Lab CudaVision
Learning Vision Systems on Graphics Cards (MA-INF 4308)

CudaLab Project

30.01.2024

PROF. SVEN BEHNKE, ANGEL VILLAR-CORRALES

Contact: villar@ais.uni-bonn.de

UNIVERSITÄT BONN AIS

Video Segmentation and Understanding of Automotive Scenes

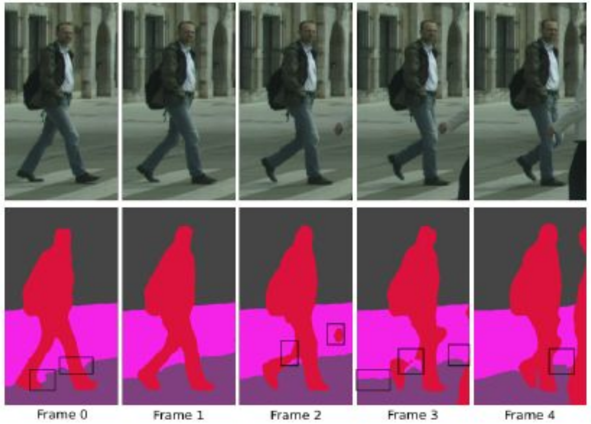
Video Semantic Segmentation

- **Semantic Segmentation:** Predicting a semantic category for every pixel in an image
- **Video Semantic Segmentation:** Predicting a semantic category for every pixel in every frame of a video sequence:
  1. Apply model frame-by-frame
  2. Exploit temporal dependencies
- **Applications:**
  - Autonomous driving
  - Robotics
  - Agriculture
  - …

Challenges

- Processing frame by frame leads to errors (flickering, ghosting, ...)
- Lots of changes in the scene, mainly due to ego-motion (our car driving)
- Difficult handling of occlusions, sensor noise, ...

➢ Temporal consistency can correct most issues



Proposed Approach

Inspiration

29th British Machine Vision Conference (BMVC), Newcastle, UK, September 2018.

Functionally Modular and Interpretable Temporal Filtering for Robust Segmentation

Jörg Wagner[1,2]
Joerg.Wagner3@de.bosch.com
Volker Fischer[1]
Volker.Fischer@de.bosch.com
Michael Herman[1]
Michael.Herman@de.bosch.com
Sven Behnke[2]
behnke@cs.uni-bonn.de

[1] Bosch Center for Artificial Intelligence, 71272 Renningen, Germany
[2] University of Bonn, Computer Science Institute VI, Autonomous Intelligent Systems, Endenicher Allee 19 A, 53115 Bonn, Germany

Abstract

The performance of autonomous systems heavily relies on their ability to generate a robust representation of the environment. Deep neural networks have greatly improved vision-based perception systems but still fail in challenging situations, *e.g.* sensor outages or heavy weather. These failures are often introduced by data-inherent perturbations, which significantly reduce the information provided to the perception system. We propose a functionally modularized temporal filter, which stabilizes an abstract feature representation of a single-frame segmentation model using information of previous time steps. Our filter module splits the filter task into multiple less complex and more interpretable subtasks. The basic structure of the filter is inspired by a Bayes estimator consisting of a prediction and an update step. To make the prediction more transparent, we implement it using a geometric projection and estimate its parameters. This additionally enables the decomposition of the filter task into static representation filtering and low-dimensional motion filtering. Our model can cope with missing frames and is trainable in an end-to-end fashion. Using photorealistic, synthetic video data, we show the ability of the proposed architecture to overcome data-inherent perturbations. The experiments especially highlight advantages introduced by an interpretable and explicit filter module.

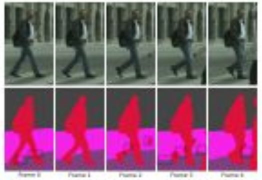
1 Introduction

The performance of autonomous systems, such as mobile robots or self-driving cars, is heavily influenced by their ability to generate a robust representation of the current environment. Errors in the environment representation are propagated to subsequent processing steps and are hard to recover. For example, a common error is a missed detection of an object, which might lead to a fatal crash. In order to increase the reliability and safety of autonomous systems, robust methods for observing and interpreting the environment are required.

Deep learning based methods have greatly advanced the state-of-the-art of perception systems. Especially vision-based perception benchmarks (*e.g.* Cityscapes [■] or Caltech [■]) are dominated by approaches utilizing deep neural networks. From a safety perspective, a

Semantic Segmentation of Video Sequences with Convolutional LSTMs

Andreas Pfeuffer[1], Karina Schulz[1], and Klaus Dietmayer[1]



I. INTRODUCTION

Multi-View Deep Learning for Consistent Semantic Mapping with RGB-D Cameras

Lingni Ma, Jörg Stückler, Christian Kerl and Daniel Cremers

arXiv:1703.08866v2 [cs.CV] 4 Dec 2017

***Abstract*— Visual scene understanding is an important capability that enables robots to purposefully act in their environment. In this paper, we propose a novel deep neural network approach to predict semantic segmentation from RGB-D sequences. The key innovation is to train our network to predict multi-view consistent semantics in a self-supervised way. At test time, its semantics predictions can be fused more consistently in semantic keyframe maps than predictions of a network trained on individual views. We base our network architecture on a recent single-view deep learning approach to RGB and depth fusion for semantic object-class segmentation and enhance it with multi-scale loss minimization. We obtain the camera trajectory using RGB-D SLAM and warp the predictions of RGB-D images into ground-truth annotated frames in order to enforce multi-view consistency during training. At test time, predictions from multiple views are fused into keyframes. We propose and analyze several methods for enforcing multi-view consistency during training and testing. We evaluate the benefit of multi-view consistency training and demonstrate that pooling of deep features and fusion over multiple views outperforms single-view baselines on the NYUDv2 benchmark for semantic segmentation. Our end-to-end trained network achieves state-of-the-art performance on the NYUDv2 dataset in single-view segmentation as well as multi-view semantic fusion.**

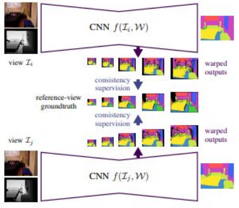


Fig. 1: We train our CNN to predict multi-view consistent semantic segmentations for RGB-D images. The key innovation is to enforce consistency by warping CNN feature maps from multiple views into a common reference view using the SLAM trajectory and to supervise training at multiple scales. Our approach improves performance for single-view segmentation and is specifically beneficial for multi-view fused segmentation.

I. Introduction

Intelligent robots require the ability to understand their environment through parsing and segmenting the 3D scene into meaningful objects. The rich appearance-based information contained in images renders vision a primary sensory modality for this task.

In recent years, large progress has been achieved in semantic segmentation of images. Most current state-of-the-art approaches apply deep learning for this task. With RGB-D cameras, appearance as well as shape modalities can be combined to improve the semantic segmentation performance. Less explored, however, is the usage and fusion of multiple views onto the same scene which appears naturally in the domains of 3D reconstruction and robotics. Here, the camera is moving through the environment and captures the scene from multiple view points. Semantic SLAM aims at aggregating several views in a consistent 3D geometric and semantic reconstruction of the environment.

In this paper, we propose a novel deep learning approach for semantic segmentation of RGB-D images with multi-view context. We base our network on a recently proposed deep convolutional neural network (CNN) for RGB and depth fusion [1] and enhance the approach with multi-scale deep supervision. Based on the trajectory obtained through RGB-D simultaneous localization and mapping (SLAM), we further regularize the CNN training with multi-view consistency constraints as shown in Fig. 1. We propose and evaluate several variants to enforce multi-view consistency during training. A shared principle is using the SLAM trajectory estimate to warp network outputs of multiple frames into the reference view with ground-truth annotation. By this, the network not only learns features that are invariant under view-point change. Our semi-supervised training approach also makes better use of the annotated ground-truth data than single-view learning. This alleviates the need for large amounts of annotated training data which is expensive to obtain. Complementary to our training approach, we aggregate the predictions of our trained network in keyframes to increase segmentation accuracy at testing. The predictions of neighboring images are fused into the keyframe based on the SLAM estimate in a probabilistic way.

In experiments, we evaluate the performance gain achieved through multi-view training and fusion at testing over single-view approaches. Our results demonstrate that multi-view max-pooling of feature maps during training best supports

Authors are with Computer Vision and Artificial Intelligence Group, Department of Computer Science, Technical University of Munich, ({lingni,stueckle,kerl,cremers}@in.tum.de).
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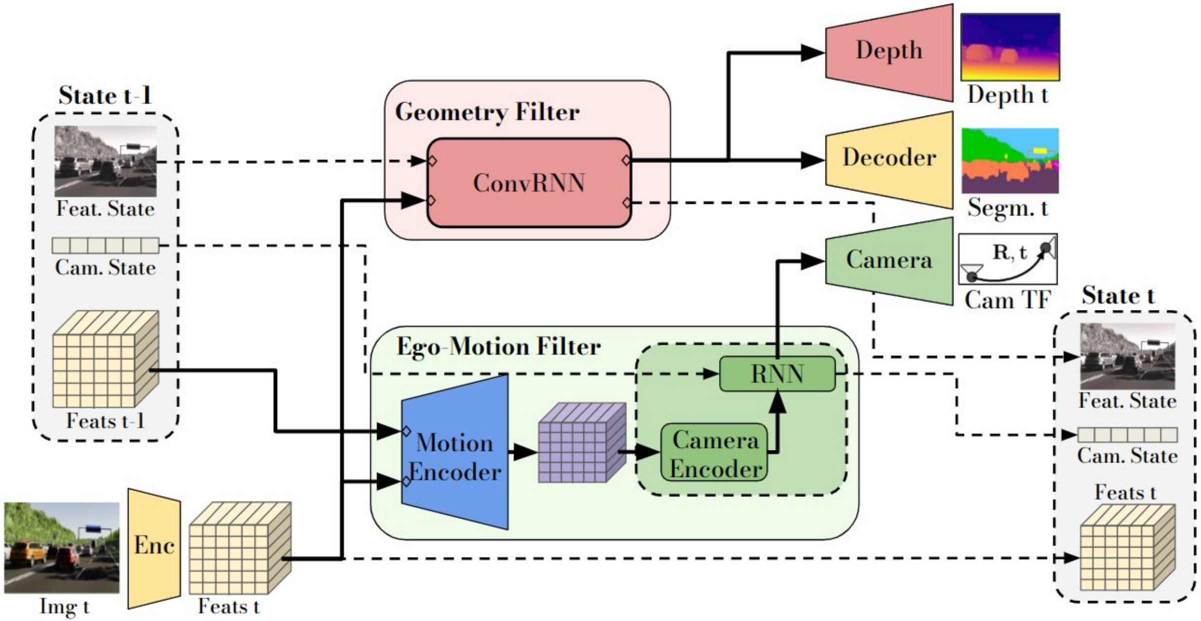
Proposed Model

- Filter model for structured and robust video segmentation
  - Robust
  - Temporally consistent

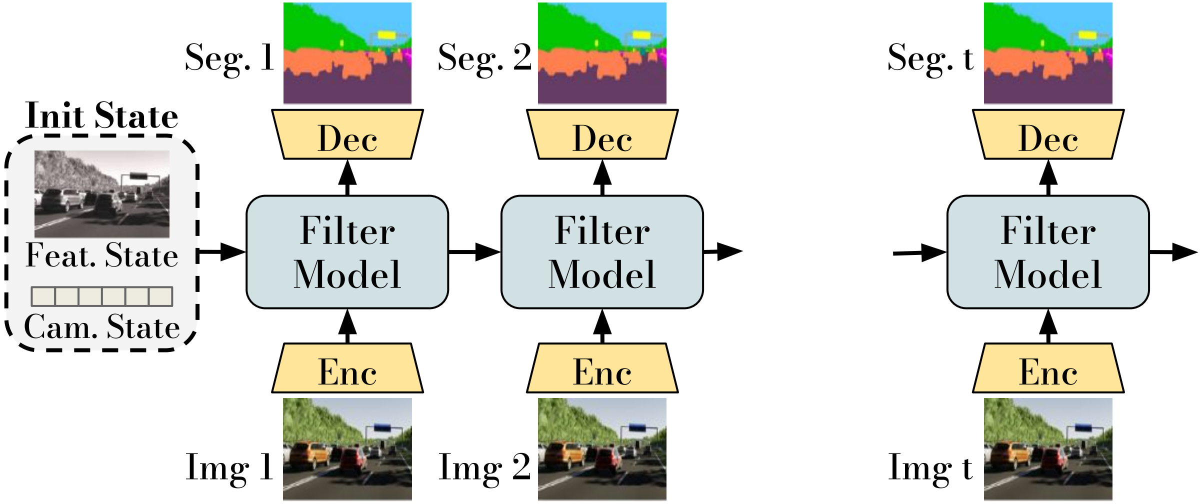
- Additional outputs:
  - Scene geometry
  - Ego-Motion

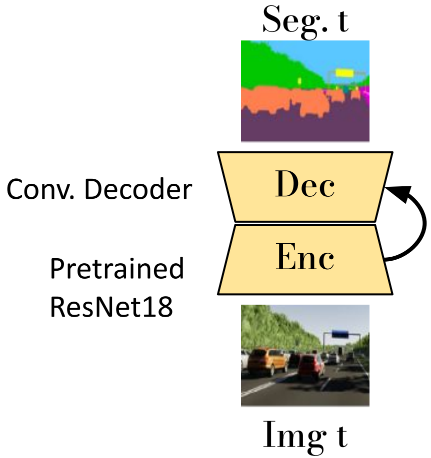


Model Overview

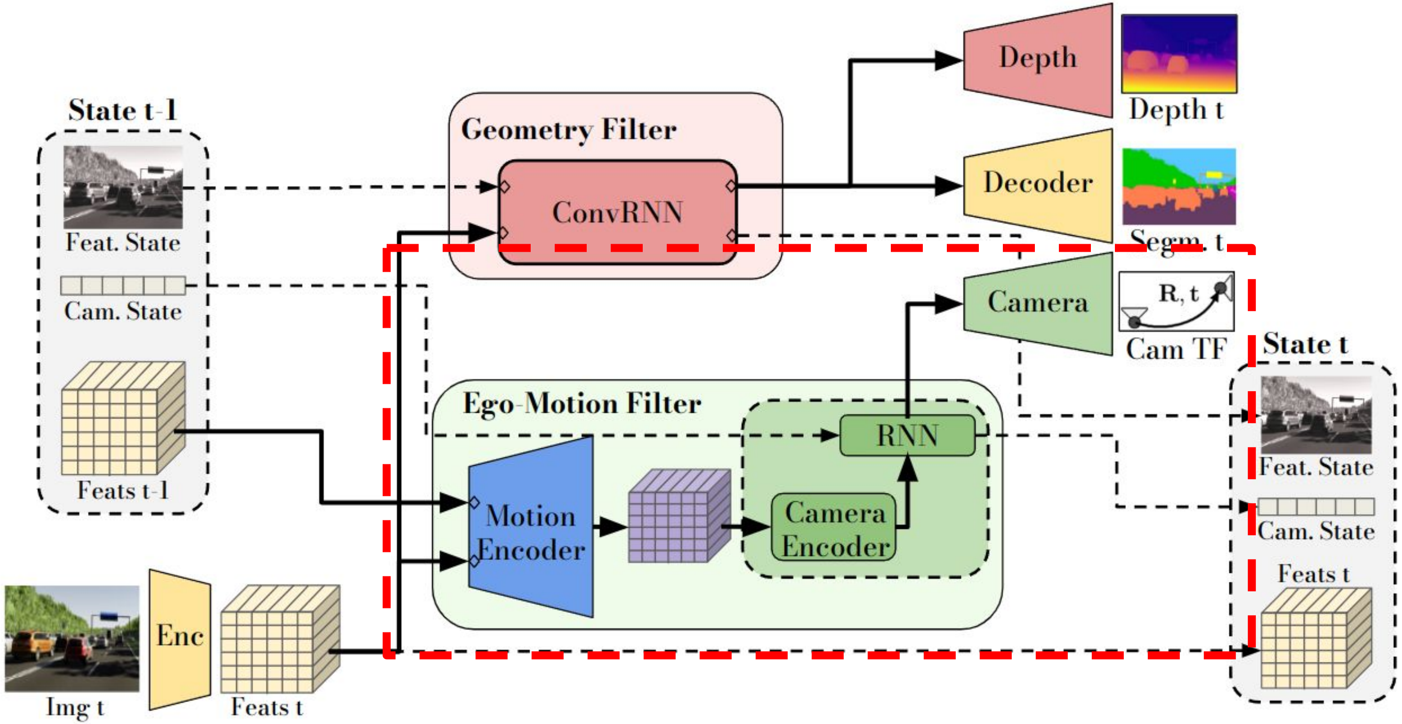
- Recurrent semantic segmentation model
  - Semantic segmentation model (e.g. UNet, DeepLabV3+)
  - Recurrent filter with structured state

Encoder & decoder can be standard segm. model, (e.g UNet, DeepLabV3+)





Model Overview

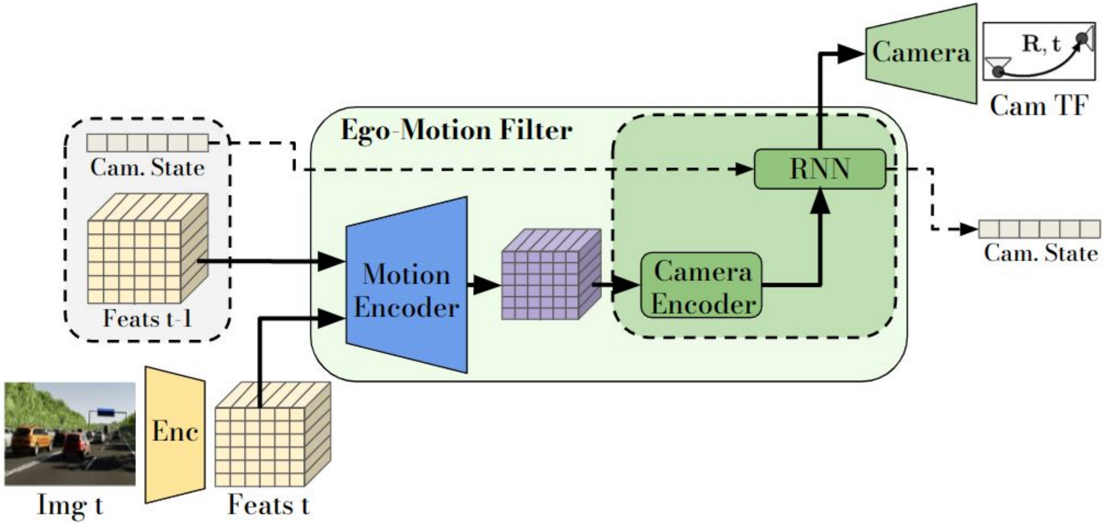


Ego-Motion Filter

- Models the motion of the camera recording the scene (motion of the car)
- Given two consecutive frames, computes the camera transformation T from the camera coordinates of the first frame to the second.

$$P1 = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$P2 = T \times P1$$



Ego-Motion Filter

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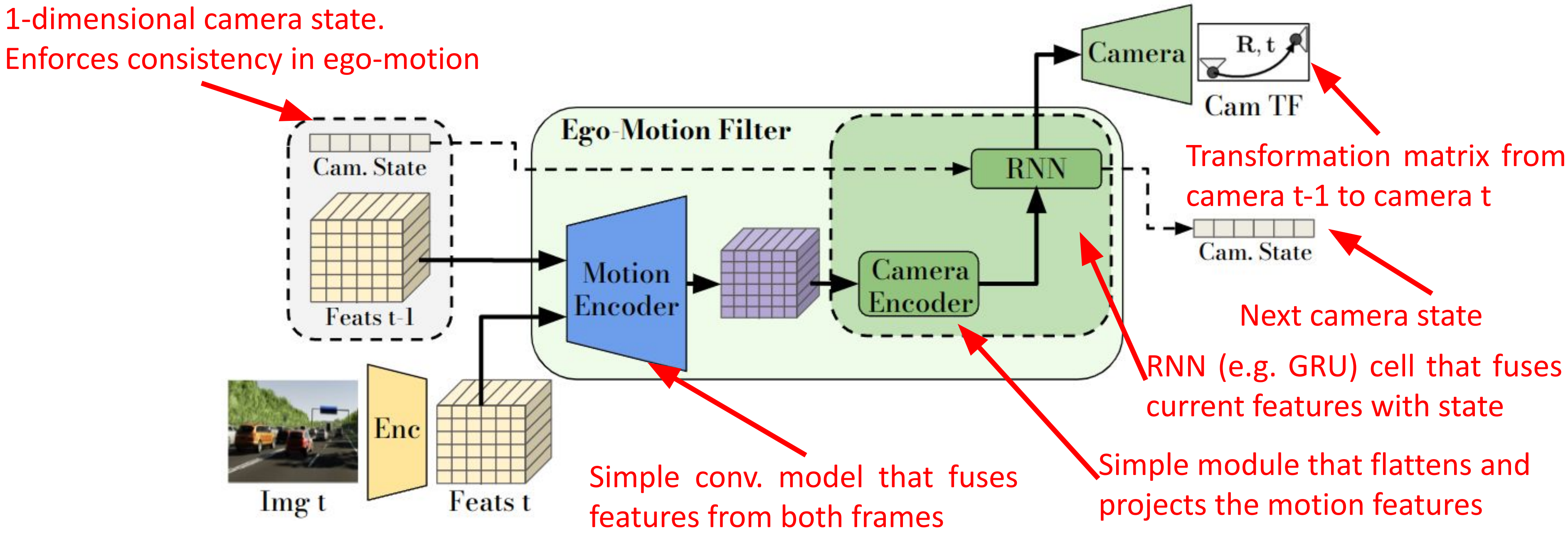
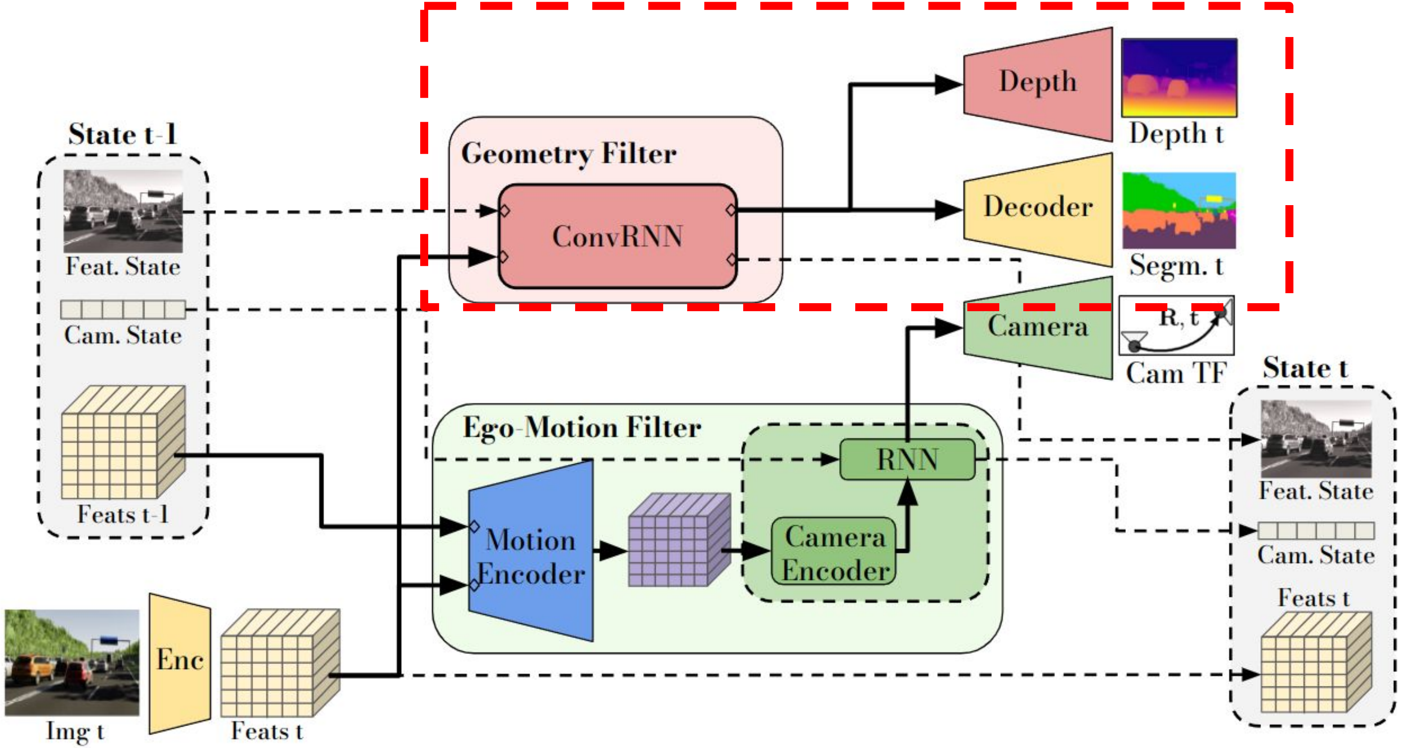


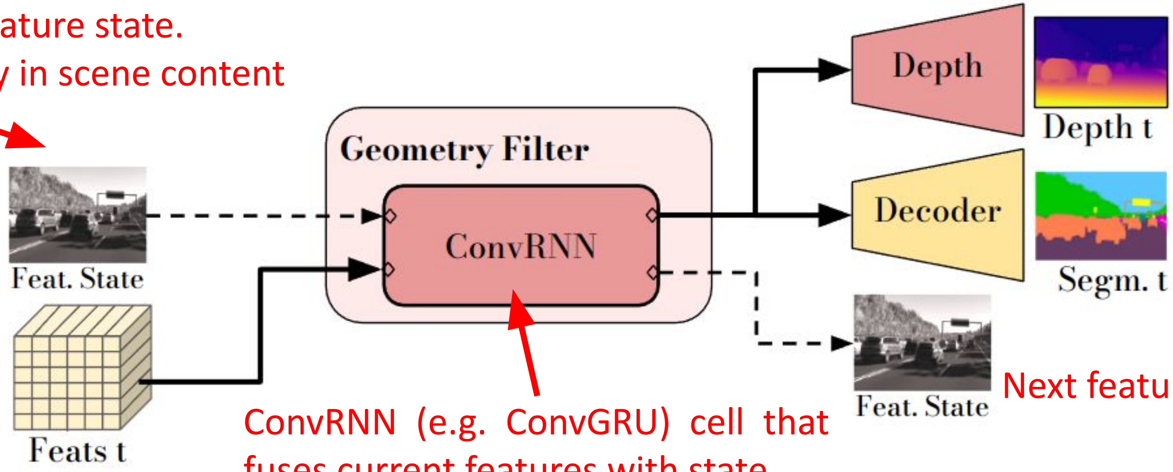
Model Overview



Geometry Filter

- Models abstract scene features, such as scene contents and geometry
  - Maintains temporal consistency of features
- Two output heads
  - Semantic Segmentation
  - Depth

High-dimensional feature state.
Enforces consistency in scene content

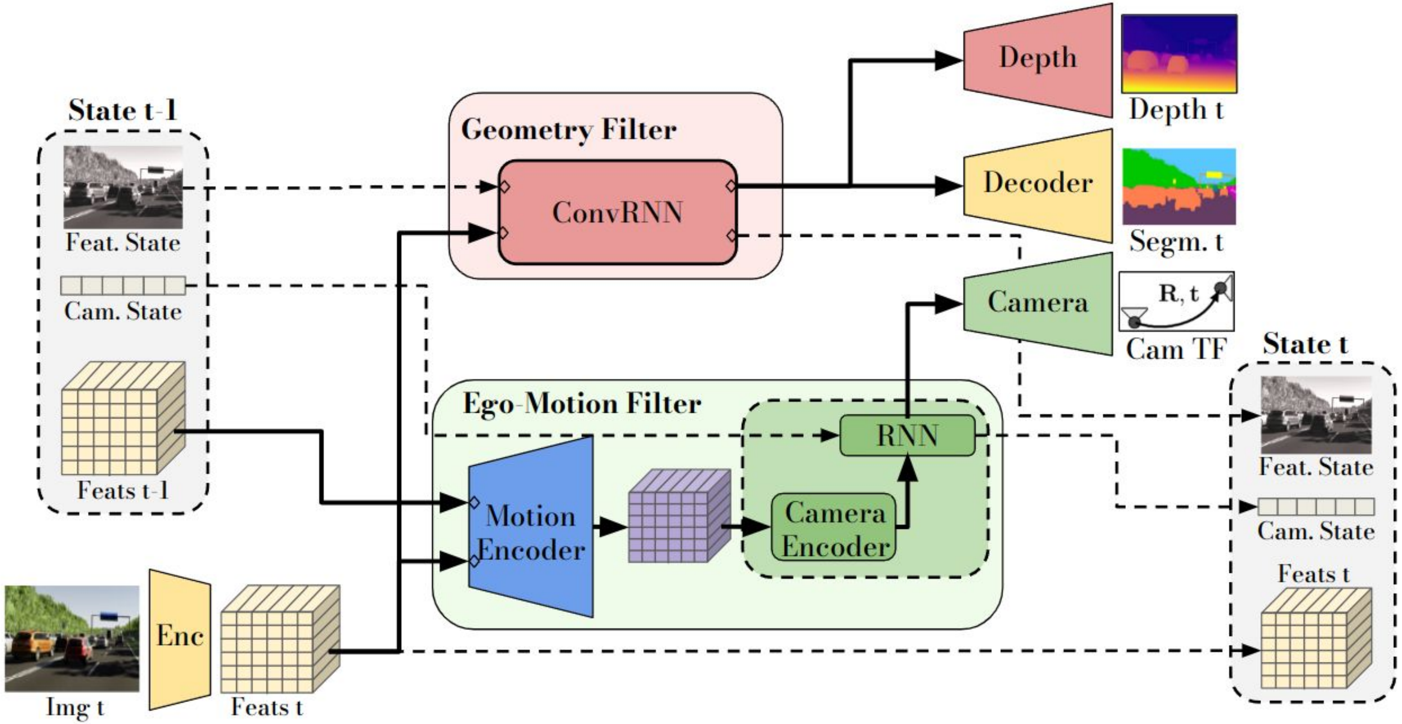


Depth and semantic segmentation heads

Next feature state

ConvRNN (e.g. ConvGRU) cell that fuses current features with state

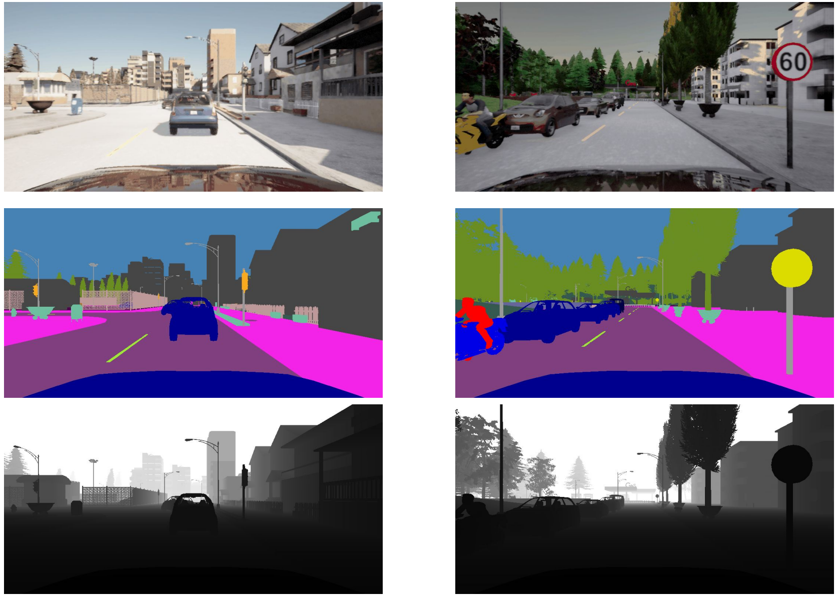
Model Overview



Datasets

CARLA Dataset

- Dataset for autonomous driving generated with the CARLA simulator
  - Camera poses and intrinsics
  - Semantic segmentation
  - Depth estimation
- Approx. 12000 sequences
  - 20 frames of size (512x1024)
  - Training: Towns 01, 03, 04, 05, 06, 07
  - Validation: Town 02
  - Test: Town 10
- Inspect the data!

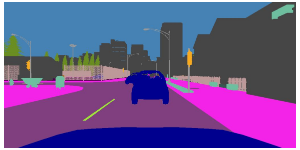
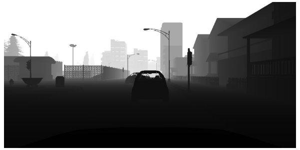


➡ Available in `/home/nfs/inf6/data/datasets/Carla_Moritz/SyncAngel3`

Dataset Variants

Base CARLA

- Sequences of 6 frames from the base dataset

Corrupted CARLA

- 6 frames corrupted by additive Gaussian noise, clutter and illumination changes
- See [1] (supplementary) for implementation details

Training & Evaluation

Multi-Stage Training

- Due to its modularity, we will train the network in multiple stages:

  1. Supervised Pretraining:
     - Training for all tasks given two consecutive images of Base-CARLA
     - Train image and motion encoders, as well as all three decoder
     - No recurrent filtering at this stage
  2. End-to-End Fine-Tuning:
     - Add the recurrent modules and the states
     - Jointly fine-tune all modules on Corrupted-CARLA

- End-to-End training:
  - Directly train the model on Corrupted-CARLA
  - This includes jointly training the encoders, RNNs and decoders

Train/Eval Details

- Details
  - Image resize/crops of size: (3, 256, 512)
  - Recommended to use augmentations: mirroring, color jittering

- Loss Functions
  - Segmentation: *CrossEntropy Loss*
  - Depth Estimation: *L1-Loss* on logarithmic depth maps.
  - Camera Poses: *MSE* on camera matrix

- Evaluation:
  - mAcc and mIoU quantitative evaluation metrics for segmentation
  - Make GIFs of depth and segmentation for qualitative evaluation
  - Visualize of camera poses and trajectories
  - Visualize RGB and semantic point-clouds (use depth, camera poses and intrinsics)

Project Goals and Deliverables

Passing Requirements

1. Implement the required model, datasets, training pipelines and utils

2. Train your models to achieve best possible results on CARLA (Base and Corrupted)
   - You must implement the described model
   - You must follow the training protocol
   - ➢ Make changes and train further model variants to achieve better results

3. Compare with a naive framewise baseline
   - **Baseline:** fine-tuning the image segmentation model (*enc* + *dec,* no filters) on the Corrupted-CARLA dataset and applying it frame-by-frame.

4. Create overview notebook

5. Write project report

Deliverables

- Complete codebase
  - Clean and structured
  - Not just a notebook!
- Trained model checkpoint and (tensorboard, WandB, …) logs
- Overview notebook (.ipynb & .html) showing main functionalities:
  - Load data and display some samples
  - Load pretrained model and display the structure or some stats
  - Display some qualitative results (e.g. results on at least 5 sequences)
  - Show the quantitative evaluation
- Project report

Grading

- Results and Experiments **55%:**
  - Performing several experiments and obtaining good results
  - **Additional experiments**: ablation study, changes in the model, …
  - This grade partly depends on how your results compare to the class
- Codebase & Overview Notebook **20%:**
  - Implement all functionalities
  - Modularity and structure
- Report **25%**

Project Report

- Document your work in the project report
- Try to be brief, but readable and informative
- Include figures and tables
- Use *BibTex* for the references
- I expect 8-12 pages, but highly depends on number and size of imgs/tables
- Use the following template
    - https://www.overleaf.com/read/tmnvhrsdmjrp

Additional Experiment Ideas

- Try your own ideas!

- Training and pretraining:
  - Compare different training strategies: direct training v.s. modular training
  - Use different loss functions

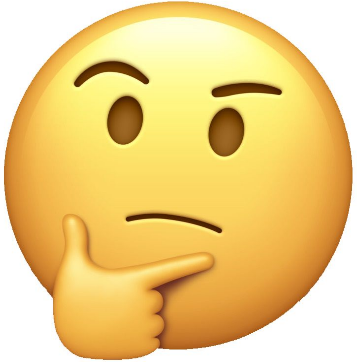
- Tweak the model
  - Use a nice backbone (e.g. ResNet or ConvNext)
  - Investigate different segmentation architectures (e.g. DeepLab v3+, UPerNet, …)
  - Investigate the type and positioning of the recurrent modules

- Investigate different training strategies:
  - Use different loss functions
  - Regularization to enforce temporal consistency
  - Advanced data augmentation (e.g. mix-up) and regularization (e.g. label smoothing)
  - Temporal data augmentation

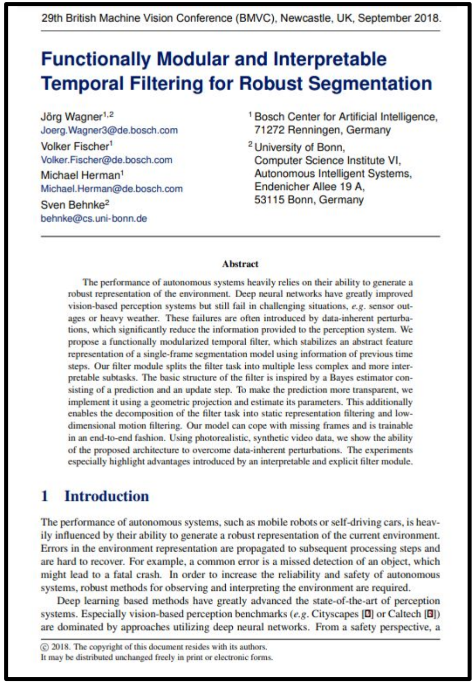
Important Dates

- **30.01**: Starting date
- **05.03-20.03**: Revision session (flexible dates)
- **21.03**: Draft submission due
- **31.03**: Final submission:

Questions?



Many details!



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Sven Behnke[2]
behnke@cs.uni-bonn.de

[1] Bosch Center for Artificial Intelligence, 71272 Renningen, Germany
[2] University of Bonn, Computer Science Institute VI, Autonomous Intelligent Systems, Endenicher Allee 19 A, 53115 Bonn, Germany

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References

1. Wagner, Jörg, et al. "Functionally Modular and Interpretable Temporal Filtering for Robust Segmentation." BMVC. 2018.
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