Intelligent Systems Laboratory

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Stereo-Vision Based Convolutional Networks for Object Detection in Driving Environments

Carlos Guindel (cguindel@ing.uc3m.es) , David Martín, José M. Armingol

Sixteenth International Conference on Computer Aided Systems Theory
Intelligent Transportation Systems and Smart Mobility Workshop

Intelligent Systems Laboratory · Universidad Carlos III de Madrid

Outline

1. Introduction
2. Object detection pipeline
3. Proposed approach
4. Results
5. Conclusions

Introduction

Object detection in driving environments

- Modern Advanced Driver Assistance Systems (ADAS) and autonomous vehicles rely on robust **object detection**.

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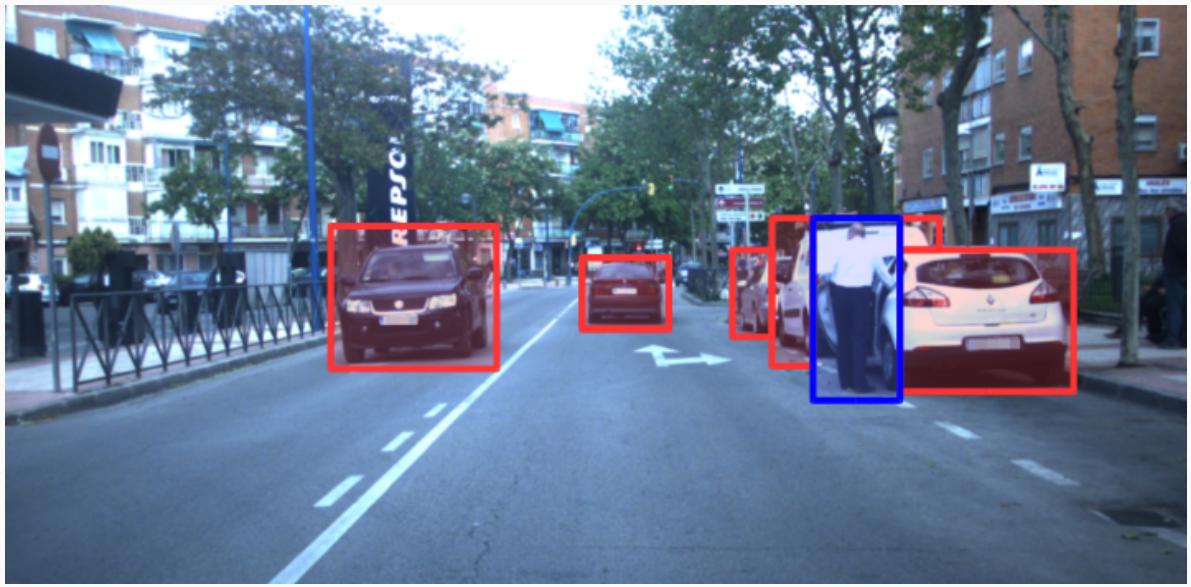
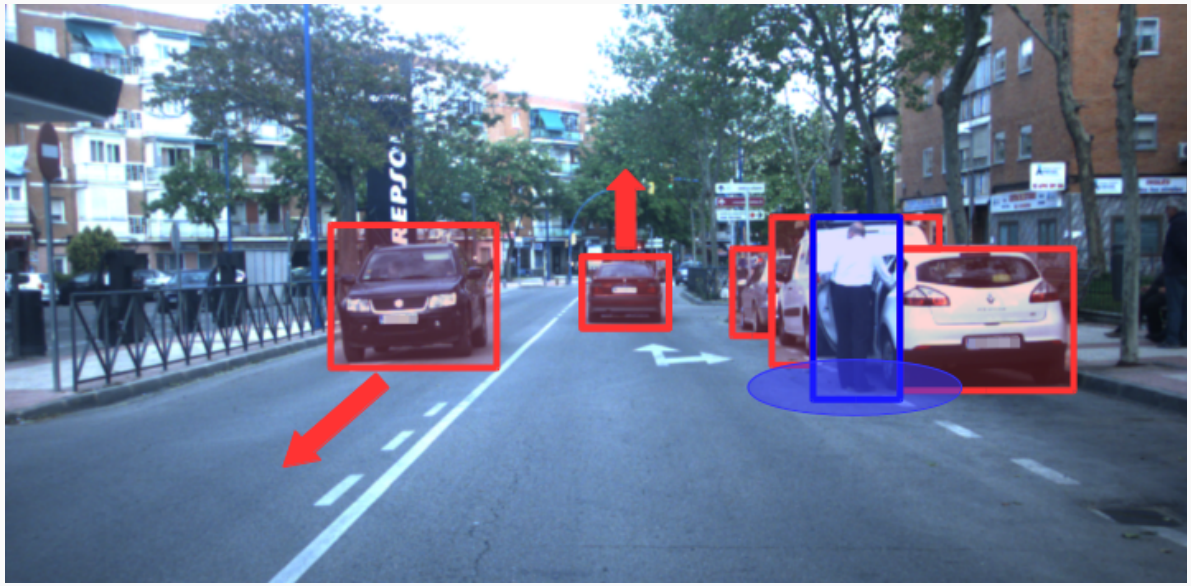


Object detection in driving environments

- Modern Advanced Driver Assistance Systems (ADAS) and autonomous vehicles rely on robust **object detection**.
- A full understanding of the traffic scene requires to correctly **classifying** the obstacles.
- Different agents are expected to exhibit different **behaviors**.



Object detection in driving environments

Driving environments

- Appearance changes
- Pose diversity
- Severe occlusions
- Background clutters

Stereo-vision based methods

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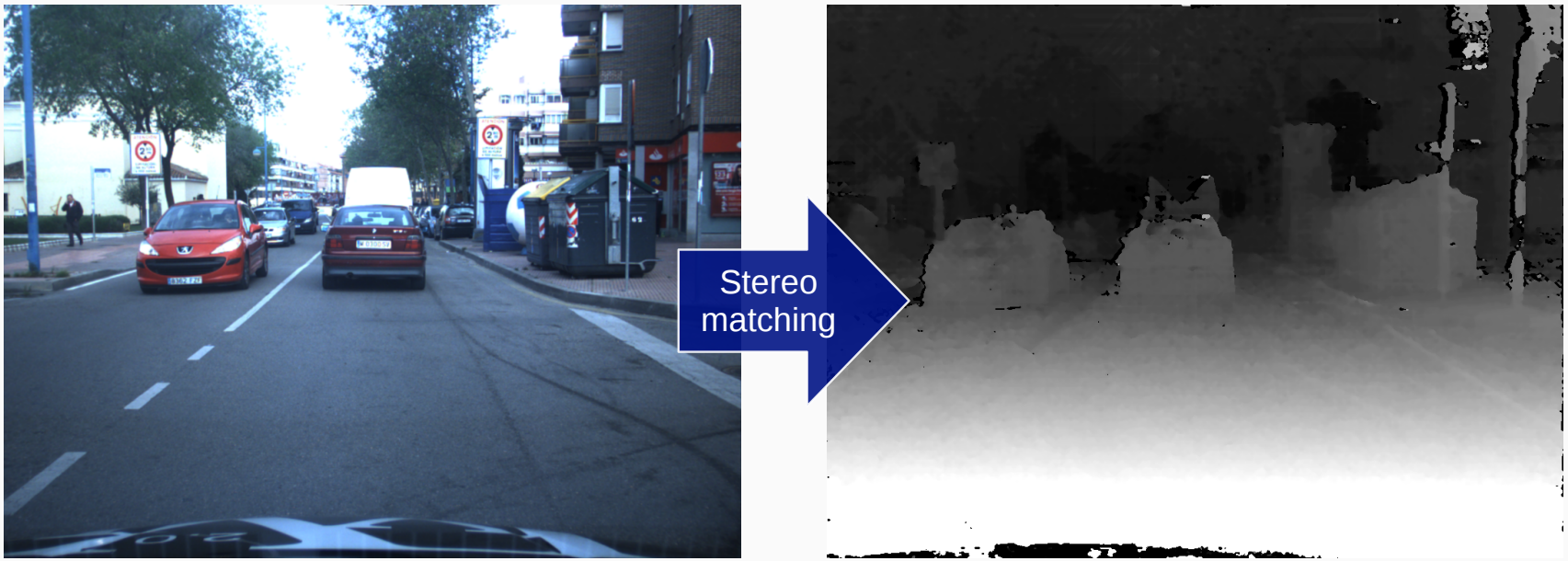

Stereo-vision based methods

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Common stereo-based approaches for obstacle detection

- Occupancy maps
- Digital elevation maps
- Scene flow
- Geometry-based clustering

State-of-art object detection methods

- **Convolutional Neural Networks** (deep learning) have recently emerged as a robust object detection paradigm.

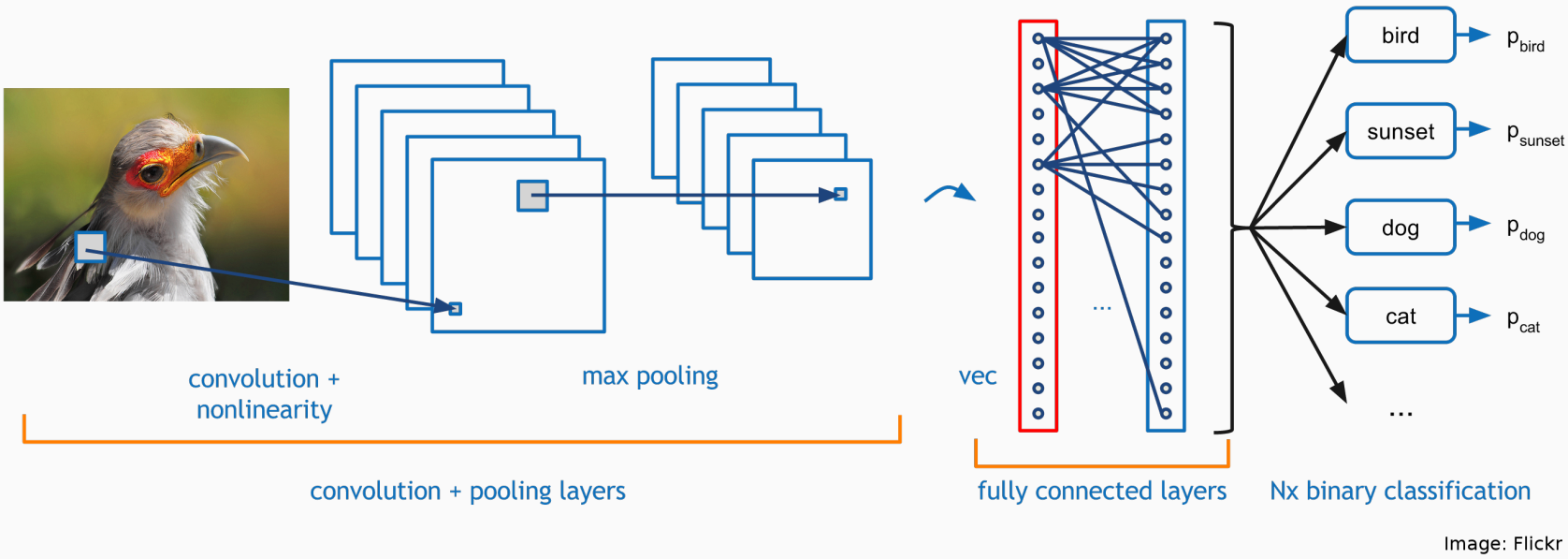

Image: Flickr

State-of-art object detection methods

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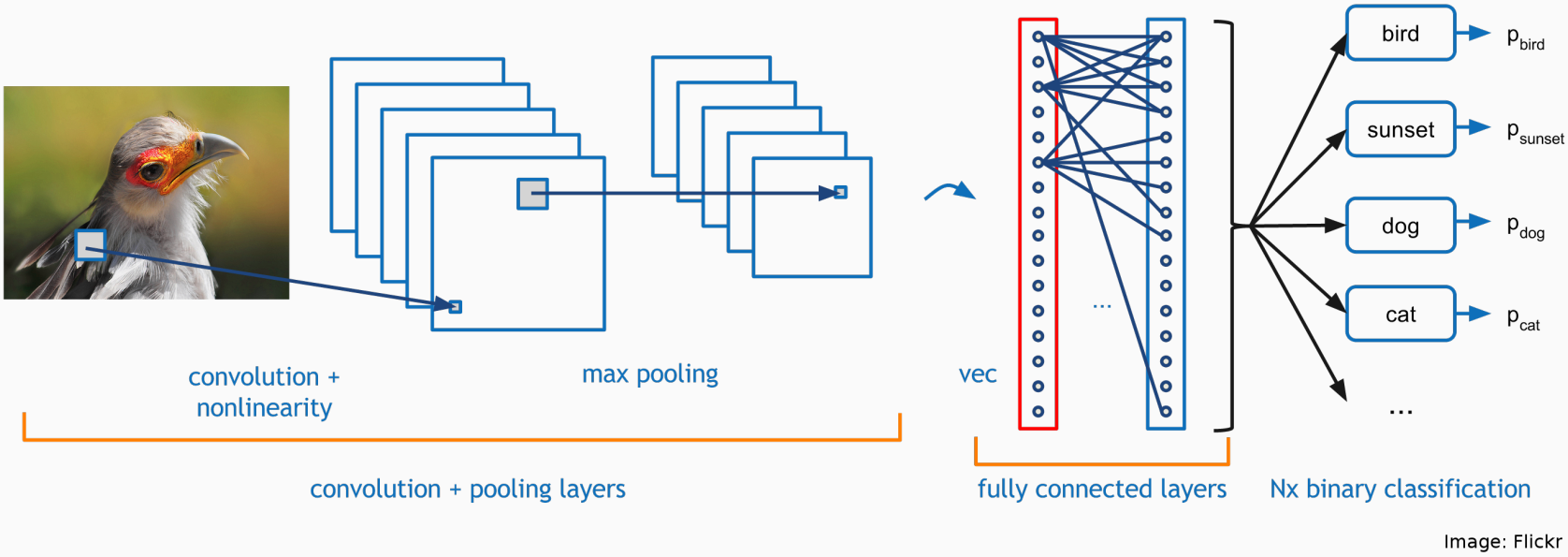
- **Traffic environments**: KITTI Object Detection Benchmark results are dominated by methods based on Convolutional Neural Networks (CNNs).



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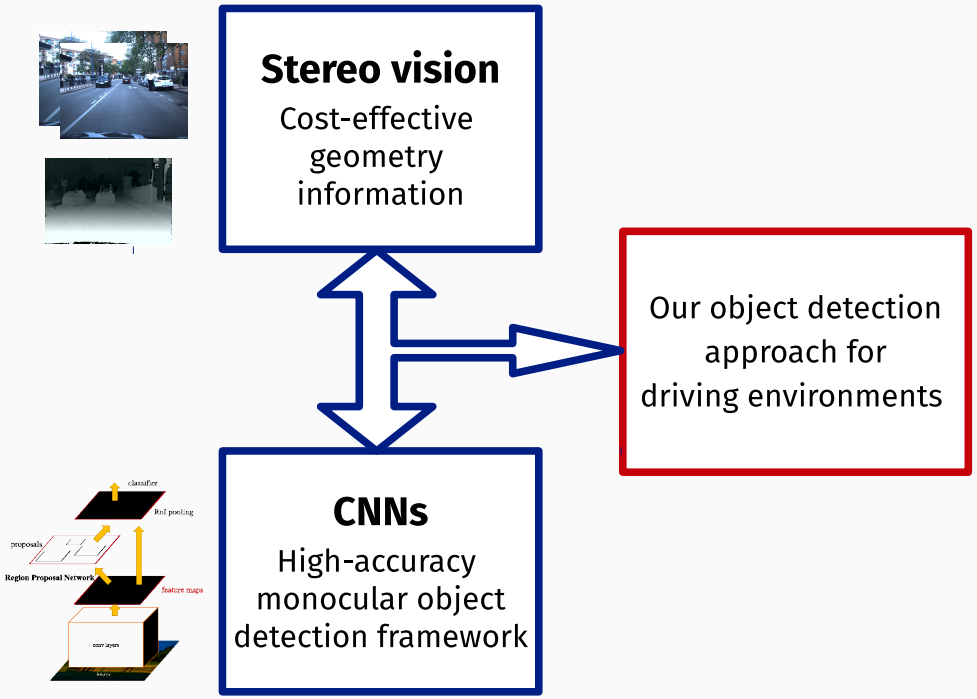
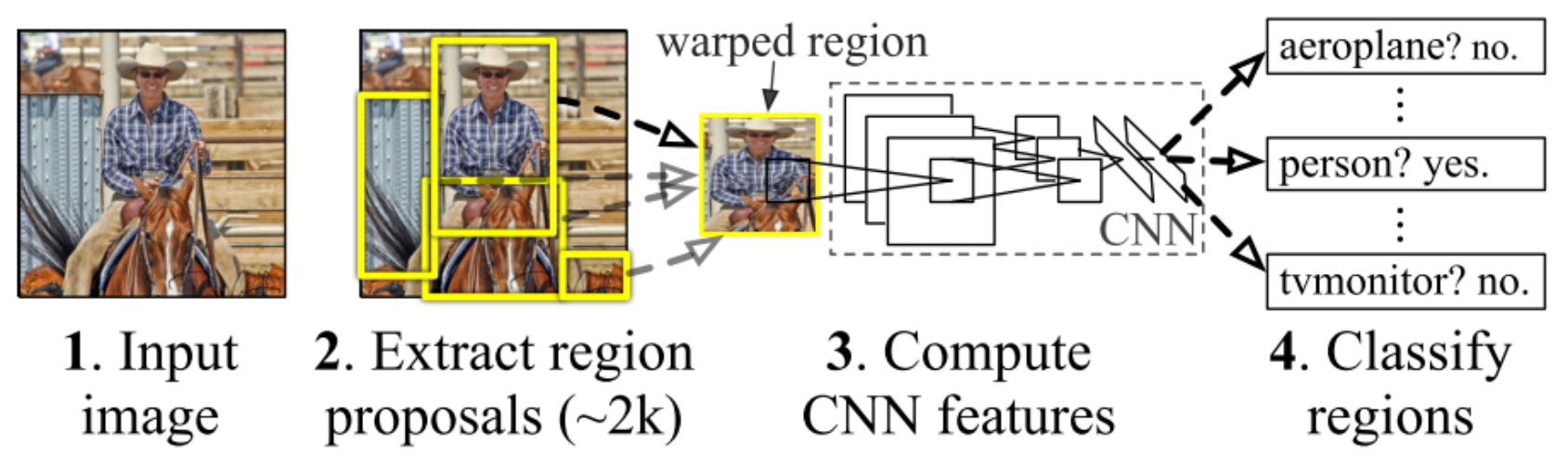
Our idea

- To integrate stereo information into a CNN object detection framework to make it more suitable for driving environments.



Object detection pipeline

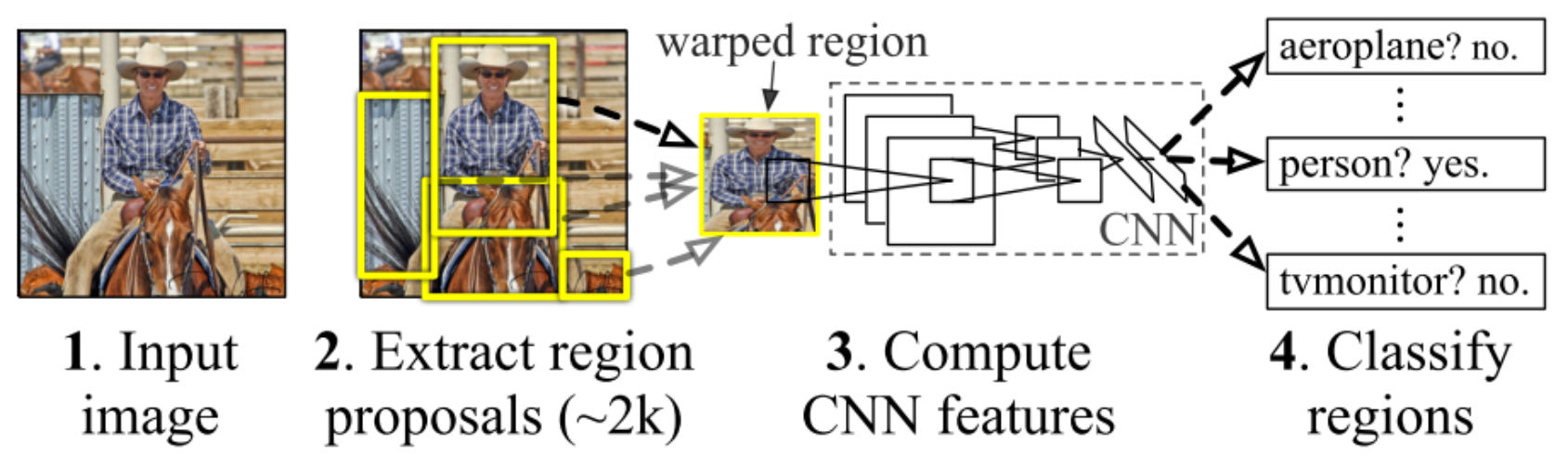
R-CNN framework



- R-CNN is a state-of-art CNN-based object detection pipeline.

R. Girshick, J. Donahue, et al., "Region-based Convolutional Networks for Accurate Object Detection and Segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 1, pp. 142–158, 2016.

R-CNN framework



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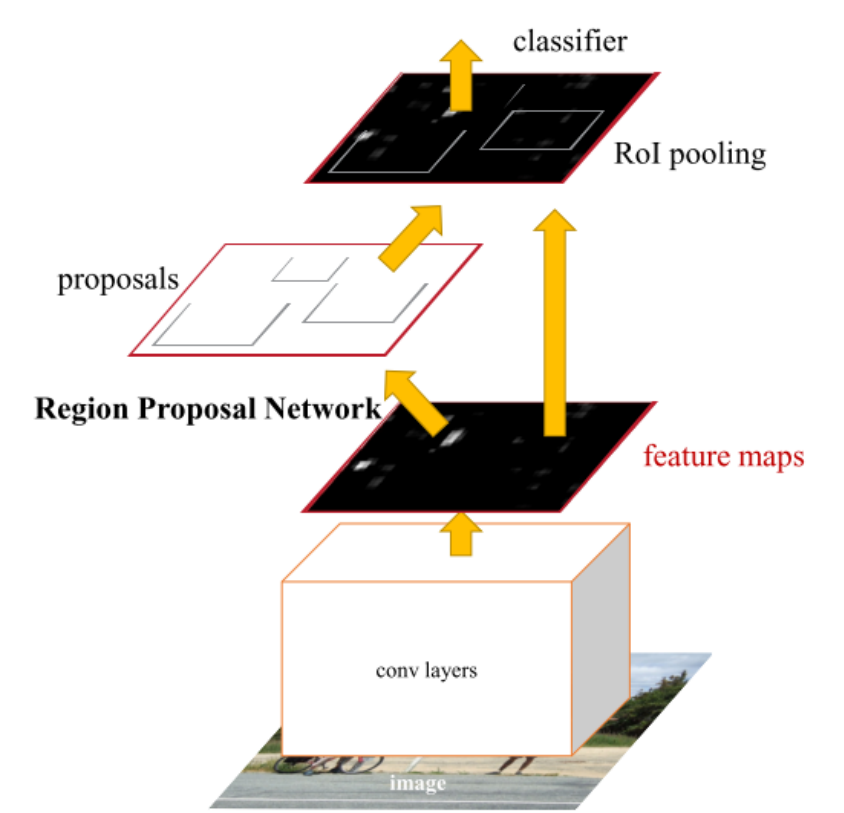
Faster R-CNN framework



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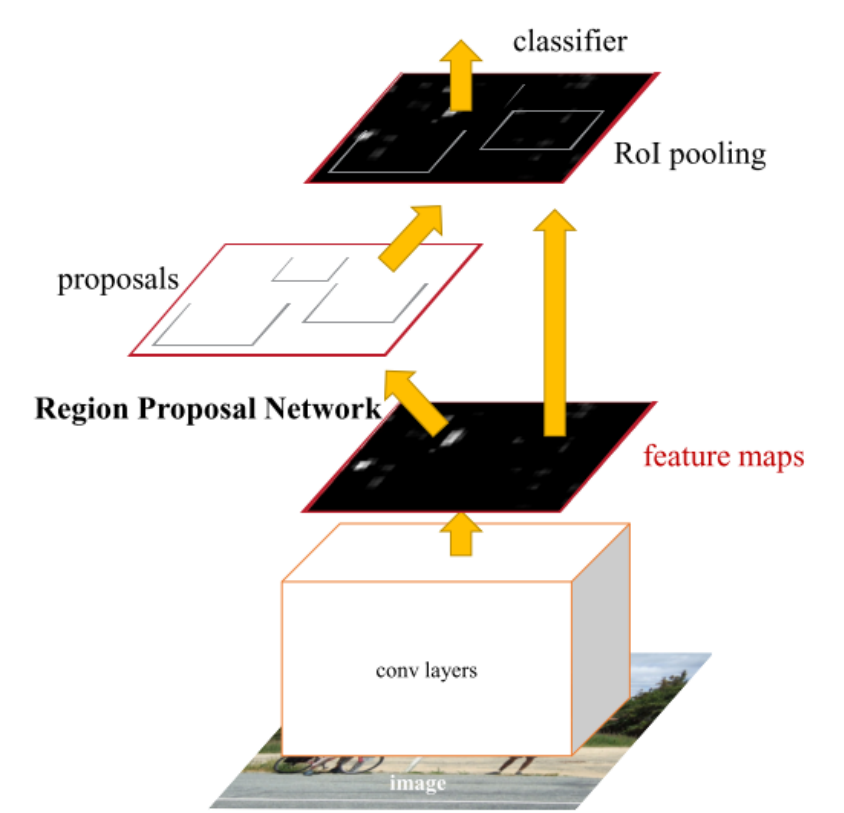

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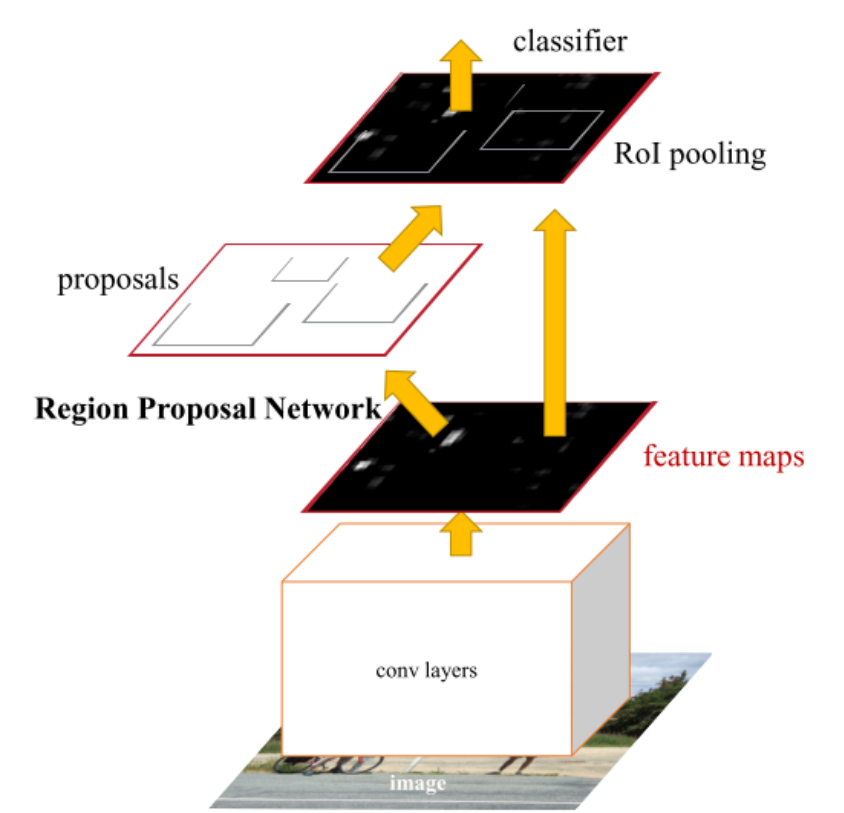

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- Regions are proposed by a **Region Proposal Network (RPN)**
- Region proposal and classification share the same convolutional layers.

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Faster R-CNN framework

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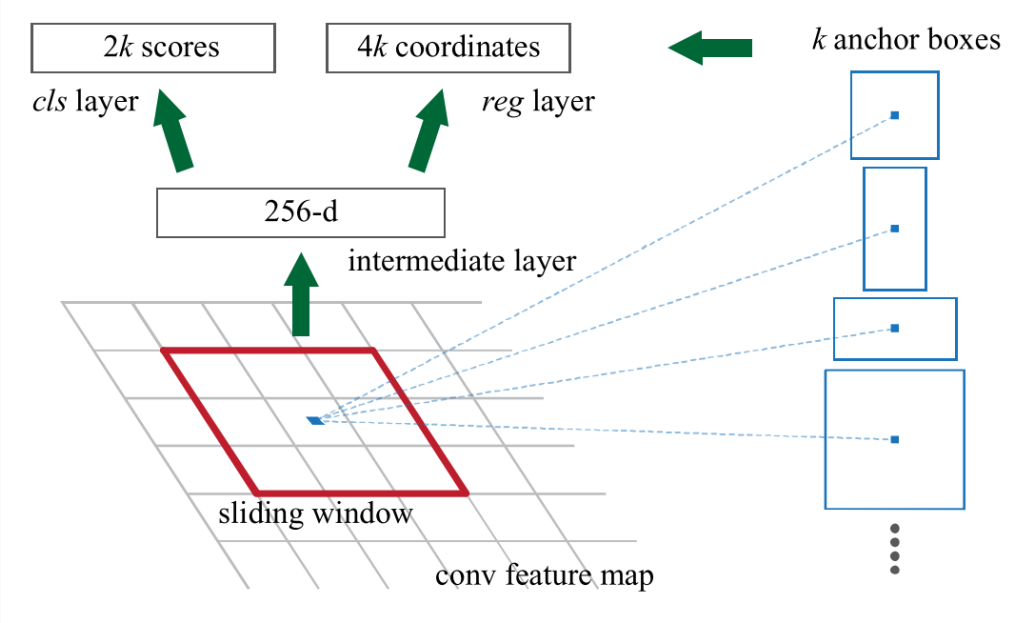

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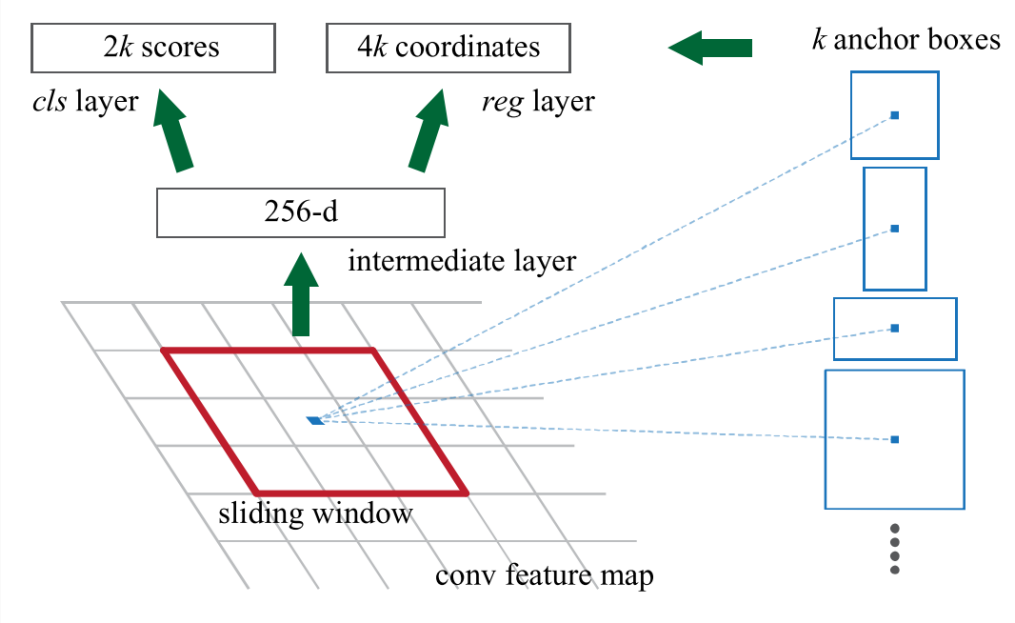
Faster R-CNN framework

- RPN proposals are relative to fixed anchors.
- Bounding boxes coordinates are refined in the final classification.



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Faster R-CNN in driving environments

Parameter optimization

- 1239 x 374 images scaled by a factor of ~1.33x (to height 500).

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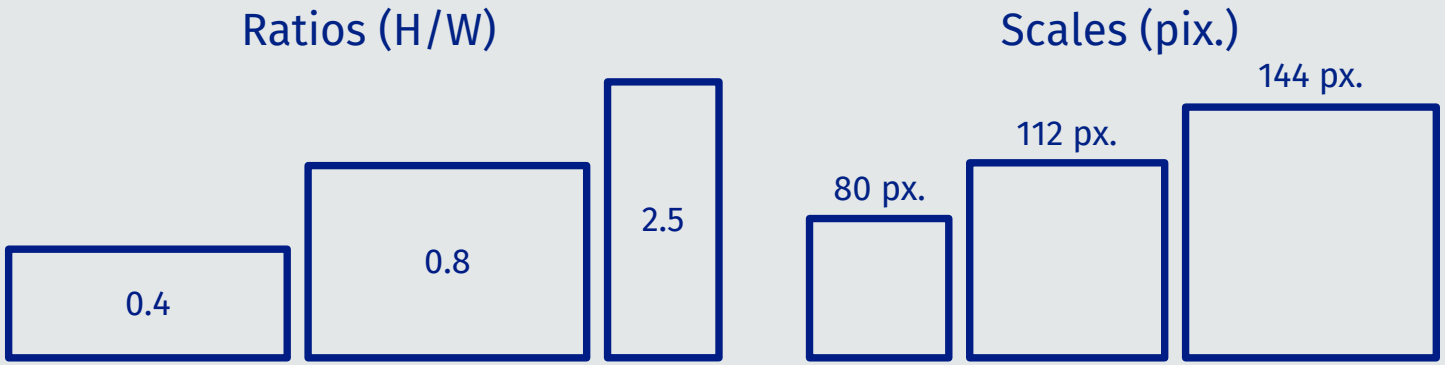
- *DontCare* areas properly discarded.
- Hard, moderate and easy samples used to train.
- RPN **anchors** selected to fit the objects in the environment.



Faster R-CNN in driving environments

Limitations

- Accuracy highly dependent on the scale.

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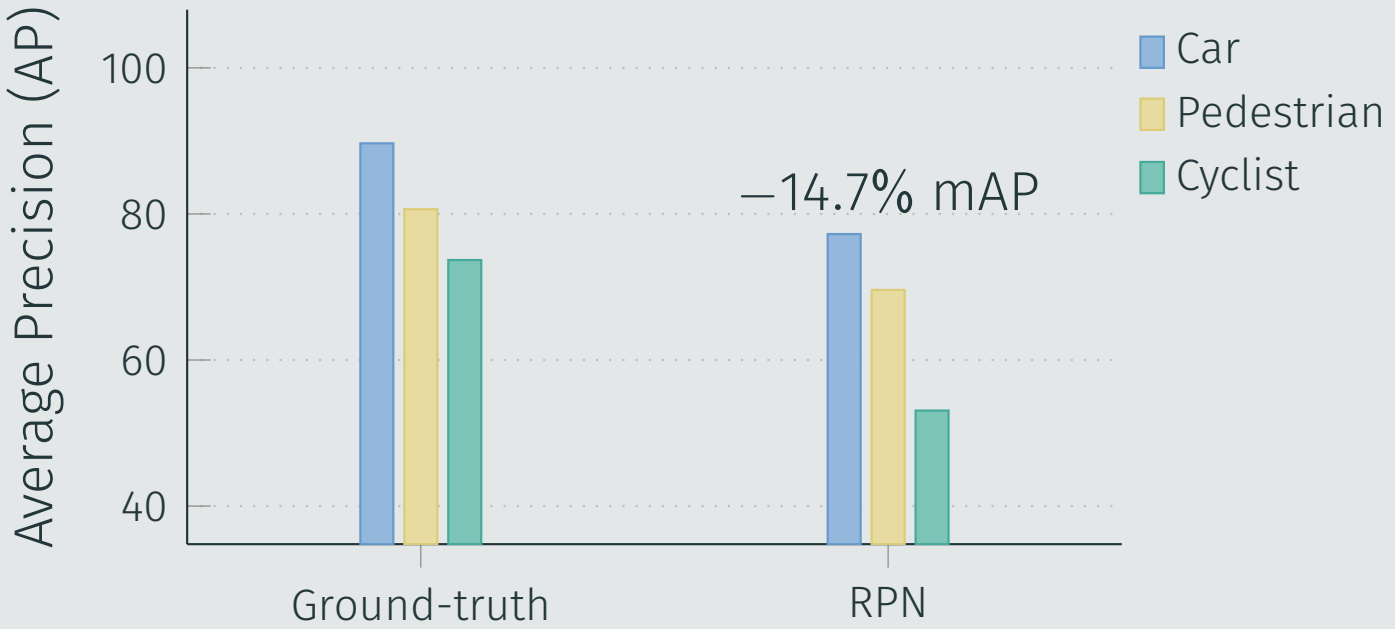
- Perfect proposals vs RPN proposals:



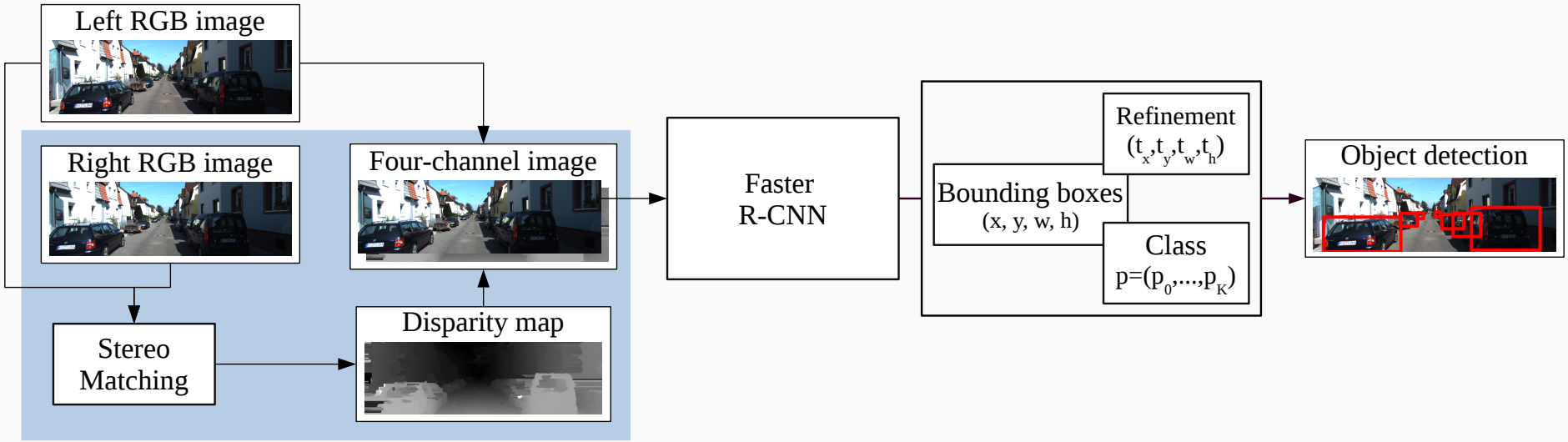
$$mAP = \frac{\sum_{i=0}^{N} AP_i}{N}$$

Proposed approach

System overview

Goal:

- To use the frequently available stereo information in a simple, straightforward way to improve the detection accuracy.



System overview

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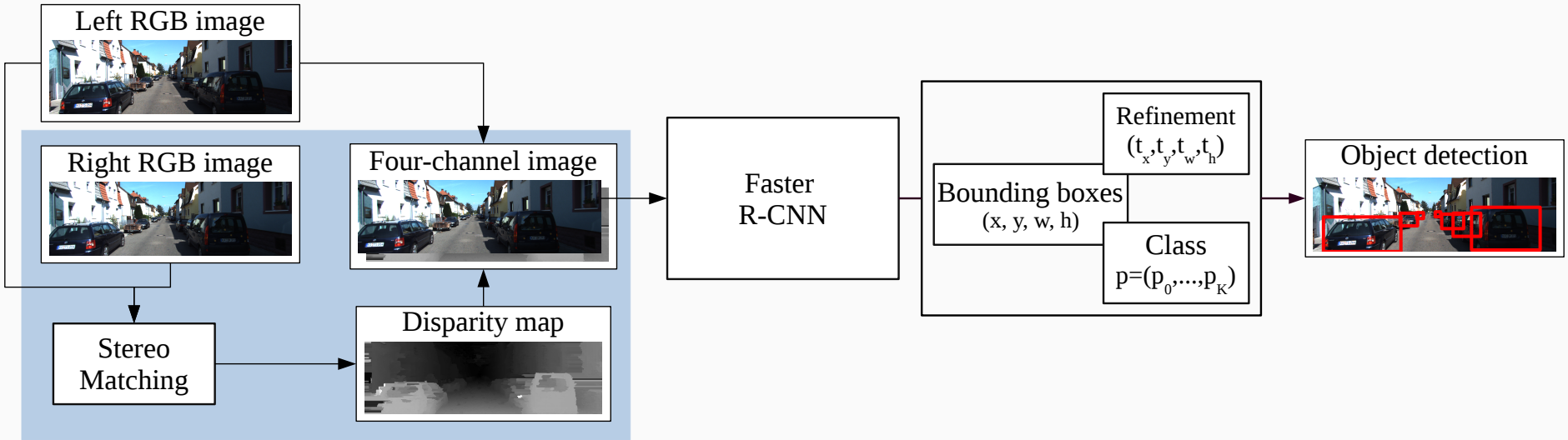
- Intuitively, spatial reasoning provided by stereo may help to better segment the objects.



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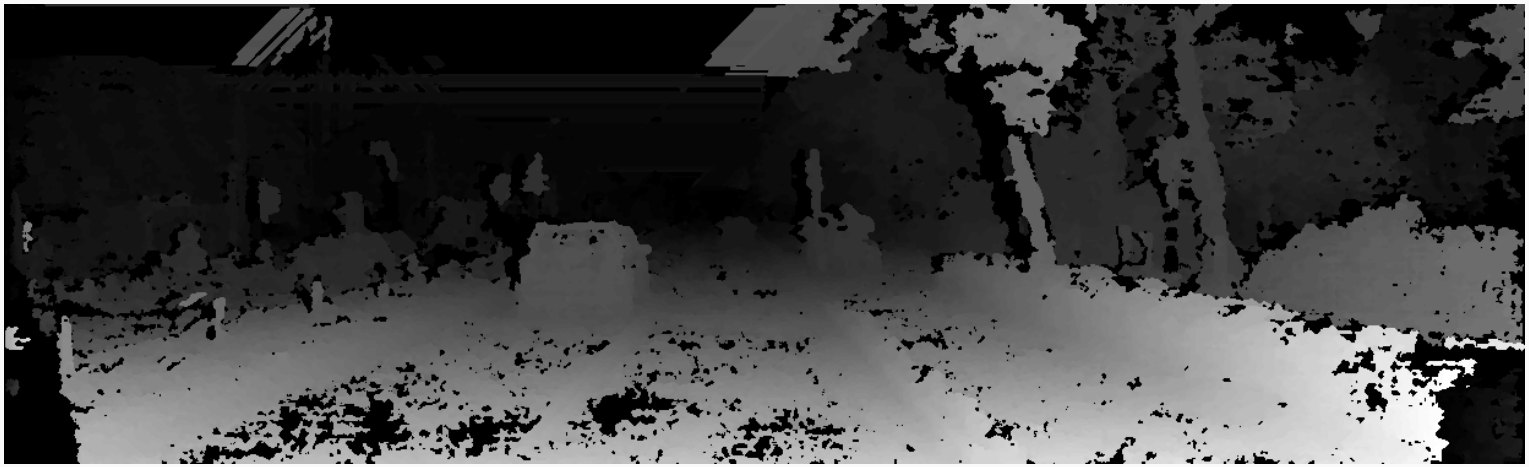
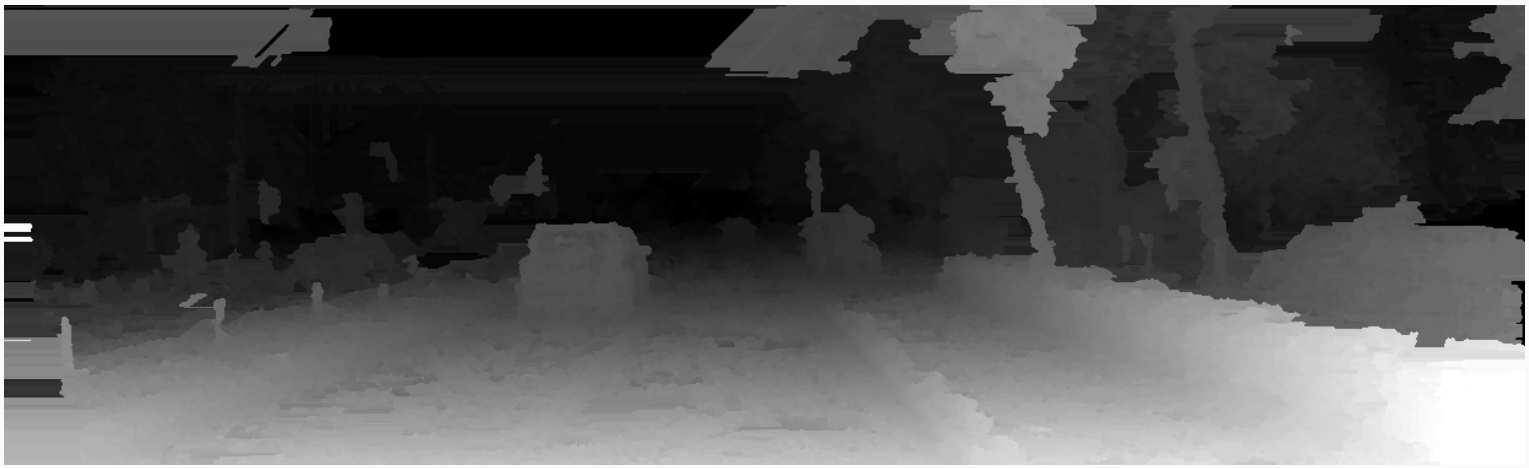


Stereo matching

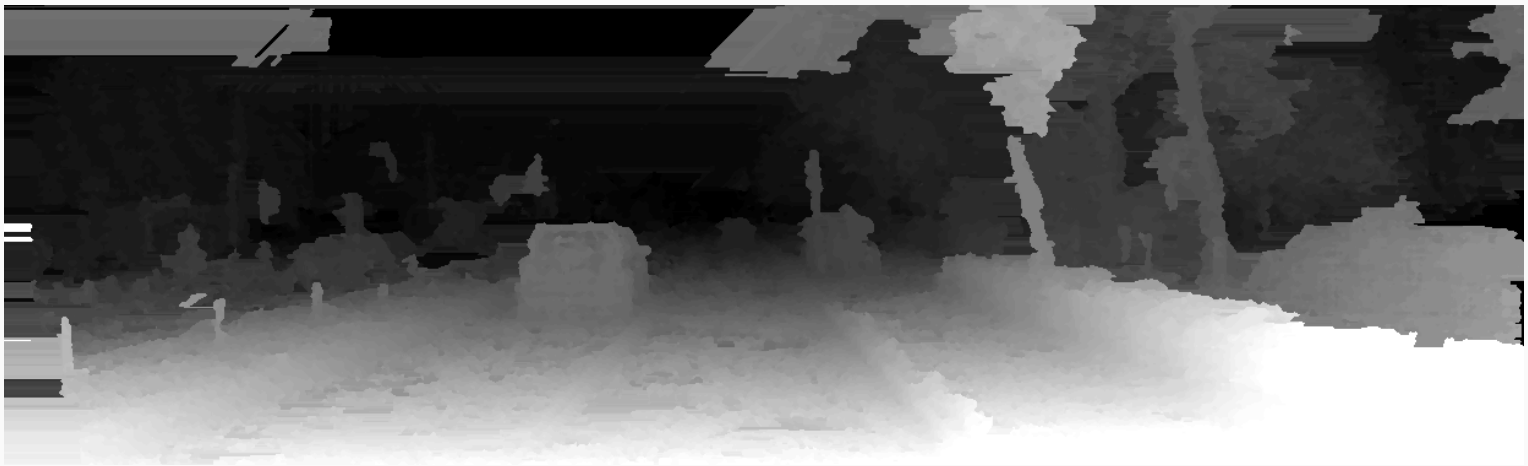
- SG(B)M stereo-matching algorithm, is used.
- Non-defined pixels may introduce spurious errors.
- Thus, a simple background interpolation is applied.

$$i\_disp[u_{NON\_DEFINED}, v] = min(disp[u_{LAST\_DEFINED}, v], disp[u_{NEXT\_DEFINED}, v])$$



CNN input

- The disparity map is normalized before entering the CNN: values between 0-63 (6 meters and further) are scaled to 0-255. Disparities between 64-127 are clipped to 255.



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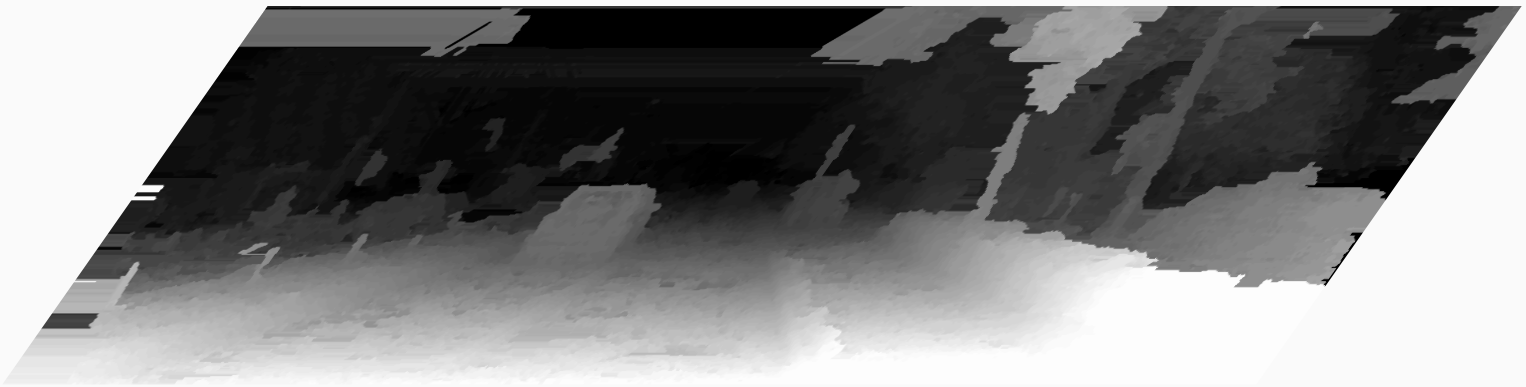
- The normalized disparity map is appended to the RGB image as a **fourth channel**.



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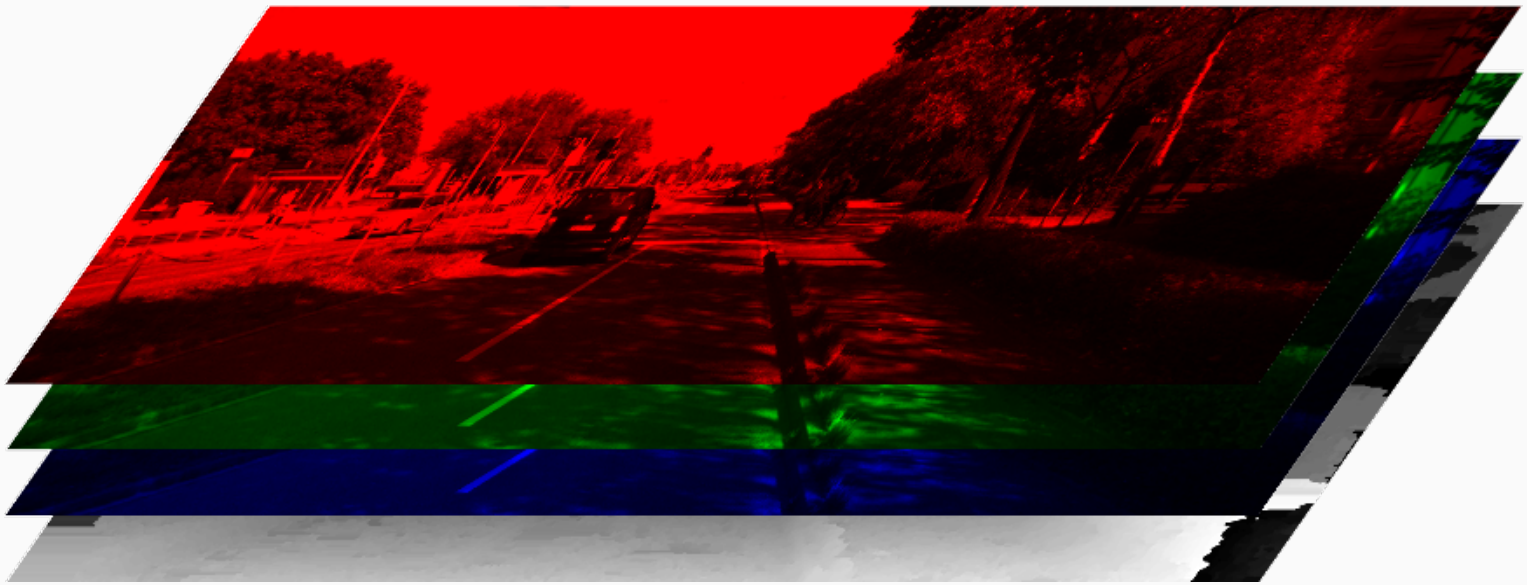

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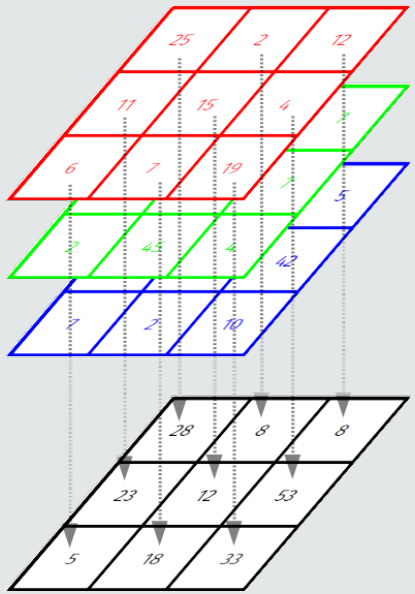
- The shared convolutional layers are initialized using a pre-trained model for ImageNet classification, as is standard practice.
- In order to re-use the available Faster R-CNN models, weights for the fourth channel are computed as the mean of the RGB weights.



Results

Setup

Architecture

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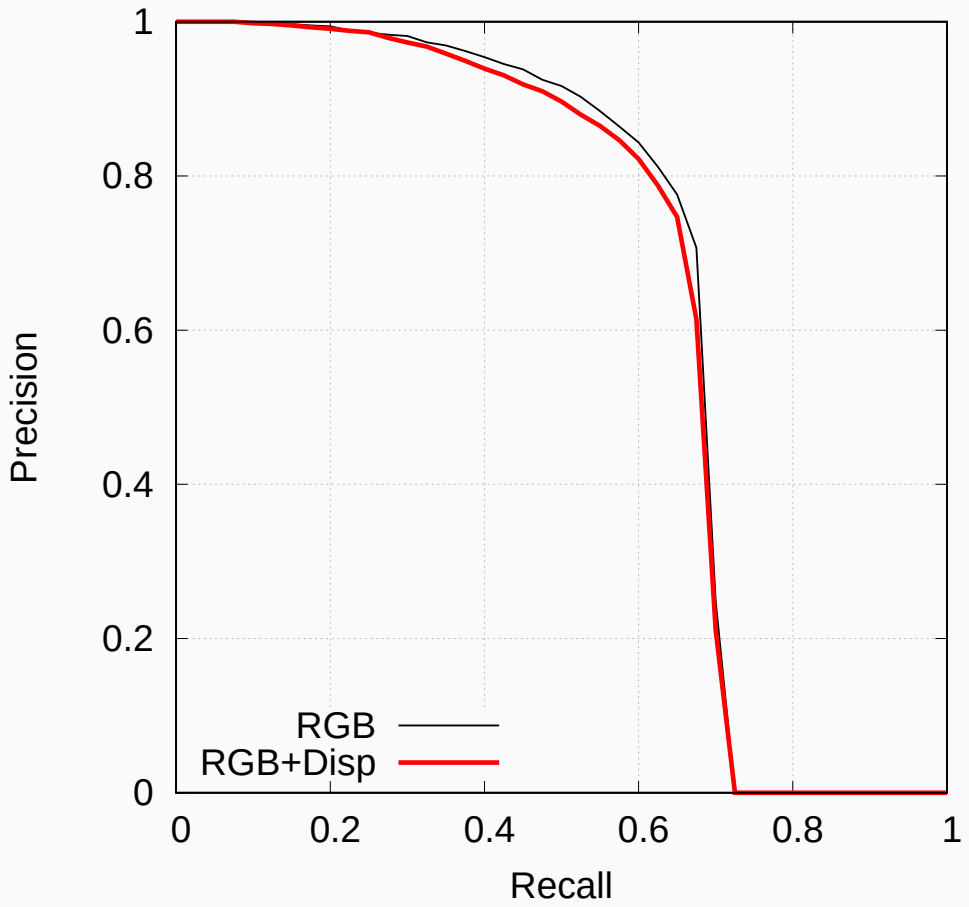
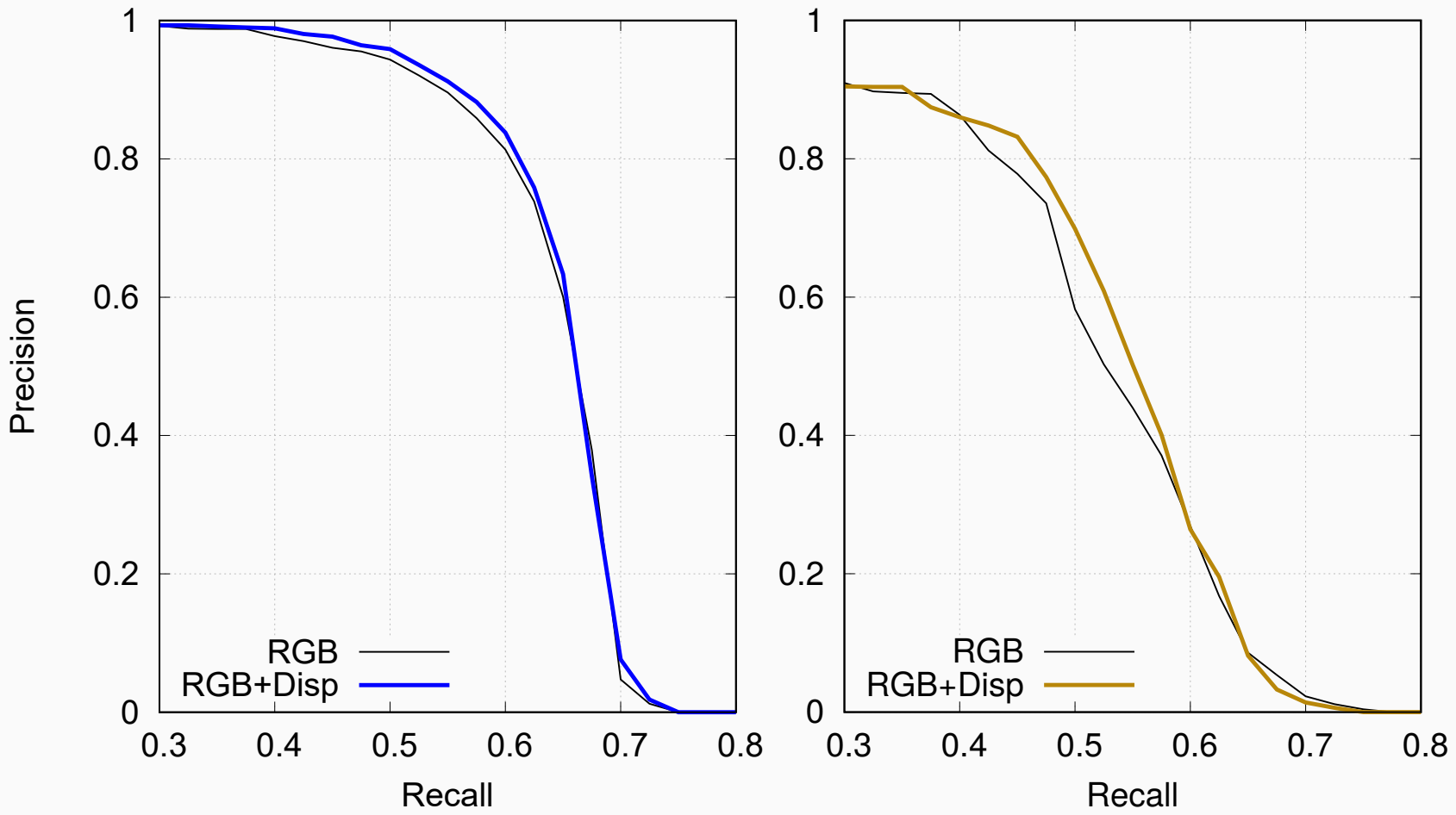
Parameters

80k iterations, learning rate: 0.001 (x0.1 after 50k)

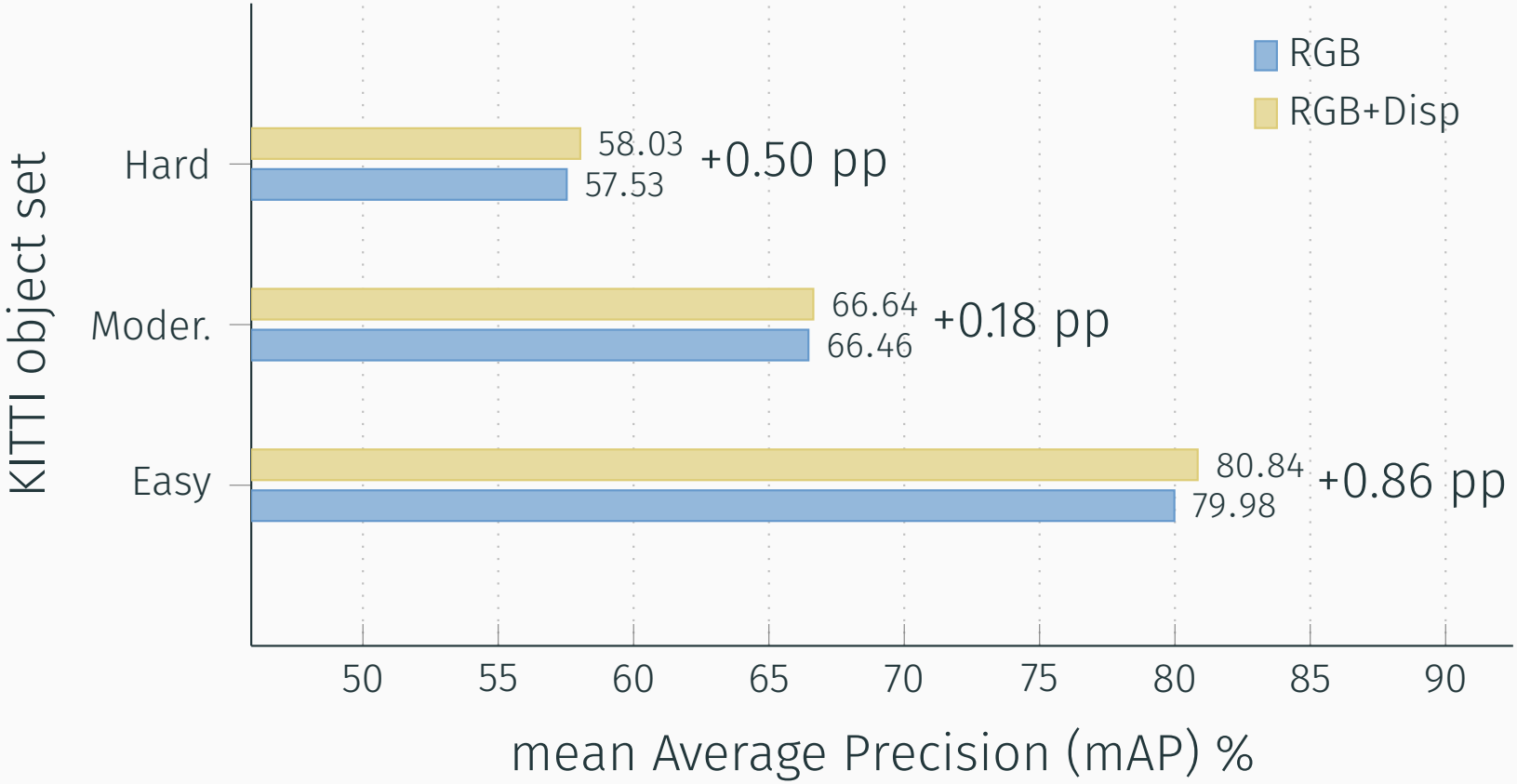
Precision-recall curves (Car)



Precision-recall curves (Pedestrian & Cyclist)



Detection AP (%)



	Car	Pedestrian	Cyclist
AP (moderate)	76.03%	69.18%	54.72%

IVVI 2.0 platform · Intelligent Systems Laboratory

Intelligent Vehicle based on Visual Information

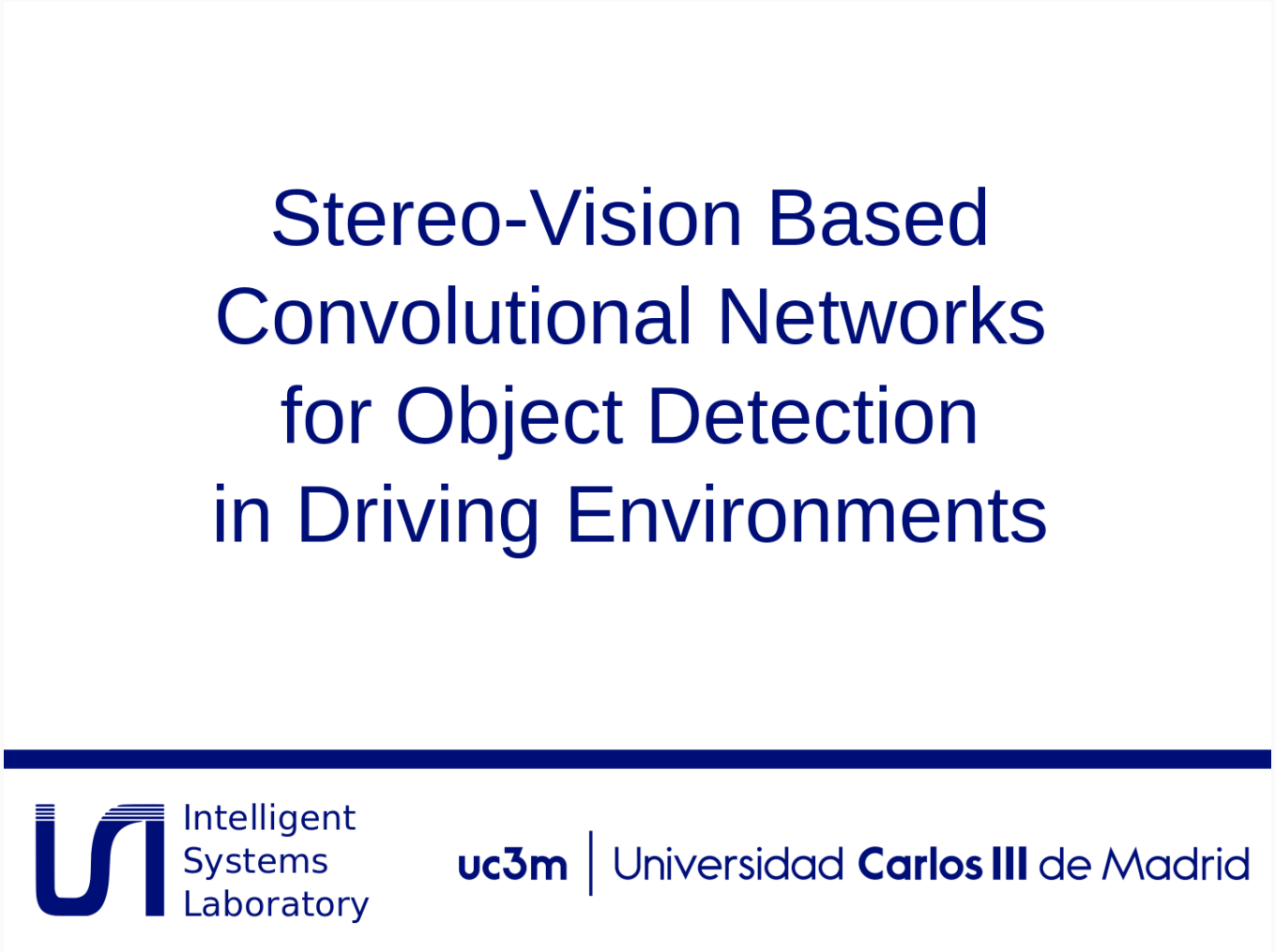
- Platform to test Advanced Driver Assistance Systems.

IVVI 2.0 platform · Intelligent Systems Laboratory

Intelligent Vehicle based on Visual Information

- Platform to test Advanced Driver Assistance Systems.
- Sensors: stereo camera, LiDAR, IMU, GPS, ...

Video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Future experiments

- CNN architectures with better accuracy/computation time trade-off (ResNets).
- Several stereo matching algorithms.
- Different hole-filling techniques (white noise).
- Methods to use features from early layers.

Thank you

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