A Global Approach to Vision-Based Pedestrian Detection for Advanced Driver Assistance Systems

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ADAS

Computer Vision Center

UAB Universitat Autònoma de Barcelona

MIPRCV

Index

- Introduction
- State of the Art (Architecture)
- Foreground Segmentation
- Object Classification
- Detections Refinement
- Pedestrian Detection System
- Conclusions

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Introduction

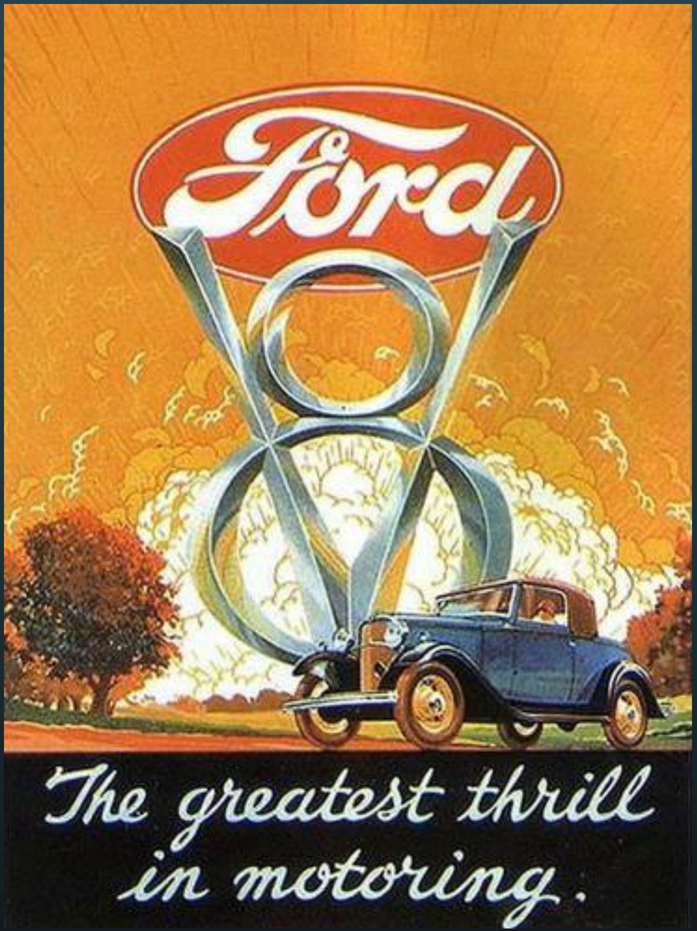
The automobile

"key technology for humans"

"changes societies"

"provides progress and freedom"

"development source"



src.: www.oldcartruckads.com

Introduction

Problem: traffic accidents

WORLDWIDE

Pedestrians in European Union

1.2 million killed every year,

50 million injured every year

7,000 killed every year,

150,000 injured every year

cost of 45 billion € every year

(more than the aid to third world)

Src.: National Photo Company Collection glass negative

Introduction

Safety measures

Traditional
- Seat belts
- Head lamps

Physical sensor-actuator
- Airbags
- Antilock Brake System (ABS)
- Electronic Stability Control (ESC)

Advanced Driver Assistance Systems (ADAS)
- Adaptive Cruise Control (ACC)
- Adaptive Headlamps
- Lane Departure Warning System
- Pedestrian Protection System (PPS)

Src.: Ford Motor Company

Src.: Gerdbrendel

Introduction

Safety measures

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- Head lamps

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- Airbags
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Advanced Driver Assistance Systems (ADAS)
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- Adaptive Headlamps
- Lane Departure Warning System
- Pedestrian Protection System (PPS)

Src.: Jeff Dean

Src.: www.aa1car.com

Introduction

Safety measures

Traditional
- Seat belts
- Head lamps

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- Antilock Brake System (ABS)
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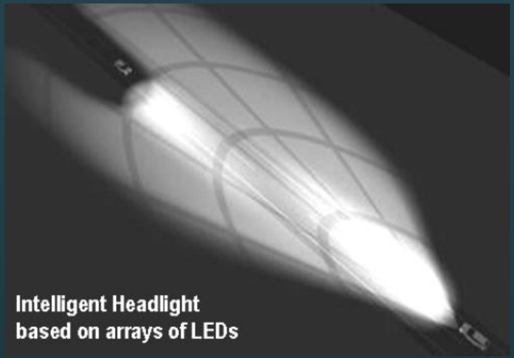
Advanced Driver Assistance Systems (ADAS)
- Adaptive Cruise Control (ACC)
- Adaptive Headlamps
- Lane Departure Warning (LDW)
- Pedestrian Protection System (PPS)



Src.: A.M. López et al., ACIVS08

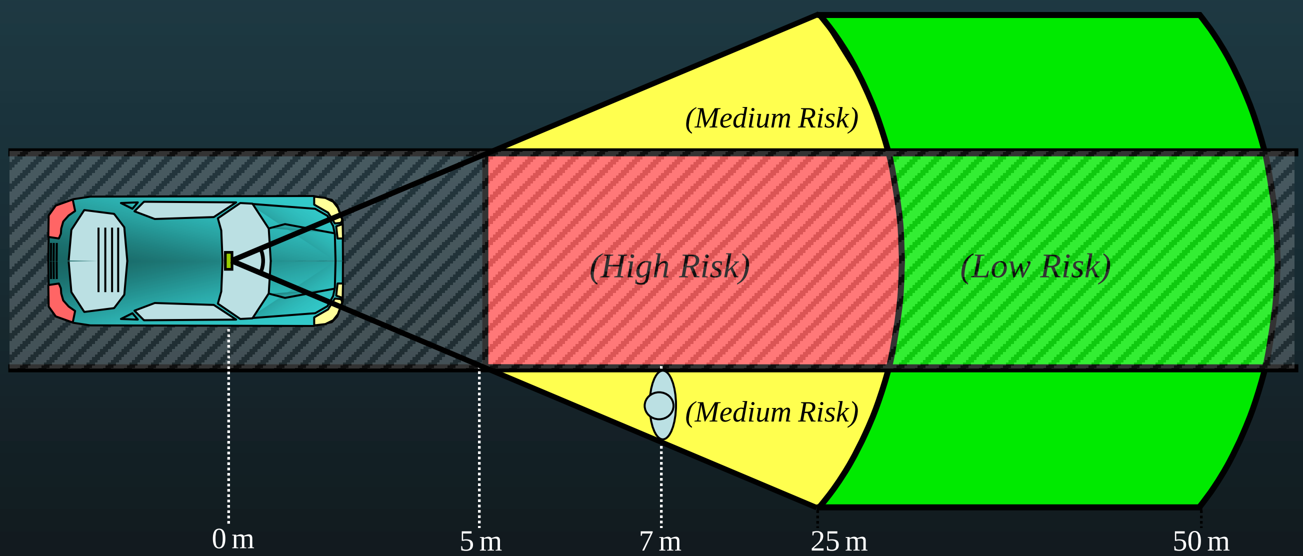
Src.: Bosch.com

Src.: A.M. López et al., ITSC05

Introduction

Pedestrian Protection System (PPS)

A PPS is formally defined as a system that detects both static and moving people in the surroundings of the vehicle (typically in the front area) in order to provide information to the driver and perform evasive or braking actions on the host vehicle if needed.



Introduction

Thesis motivation

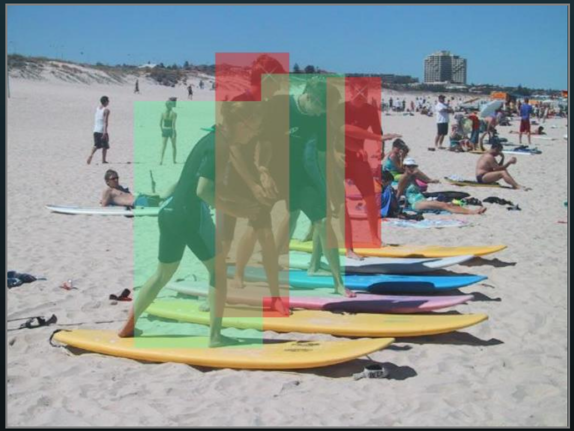
A global approach
to vision-based
pedestrian detection
for advanced driver assistance systems

Introduction

Main objective

A global approach
to vision-based
pedestrian detection
for advanced driver assistance systems

general human detection



Src.: N. Dalal,PhDThesis06

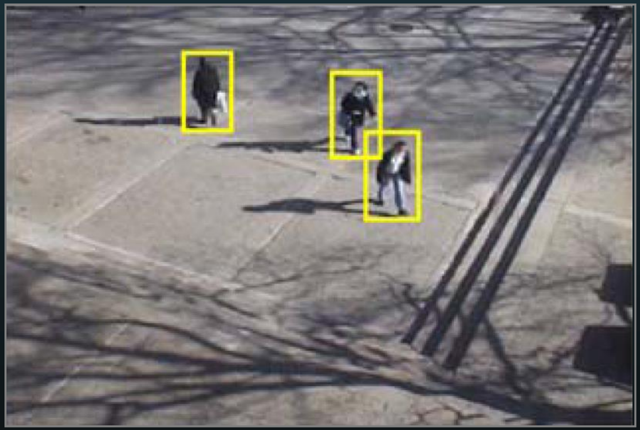
ADAS

Introduction

Main objective

A global approach
to vision-based
pedestrian detection
for advanced driver assistance systems

surveillance, retrieval, etc.



Src.: P. Viola et al., IJCV05

ADAS

Introduction

Main objective

A global approach
to vision-based
pedestrian detection
for advanced driver assistance systems

LIDAR, RADAR, etc.

Src.: K. Fuerstenberg., IV02

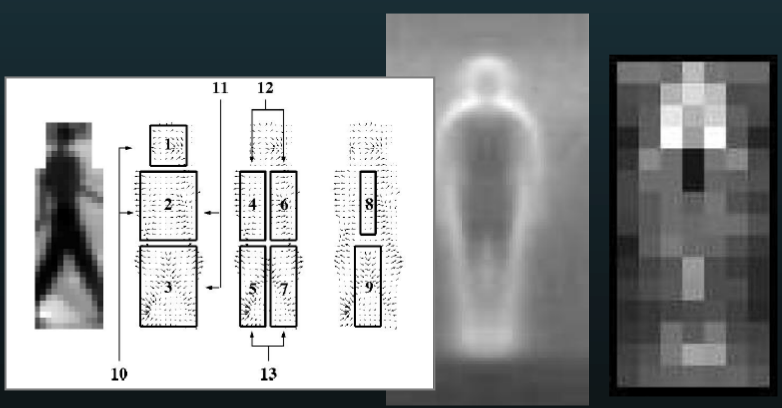
Camera-based (daytime)

Introduction

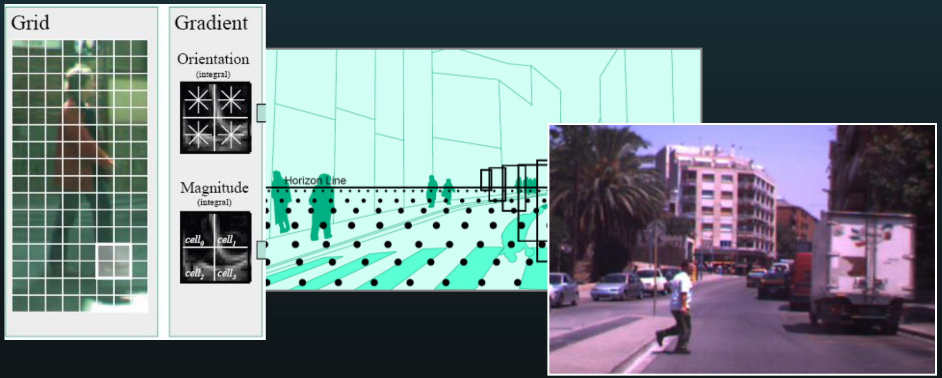
Main objective

A global approach
to vision-based
pedestrian detection
for advanced driver assistance systems

Classification viewpoint



Global viewpoint



Src.: A. Shashua et al., IV04 Src.: N. Dalal et al., CVPR05

Introduction

Objectives of the thesis

- ✓ Review of the state of the art (define general architecture)
- ✓ Foreground segmentation (new proposals and algorithms evaluation)
- ✓ Object classification
- ✓ Refinement techniques (clustering and shape extraction)
- ✓ System (based on 3 components)
- ✓ Pedestrian datasets

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State of the Art

Contributions

- ✓ Generic architecture of pedestrian protection systems
- ✓ Review of vision-based approaches (both visible and infrared)
- ✓ Review of sensor fusion approaches
- ✓ Review of evaluation protocols and datasets
- ✓ Discussion on future trends

State of the Art

State of the Art

Architecture

Preprocessing → Foreground Segmentation → Object Classification → Verification & Refinement → Tracking → Applications

State of the Art

Architecture

Preprocessing ▶ Foreground Segmentation ▶ Object Classification ▶ Verification & Refinement ▶ Tracking ▶ Applications

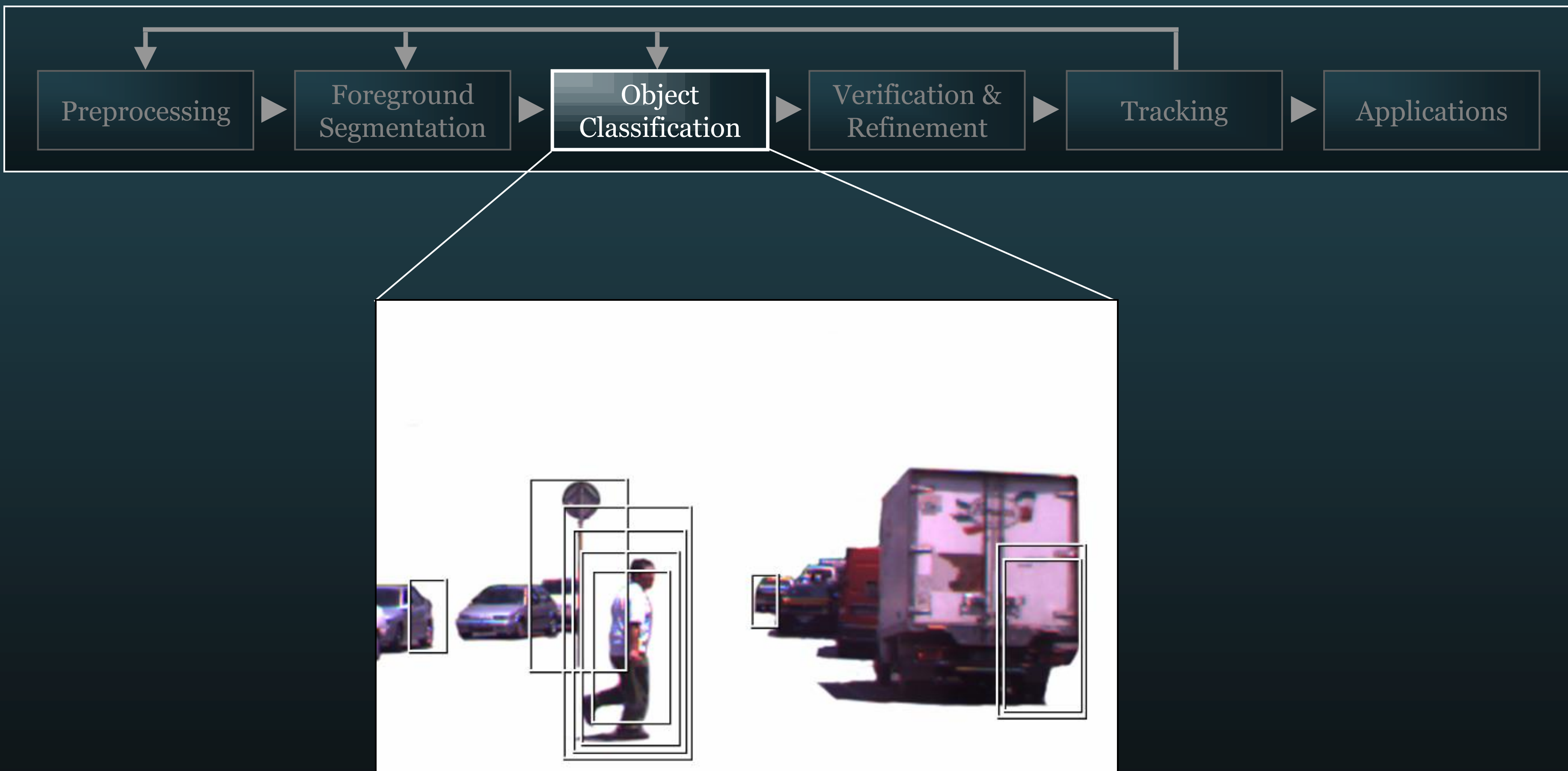
State of the Art

Architecture

Preprocessing ▶ **Foreground Segmentation** ▶ Object Classification ▶ Verification & Refinement ▶ Tracking ▶ Applications

State of the Art

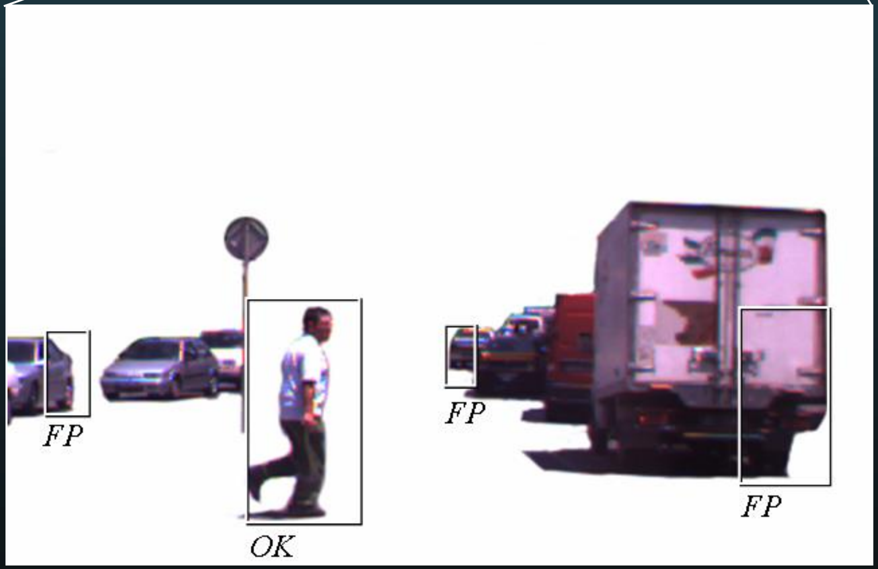
Architecture



State of the Art

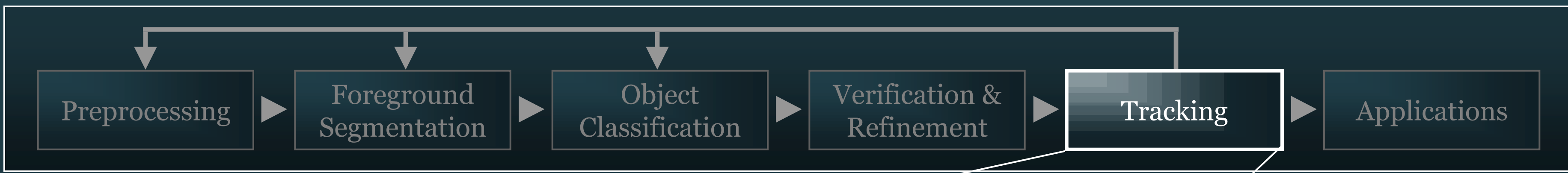
Architecture

Preprocessing ▶ Foreground Segmentation ▶ Object Classification ▶ **Verification & Refinement** ▶ Tracking ▶ Applications



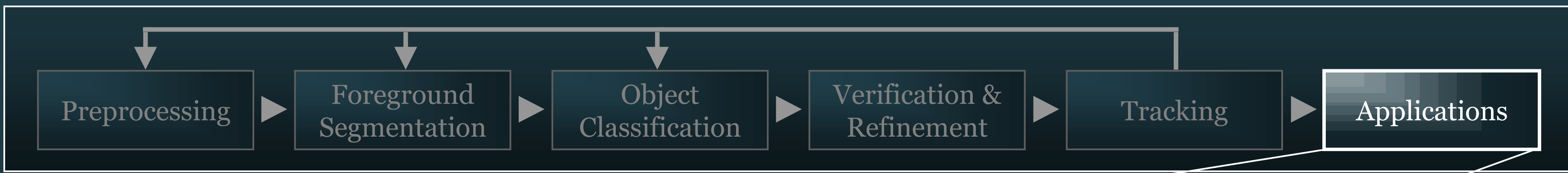
State of the Art

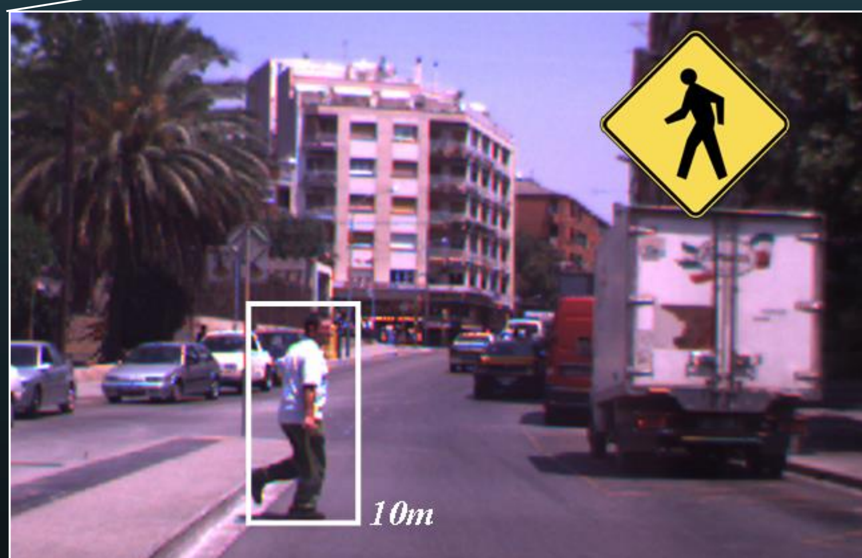
Architecture



State of the Art

Architecture





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Foreground Segmentation

Contributions

- ✓ New evaluation dataset
- ✓ New evaluation protocol
- ✓ Performance study of five different algorithms
- ✓ New algorithm: adaptive road scanning (with and without 3D filtering)
- ✓ New algorithm: probabilistic 3D scanning

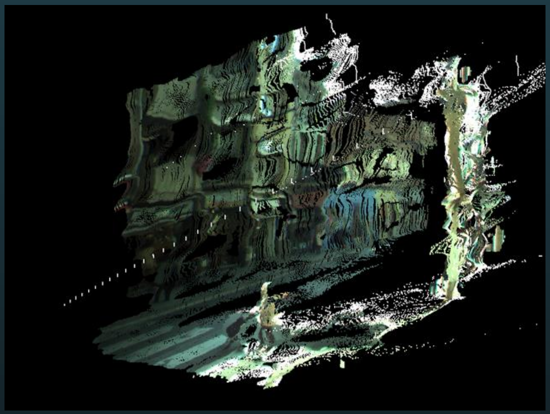
Foreground Segmentation

Evaluation Methodology

Computer Vision Center Candidate Generation Pedestrian Dataset
(CVC-02-CG)

Color

Depth map

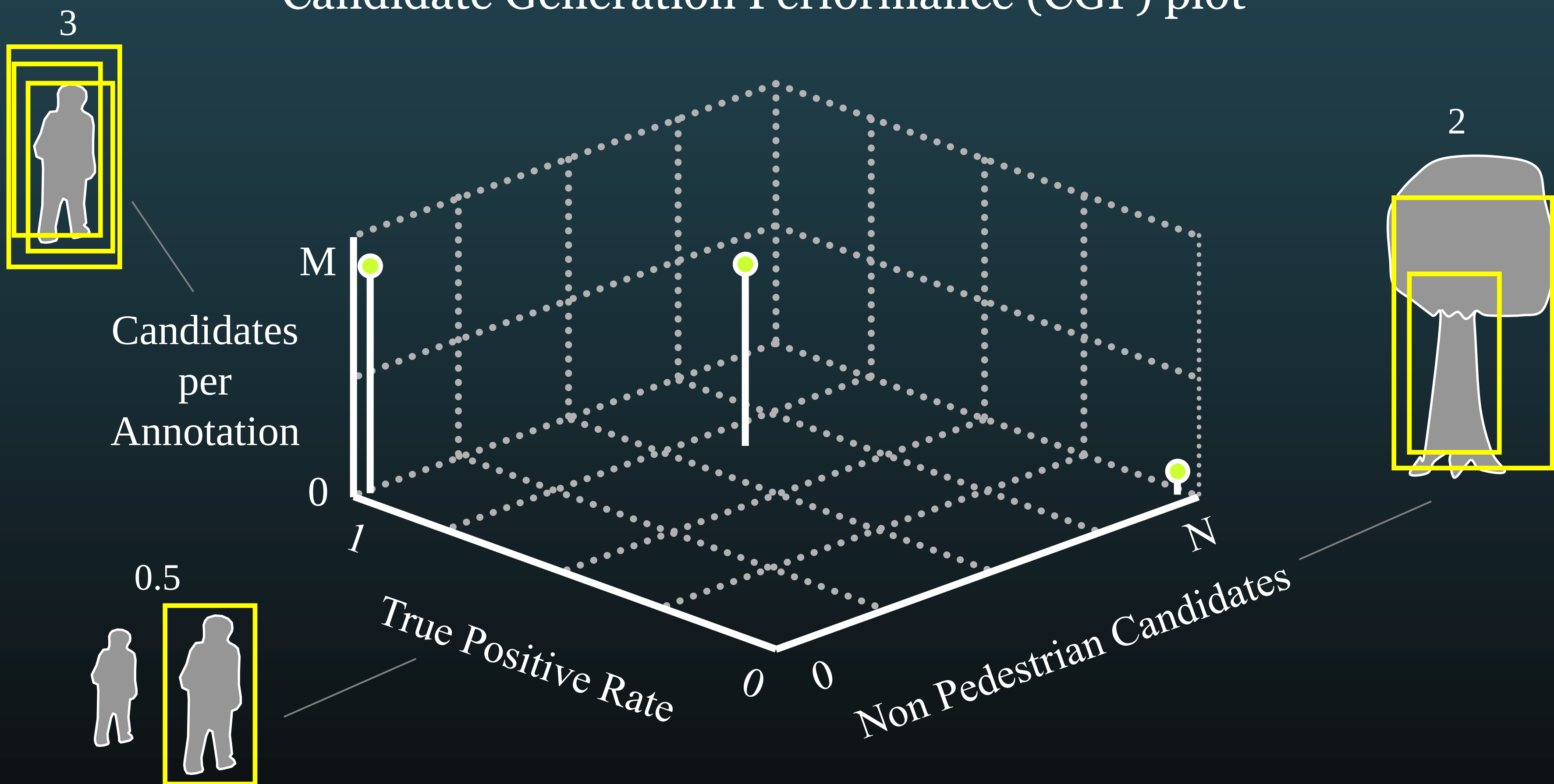


3D points

Foreground Segmentation

Evaluation Methodology

Candidate Generation Performance (CGP) plot



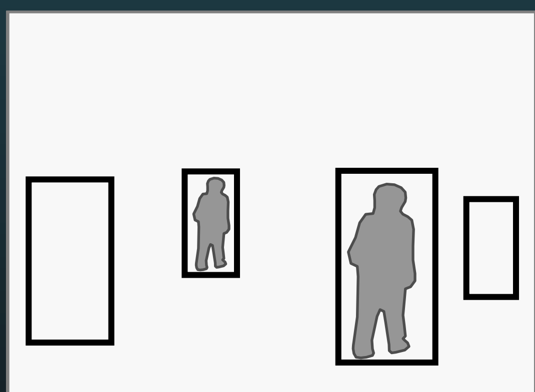
Foreground Segmentation

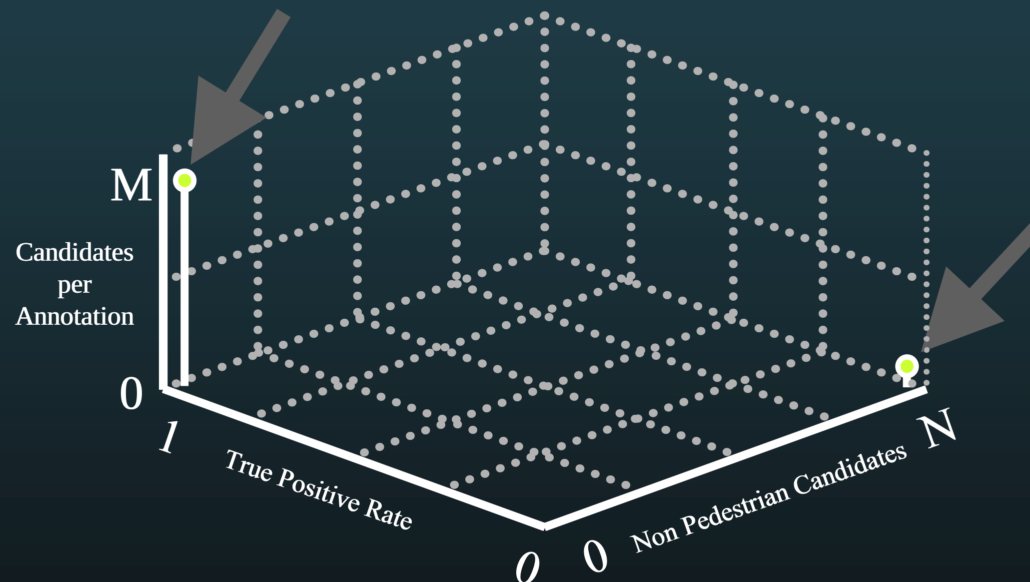
Evaluation Methodology

Candidate Generation Performance (CGP) plot

Good algorithm

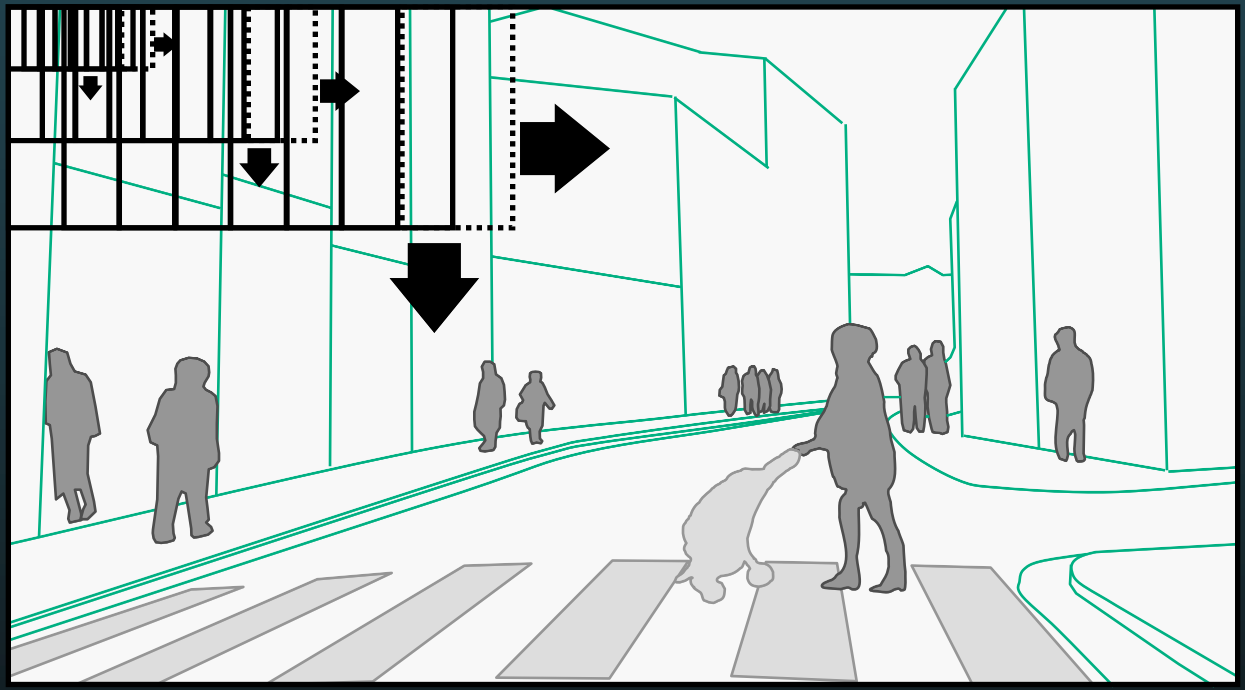
Bad algorithm





Foreground Segmentation

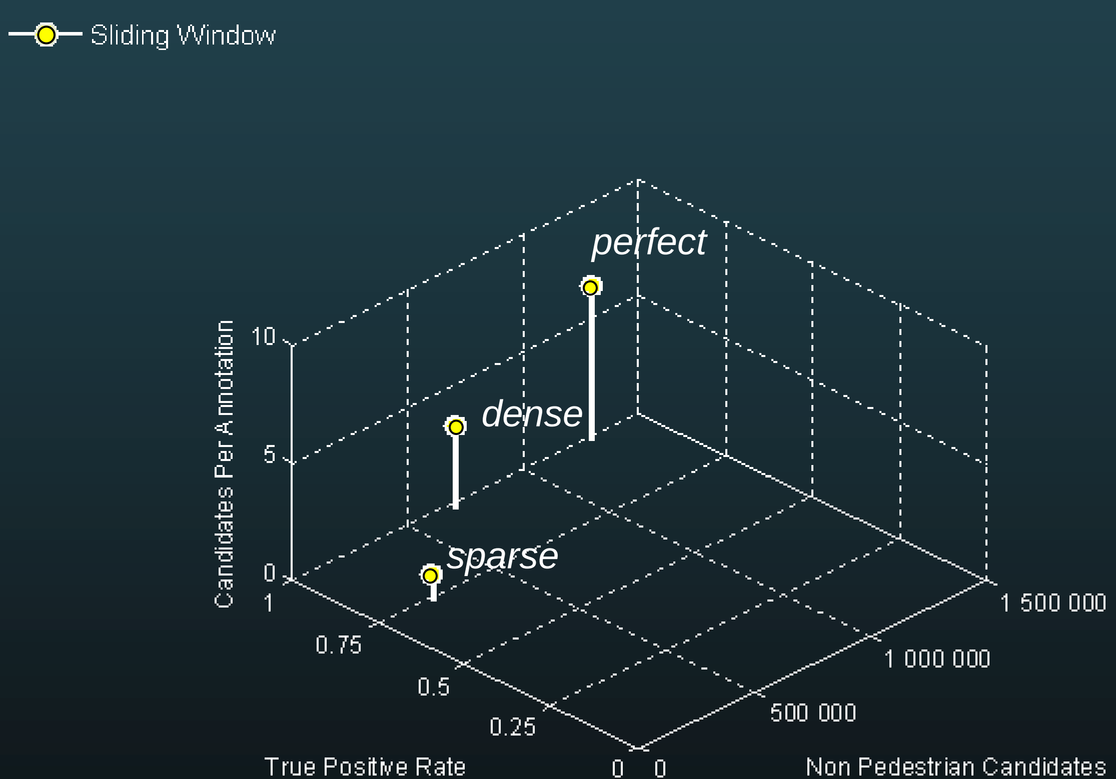
Sliding Window



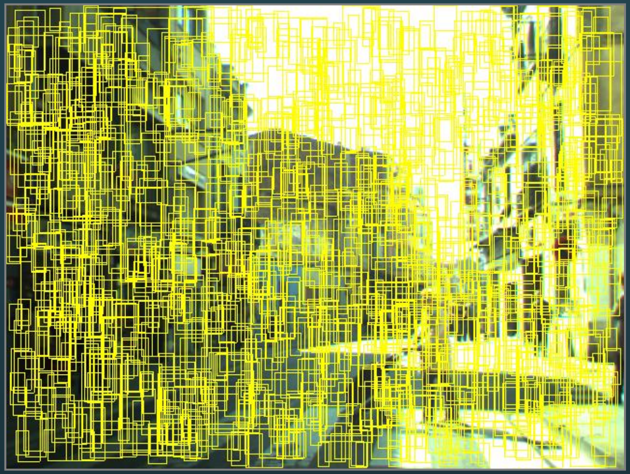
[Papageorgiou00,Dalal05]

Foreground Segmentation

Sliding Window



(0.1% shown)



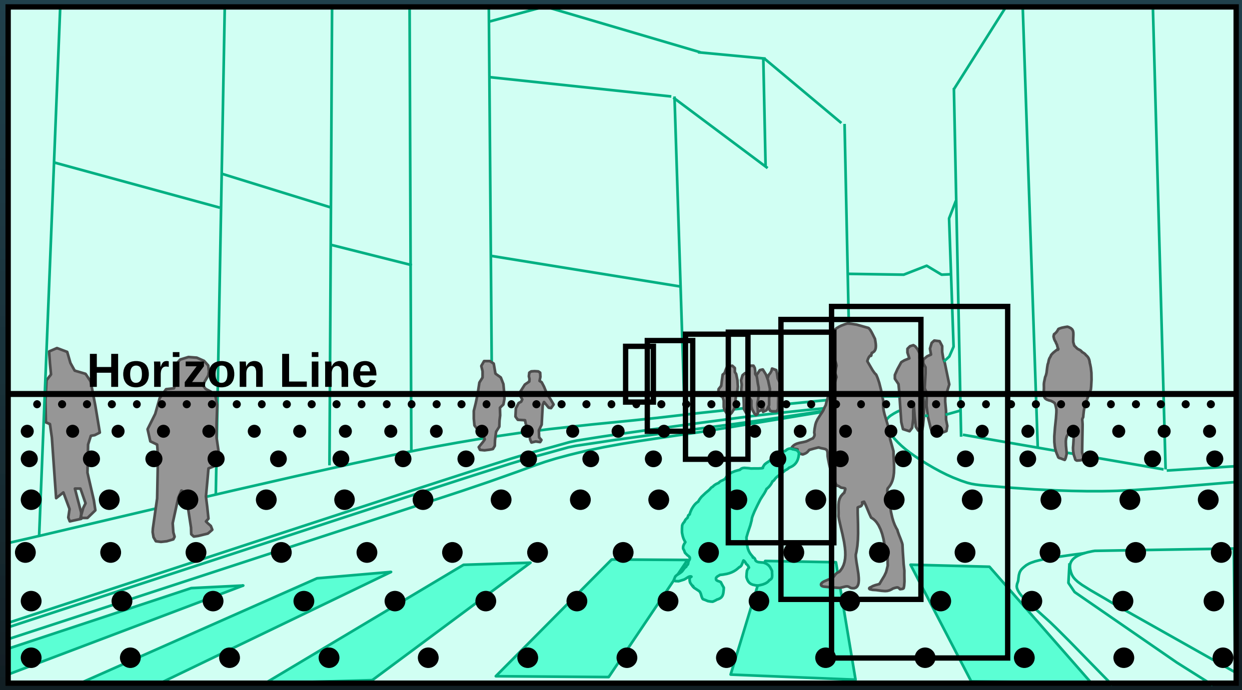
220,000 to 1,300,000 candidates

0 s generation

22 to 130 s classification
(assuming 0.1 ms/window)

Foreground Segmentation

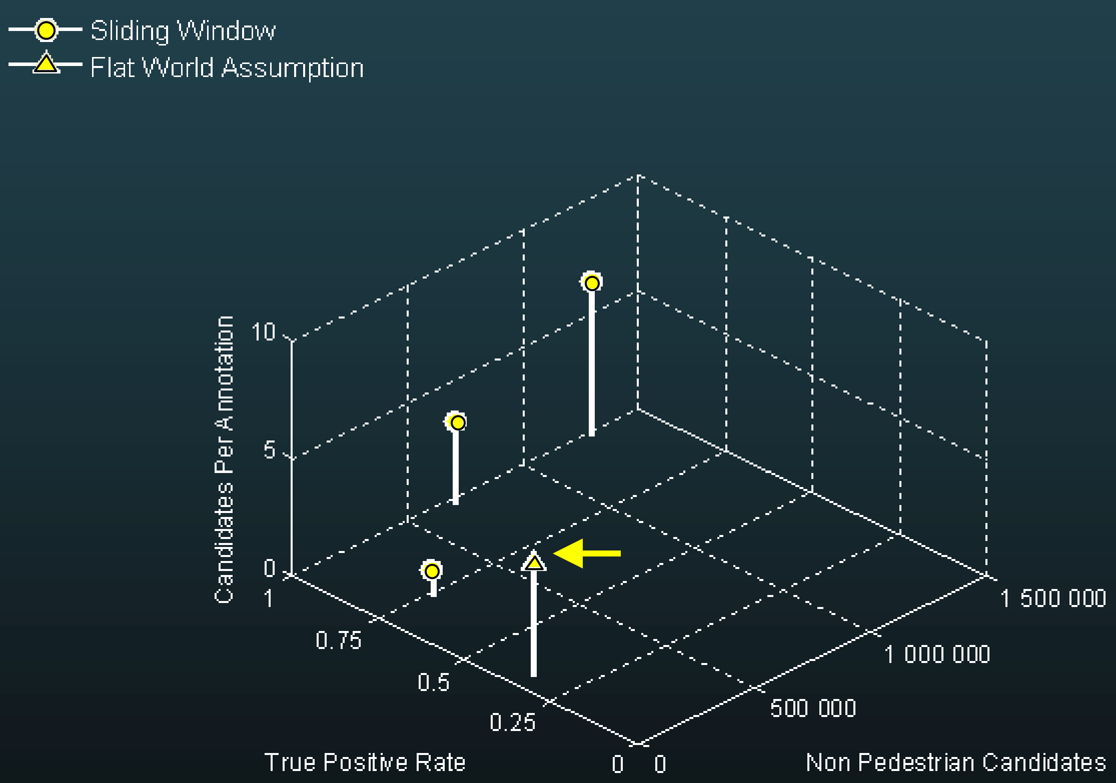
Flat World Assumption



[Bertozzi03,Gavrila04,Ponsa05]

Foreground Segmentation

Flat World Assumption



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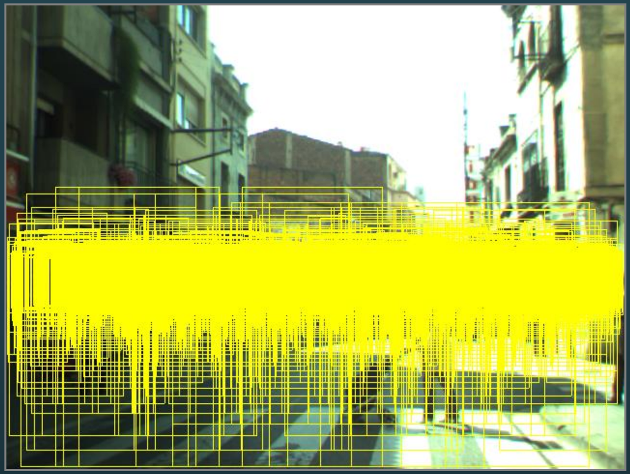


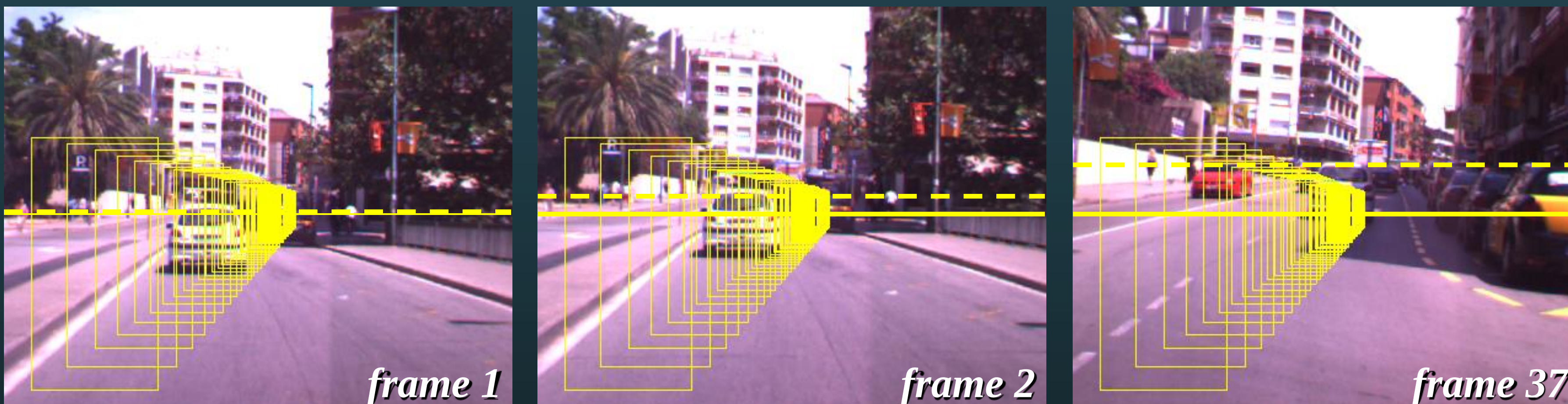
42,000 candidates

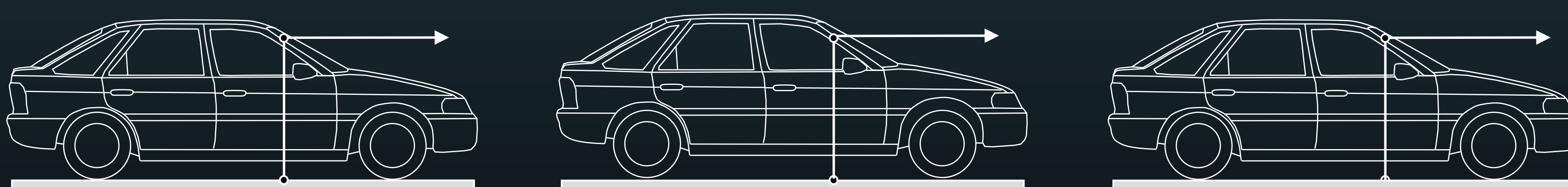
0 s generation

4.2 s classification

Foreground Segmentation

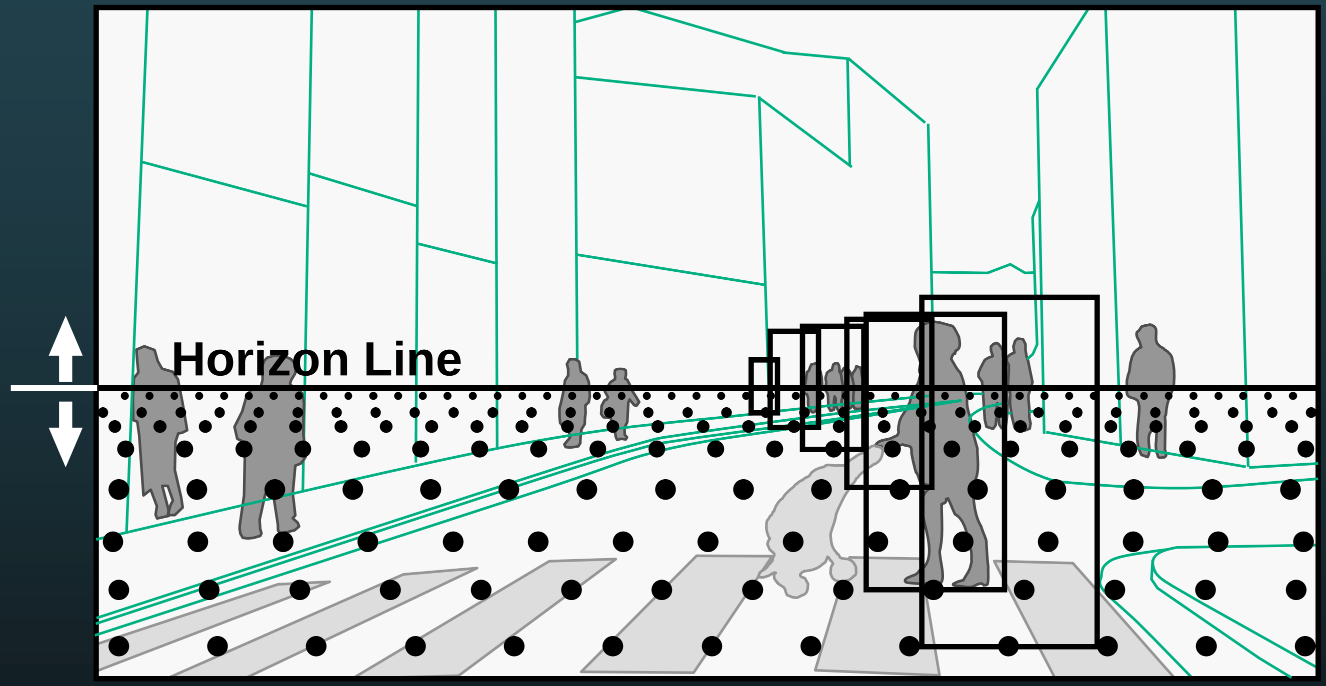
Flat World Assumption





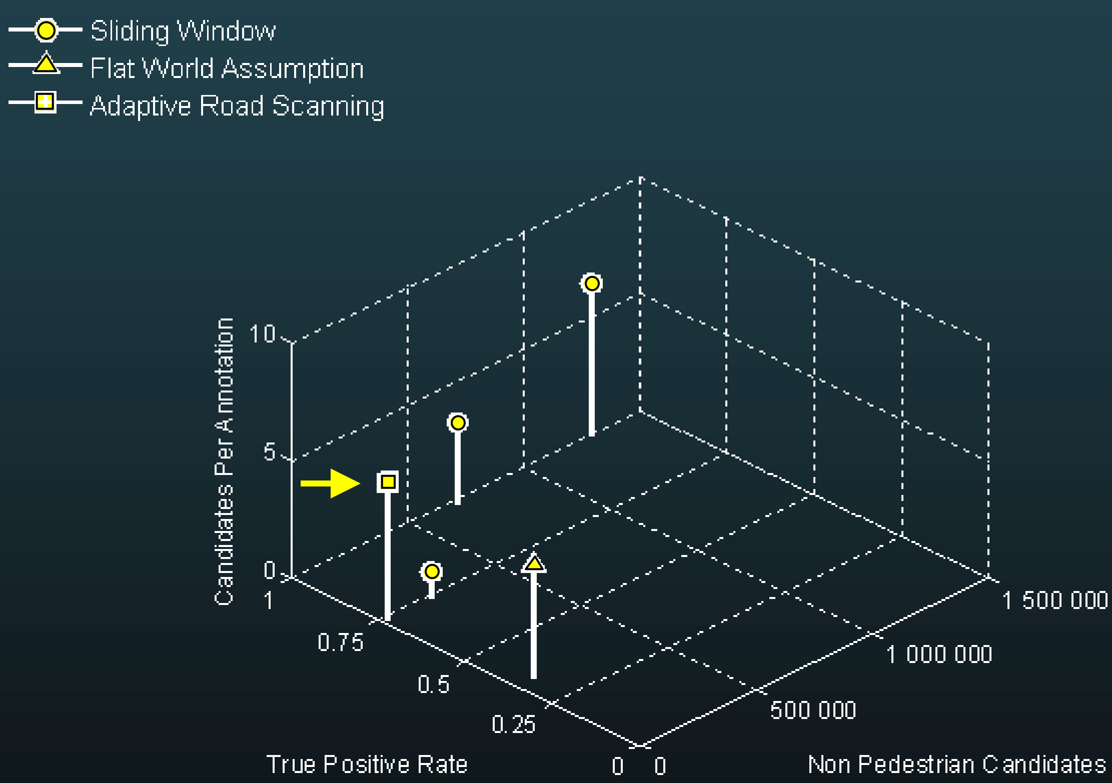
Foreground Segmentation

Adaptive Road Scanning

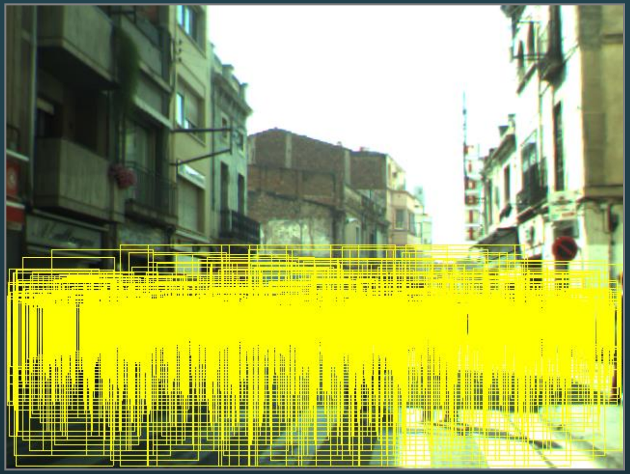


Foreground Segmentation

Adaptive Road Scanning



(5% shown)



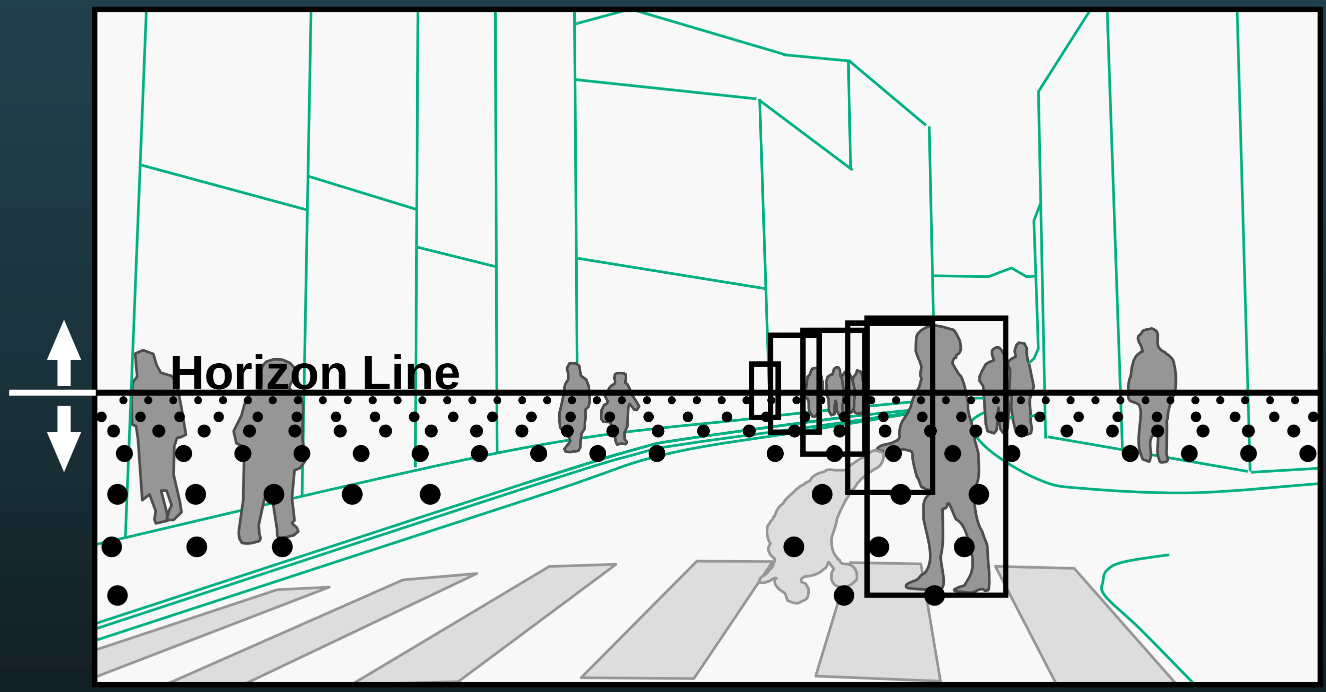
32,000 candidates

0.16 s generation

3.2 s classification

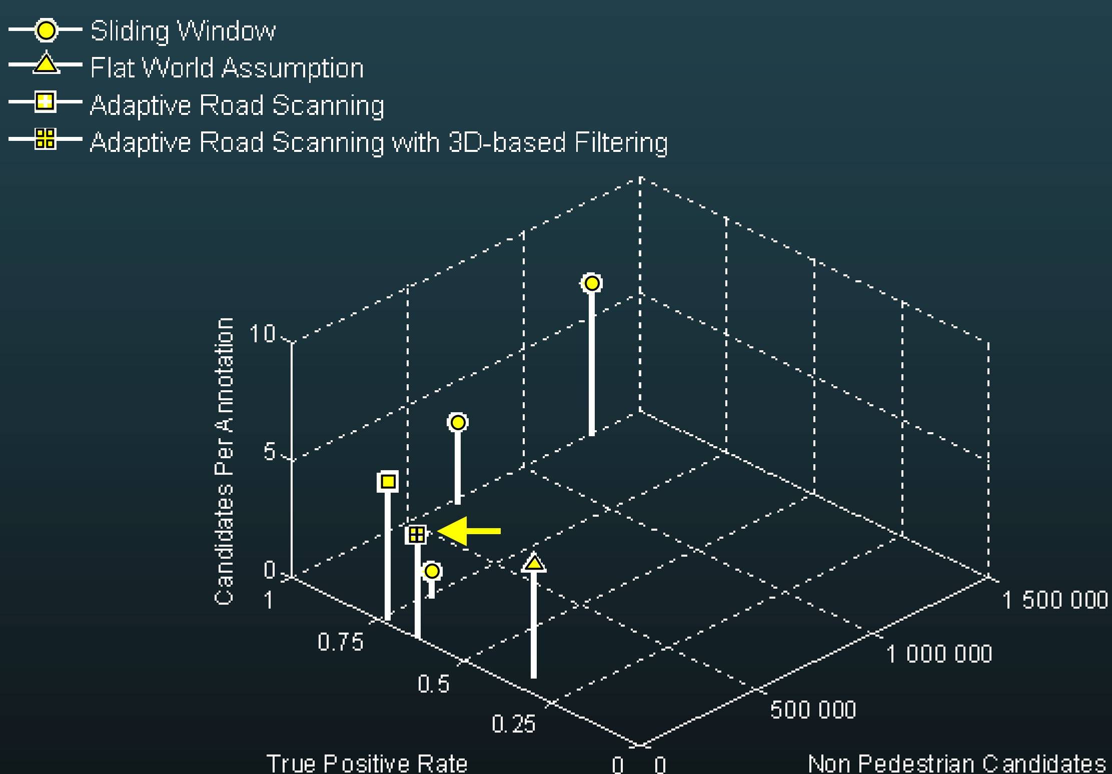
Foreground Segmentation

Adaptive Road Scanning with 3D-based filtering



Foreground Segmentation

Adaptive Road Scanning with 3D-based filtering



(100% shown)

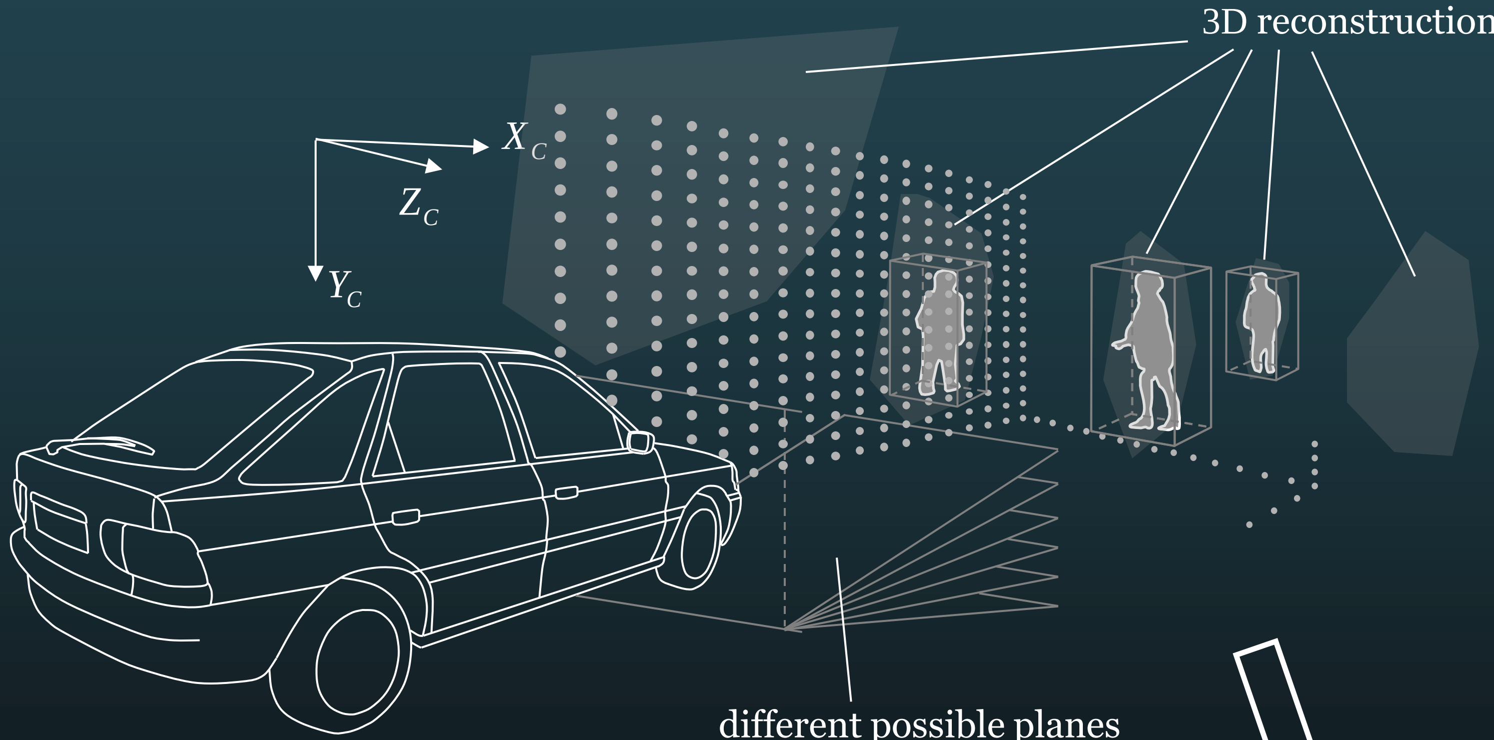
7,000 candidates

0.19 s generation

0.7 s classification

Foreground Segmentation

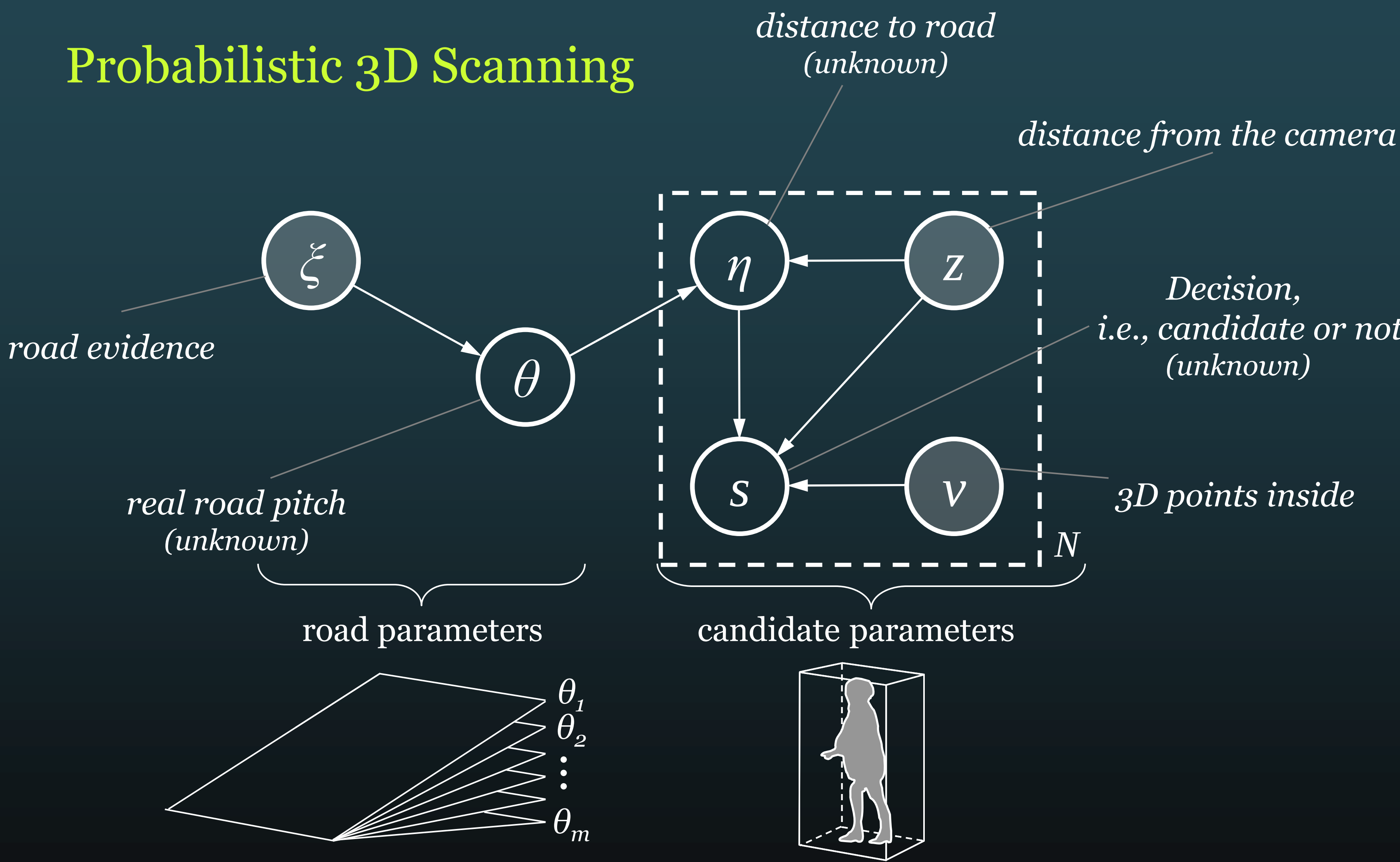
Probabilistic 3D Scanning



Bayesian Network

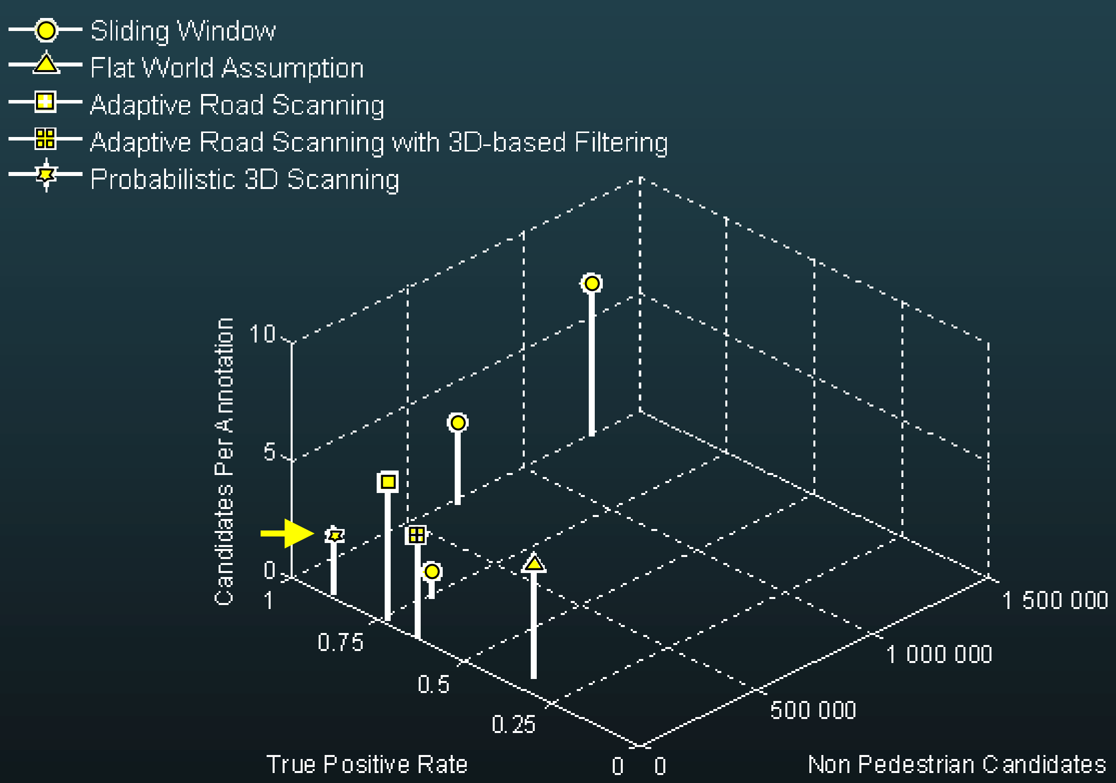
Foreground Segmentation

Probabilistic 3D Scanning



Foreground Segmentation

Probabilistic 3D Scanning



(5% shown)

36,000 candidates

40 s generation

3.6 s classification

Foreground Segmentation

Statistics

Algorithm	#candidates	TPR	Total time (foreg.+classif.)
Sliding window (perfect)	1 300 000	1.00	130 s
Sliding window (dense)	700 000	0.98	70 s
Sliding window (sparse)	220 000	0.75	22 s
Flat world assumption	42 000	0.35	4.2 s
Adaptive road scanning	32 000	0.74	3.36 s
Adaptive + 3D filtering	7 000	0.66	0.89 s
Probabilistic 3D scanning	36 000	0.90	43.6 s

(Note: assuming that the classifier takes 0.1ms per candidate)

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Object Classification

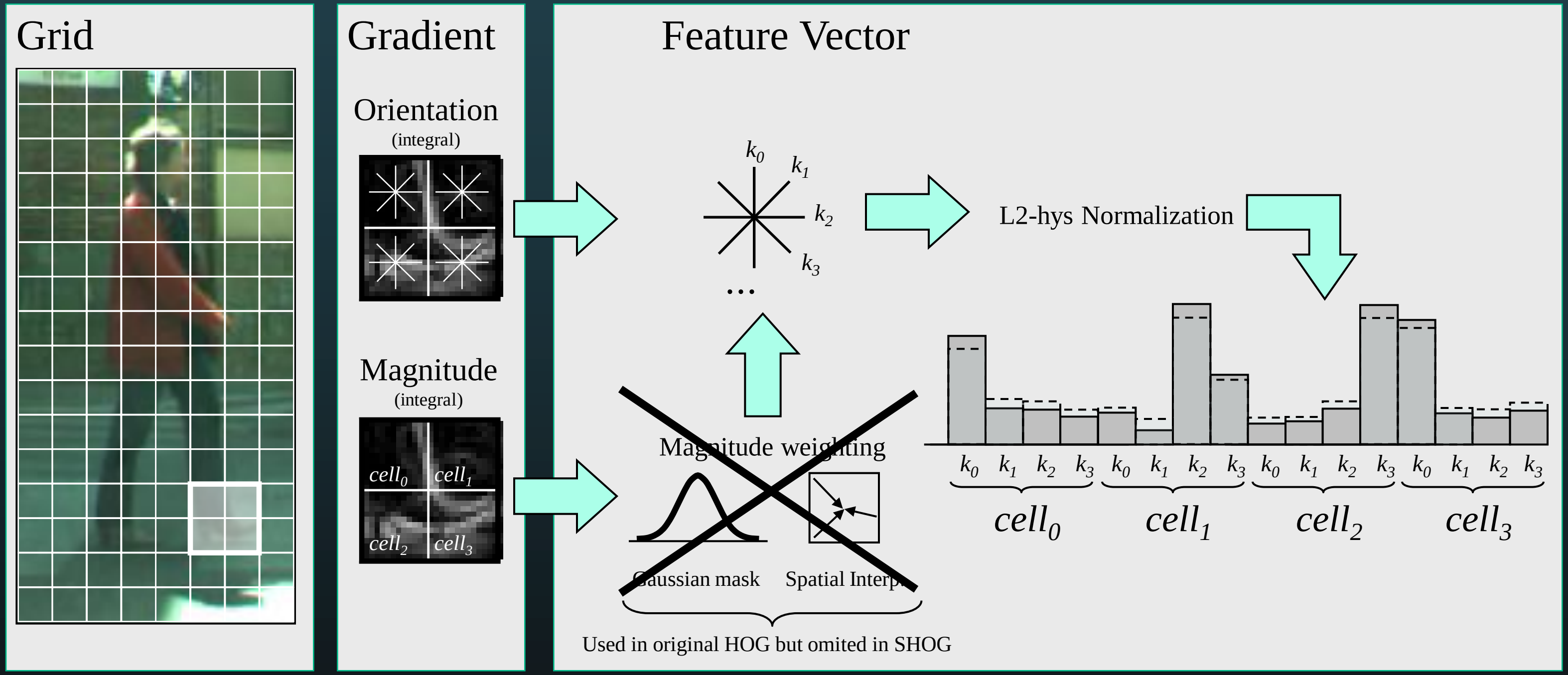
Contributions

- ✓ New dataset
- ✓ Simplified HOG (+ SVM)
- ✓ HaarEOH (+ AdaBoost)
- ✓ Comparisons using different algorithms
  - ✓ Classifiers
  - ✓ Candidate Generation
  - ✓ Source of training samples
- ✓ Analysis of results (intersection of TP,FN,FP)

Object Classification

A study of classifiers

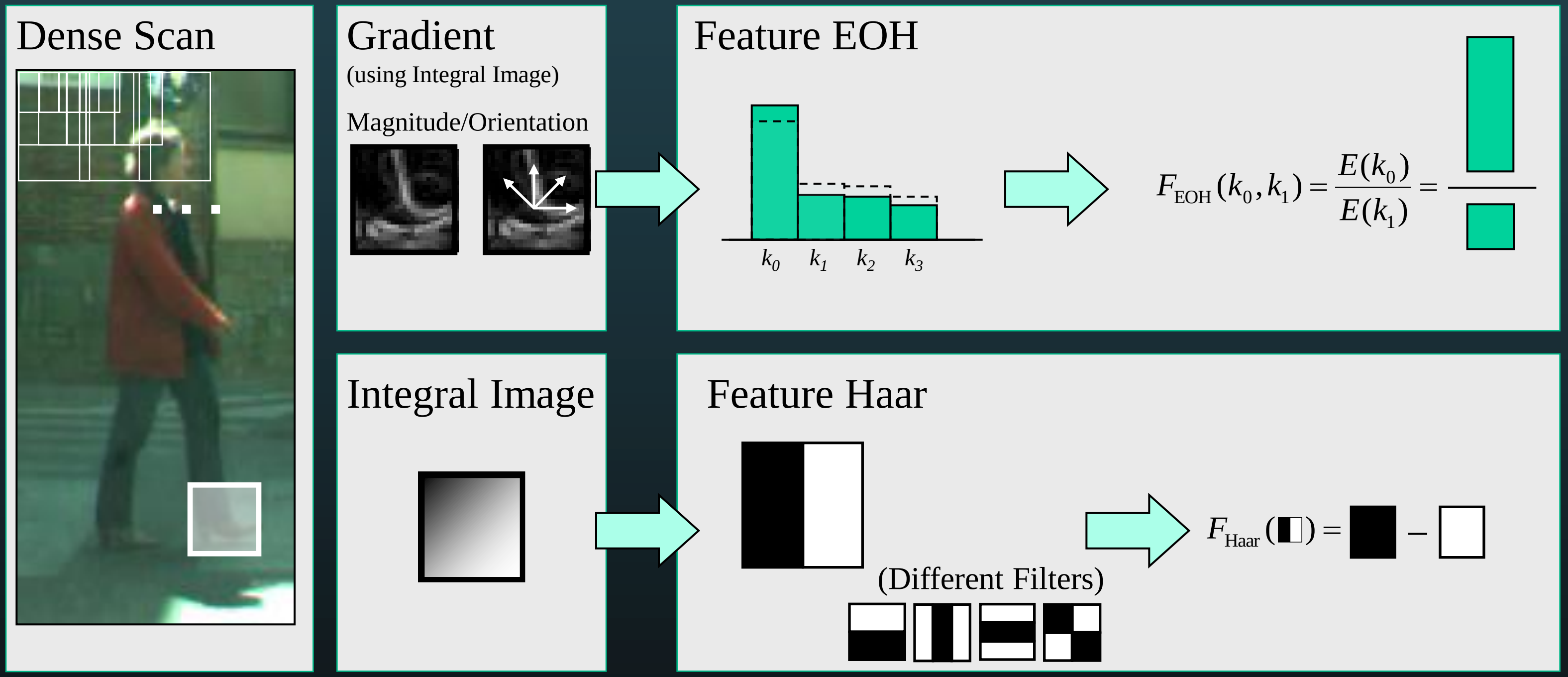
Simplified Histograms of Oriented Gradients (SHOG+SVM)



Object Classification

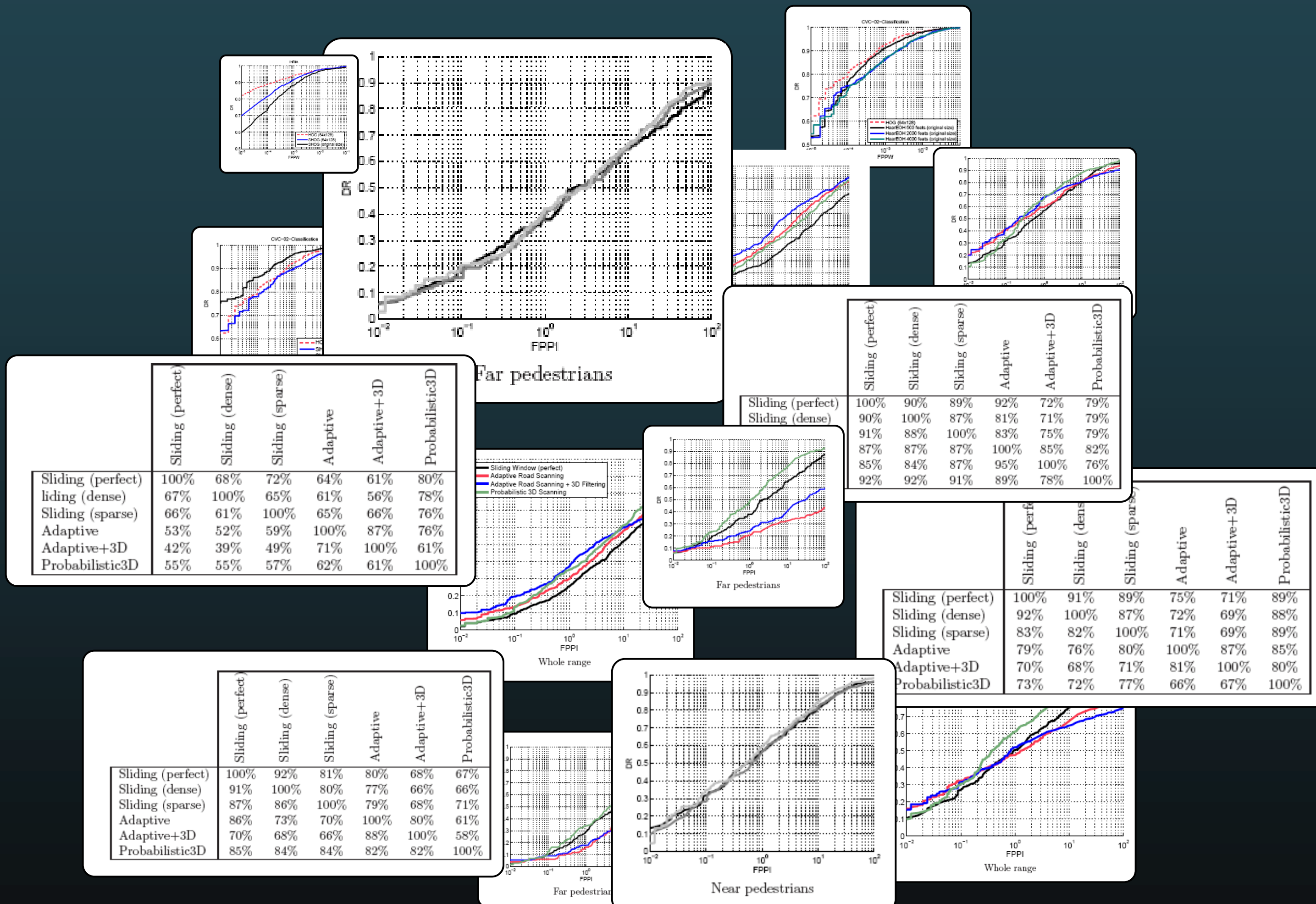
A study of classifiers

HaarEOH+AdaBoost



Object Classification

Experimental Results



	Sliding (perfect)	Sliding (dense)	Sliding (sparse)	Adaptive	Adaptive+3D	Probabilistic3D
Sliding (perfect)	100%	68%	72%	64%	61%	80%
liding (dense)	67%	100%	65%	61%	56%	78%
Sliding (sparse)	66%	61%	100%	65%	66%	76%
Adaptive	53%	52%	59%	100%	87%	76%
Adaptive+3D	42%	39%	49%	71%	100%	61%
Probabilistic3D	55%	55%	57%	62%	61%	100%

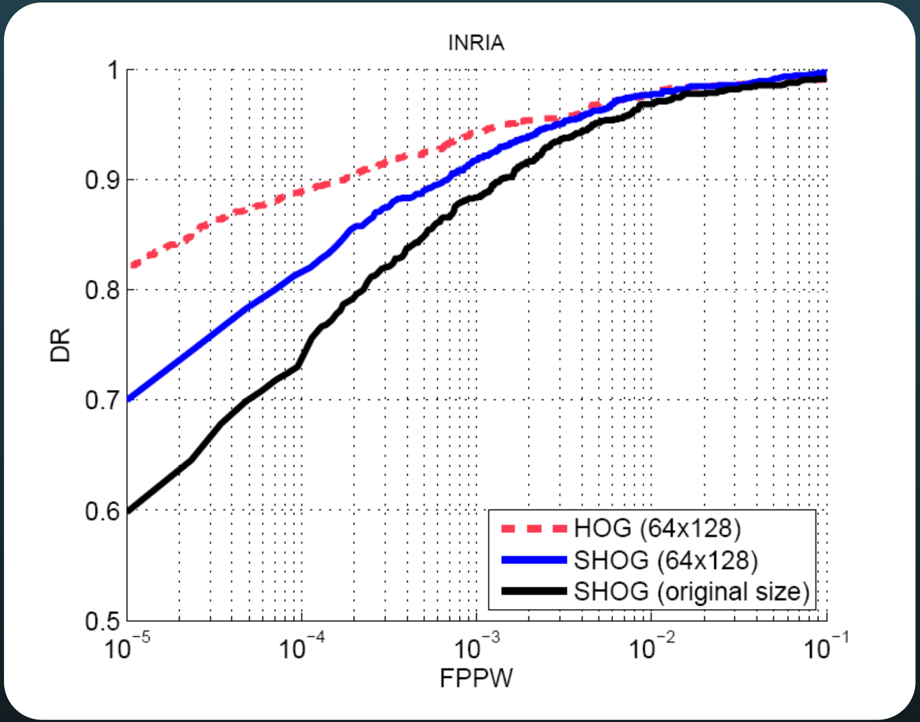
	Sliding (perfect)	Sliding (dense)	Sliding (sparse)	Adaptive	Adaptive+3D	Probabilistic3D
Sliding (perfect)	100%	90%	89%	92%	72%	79%
Sliding (dense)	90%	100%	87%	81%	71%	79%
	91%	88%	100%	83%	75%	79%
	87%	87%	87%	100%	85%	82%
	85%	84%	87%	95%	100%	76%
	92%	92%	91%	89%	78%	100%

	Sliding (perfe	Sliding (dens	Sliding (sparse)	Adaptive	Adaptive+3D	Probabilistic3D
Sliding (perfect)	100%	91%	89%	75%	71%	89%
Sliding (dense)	92%	100%	87%	72%	69%	88%
Sliding (sparse)	83%	82%	100%	71%	69%	89%
Adaptive	79%	76%	80%	100%	87%	85%
Adaptive+3D	70%	68%	71%	81%	100%	80%
Probabilistic3D	73%	72%	77%	66%	67%	100%

	Sliding (perfect)	Sliding (dense)	Sliding (sparse)	Adaptive	Adaptive+3D	Probabilistic3D
Sliding (perfect)	100%	92%	81%	80%	68%	67%
Sliding (dense)	91%	100%	80%	77%	66%	66%
Sliding (sparse)	87%	86%	100%	79%	68%	71%
Adaptive	86%	73%	70%	100%	80%	61%
Adaptive+3D	70%	68%	66%	88%	100%	58%
Probabilistic3D	85%	84%	84%	82%	82%	100%

Object Classification

Experimental Results

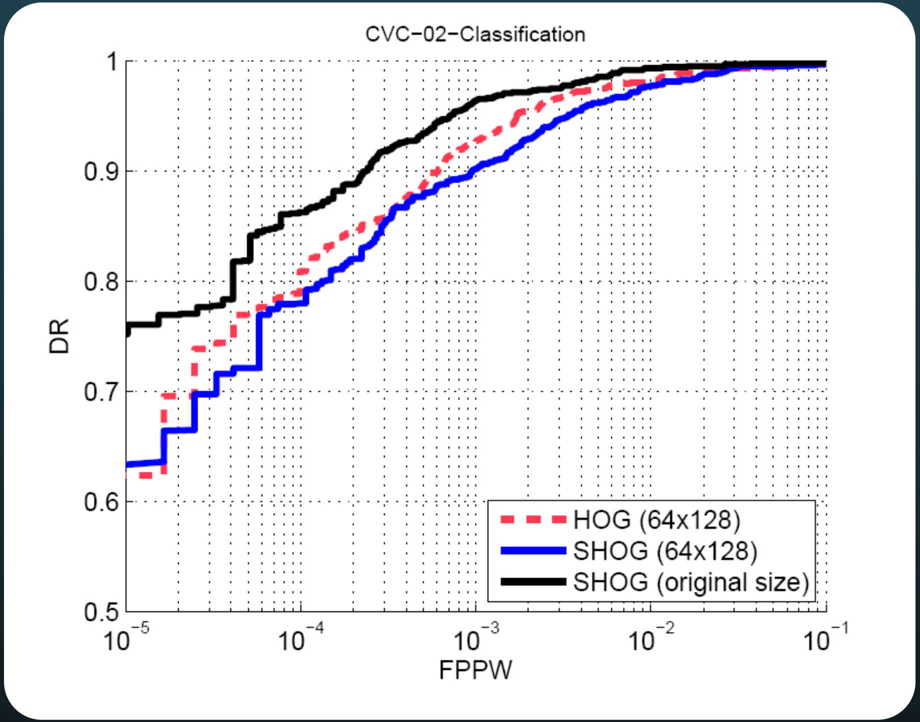


(detection rate vs false positive per window plot)

HOG outperforms SHOG in INRIA dataset
(-13% DR at 10^{-4} FPPW)

Object Classification

Experimental Results



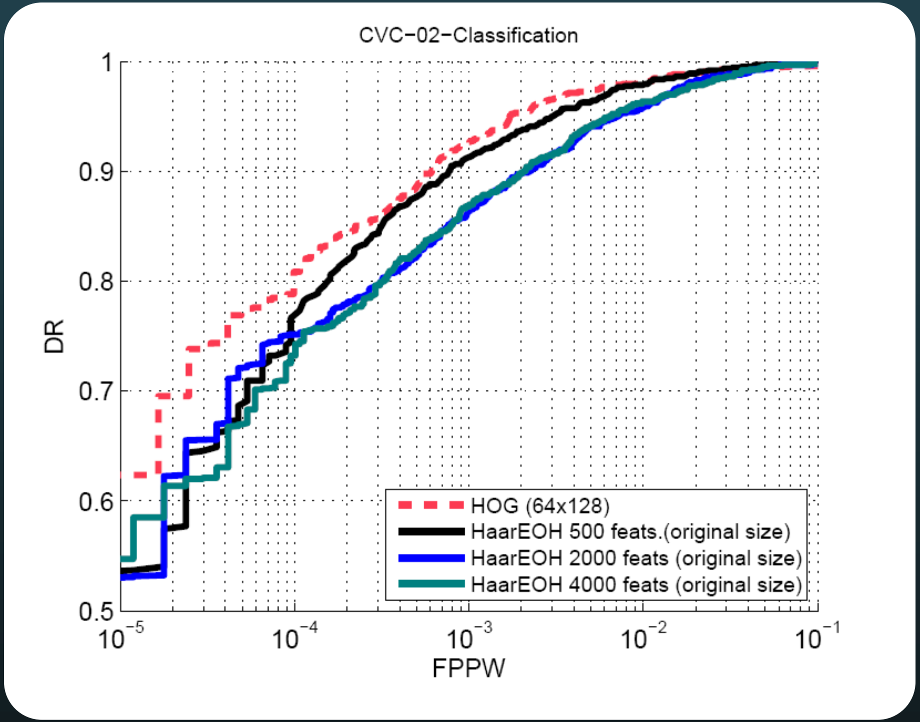
(detection rate vs false positive per window plot)

HOG outperforms SHOG in INRIA dataset
(-13% DR at 10^{-4} FPPW)

SHOG outperforms HOG in CVC-02 dataset
(+5% DR at 10^{-4} FPPW)

Object Classification

Experimental Results



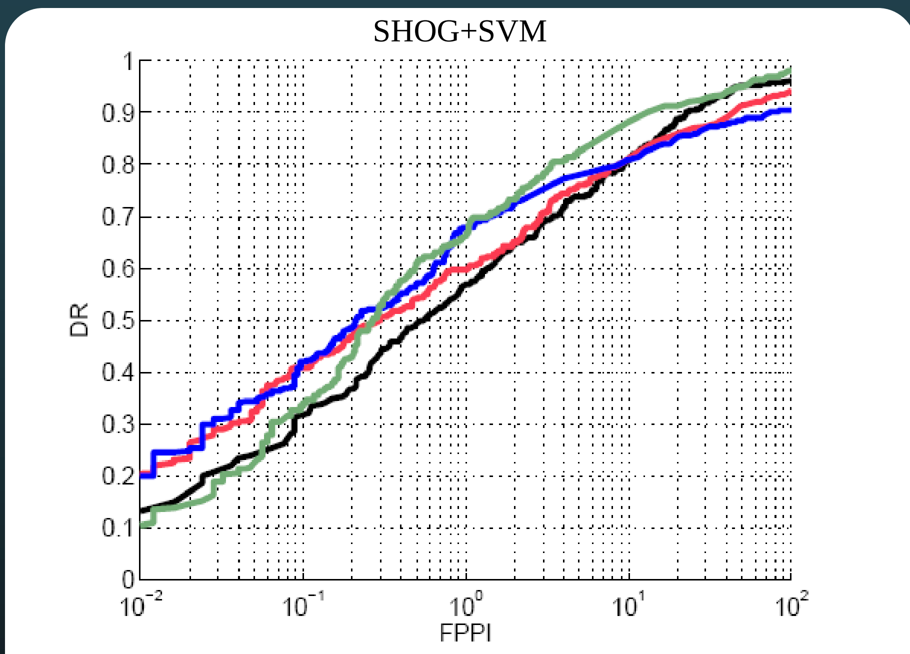
(detection rate vs false positive per window plot)

HOG outperforms HaarEOH in CVC-02 dataset
(-3% DR at 10^{-4} FPPW)

More features in HaarEOH gives poorer results
(-10% DR at 10^{-4} FPPW)

Object Classification

Experimental Results

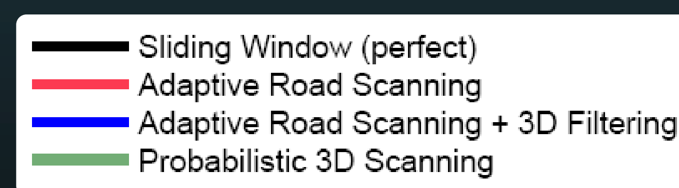


Near pedestrians

(detection rate vs false positive per image plot)

In the near range, foreground segmentation algorithms are similar, although probabilistic and adaptive+3D are better.

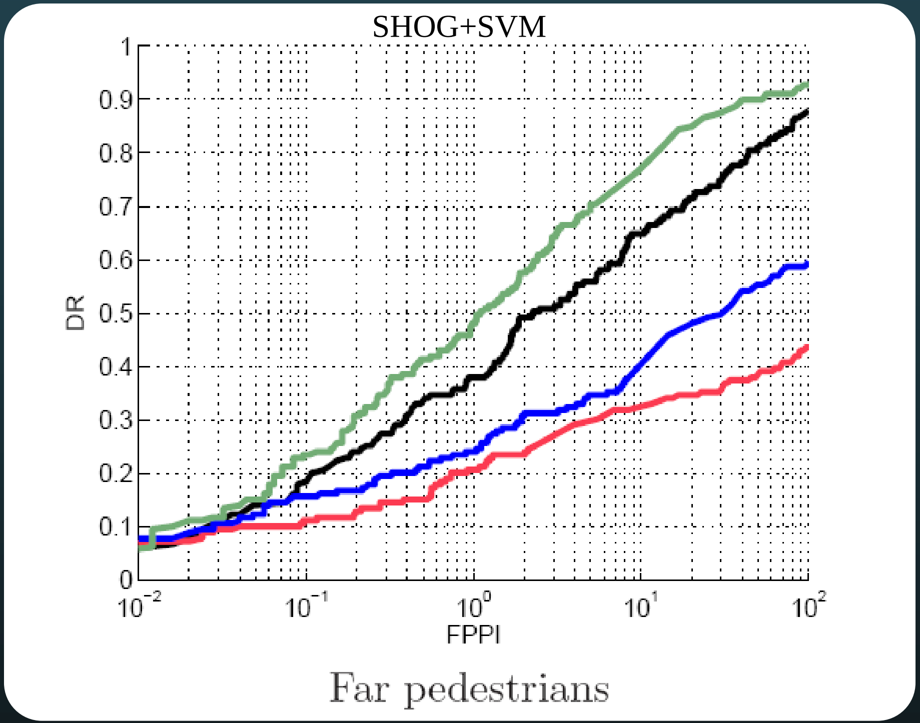
(happens in both classifiers)



(Foreground segmentation + Classification)

Object Classification

Experimental Results



(detection rate vs false positive per image plot)

In the far range, <u>probabilistic</u> and <u>sliding window</u> are the best.

(happens in both classifiers)

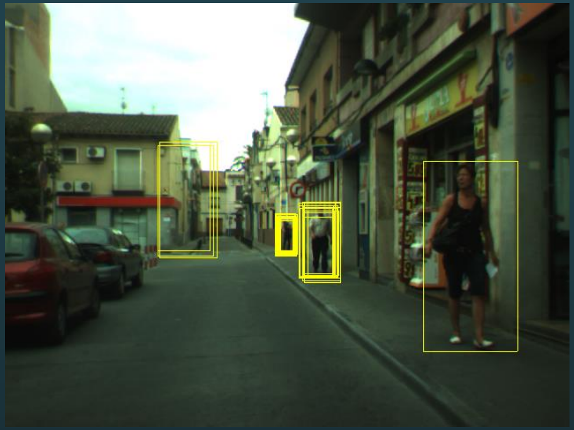
(+10..+20% DR at 10^0 FPPI)

(Foreground segmentation + Classification)

Object Classification

Experimental Results

SHOG



Sliding window

Adaptive road scanning

Adaptive road scanning + 3D

Probabilistic 3D

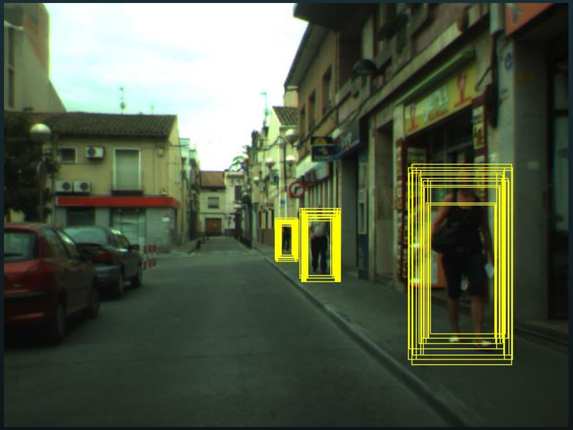
Object Classification

Experimental Results

HaarEOH

Sliding window

Adaptive road scanning



Adaptive road scanning + 3D

Probabilistic 3D

Object Classification

Experimental Results

SHOG

Sliding window

Adaptive road scanning

Adaptive road scanning + 3D

Probabilistic 3D

Object Classification

Experimental Results

HaarEOH

Sliding window

Adaptive road scanning

Adaptive road scanning + 3D

Probabilistic 3D

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Detections Refinement

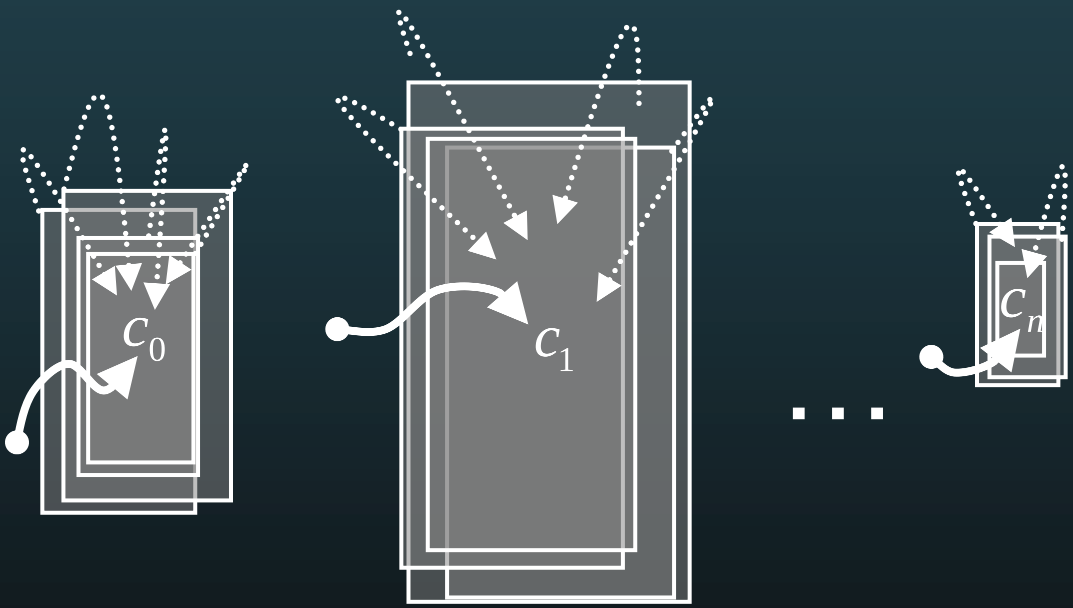
Contributions

- ✓ New clustering algorithm: accumulative.
- ✓ Clustering algorithms comparison, together with the other components of the system.
- ✓ Shape extraction method that does not require segmented models.

Detections Refinement

Detections clustering

Meanshift clustering

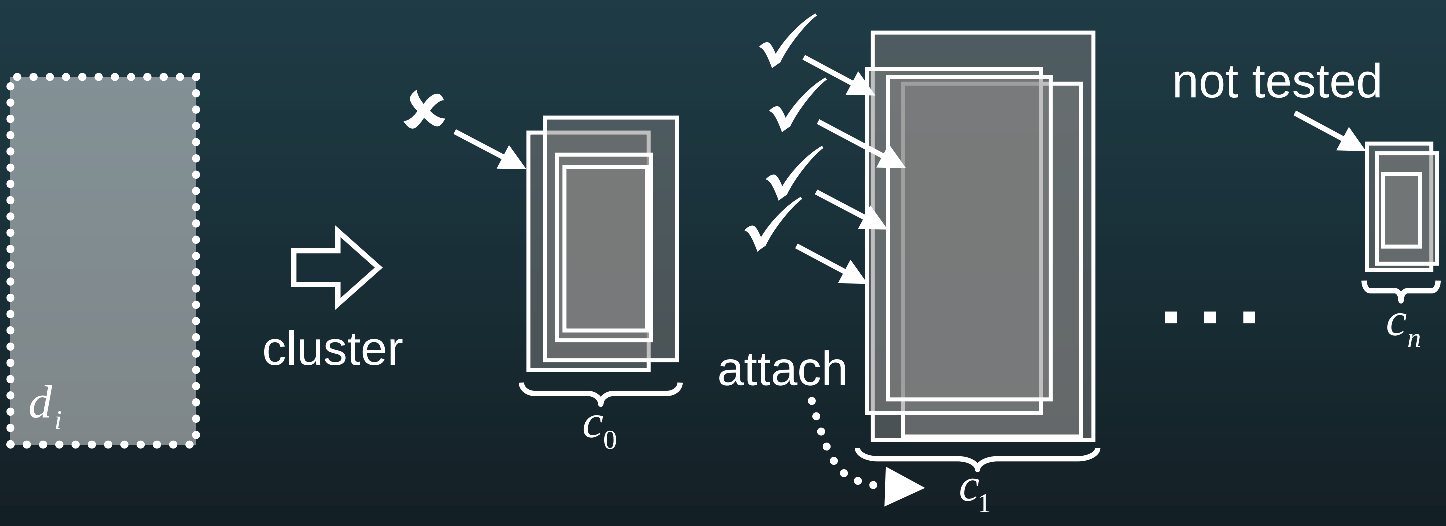


[Comaniciu03, Dalal06PhD]

Detections Refinement

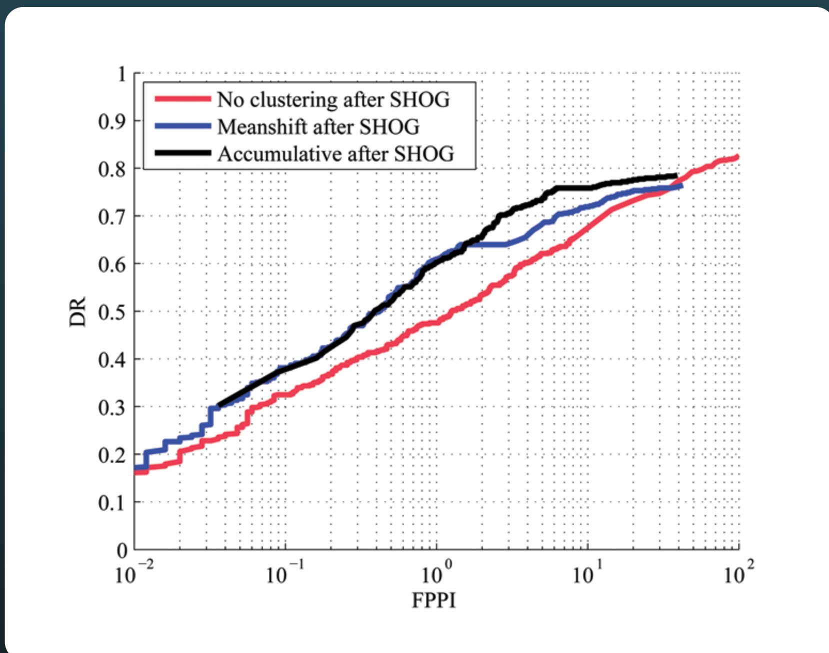
Detections clustering

Accumulative clustering



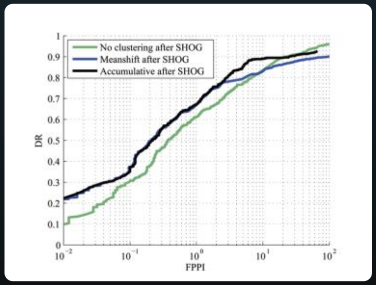
Detections Refinement

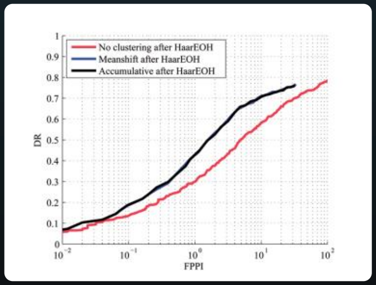
Experimental Results

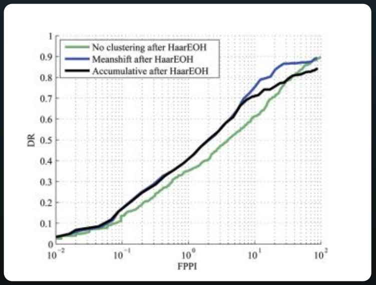


There is <u>no significant difference</u> between the algorithms performance.

But <u>accumulative is 6 times faster</u> than meanshift.

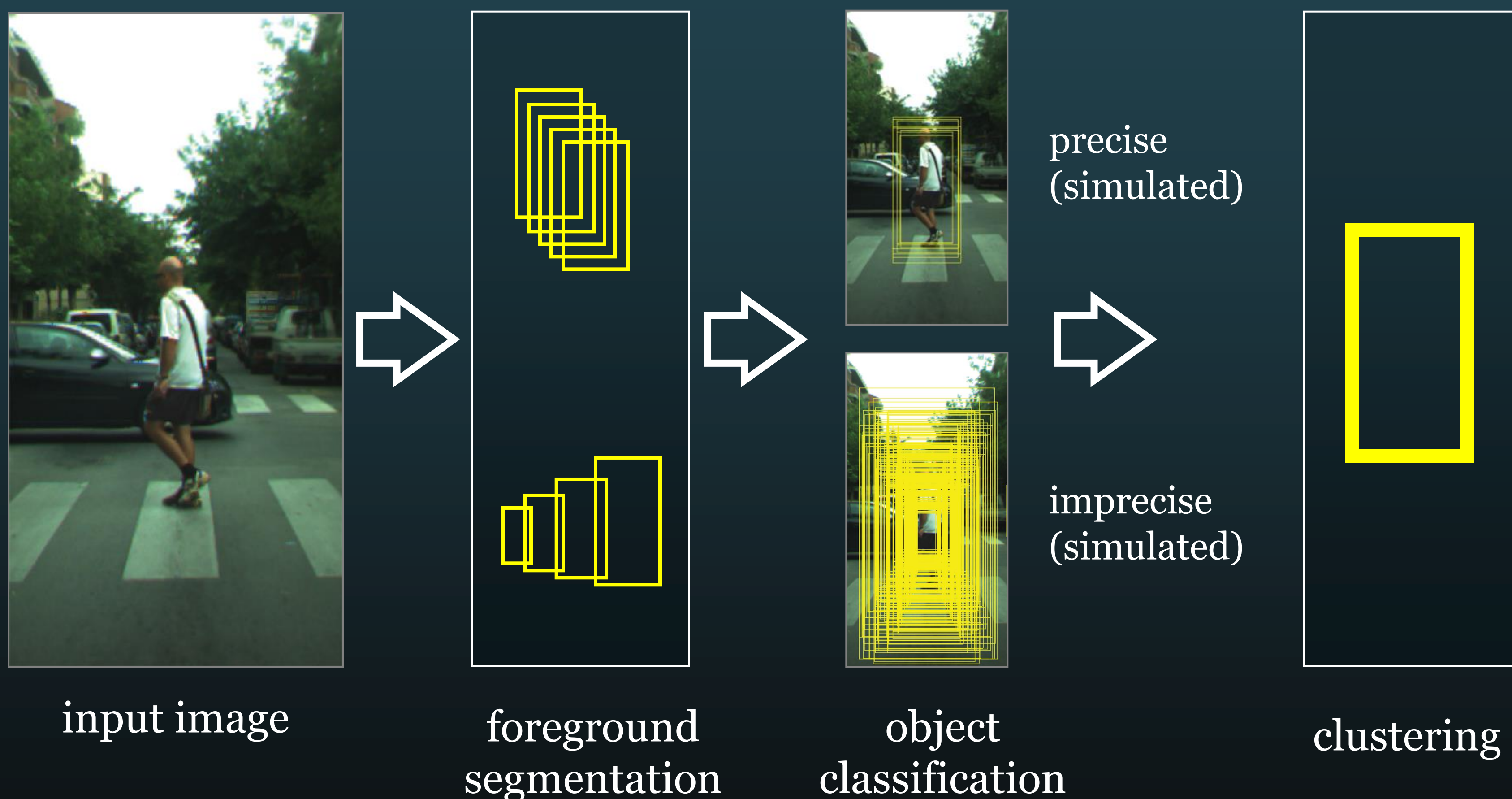






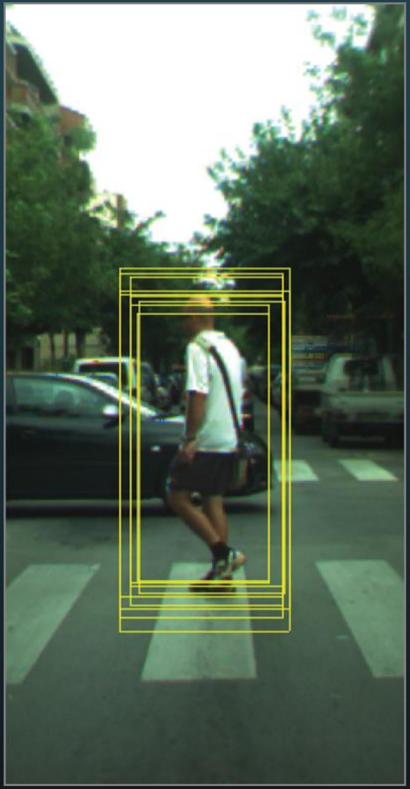
Detections Refinement

Experimental Results

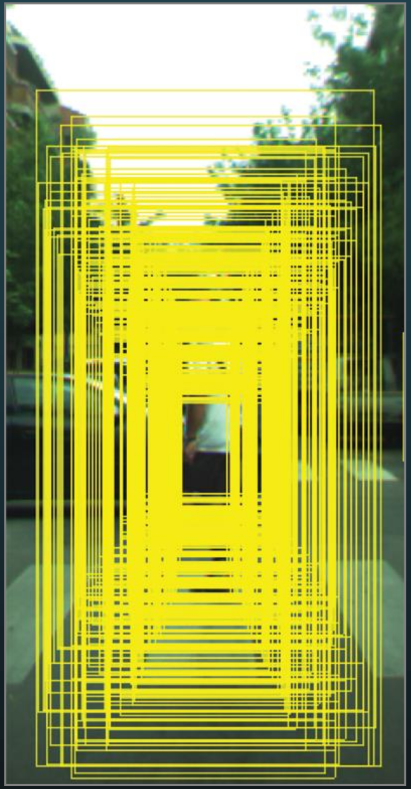


Detections Refinement

Experimental Results



precise
(simulated)

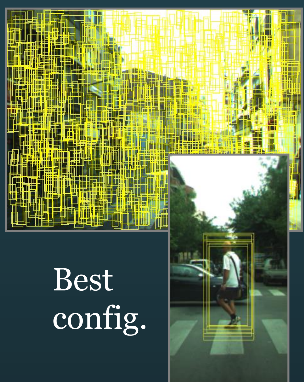


imprecise
(simulated)

Which is
the best?

Detections Refinement

Experimental Results



Best config.

sliding window

	precise	Imprecise
precision	0.9195	0.8856
recall	0.9924	0.9792
f-measure	**0.9545**	0.9300

Best config.

adaptive road scanning

	precise	Imprecise
precision	0.9457	0.8695
recall	0.5924	0.9056
f-measure	0.7284	**0.8871**

It depends: the clustering is affected both by the <u>classifier and foreground segmentation</u>.

Detections Refinement

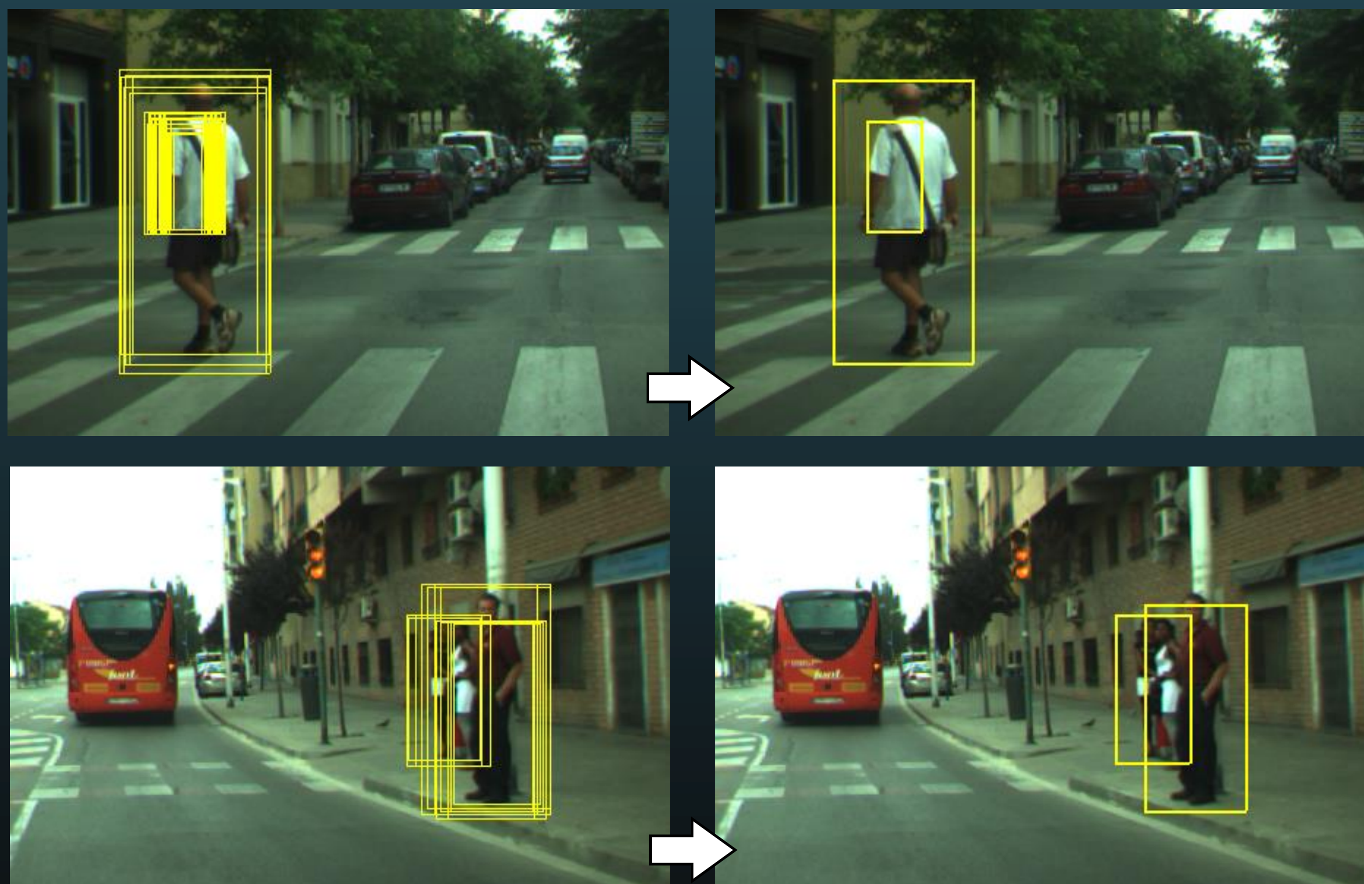
Experimental Results

SHOG + Accumulative

Detections Refinement

Experimental Results

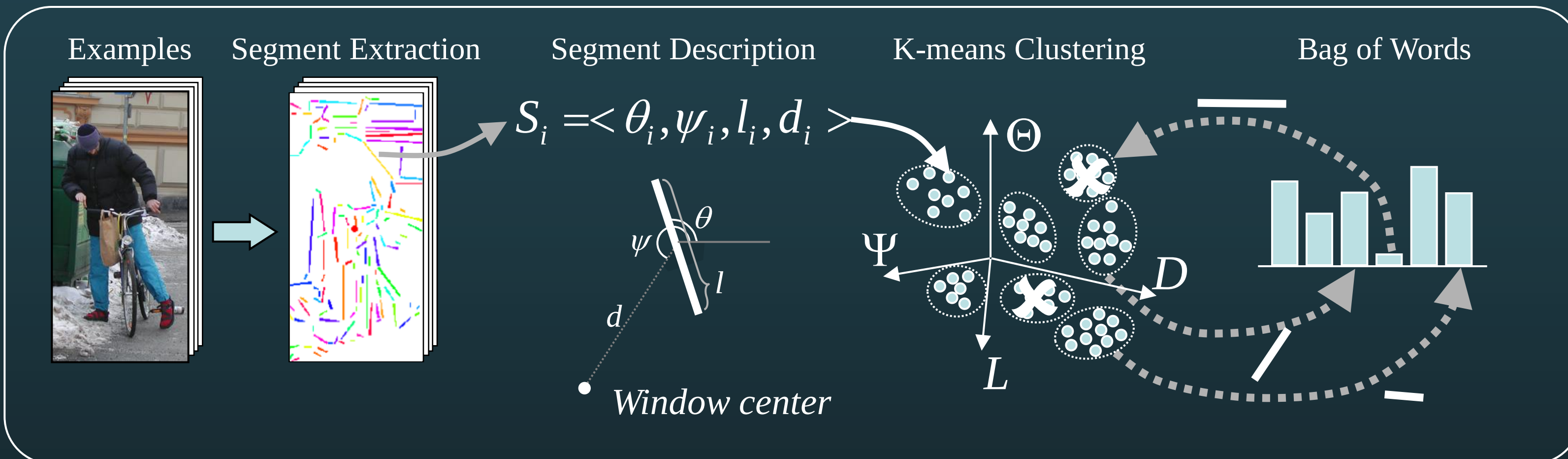
SHOG + Accumulative



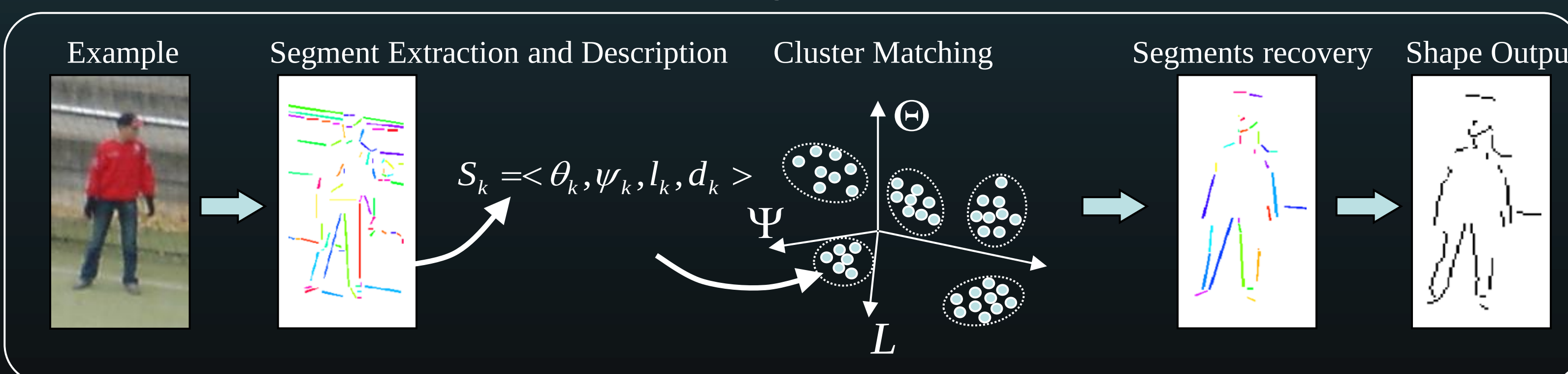
Detections Refinement

Shape extraction via non-explicit shape models

TRAIN

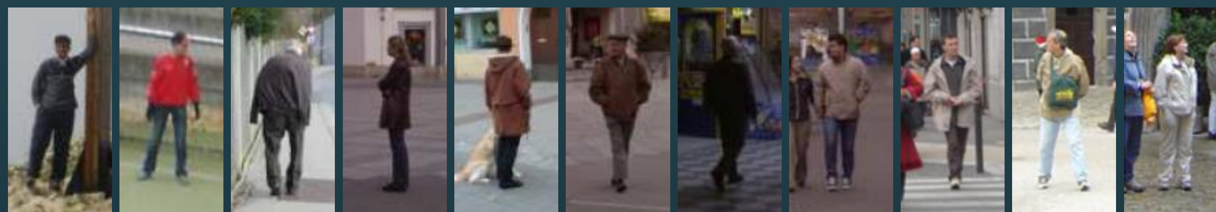


TEST



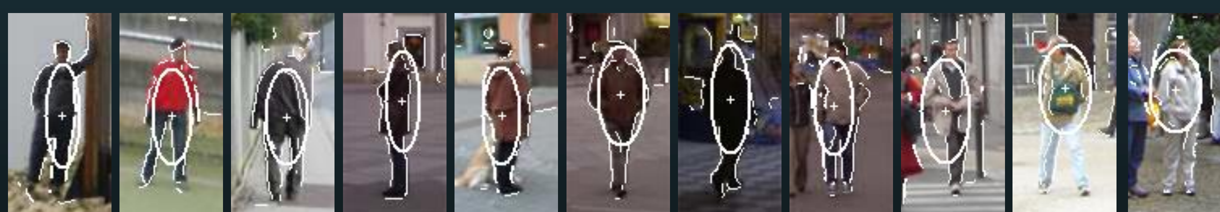
Detections Refinement

Experimental Results



Original detections

Algorithm output



Overlayed output and center of mass

Index

- Introduction
- State of the Art (Architecture)
- Foreground Segmentation
- Object Classification
- Detections Refinement
- Pedestrian Detection System
- Conclusions

Pedestrian Detection System

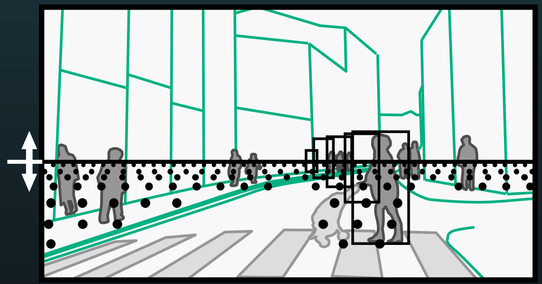
Contributions

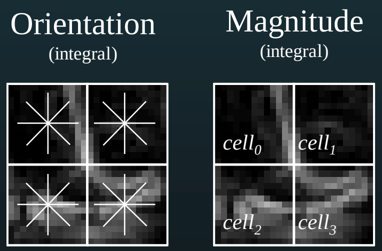
- ✓ Novel pedestrian detection system.
- ✓ New dataset of real complex urban scenarios.

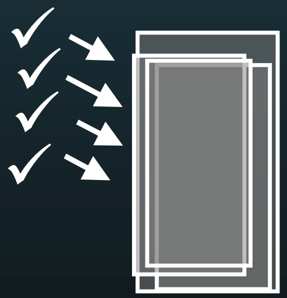
Pedestrian Detection System

System components

Foreground Segmentation	Object Classification	Refinement
Adaptive Road Scanning *0..25 m*: 3D filtering *25..50 m*: no filtering	SHOG+SVM	Accumulative clustering Overlapping, thresh=0.5



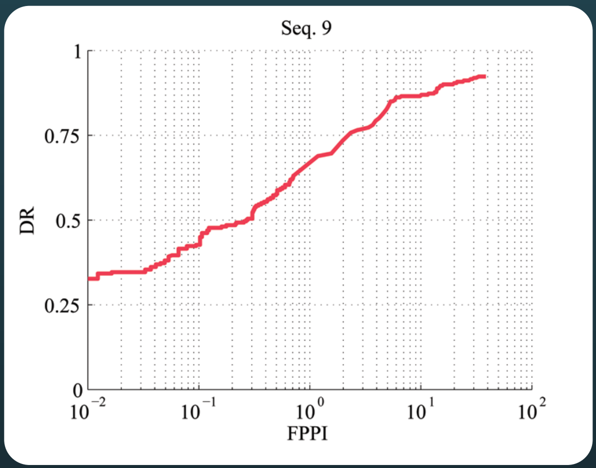




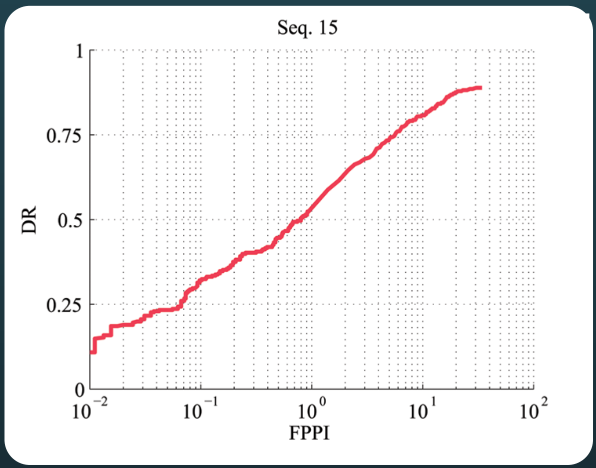
Pedestrian Detection System

Experimental Results (quantitative)

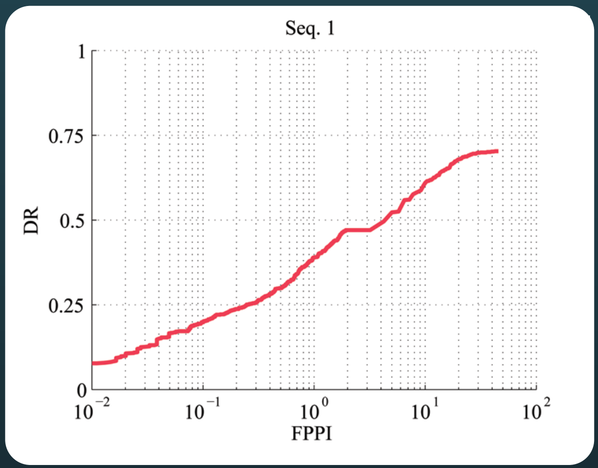
(tested on 15 sequences)



High performance



Average performance



Low performance

Pedestrian Detection System

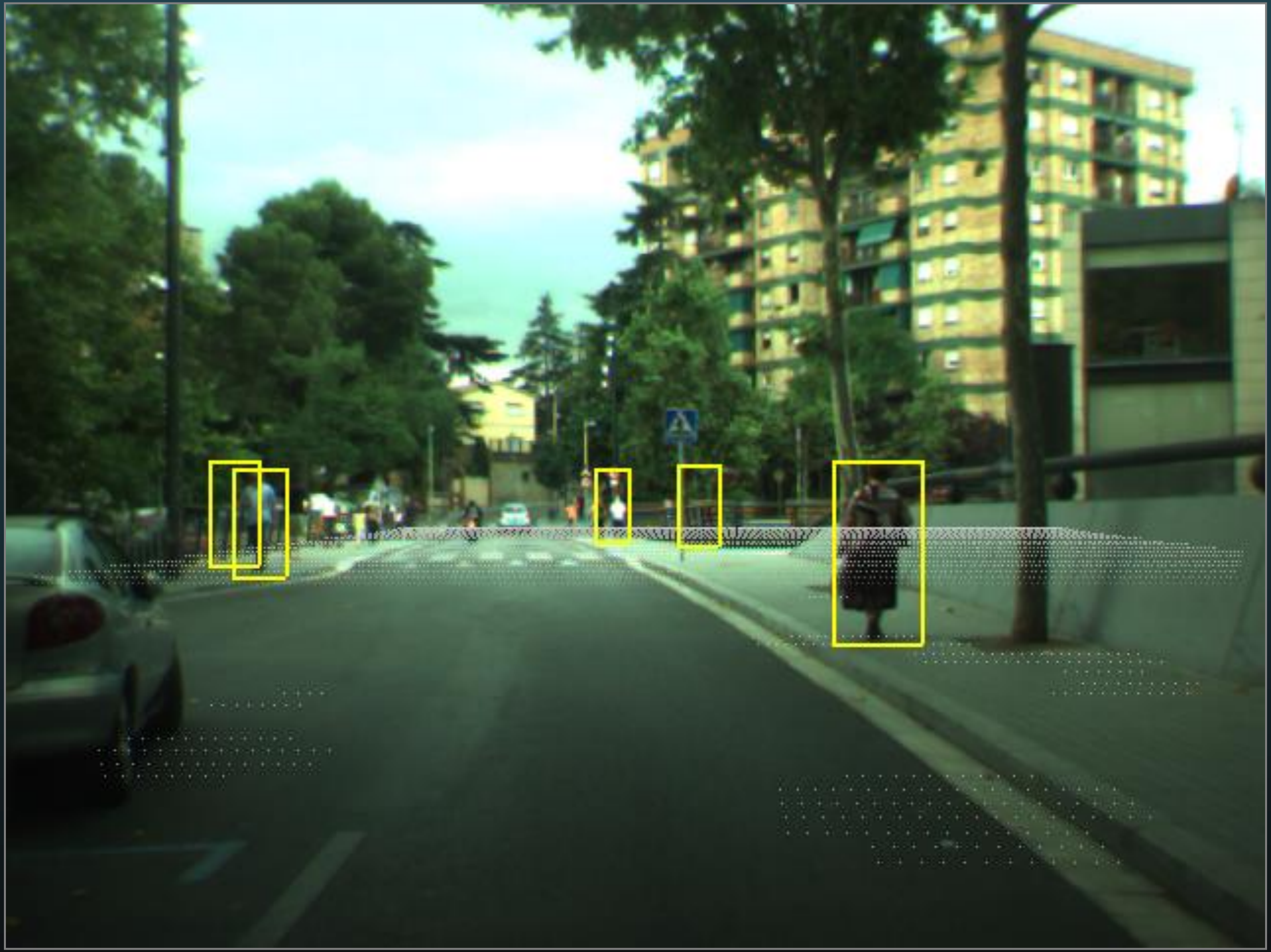
Experimental Results (qualitative)

(seq. 6 - low performance)
Adaptive road scanning, SHOG+SVM, accumulative clustering

Pedestrian Detection System

Experimental Results (qualitative)

(seq. 5 – average performance)
Adaptive road scanning, SHOG+SVM, accumulative clustering



Pedestrian Detection System

Experimental Results (qualitative)

(seq. 9 – high performance)
Adaptive road scanning, SHOG+SVM, accumulative clustering

Index

Conclusions

Summary and Contributions

✓ Survey of the state of the art

D. Gerónimo, A.M. López, A.D. Sappa and T. Graf. ***Survey of Pedestrian Detection for Advanced Driver Assistance Systems***. IEEE Trans. on Pattern Analysis and Machine Intelligence, 2009. (in press)

Conclusions

Summary and Contributions

- ✓ Survey of the state of the art
- ✓ Foreground segmentation

D. Gerónimo, A.D. Sappa, J. Serrat and A.M. López. ***Candidate Generation for On-Board Pedestrian Detection.*** IEEE Trans. on Pattern Analysis and Machine Intelligence (submitted).

D. Gerónimo, A.D. Sappa and A.M. López. ***Stereo-based candidate generation for pedestrian proetection systems.*** In Binocular Vision: development, depth and disporders, NOVA Publishers (in press), 2009.

A.D. Sappa, F. Dornaika, D. Ponsa, D. Gerónimo and A.M. López. ***An Efficient approach to Onboard Stereo Vision System Pose Estimation***. IEEE Trans. on Intelligent Transportation Systems, vol.9, num. 3, pp. 476-490, 2008.

A.D. Sappa, D. Gerónimo, F. Dornaika and A.M. López. ***On-board camera extrinsic parameter estimation.*** IEE Electronics Letters, 42(13), pp.745-747, 2006.

Conclusions

Summary and Contributions

- ✓ Survey of the state of the art
- ✓ Foreground segmentation
- ✓ Object classification in the context of the system (specially fore. segm.)

Conclusions

Summary and Contributions

- ✓ Survey of the state of the art
- ✓ Foreground segmentation
- ✓ Object classification in the context of the system (specially fore. segm.)
- ✓ Detections refinement

Conclusions

Summary and Contributions

- ✓ Survey of the state of the art
- ✓ Foreground segmentation
- ✓ Object classification in the context of the system (specially fore. segm.)
- ✓ Detections refinement
- ✓ Three techniques integrated in a system

> D. Gerónimo, A.D. Sappa, D. Ponsa and A.M. López. ***2D-3D based on-board pedestrian detection system***. Computer Vision and Image Understanding, Special Issue on Intelligent Systems, 2010. (in press)

Conclusions

Summary and Contributions

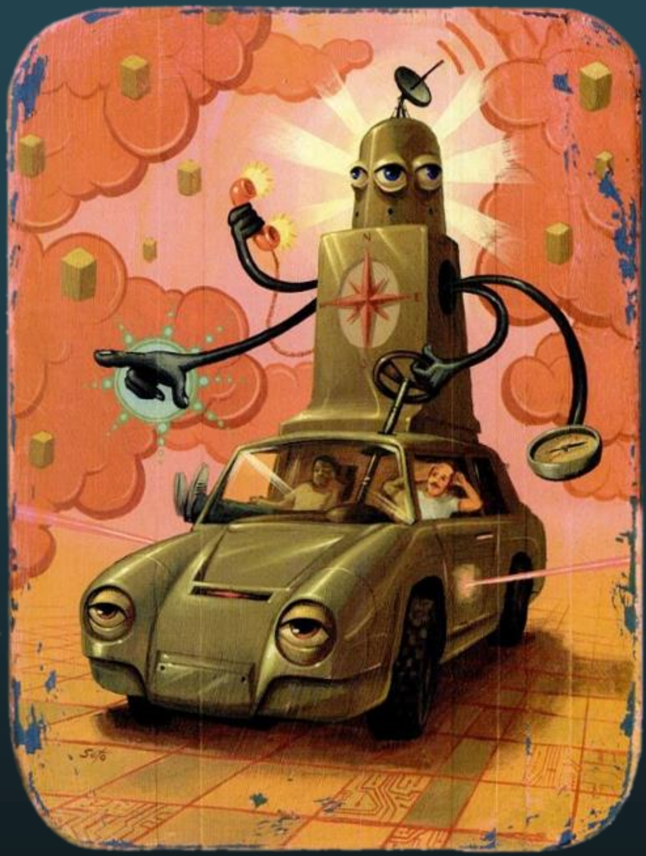
- ✓ Survey of the state of the art
- ✓ Foreground segmentation
- ✓ Object classification in the context of the system (specially fore. segm.)
- ✓ Detections refinement
- ✓ Three techniques integrated in a system
- ✓ Pioneer multi-purpose pedestrian dataset

CVC-02 Pedestrian Dataset
http://www.cvc.uab.es/adas/datasets

Conclusions

Future lines of research

- ✓ Keep improving foreground segmentation
- ✓ Incorporating new classification algorithms
- ✓ Add verification and tracking to the system
- ✓ Research unexplored problems (occlusions, nighttime, etc.)



Src.: Popular Science, Sept. 2004

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