Joint Object Detection and Viewpoint Estimation using CNN features

VII LSI PhD Workshop

Carlos Guindel
cguindel@ing.uc3m.es
Intelligent Systems Laboratory · Universidad Carlos III de Madrid

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C. Guindel, D. Martín, and J. M. Armingol, “Joint Object Detection and Viewpoint Estimation using CNN features,” in IEEE International Conference on Vehicular Electronics and Safety (ICVES), 2017.

Outline

- Introduction
- Object detection
- Viewpoint estimation
- Results
- Conclusion

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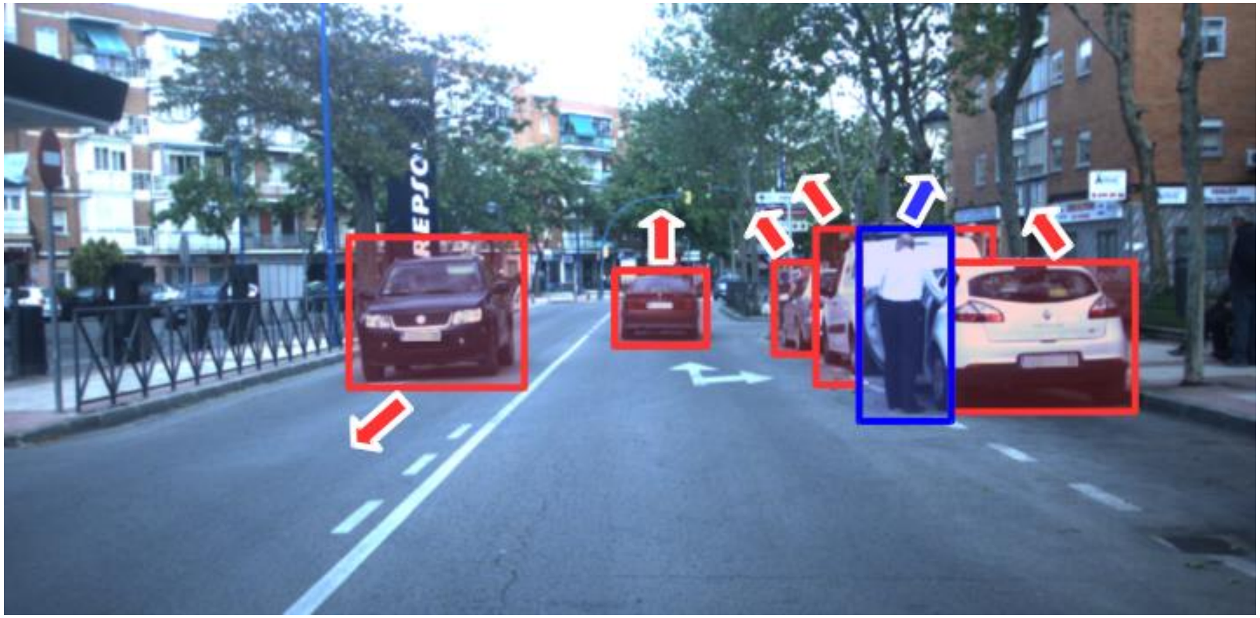
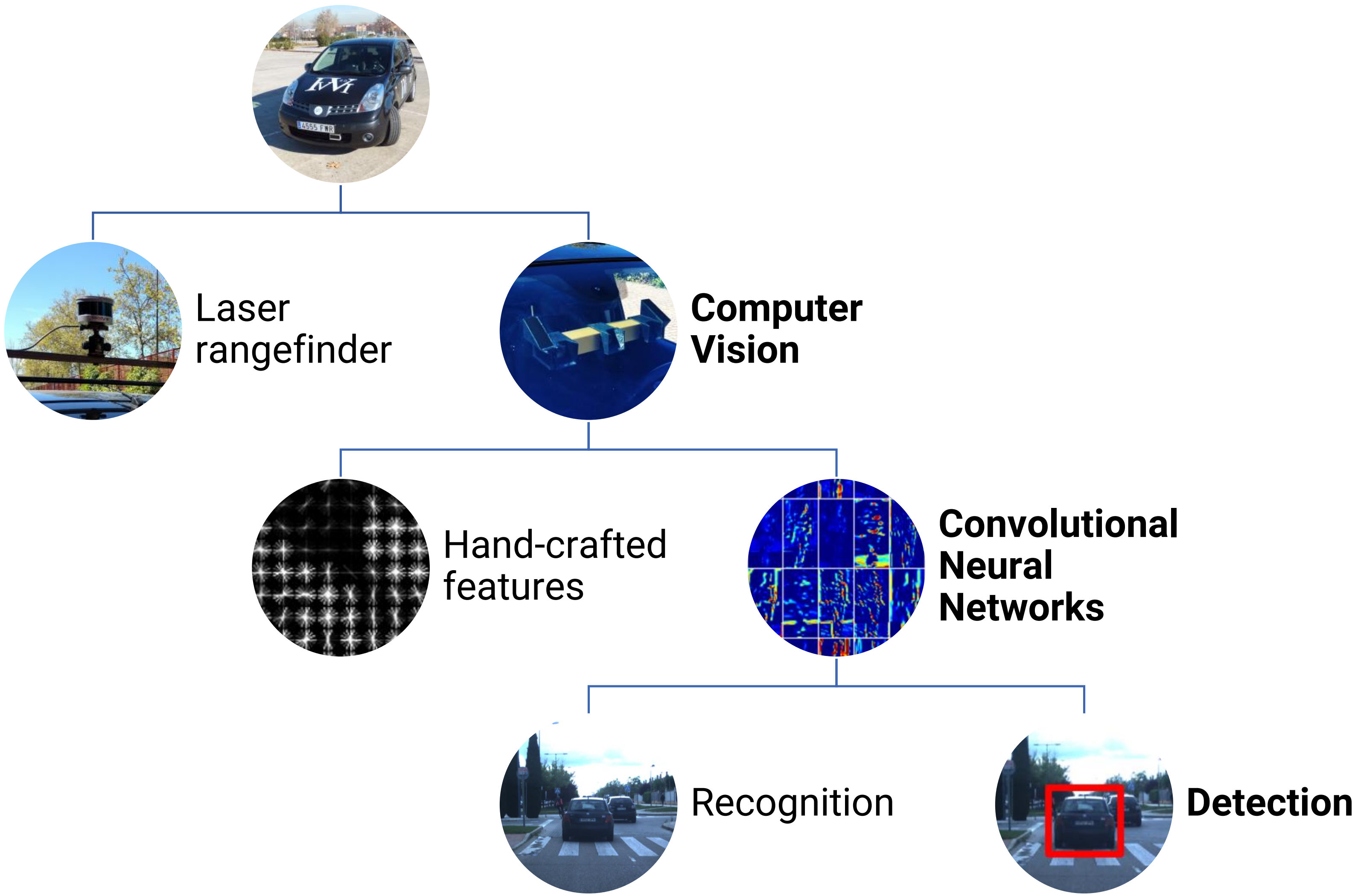
Situational awareness for vehicles

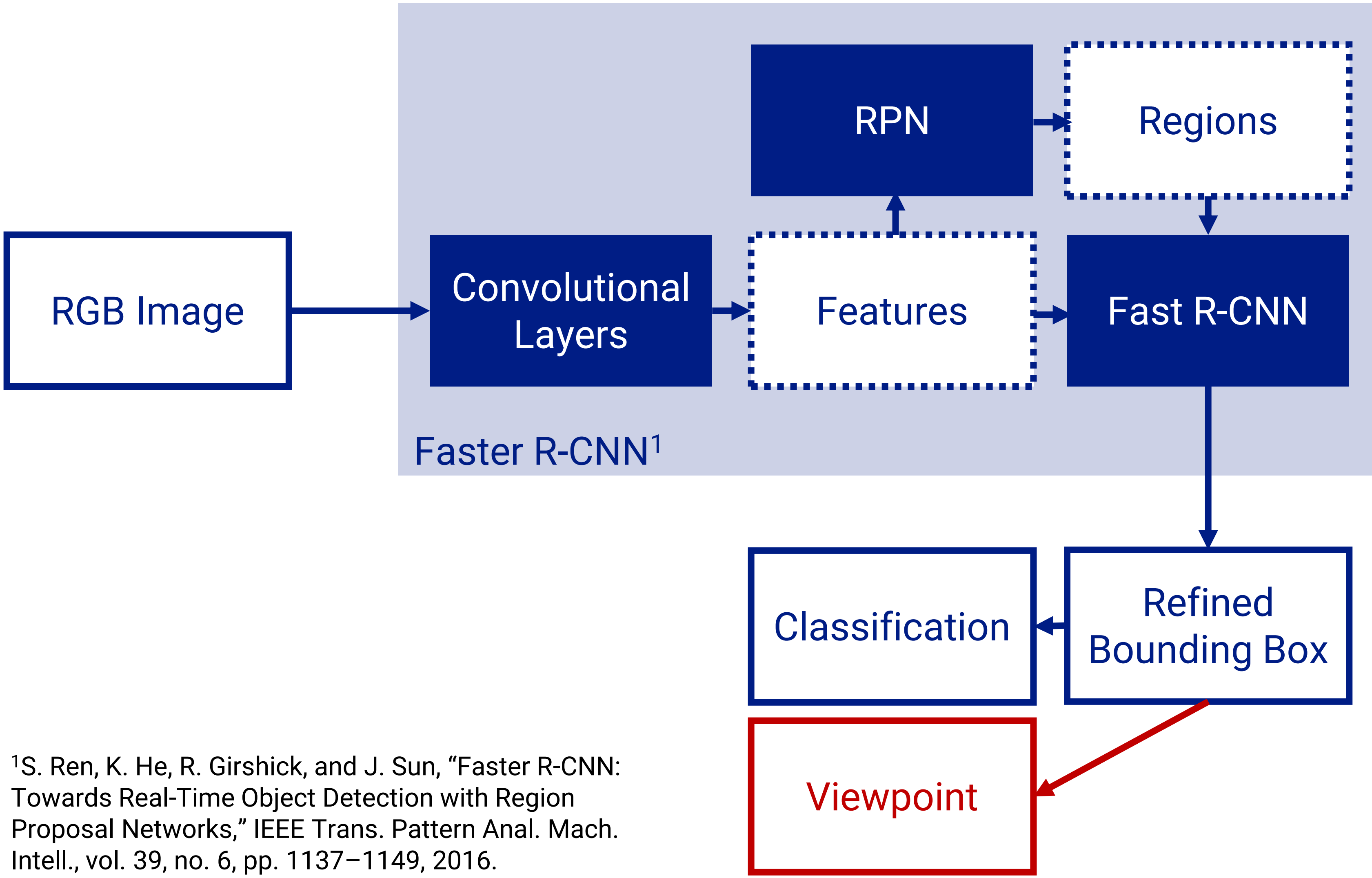
- Advanced Driver Assistance Systems (ADAS) and autonomous vehicles rely on a trustable on-board **obstacle detection** module.
- A precise **classification** of the obstacles enables accurate predictions of future traffic situations, including those involving VRU.
- Another significant cue that can be used to anticipate future events is the **orientation** of the objects moving on the ground plane.



On-board object detection



Proposal overview



[1] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2016.

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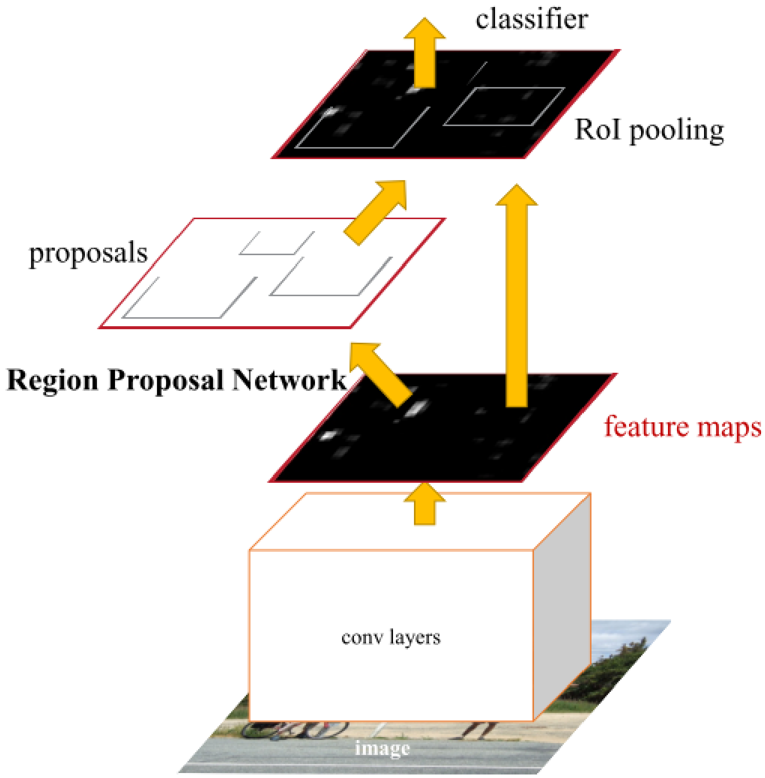
Object detection

- Traffic environments
  - Diversity of agents
  - Unstructured environment
- Faster R-CNN
  - End-to-end feature learning
  - Highly efficient
  - No prior constraints about the location of objects in the image
  - Meant for more than 21 classes



S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2016.

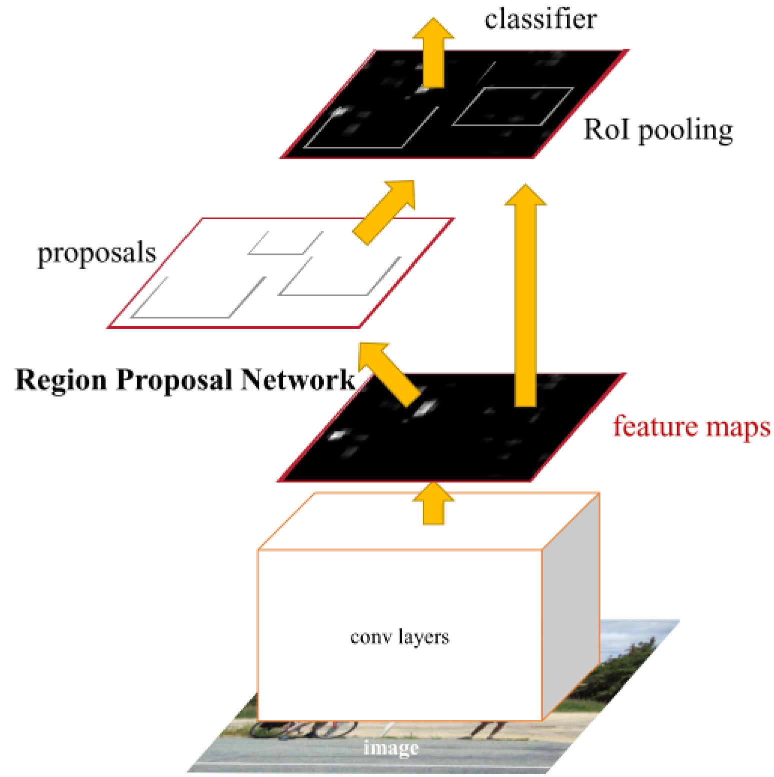
Faster R-CNN framework

Parameters are learned through a multi-task loss

Conv. features in these regions are pooled for **classification**

A **RPN** generates proposals wrt. a fixed set of anchors

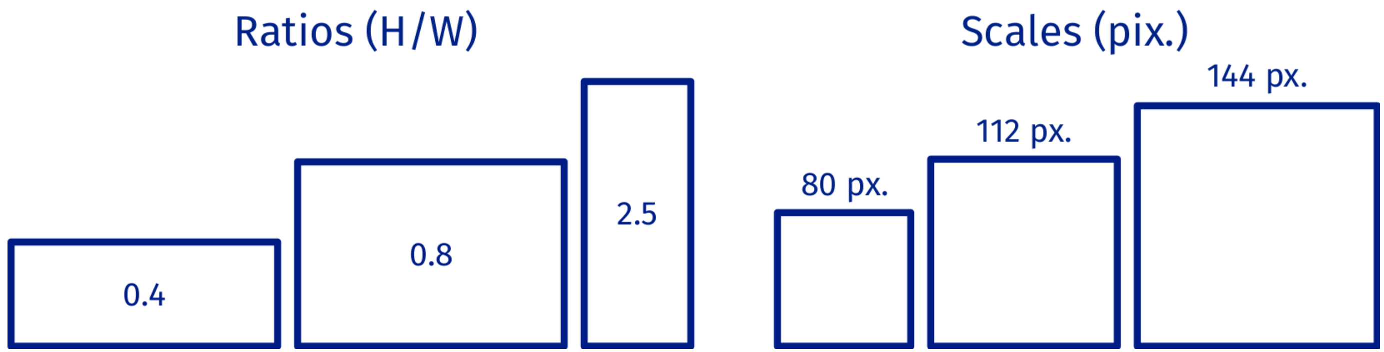
Convolutional features computed **only once** per image



S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, 2016.

Fine-tuning for traffic environments

- Optimized anchors



- Management of class imbalance
  - Information gain multinomial logistic loss for the **class** inference

$$L = -\frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K} H_{l_n,k} \log(\hat{p}_{n,k})$$

Infogain matrix

$$\begin{pmatrix} H_{0,0} & \cdots & 0 \\ 0 & & \\ \vdots & \ddots & \vdots \\ & & 0 \\ 0 & \cdots & H_{K,K} \end{pmatrix}$$

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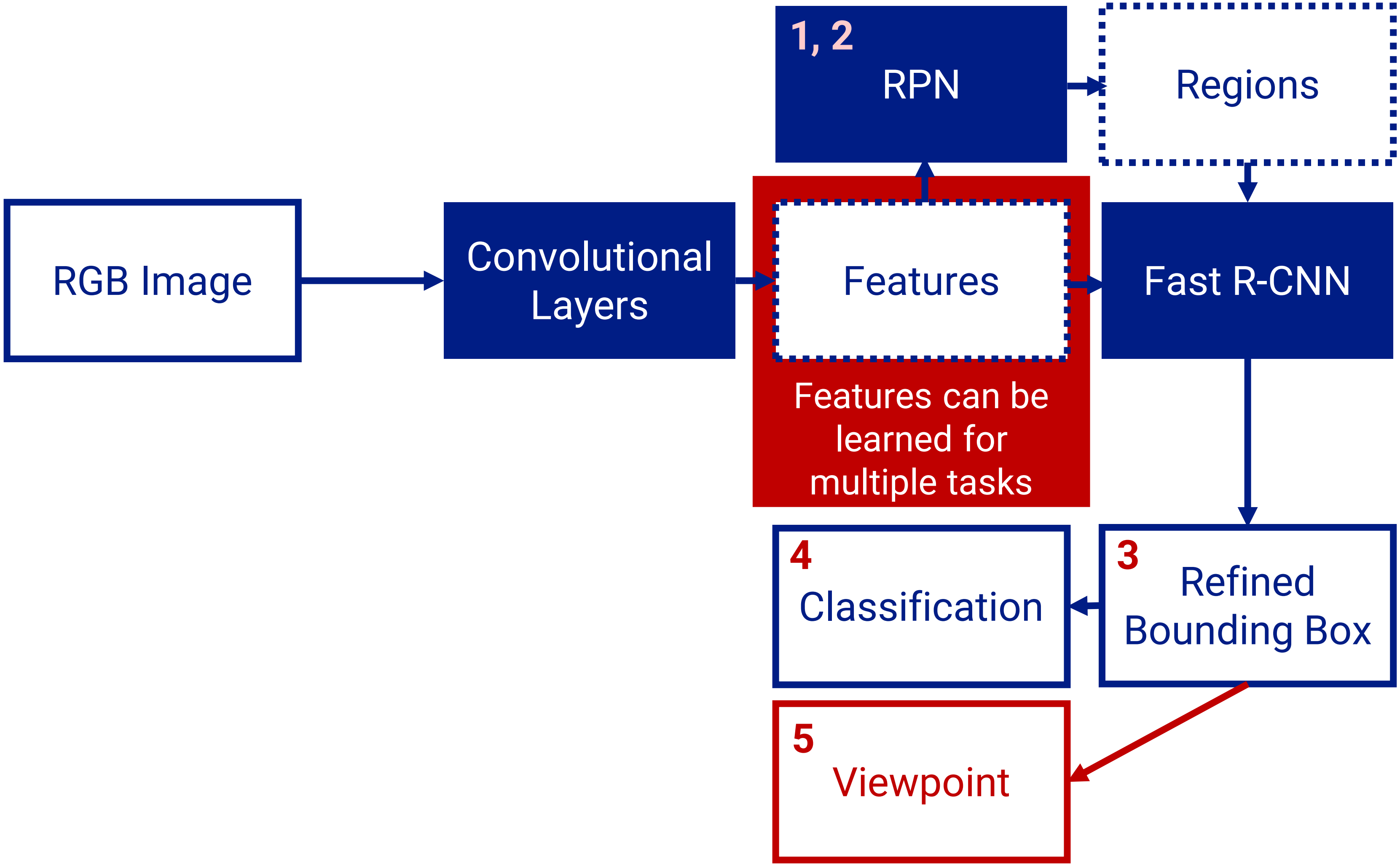
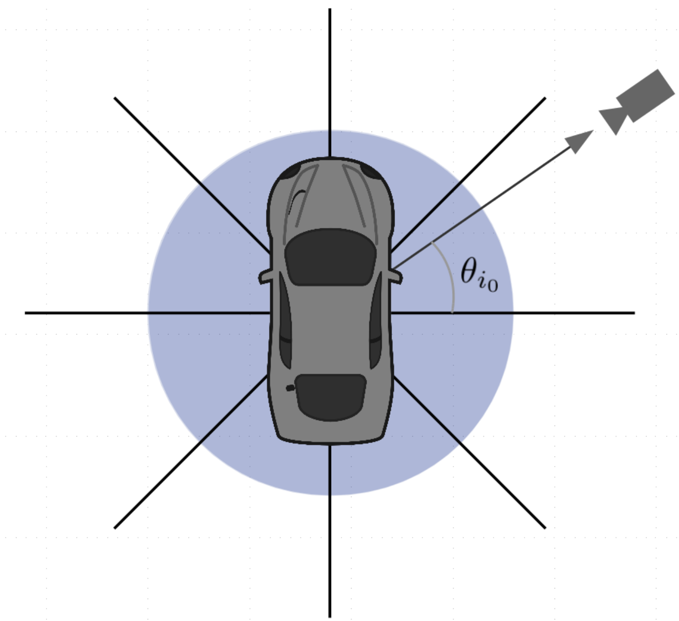
Viewpoint estimation



Discrete viewpoint inference

N_b **angle bins** $\Theta_i \dots \Theta_{N_b}$

$N_b = 8$



Training: $\theta_{i_0} \rightarrow \Theta_i$

$$\Theta_i = \left\{ \theta \in [0, 2\pi) \;\middle|\; \frac{2\pi}{N_b} \cdot i \leq \theta < \frac{2\pi}{N_b} \cdot (i+1) \right\}$$

Inference output: $\mathrm{r} \in \Delta^{N_b - 1}$

$$\Delta^N = \left\{ x \in \mathbb{R}^{N+1} \;\middle|\; \sum_{i=1}^{N+1} x_i = 1 \;\wedge\; \forall i\colon x_i \geq 0 \right\}$$

r

$$i^* = \arg\max_i (x_i)$$

Elements of r

Final estimation: $\Theta_{i^*} \rightarrow \hat{\theta}$

$$\hat{\theta} = \frac{\pi(2i^* + 1)}{N_b}$$

Joint detection and viewpoint estimation

CNN outputs

RPN

For each anchor:

- Objectness

  $a \in \{0,1\}$

- Predicted bounding box

  $b = (b_x, b_y, b_w, b_h)$

Fast R-CNN

For each proposal:

- Class

  $p = (p_0, \ldots, p_K)$

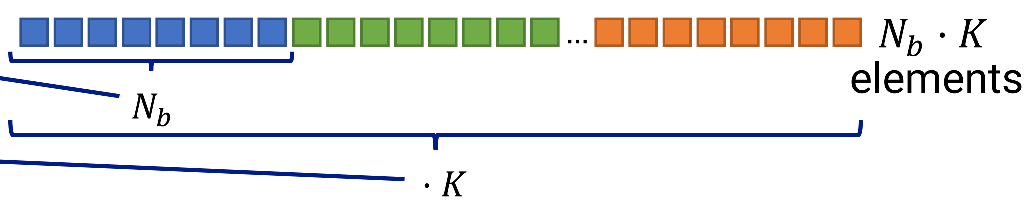
- Bounding box refinement

  $t^k = (t^k_x, t^k_y, t^k_w, t^k_h)$ for $k = 0, \ldots, K$

Per class

- Viewpoint

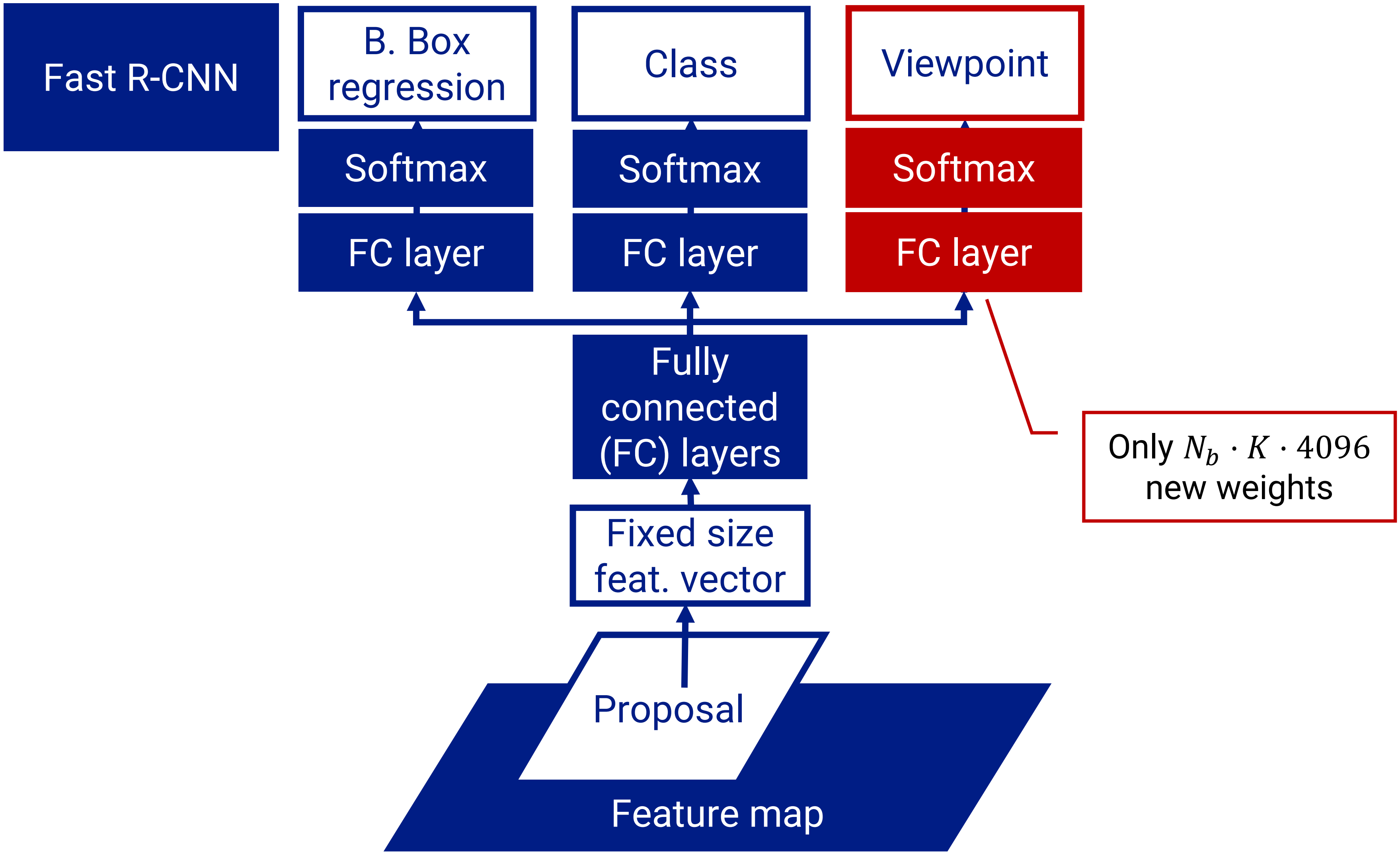
  $r^k = (r^k_0, \ldots, r^k_{N_b})$ for $k = 0, \ldots, K$



Number of angle bins

Number of classes

Joint detection and viewpoint estimation



Loss function and training

- **Approximate joint** training strategy
- Unweighted muli-task loss with **five** components

Logistic loss
for RPN objectness

Smooth-L1 loss
for RPN b.box regression

$$L = \frac{1}{N_{B_1}} \sum_{j \in B_1} L_{cls}(a_j, u_j) + \frac{1}{N_a} \sum_{j \in B_1} u_j L_{loc}(b_j, b_j^*) +$$
$$\frac{1}{N_{B_2}} \sum_{i \in B_2} L_{inf}(p_i, v_i) + \sum_{i \in B_2} [u \geq 1] \, L_{loc}(t_i^v, t_i^{v*}) +$$
$$\frac{1}{N_{B_2}} \sum_{i \in B_2} [u \geq 1] \, L_{cls}(r_i^u, \Theta_i)$$

Smooth-L1 loss
for b.box regression

Infogain loss
for class

$$L_{inf}(p_i v_i) = \sum_{n=1}^{N} H_{v_i,k} \log(p_{i,k})$$

↓ frequent → ↑ $H_{v_i,k}$

Logistic loss
for viewpoint estimation

Only the N_b elements of the ground-truth class

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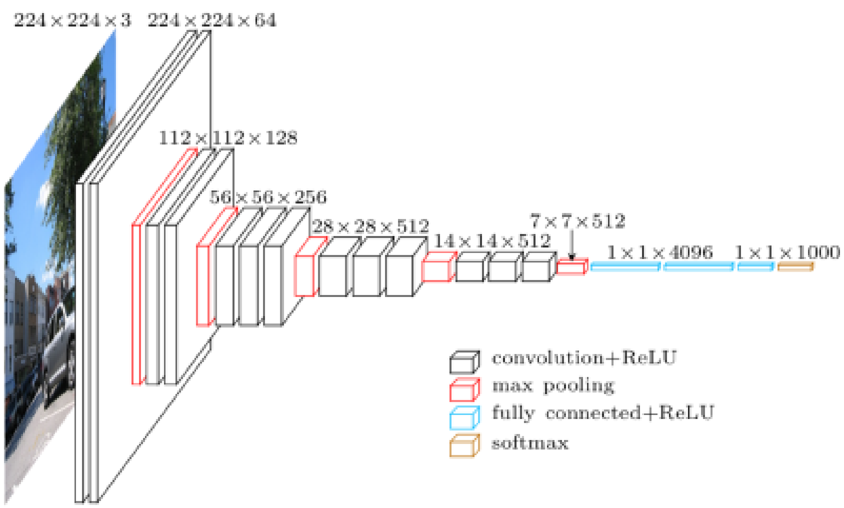
Experiments

- On the KITTI Vision Benchmark Suite – Object detection set
- **Training parameters:**
  - **Scale**: 500 px. in height
  - 50k iter. $l_r = 0.001$ **+** 50k iter. $l_r = 0.0001$ **+** 50k iter. $l_r = 0.00001$
  - **VGG16** architecture, initialized with ImageNet weights.



KITTI: A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2012, pp. 3354–3361.

VGG16 Image: https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/

Experiments

- $N_b = 8$ (resolution: $\pi/4$ rad)
- Infogain matrix values:

$$H_{k,k} = 2 \cdot \left(\frac{f_{min}}{f_k}\right)^{\frac{1}{8}}$$

Number of ocurrences of the less frequent class

Number of instances of class k

Evaluation criteria

- Average precision
- Average orientation similarity (performance of **detection + orientation**)

$$AOS = \frac{1}{11} \sum_{r \in \{0, 0.1, .., 1\}} \max_{\tilde{r}:\tilde{r} \geq r} s(\tilde{r}) \qquad s(r) = \frac{1}{|\mathcal{D}(r)|} \sum_{i \in \mathcal{D}(r)} \frac{1 + \cos \Delta_\theta^{(i)}}{2} \delta_i$$

- Minimum overlaps established by the KITTI benchmark

KITTI submission

The KITTI Vision Benchmark Suite
A project of Karlsruhe Institute of Technology and Toyota Technological Institute at Chicago

Karlsruhe Institute of Technology

home | setup | stereo | flow | scene flow | odometry | object | tracking | road | semantics | raw data | submit results | jobs

Andreas Geiger (MPI Tübingen) | Philip Lenz (KIT) | Christoph Stiller (KIT) | Raquel Urtasun (University of Toronto)

Method

Joint Object Detection and Viewpoint Estimation using CNN features [FRCNN+Or]

Submitted on 7 Jun. 2017 10:58 by
Carlos Guindel (Universidad Carlos III de Madrid)

Running time: 0.1 s
Environment: GPU @ 1.5 Ghz (Python + C/C++)

Method Description:
We enhance the well-known Faster R-CNN method by adding viewpoint inference capabilities. Convolutional features are computed and shared for use in the tasks of region proposal, classification, and orientation estimation, for efficiency reasons.

Parameters:
Scale=500, 300 RPN proposals, 3 anchor scales and 3 anchor ratios, \N_b=8, \l_r=0.001, 150k iterations. Running time given for a NVIDIA Titan X Pascal.

Latex Bibtex:
```
@inproceedings{GuindelICVES,
author = {Guindel, Carlos and Martin, David and Armingol, Jose
M.},
booktitle = {IEEE International Conference on Vehicular
Electronics and Safety (ICVES)},
title = {{Joint Object Detection and Viewpoint Estimation
using CNN features}},
year = {2017}
}
```

Results (KITTI submission: FRCNN+Or)

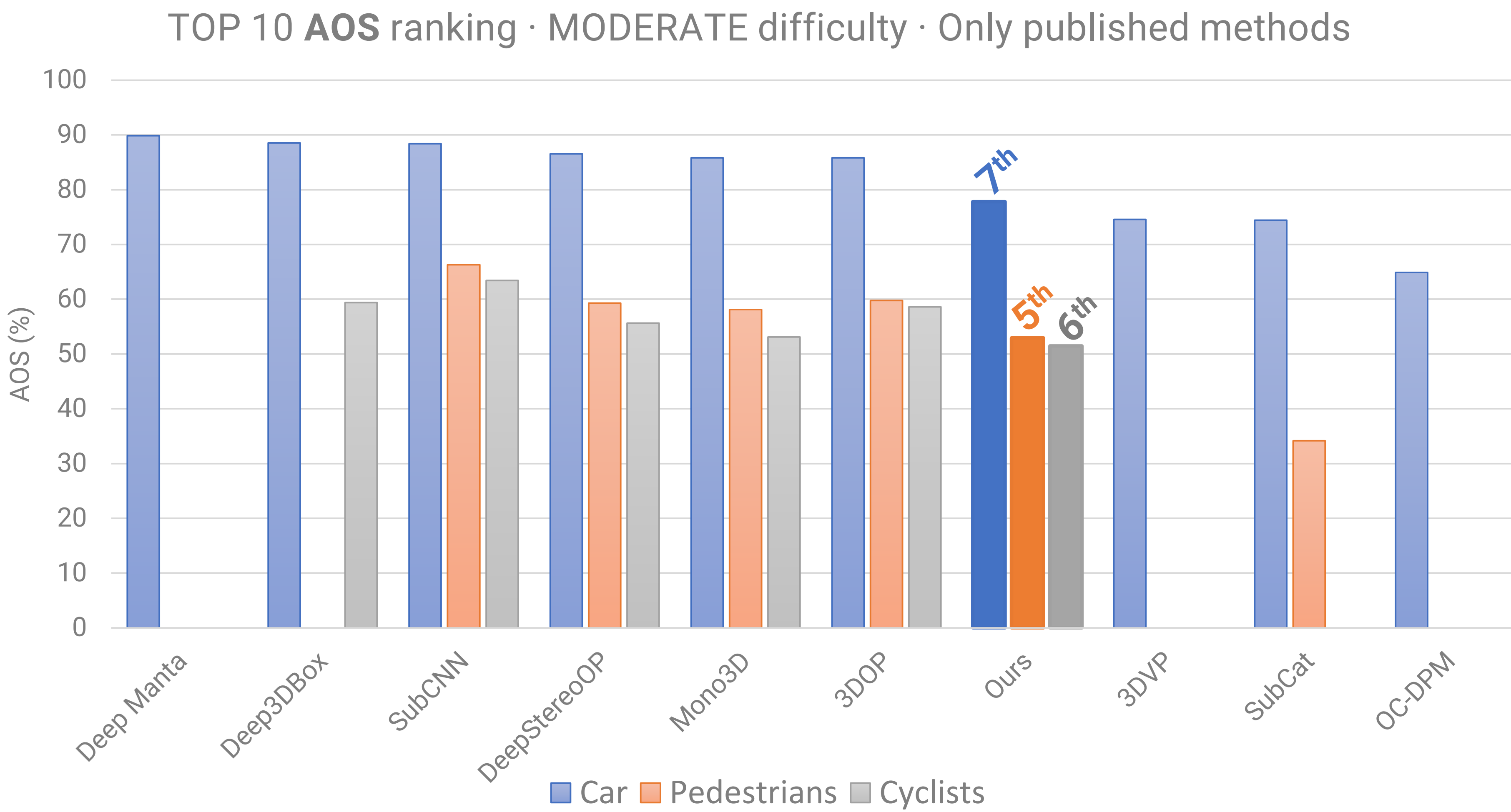
Detection (AP as %)	Easy	Moderate	Hard
Car	89.60	78.59	68.69
Pedestrian	72.21	56.99	53.72
Cyclist	68.81	55.80	50.52
mAP	**76.87**	**63.79**	**57,64**
SubCNN	*84.52*	*77.14*	*64.44*

- Slightly different (generally better) than the ones in the paper:
  - Used the whole KITTI training set
  - Trained only with Car, Pedestrian and Cyclist
  - Non-fixed weights (and bias) at the first convolutional layers

Det + Or (AOS as %)	Easy	Moderate	Hard
Car	88.93	77.8	67.87
Pedestrian	67.92	52.96	49.61
Cyclist	64.90	51.47	46.48
mAOS	**73.92**	**60.74**	**54,65**
SubCNN	*80.37*	*72.85*	*65.45*

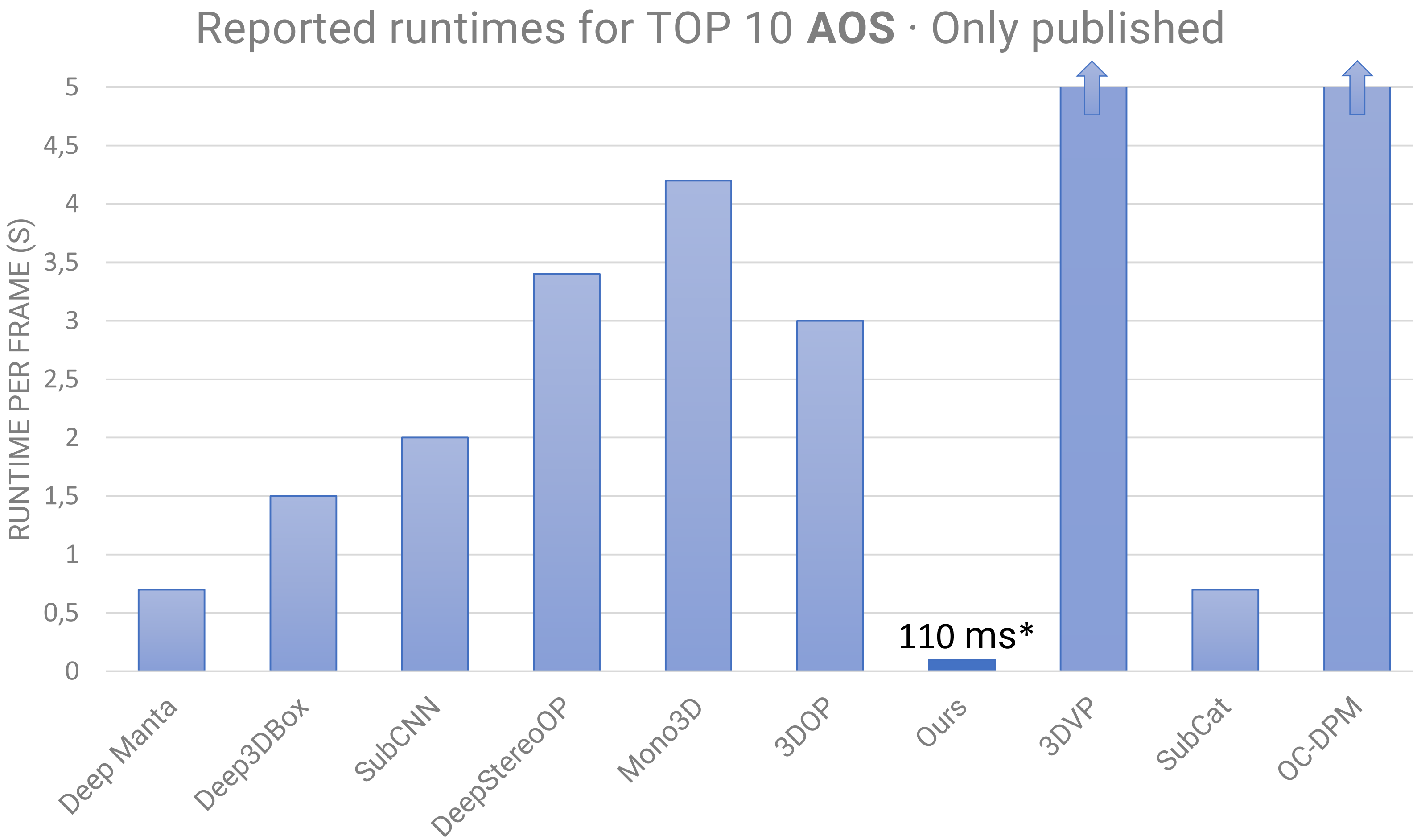
SubCNN: Y. Xiang, W. Choi, Y. Lin and S. Savarese, “Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection,” in IEEE Winter Conference on Applications of Computer Vision (WACV), 2017, pp. 924-933.

Comparison with published KITTI submissions



Global rankings (including unpublished methods): Car: 11st · Pedestrian: 9th · Cyclist: 10th

Comparison with published KITTI submissions



*Average running time using an implementation based on py-faster-rcnn (Python & Caffe) and a NVIDIA **Titan Xp** donated by NVIDIA Corporation

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Conclusion

- Monocular approach for object detection focused on traffic environments.
- Based on a state-of-the-art CNN and adding viewpoint inference.
- Results comparable with non-real-time sophisticated approaches.
- Orientation is a step towards a complete scene understanding.

Future work

- Fine-grained orientation inference using the **cross-entropy logistic loss**

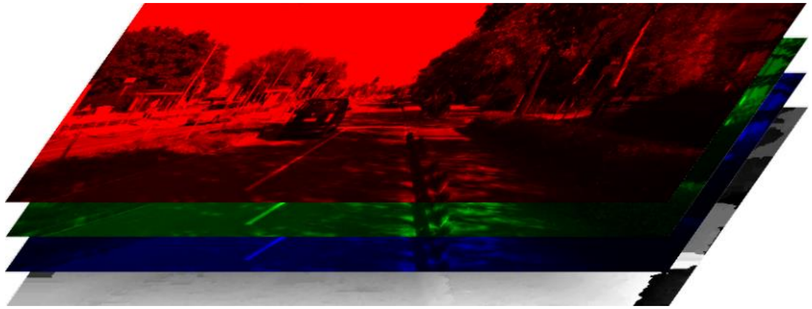
$$L = -\frac{1}{n}\sum_{n=1}^{n}[p_n \log \hat{p}_n + (1 - p_n)\log(1 - \hat{p}_n)]$$

- Improvements:
  - Network architecture
  - Methods to overcome the fixed-size receptive field

Other Developments

Additional data for the CNN

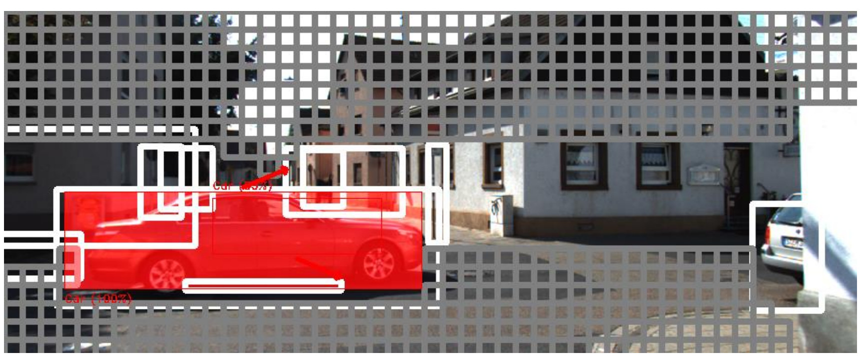
- Stereo. Using the disparity map as a fourth channel

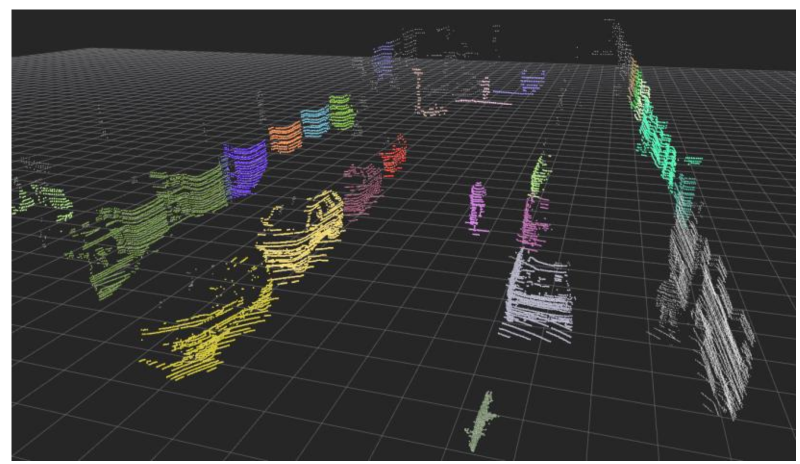


Input	Easy	Moderate	Hard
RGB	79.98	66.46	57.53
RGB+SGM	+0.30	+0.01	+2.52
RGB+DispNet	**+1.03**	**+1.14**	**+3.57**

C. Guindel, D. Martín, and J. M. Armingol, “Stereo Vision-Based Convolutional Networks for Object Detection in Driving Environments,” in EUROCAST 2017 - Extended Abstracts, 2017, pp. 288–289.

- Laser. Classifying object proposals coming from the Velodyne

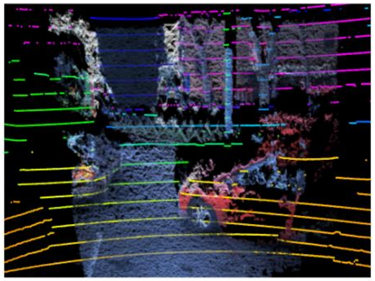




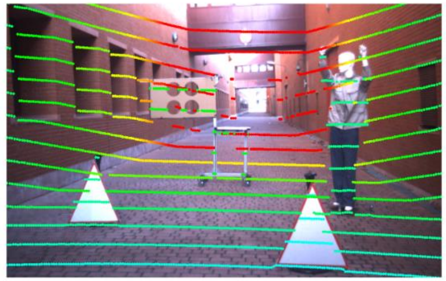
Work in progress!

Teamwork

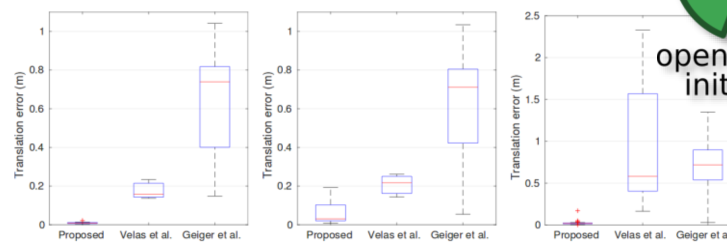
- Lidar-camera calibration. Solving a recurrent problem.



(a)



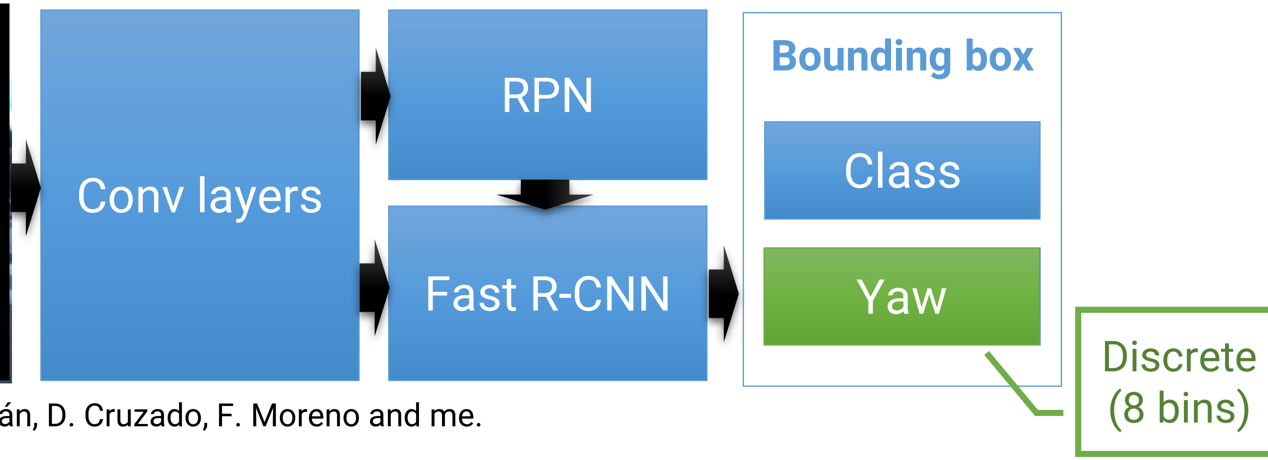
(b)



(a) 16-layer, trans. error (b) 32-layer, trans. error (c) 64-layer, trans. error

C. Guindel, J. Beltrán, D. Martín and F. García. "Automatic Extrinsic Calibration for Lidar-Stereo Vehicle Sensor Setups." arXiv:1705.04085 [cs.CV], 2017.

- Didi Challenge. Faster R-CNN applied over image-like inputs (bird-view).

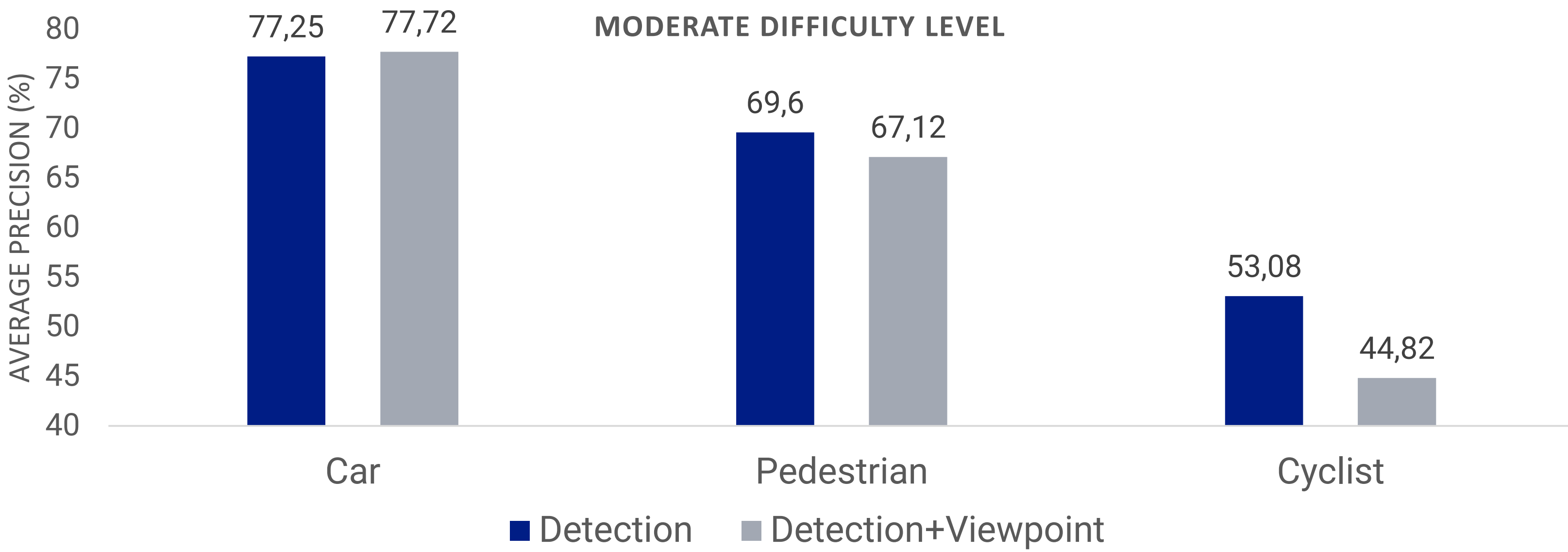


Proudly brought to you by J. Beltrán, D. Cruzado, F. Moreno and me.

Thank you for your attention!

Questions?

Precision change when introducing viewpoint



Detection (ΔAP as %)	Easy	Moderate	Hard
Car	+0,72	+0,47	+0,26
Pedestrian	-1,85	-2,47	-3,00
Cyclist	-12,16	-8,25	-8,11