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Accident avoidance by active intervention for Intelligent Vehicles

Fusion Framework for Moving-Object Classification

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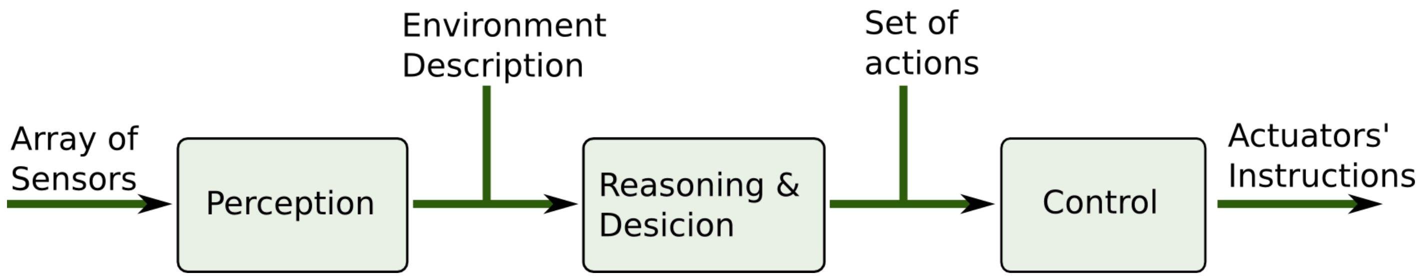
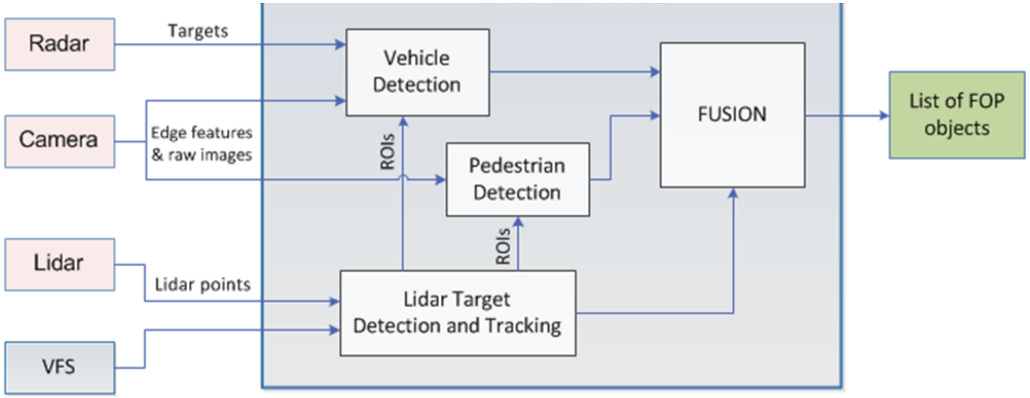
Introduction

- Advance Driver Assistant Systems (ADAS) help drivers to perform complex driving tasks and avoid dangerous situations
- ADAS generally have three components: perception, reasoning & decision and control
- Perception provides, by processing sensor measurements, information of the environment the robot is immerse in
    - Simultaneous localization and mapping (SLAM) deals with modeling static parts
    - Detection and tracking moving objects (DATMO) is responsible for modeling dynamic parts



Frontal Object Perception Application

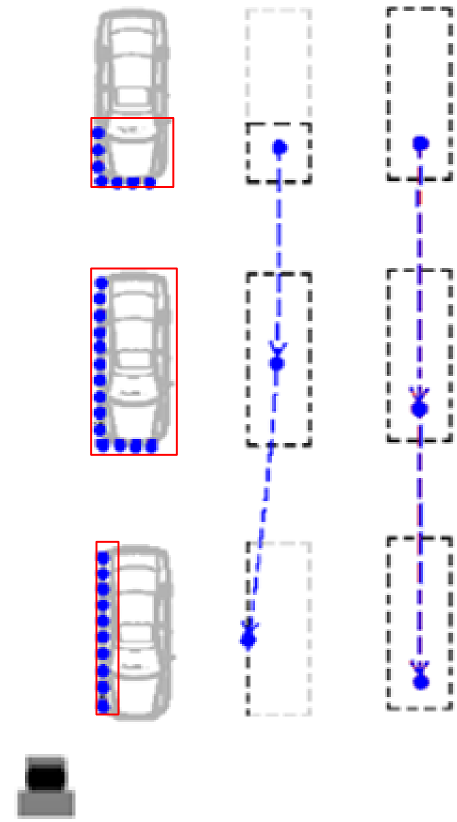
- Our work at interactIVe project aims at providing a reliable list of objects of interest using two modules:
  - Frontal Object Perception (FOP) delivers descriptions about relevant objects of interest (e.g.: location, speed) in the frontal area of the ego vehicle
  - Moving Object Classification (MOC) aims to provide estimated information about the class of moving objects detected by the FOP module
- An object could be categorized into different classes: pedestrian (or group of pedestrians), bike, car and truck



Sensor processing (1)

Target Detection:

- Segmentation based on lidar point clouds from several frames
- Taking into account spatial and temporal information (similar to optical flows technique)



Model-based tracking

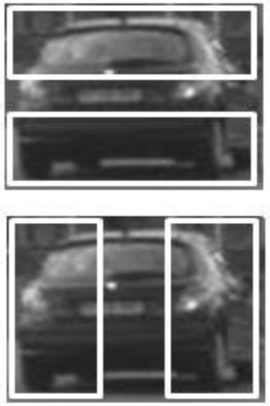
- Better tracking result
- Able to estimate object geometry: updated over time from new observations
- Provide a likelihood of object class for moving objects (classes of moving objects are quite limited)

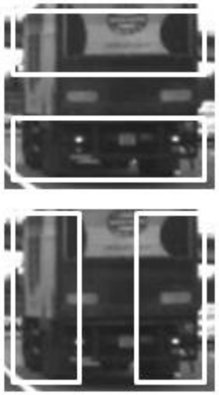
Sensor processing (2)

Train multiple binary-classifiers:

- One classifier for each view of object: pedestrian, car(rear, front), truck(rear, front)
- Sparse-HOG features: compact, fast to compute using integral image
- Learning method: Adaboost

Final classifiers:



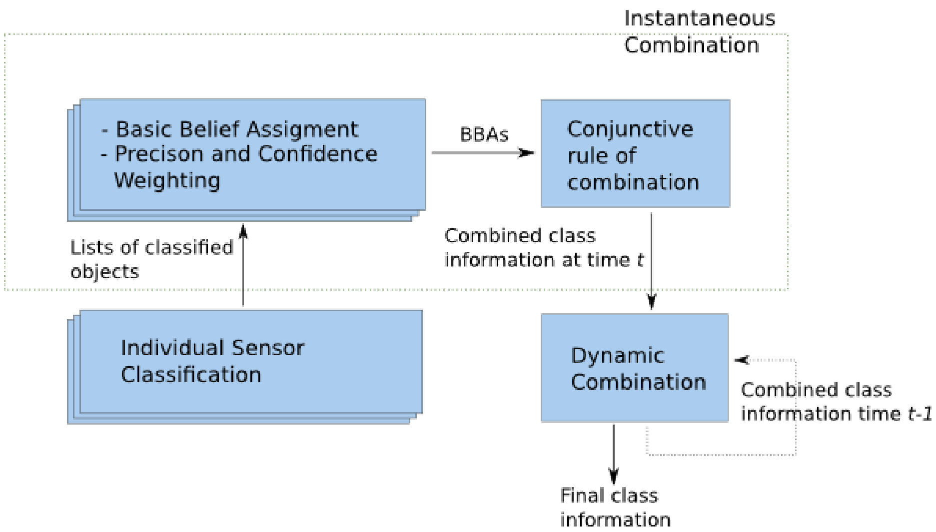


Classification-based Detectors:

- Input: ROIs computed from Lidar Targets & Radar Targets
- Apply a classic sliding window strategy inside ROIs (not entire image): ~2ms/100 img patches

Fusion for Moving Object Classification

- Generic framework to fuse classification information from different sources (detector modules)
- Based on DS theory
  - Class information is represented as evidence masses
  - Manage conflict situations when evidence sources don't agree
- Takes into account the reliability of the sources and their precision to classify specific objects



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Fusion for Moving Object Classification

- Set of possible class hypothesis per object $\Omega = \{car, truck, pedestrian, bike\}$

$$m(\emptyset) = 0;$$
$$\sum_{A \subseteq \Omega} m(A) = 1$$

$$m_r(A) = \sum_{B \cap C = A} m_b(B) m_c(C); \;\; A \neq \emptyset$$

$$K = \sum_{B \cap C = \emptyset} m_b(B) m_c(C)$$

$$m_r(\Omega) = m'_r(\Omega) + K$$

- Instantaneous fusion: combine information from different sources at current time t.

applaying reliability factor

$$m_b(A) = \quad r_{ab} \times m'_b(A); A \subseteq 2^{\Omega}, A \neq \Omega$$

$$m_b(\Omega) = \quad m'_b(\Omega) + \sum (1 - r_{ab} \times m(A));$$
$$for A \subseteq 2^{\Omega}, A \neq \emptyset, A \neq \Omega$$

weighting specific hypothesis

$$m_a(A_i) = \quad m'_a(A_i) \times f_i; A_i \subseteq 2^{\Omega}, A_i \neq \emptyset$$

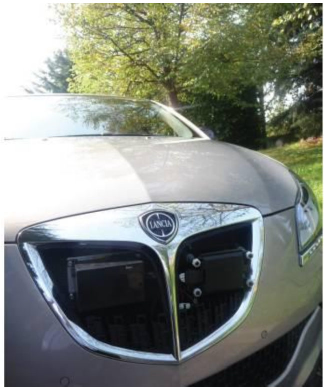
$$m_a(\Omega) = \quad m'_{\Omega} + \sum (1 - f_i) \times m'_a(A_i);$$
$$for A_i \subseteq 2^{\Omega}, A_i \neq \emptyset, A_i \neq \Omega$$

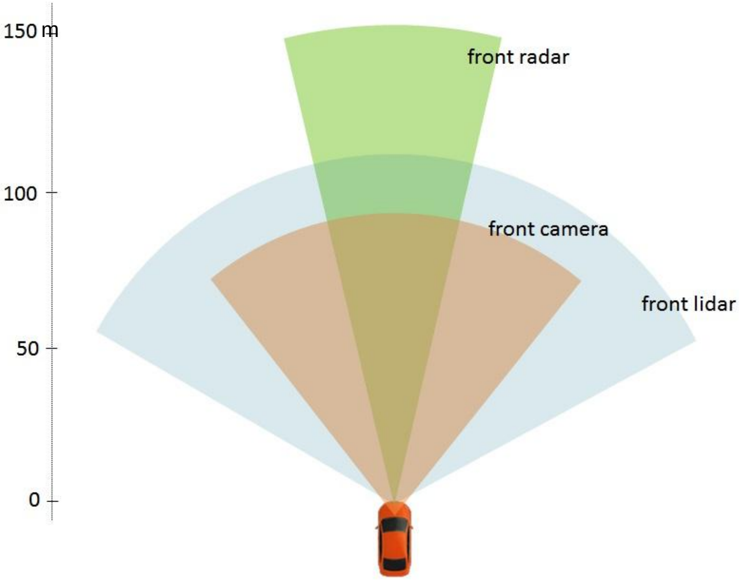
- Dynamic fusion: instantaneous result is combined with fused information at time t-1

Experiments

Setup

- Four class hypothesis: car, truck, pedestrian, bike
- Three different classification sources:
    - Vehicle detector, pedestrian detector and lidar-based detector
- CRF vehicle demonstrator includes three main sensors: radar, lidar and camera
- Reliability and precision factors are obtained experimentally using real datasets





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Results


Frontal Object Perception
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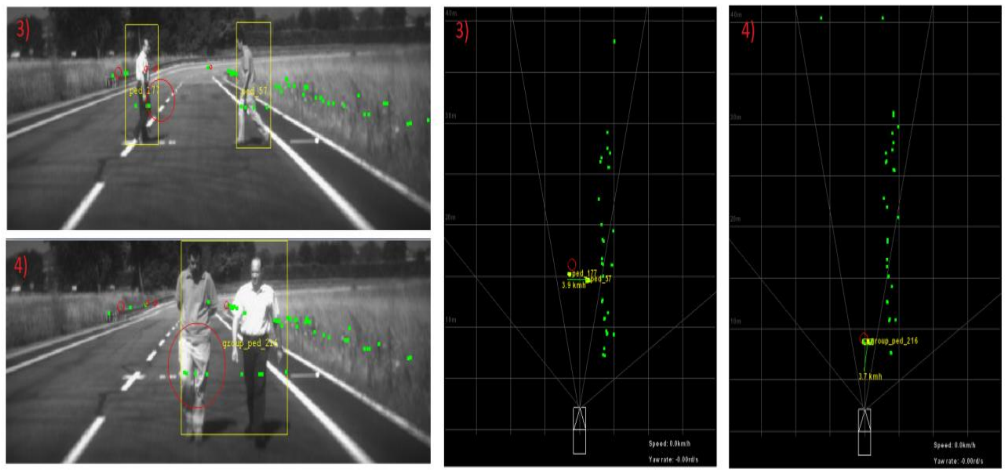
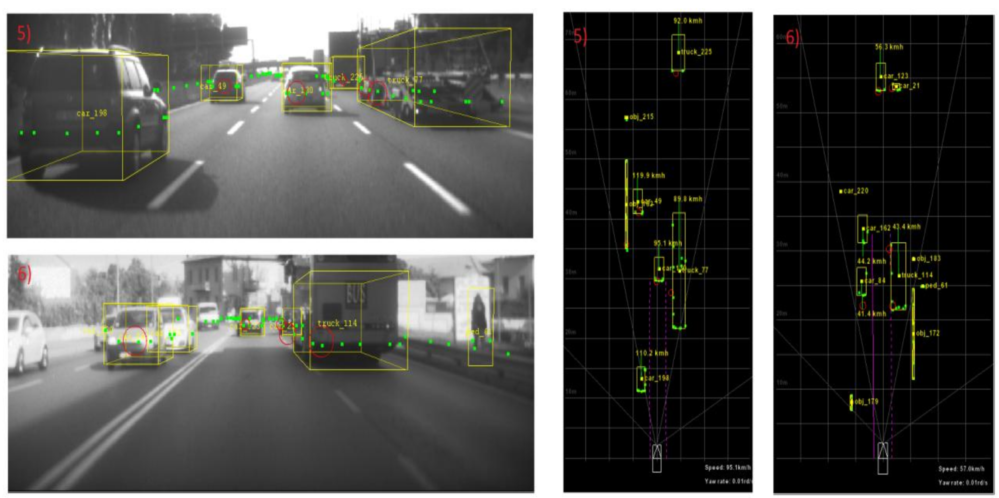
Qualitative performance

Test track



Real scenarios



Results

Quantitative performance

- Real time performance of FOP-MOC

Vehicle class

Dataset	Lidar processing	Vehicle detector	Fusion approach
highway 1	9	10	4
highway 2	8	12	6
urban 1	15	19	10
urban 2	18	23	12

Pedestrian class

Dataset	Lidar processing	Pedestrian detector	Fusion approach
urban 1	10	8	5
urban 2	13	7	3

General performance

Scenarios	Total objects			Correct Detection			False Detection			Correct Classification			False Classification		
	ped	car	truck	ped	car	truck	ped	car	truck	ped	car	truck	ped	car	truck
Motorway	0	682	216	0	655	201	0	20	0	0	630	175	0	2	0
				n/a	**96,0%**	**93,1%**	n/a	**2,9%**	**0%**	n/a	**92,4%**	**81,0%**	n/a	**0,3%**	**0,0%**
Urban	33	525	87	27	495	72	4	0	0	26	483	63	5	4	5
				81,8%	**94,3%**	**82,8%**	**12,1%**	**0,0%**	**0,0%**	**78,8%**	**92,0%**	**72,4%**	**15,2%**	**0,8%**	**5,7%**
Test track	248	301	0	247	300	0	0	1	0	240	300	0	0	0	0
				99,6%	**100%**	n/a	**0,0%**	**0,3%**	n/a	**96,8%**	**100%**	n/a	**0,0%**	**0,0%**	n/a

Conclusions

- Fusion approach includes information about reliability of the sources and specific precision factors
- Architecture can be extended by including more detector modules
- Several class of objects involved
- Improves the performance of individual single sensor-based modules
- Provides a confidence value along the final object classification

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Thank you.

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SEVENTH FRAMEWORK PROGRAMME

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