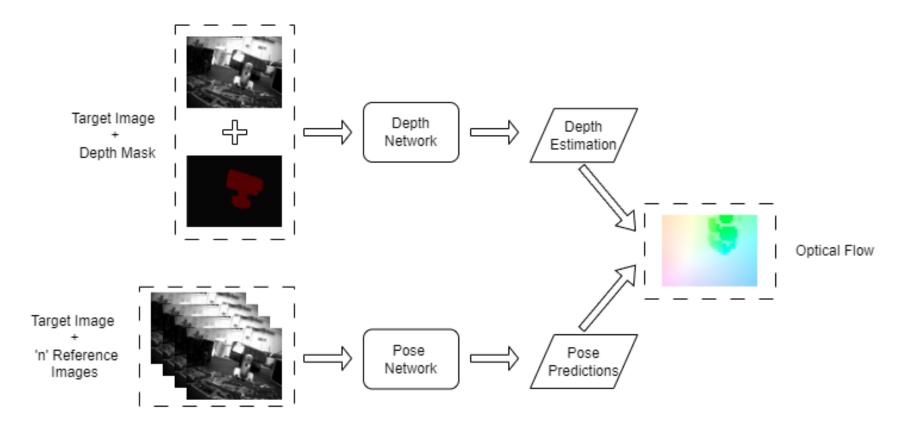
- Sensitive to Noise
- High Computational Cost for Large Datasets
- Scene-Specific Parameter Tuning
- Difficulty with Non-Rigid or Complex Motion
- Over-segmentation or under-segmentation





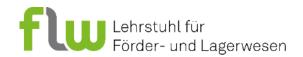


Deep Learning Approach: Neural Networks

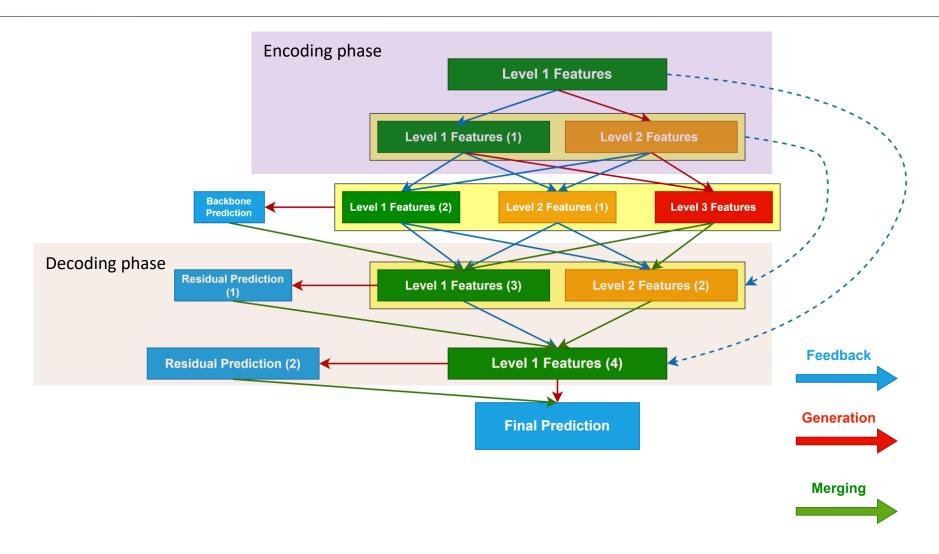




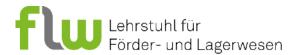




Evenly Cascaded Network (ECN)







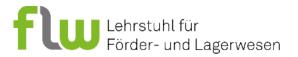
Experiments - ECN

Motion Segmentation task

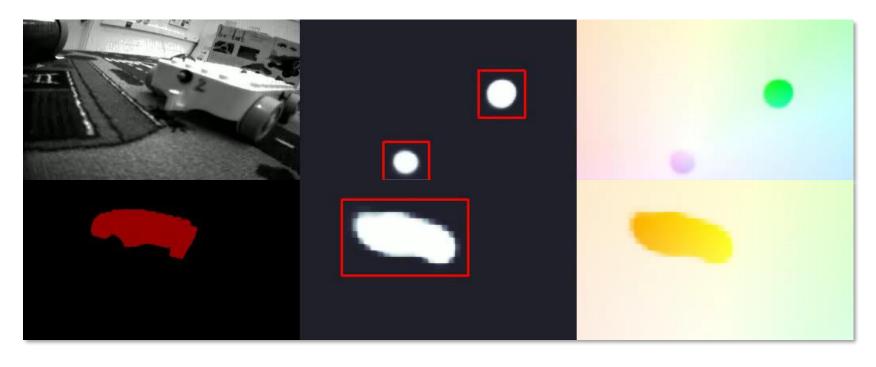
Sr. No	learn_rate	epochs	batch_size	growth_rate	final_map_size
1	5e-05	100	15	8	4
2	1e-03	30	32	4	8
3	1e-05	500	32	4	8

Table: Overview of the hyperparameters used in ECN experiments, with varying results across configurations



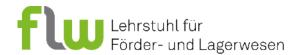


Results - ECN

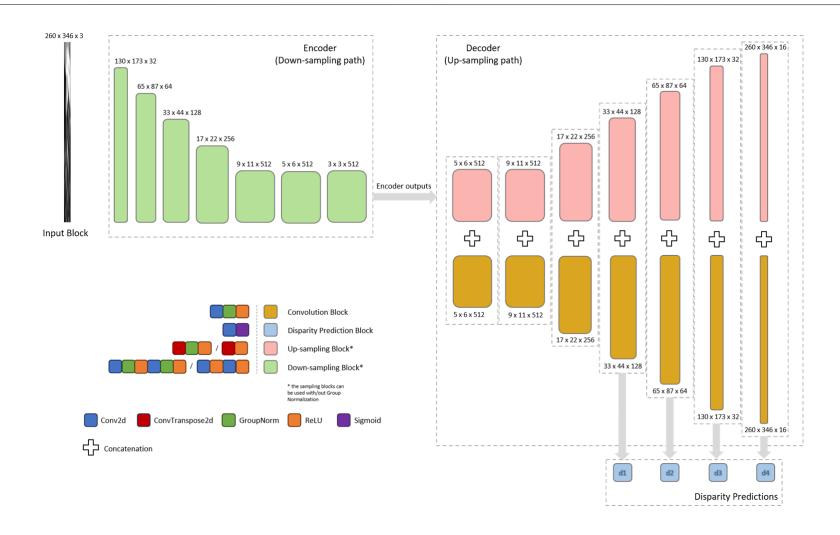


ECN: learn_rate = 1e-03, epochs = 30, batch_size = 32, growth_rate = 4, final_map_size = 8



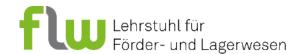


Encoder-Decoder Network (EDN) - DispNetS

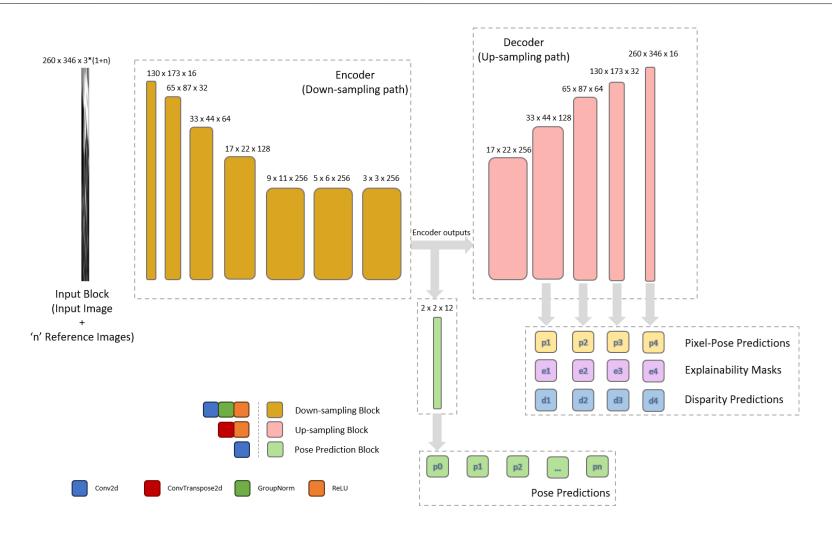






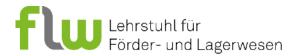


Encoder-Decoder Network (EDN) - PoseExpNet









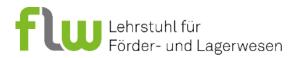
Experiments - EDN

Motion Segmentation task

Sr. No	learn_rate	epochs	batch_size	growth_rate	final_map_size
1	5e-04	30	32	4	8
2	5e-05	30	15	8	4
3	1e-05	30	20	8	4

Table: Overview of the hyperparameters used in EDN experiments, with varying results across configurations



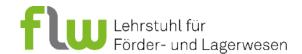


Results - EDN

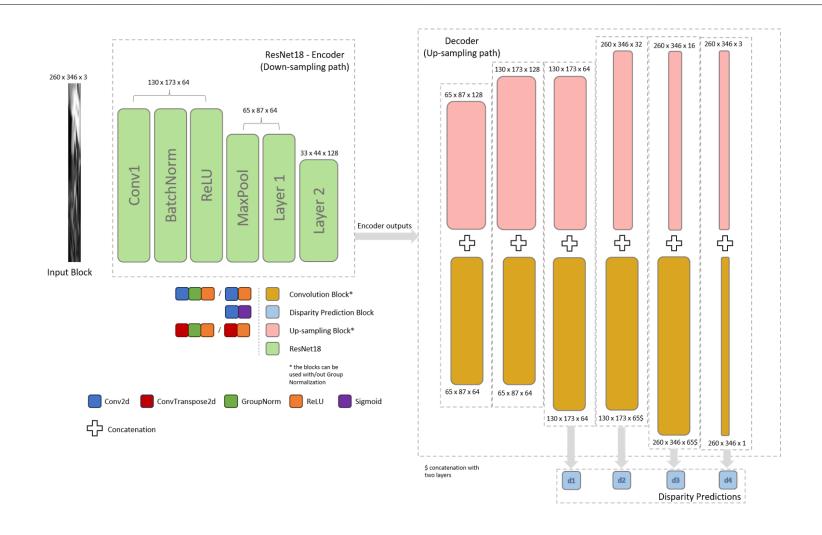


EDN: learn_rate = 5e-04, epochs = 30, batch_size = 32, growth_rate = 4, final_map_size = 8



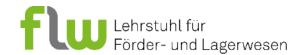


ResNet18 Encoder-Decoder Network (REDN) - ResDepthNet

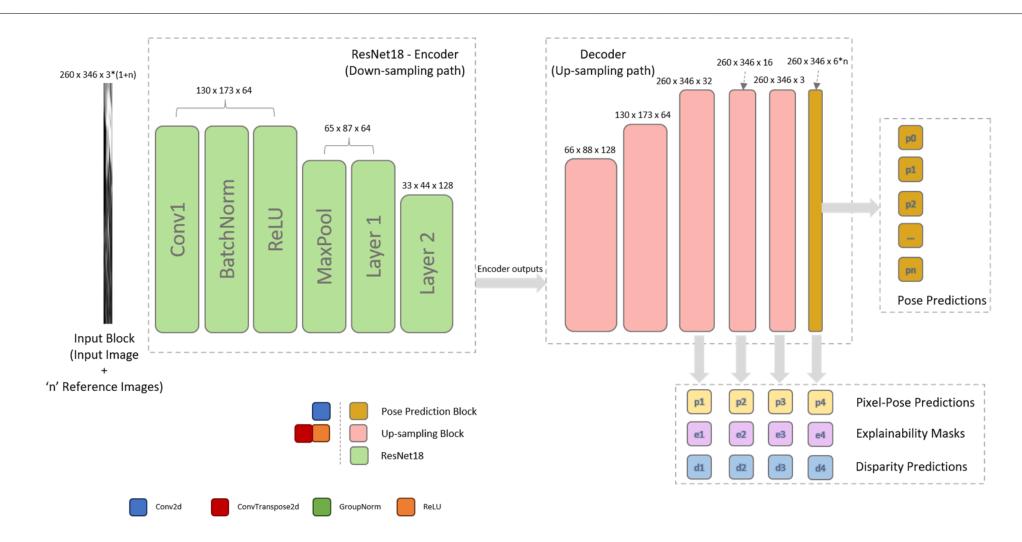






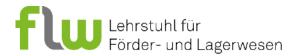


ResNet18 Encoder-Decoder Network (REDN) - ResPoseNet









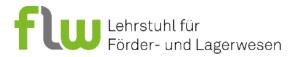
Experiments - REDN

Motion Segmentation task

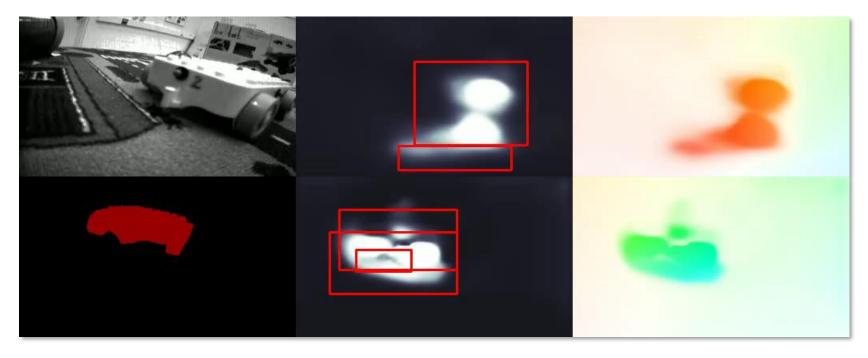
Sr. No	learn_rate	epochs	batch_size	growth_rate	final_map_size
1	1e-02	50	32	4	8
2	1e-05	50	25	8	4

Table: Overview of the hyperparameters used in REDN experiments, with varying results across configurations



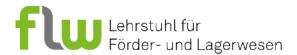


Results - REDN



REDN: learn_rate = 1e-02, epochs = 50, batch_size = 32, growth_rate = 4, final_map_size = 8

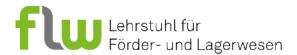




Challenges

- High Computational Demand
 - High quality and diverse dataset required
 - HPC is required to cater to the significant computational resources
- Optimization Complexity
 - Limitations of the approach to generalize across different scenes and variations is limited
 - Extensive hyperparameter tuning





Conclusions

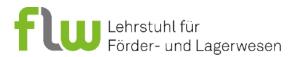
Classical Approach:

- Strong performance in controlled settings, but slow processing and scene-specific parameter tuning limit scalability
- Impractical for real-time applications

Deep Learning Approach:

- Applied optical flow logic via deep learning, achieving better results:
 - ECN Model: Most accurate and reliable
 - EDN Model: Mixed results, needs optimization
 - REDN Model: Underperformed due to lower-quality training data and suboptimal hyperparameters



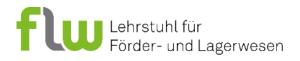


Future Scope



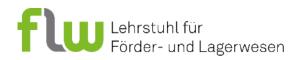
- Enhancing Data Quality
- Optimizing for Real-Time Performance
- Expand to Multi-Object Segmentation
- Multi-Sensor Fusion





Q&A





Thank You!

