



# Driver Assistance Systems (DAS)

Short Overview

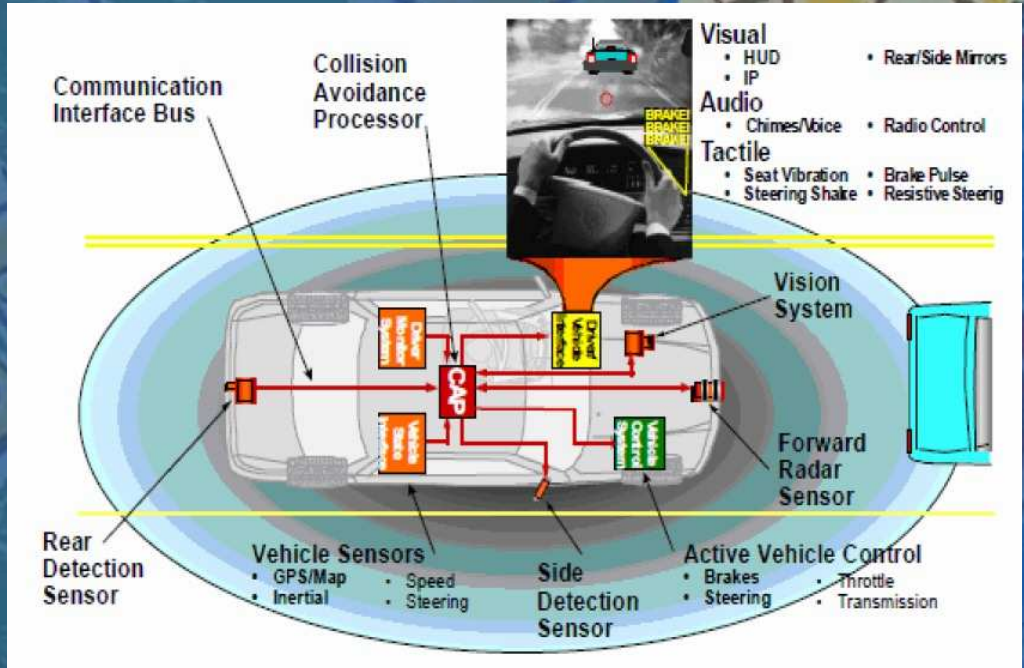
László Czúni

University of Pannonia



# What is DAS?

- DAS: electronic systems helping the driving of a vehicle
- ADAS (advanced DAS): the collection of systems and subsystems on the way to a fully automated driving system
- Vision-based DAS: DAS using optical sensors



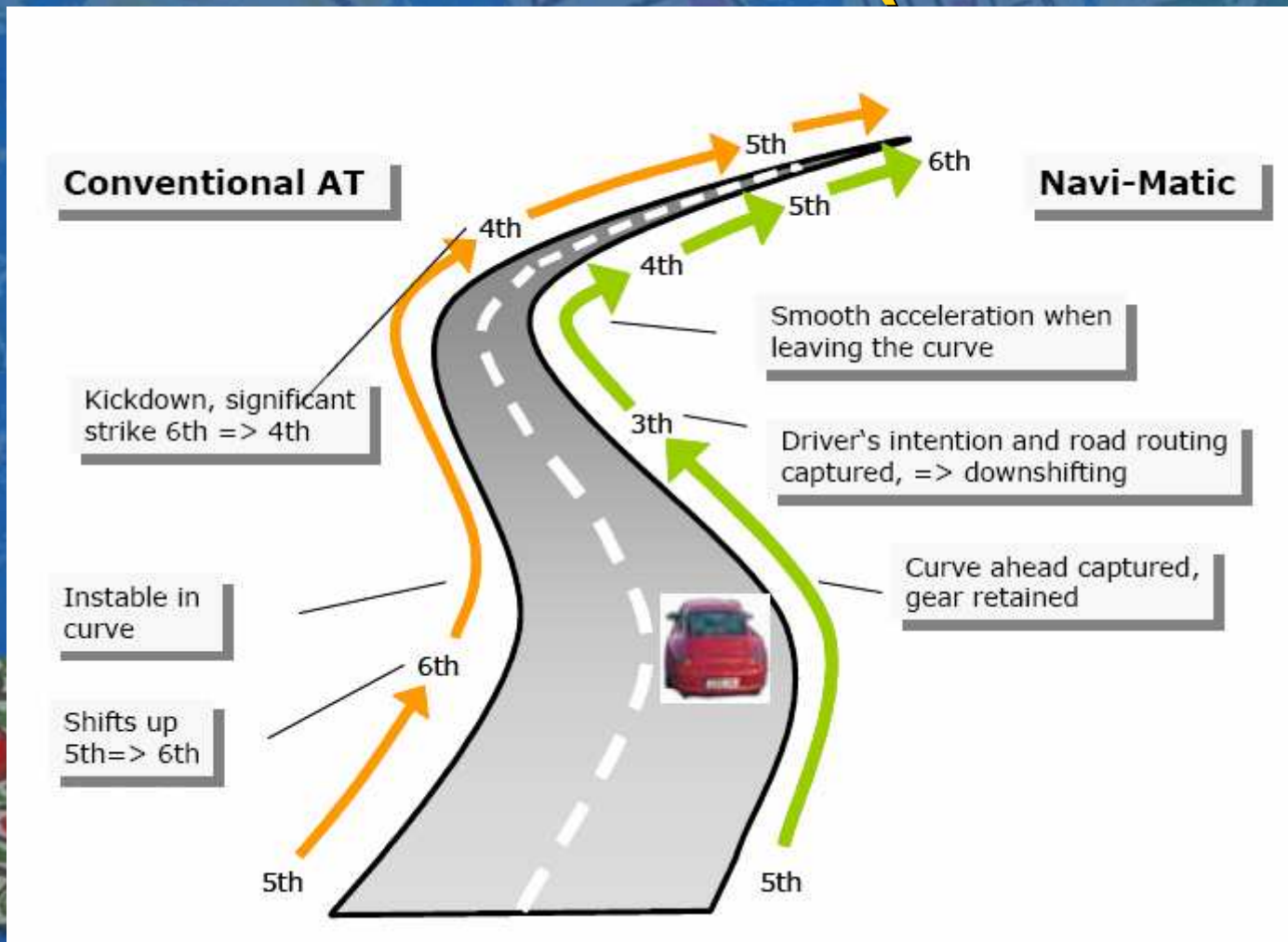


# Purposes of DAS

- Economy:
  - Lower fuel consumption
  - Lower cost of ownership
  - Less pollution of environment
- Comfort:
  - Easier driving
  - Information about traffic
  - Route planning
- Safety:
  - Lower risk of accidents
  - Less serious accidents

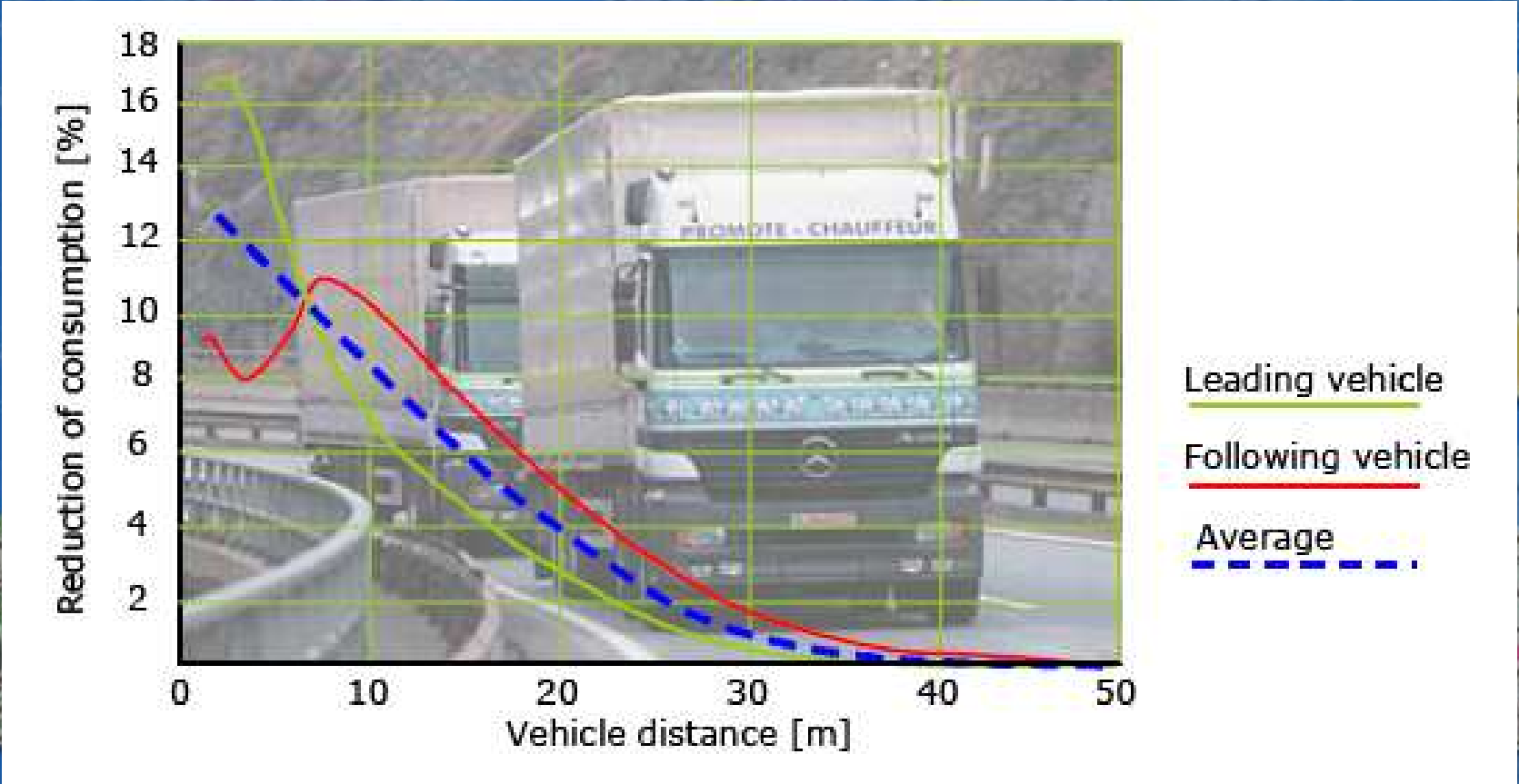


# Lower Consumption by Navi-Matic (Aisin AW)



More economic gear selection based on digital map information

# Drive in line





# Regulations

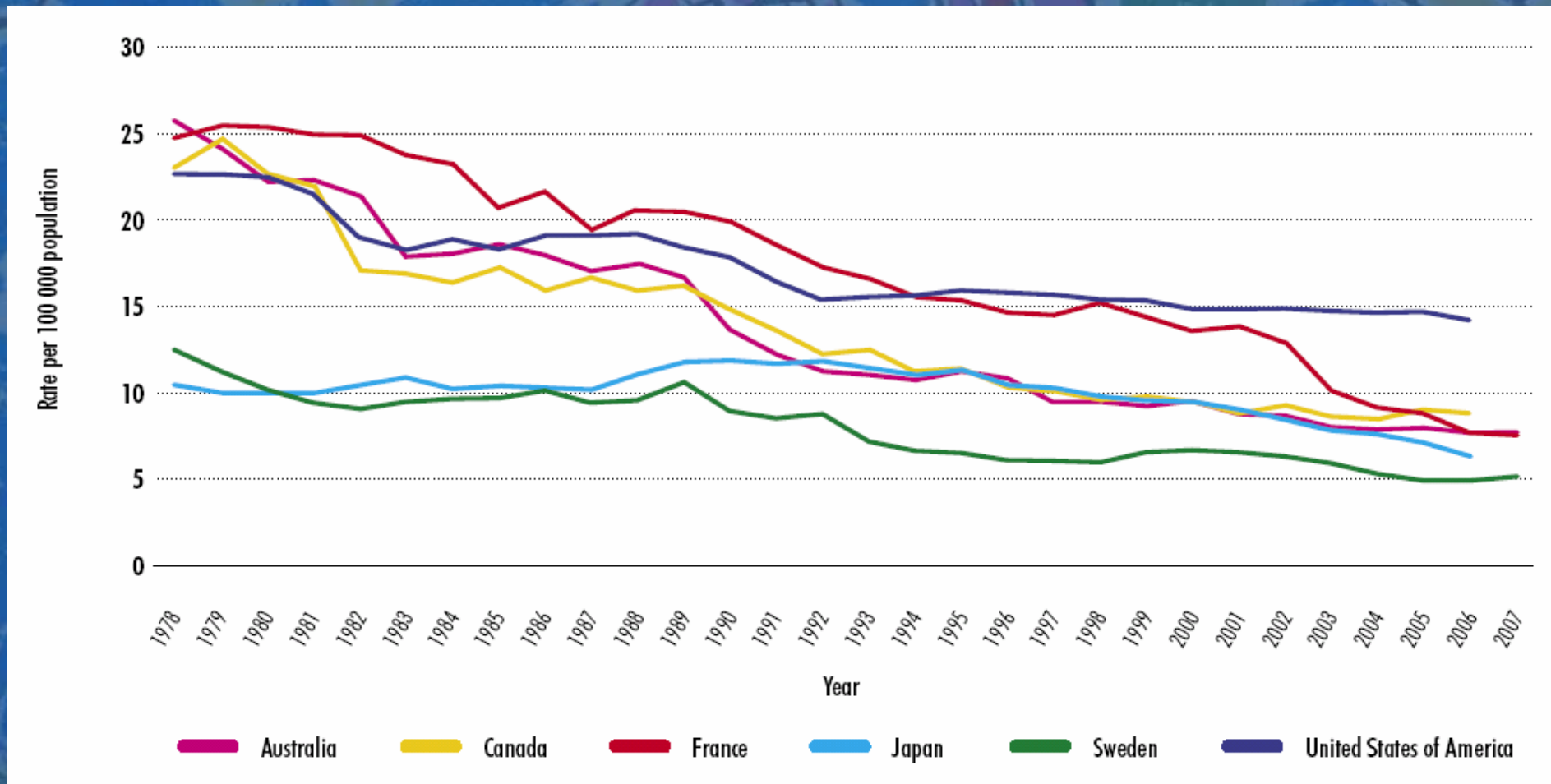
- The European Union's Transport Policy 2011 – 2020
  - reduce fatalities on European roads by half over the next decade.
  - introduces a focus on the reduction of severe injuries;
- The EU Safety Regulation makes ESP mandatory as of November 2014 for all vehicle classes.



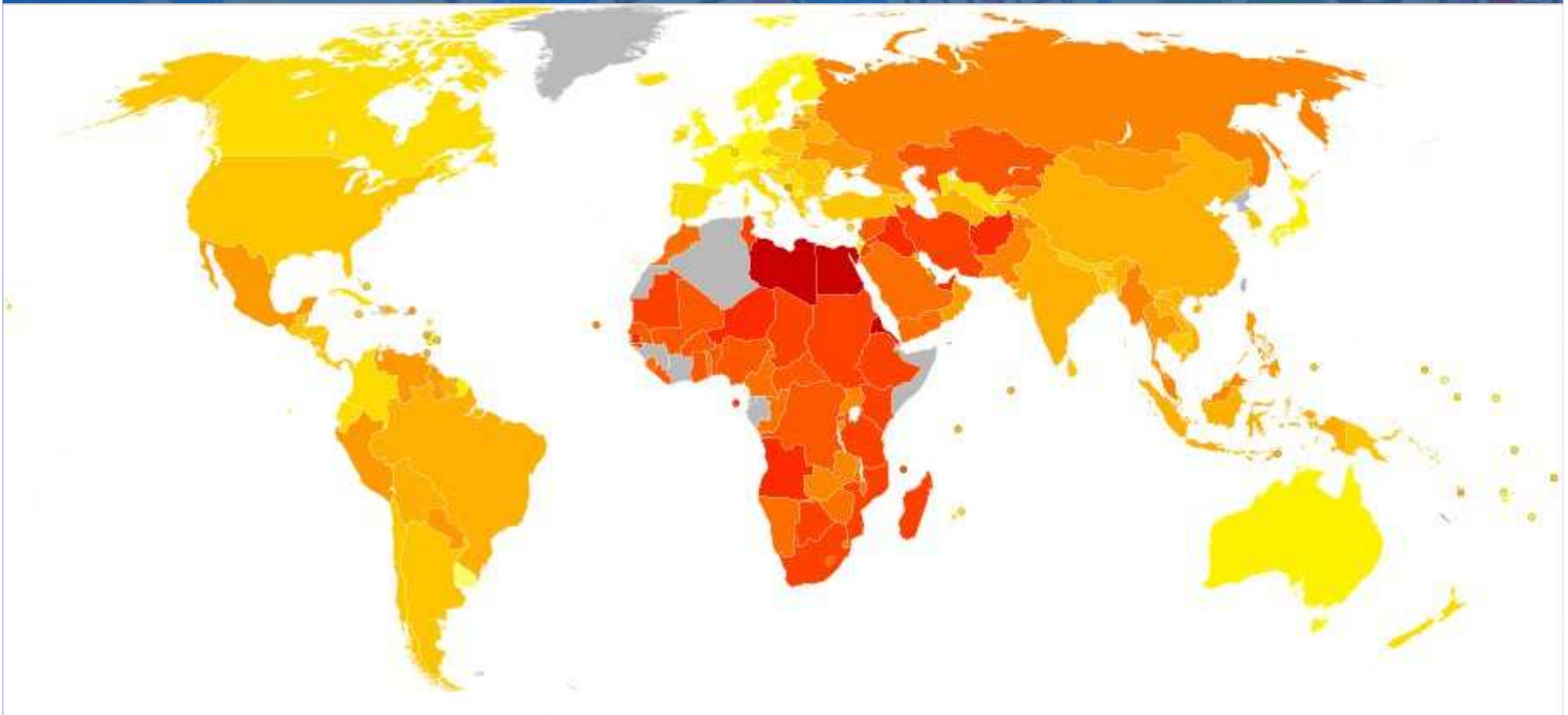
(Since ESP is an important component of



# Road Fatality Trends in High-income Countries



# Road Fatalities Worldwide

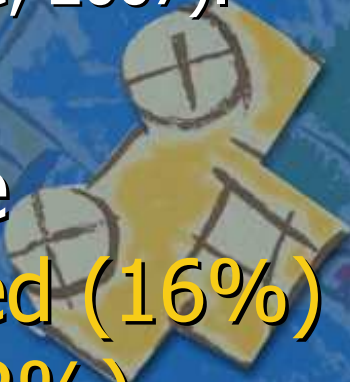




- Road fatalities per 100,000 inhabitants per year, 2000, Global Status Report On Road Safety, WHO





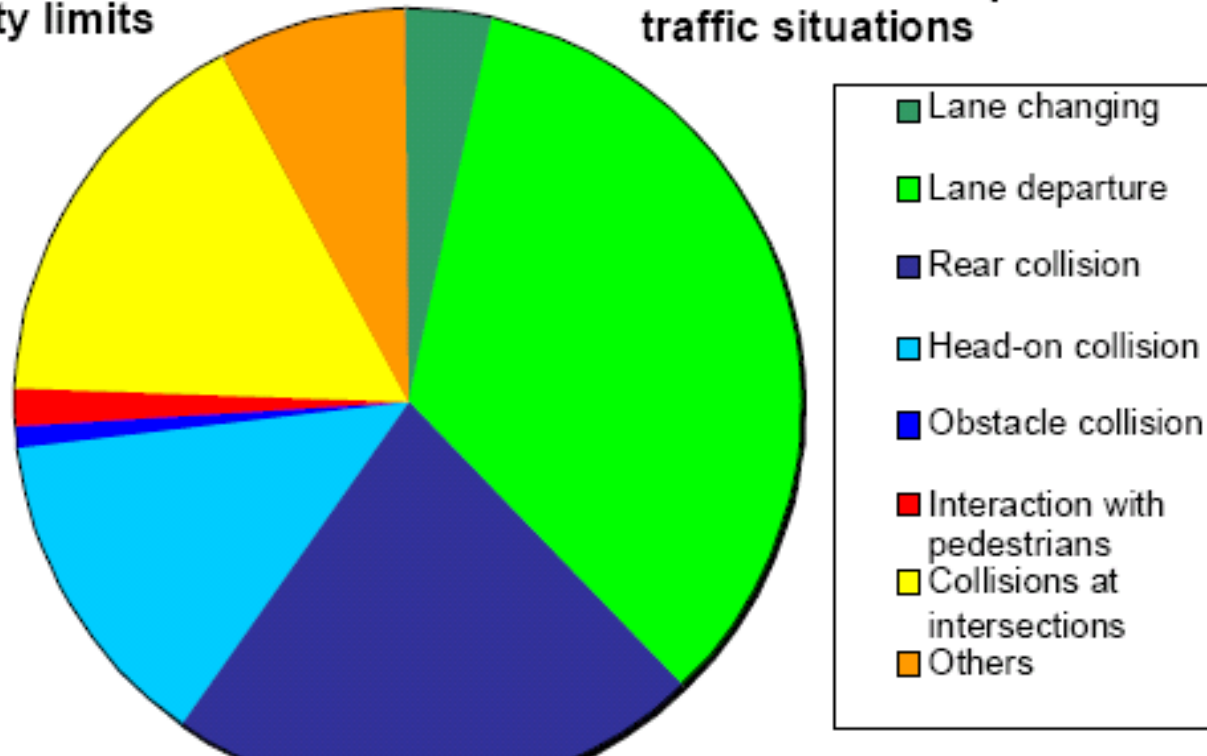
# Some Statistics

- The main cause of **90%** of traffic **accidents** is **human error** (German Federal Statistical Office, 2007).
  - Accidents with physical **injuries** can be attributed either to **inappropriate speed (16%)** or to **insufficient stopping distance (12%)**.
  - **40%** of all **people killed** in road traffic were due to **unadapted speed** (2010, Germany)
- 
- 
- 

# Accidents is Complex Traffic Situations

Accidents outside city limits

Accidents in complex traffic situations



**What are the real causes behind human errors?**

Unseen obstacles, misunderstood information, too long reaction time, alcohol...?



# Traffic Psychology

- Traffic psychology is primarily related to the study of the behavior of road users and the psychological processes underlying that behavior (Rothengatter, 1997)
- Important question is the **relationship** between
  - behavior of drivers
  - cars' features and equipments
  - environment
  - accidents



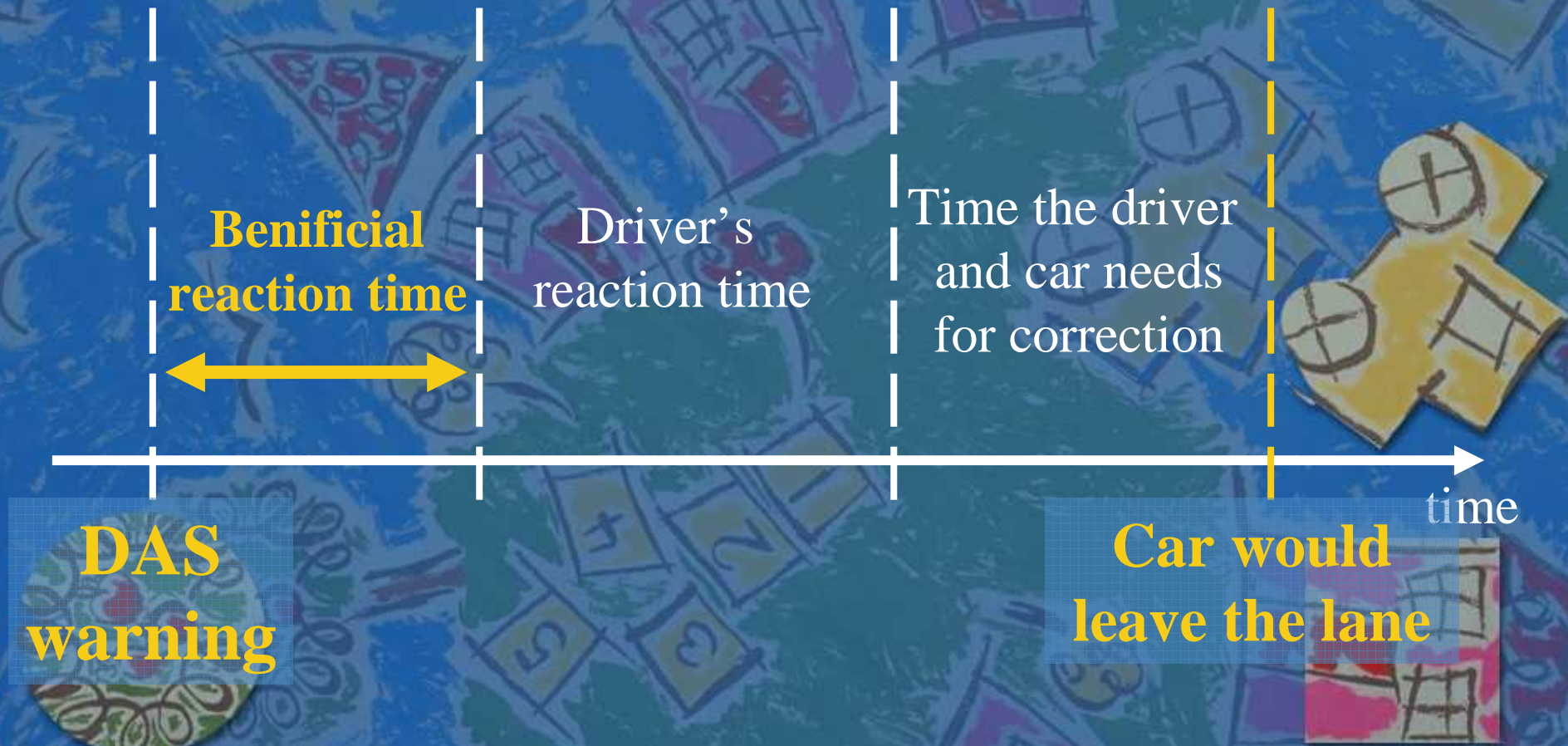
# Example 1: Reaction time of drivers and its effect on breaking distance

	figures		
	Most possible	2% (only 2% are faster)	98% (only 2% are slower)
Reaction			
Without view turning	0.64	0.36	0.78
With view turning 0.5-5°	1.12	0.68	1.33
With view turning > 5°	1.25	0.77	1.48
Response time	0.05	0.03	0.06
Build-up time	0.17	0.14	0.18

**Reaction time (s) and distance (m) at 100km/h**

0,1	0,2	0,5	0,67	1	1,5
2,778	5,556	13,89	18,6	27,78	41,67

# Example 2: Quality measure for lane departure alert systems



# **DARPA** (*Defense Advanced Research Projects Agency*)

## **prize competitions for driverless vehicles**

- 2004: only 12km of the desert route succeeded
- 2005: 5 cars ran the whole 212km off-road route
- 2007: 6 teams succeeded the 96km urban area course, the winner with 23km/h average speed



**Tatran Racing, 1<sup>st</sup> Place of  
Urban Challenge 2007**

# A description of the sensors incorporated onto the Tartan Racing Robots



Sensor	Characteristics
Applanix POS-LV 220/420 GPS / IMU	<ul style="list-style-type: none"> <li>• sub-meter accuracy with Omnistar VBS corrections</li> <li>• tightly coupled inertial/GPS bridges GPS-outages</li> </ul>
SICK LMS 291-S05/S14 Lidar	<ul style="list-style-type: none"> <li>• 180° / 90° x 0.9° FOV with 1° / 0.5° angular resolution</li> <li>• 80m maximum range</li> </ul>
Velodyne HDL-64 Lidar	<ul style="list-style-type: none"> <li>• 360° x 26° FOV with 0.1° angular resolution</li> <li>• 70m maximum range</li> </ul>
Continental ISF 172 Lidar	<ul style="list-style-type: none"> <li>• 12° x 3.2° FOV</li> <li>• 150m maximum range</li> </ul>
IBEO Alasca XT Lidar	<ul style="list-style-type: none"> <li>• 240° x 3.2° FOV</li> <li>• 300m maximum range</li> </ul>
Ma/Com Radar	<ul style="list-style-type: none"> <li>• 80° FOV</li> <li>• 27m maximum range</li> </ul>
Continental ARS 300 Radar	<ul style="list-style-type: none"> <li>• 60° / 17° x 3.2° FOV</li> <li>• 60m / 200m maximum range</li> </ul>
MobilEye Vision System	<ul style="list-style-type: none"> <li>• 45° x 45° FOV</li> <li>• ~35m effective range</li> </ul>

# History: first commercial appearances

- 1970s - ABS (Anti-lock Braking System - Bosch)
- 1990s – ESC/ESP (Electronic Stability Control/Program - Bosch)
- Early 1990s
  - Park Distance Control
  - GPS based navigation systems
- 1995 ACC (Adaptive Cruise Control - Mitsubishi)
- 2001 Lane keeping support (Nissan)
- 2002 Night Vision (Toyota)
- 2003 Intelligent Parking Assist System (Toyota)
- 2003 Collision Mitigation Brake System (Honda)
- 2005 Blind Spot Detection (Volvo)
- 2007 Around View Monitor (Nissan)
- 2008 Traffic Sign Recognition (MobilEye and Continental)
- 2009 Adaptive Light Control (Mercedes)
- 2009 Attention Assist - Driver drowsiness detection (Mercedes)
- 2011 Pedestrian Detection (Volvo)





# Sensors for DAS

- Rotation (yaw) and acceleration sensors
- Wheel speed sensor
- Steering wheel angle sensor
- Mono or Stereo Camera
- Infra camera
- Ultrasound
- Radar
- Lidar
- GPS (incl. map based data)
- Combination of these...

**In focus of  
vision-based DAS**





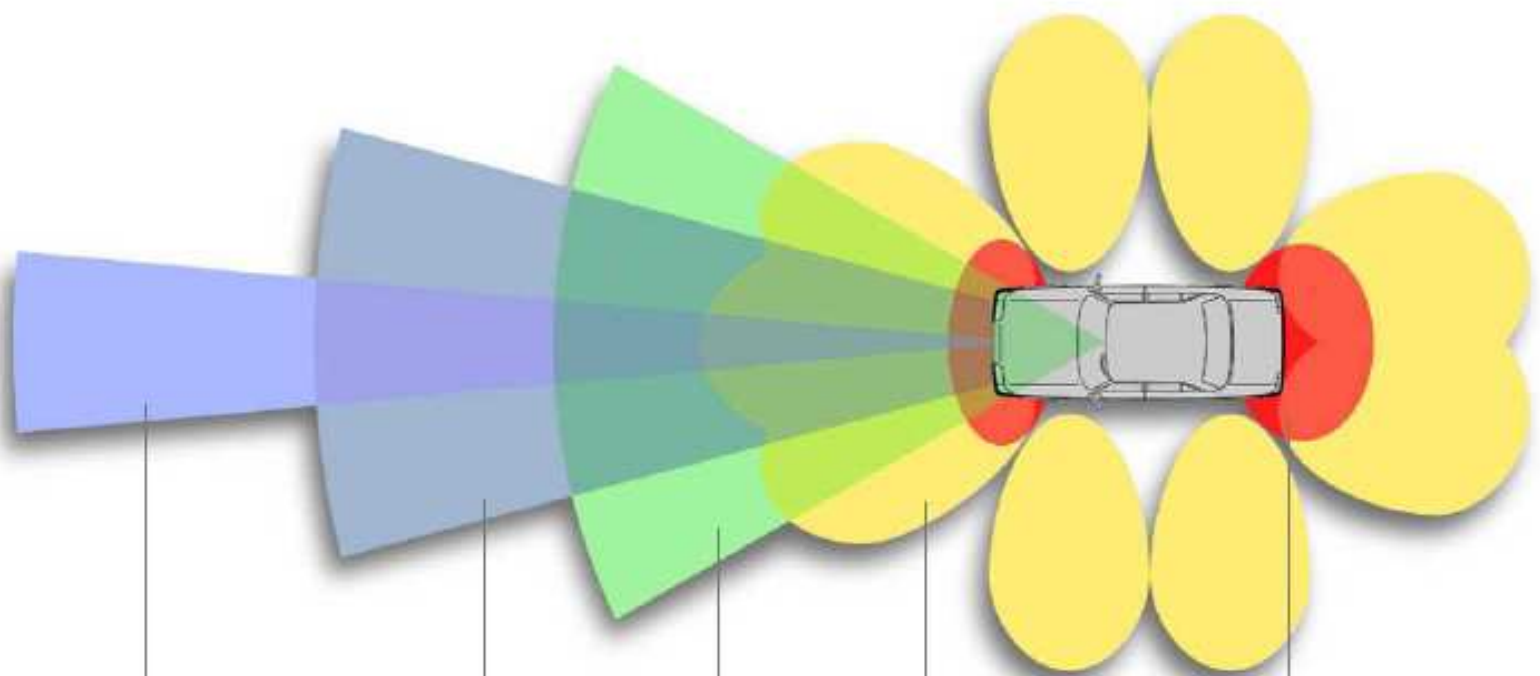
# Sensors for DAS

- Night vision (infra camera)
- Around view monitor (camera)
- Collision warning (radar, lidar, and camera)
  - Object (pedestrian) detection (camera)
- Lane departure alert, Lane change assistance, Lane keeping - Automatic steering (camera)
- Adaptive light control (camera)
- Adaptive cruise control (radar and camera)
- Parking systems (radar, ultrasound and camera)
- Traffic Sign recognition (camera)
- Blind spot detection (radar/camera)
- Driver drowsiness detection (steering and camera)





# Sensor ranges



**77 GHz Long Range Radar (Lidar)**

Far Range  
1 m to  $\leq 120\text{m}$

**Infrared**

Night Vision Range  
0 to  $\leq 200\text{m}$

**Video**

Midrange  
0 to  $\leq 80\text{m}$

**24 GHz Short Range Radar**

Near Range  
0,2 to  $\leq 20\text{m}$

**Ultrasonic**

Ultra Near Range  
0,2 to  $\leq 1,5 (2,5)\text{m}$



# Vision-based DAS

## ■ Pros:

- Rich information source
- Can directly enhance visual sensing
- Wide field of application

## ■ Cons:

- Expensive (special cameras, processors)
- High computational load (high power consumption)



# Night Vision

- IR sensors
  - Active (Mercedes), ~150m
  - Passive (BMW), ~300m
  - Combined with motion (pedestrian) detection (Night Vision Assist Plus)



## A better view for the driver...

- 360 degree view to help parking
- Integration of images of 4 (or more) cameras
- Image geometry transformations
  - Warping
  - Homography



Bird view of the car from the cockpit of an Infinity

# Homography (H)

- Can be applied for plain objects
- Transformation from Camera 1 to Camera 2:

$$\mathbf{X}_2 = H \mathbf{X}_1 \quad \mathbf{X}_1, \mathbf{X}_2 \in \mathbb{R}^3$$

- Using homogeneous coordinates:

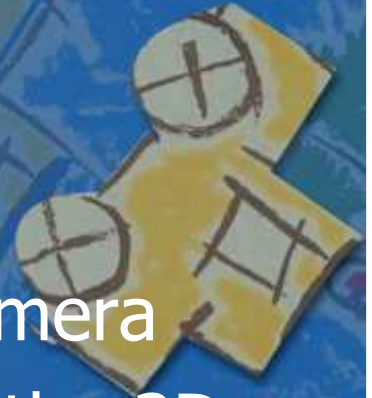
$$\lambda_1 \mathbf{x}_1 = \mathbf{X}_1, \quad \lambda_2 \mathbf{x}_2 = \mathbf{X}_2$$

- By image coordinates:  $\lambda_2 \mathbf{x}_2 = H \lambda_1 \mathbf{x}_1$
- H is estimated by calibration



# How DAS understands the visual information?

- Use only 2D information?
  - Classical 2D pattern recognition
- Use motion information?
  - Consider the ego-motion of the camera
  - Image motion greatly depends on the 3D structure of the scene
- or combine the two approaches...



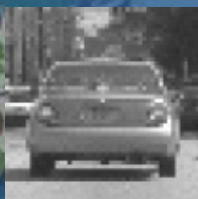


# Boosted classifier for car detection

- Large pool of weak classifiers
- AdaBoost to select and combine weak classifiers

Paul Viola and Michael Jones, "Robust Real-time Object Detection"  
*International Journal of Computer Vision (IJCV)*, 2004.

David C. Lee, and Takeo Kanade.  
"Boosted Classifier for Car Detection." 2007.



**Input  
image**

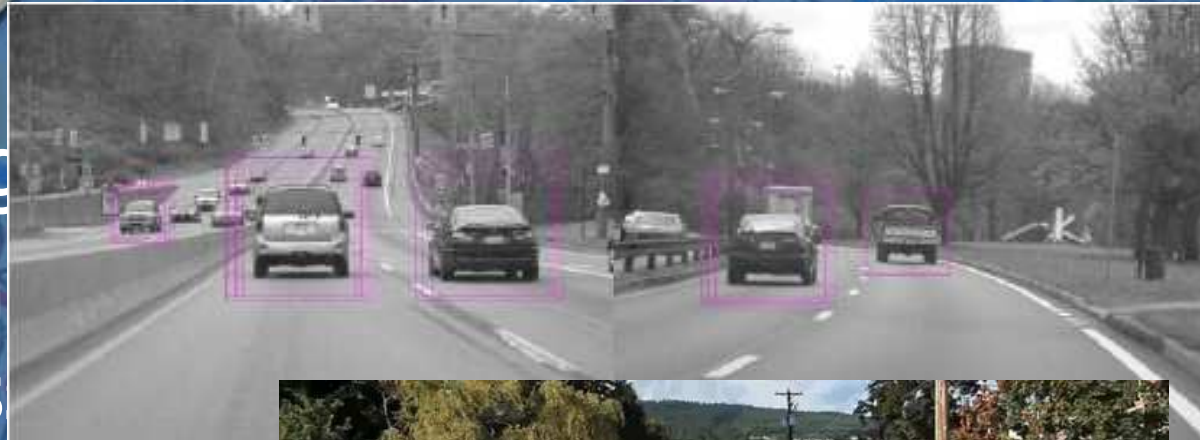


**Three filters selected  
by AdaBoost**



# Boosted classifier for car detection

- Large
- Ada
- clas



Relatively  
*Internation*

ak  
"S detection"

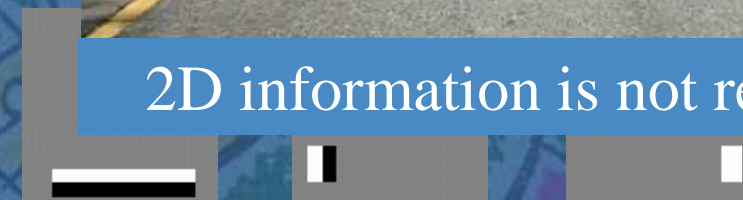
David C. Lee, and Tal  
"Boosted Classifier fo



2D information is not reliable



Input  
image



Three filters selected  
by AdaBoost

# Pedestrian detection

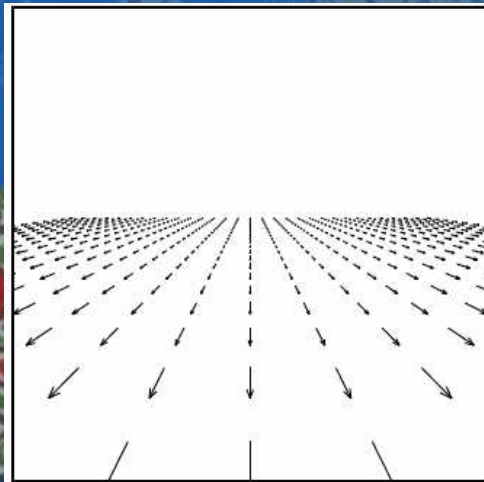
Paper	Approach	Description				
Papageorgiou IJCV00[5]	Shape	Based on local multiscale oriented intensity differences using Haar wavelet				
		<b>Paper</b>	<b>Objective</b>	<b>Sensors</b>	<b>Approach</b>	<b>Description</b>
Abramson IV04 [6]	St	Broggi IV04 [16]	Detection	FIR	Shape	Detects warm symmetric objects with specific size and ratio at multiple resolutions.
Hashiyama C- SMC03 [7]	M	Fang VT04 [17]	Detection	FIR		Shape independent approach using horizontal and vertical projection profiles. Classification based on multi-dimensional histogram, inertia, contrast features.
Viola ICCV03 [8]	M	Meis IV04 [18]	Detection	FIR	Head detection	Statistical approach for pixel classification for head detection. Comparison with classifier for body detection.
Havasi 04 [9]	St	Xu ITS05 [19]	Detection, tracking	FIR	Shape	Uses SVM for detection, Kalman filter and mean shift for tracking pedestrians. Output of road-detection module also used for validation.
		Liu VT04 [20]	Detection	FIR	Stereo, motion	Detects objects with motion not consistent with background without explicit ego-motion computation. Works well with dominant translation but small rotation of camera.
Shashua 04 [10]	St					
Zhao ITS00 [11]	St ne	Tsuji ITS02 [21]	Detection, collision prediction	FIR	Stereo, motion	Design of overall system. Discusses configuration, coordinate systems, simple IR based detection, tracking, computation of relative motion vectors, and conditions for collision judgment.
Gavrila IV04 [12]	St	Fang 03 [22]	Detection comparison	Visible, FIR	Feature-based	Compares use of visible and IR sensors. Introduces multi-dimensional feature-based segmentation and classification. Proposes novel features for segmentation to take advantage of unique properties of IR.
Hilario 05 [13]	St	Milch [23]	Detection	RADAR, monocular vision	Time-of-flight, shape	Target-list is generated using RADAR. These are verified by vision using flexible shape models trained from manually extracted pedestrians.
Gandhi ICIP05 [14]	St					
Lombardi IV04 [15]	St he	Scheunert IV04 [24]	Tracking	FIR, LASER scanner	Time-of-flight, hot object detection	LASER scanner detection using 1 <sup>st</sup> and 2 <sup>nd</sup> derivatives w.r.t. azimuth angles. IR detection using brightness and orientation. Uses Kalman filter for sensor fusion.

Tarak Gandhi and Mohan M. Trivedi: Pedestrian Collision Avoidance Systems: A Survey of Computer Vision Based Recent Studies, IEEE International Transportation Systems Conf., 2006

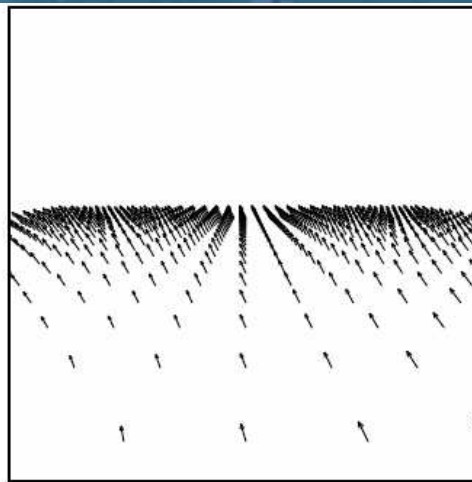


# Motion Detection

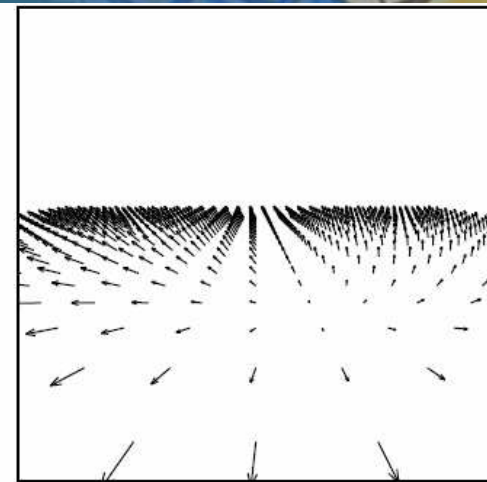
- Find changing areas in videos
- In case of moving cameras everything seems to move
- Motion patterns greatly depend on the camera ego-motion and on the 3D structure of the scene



Translation



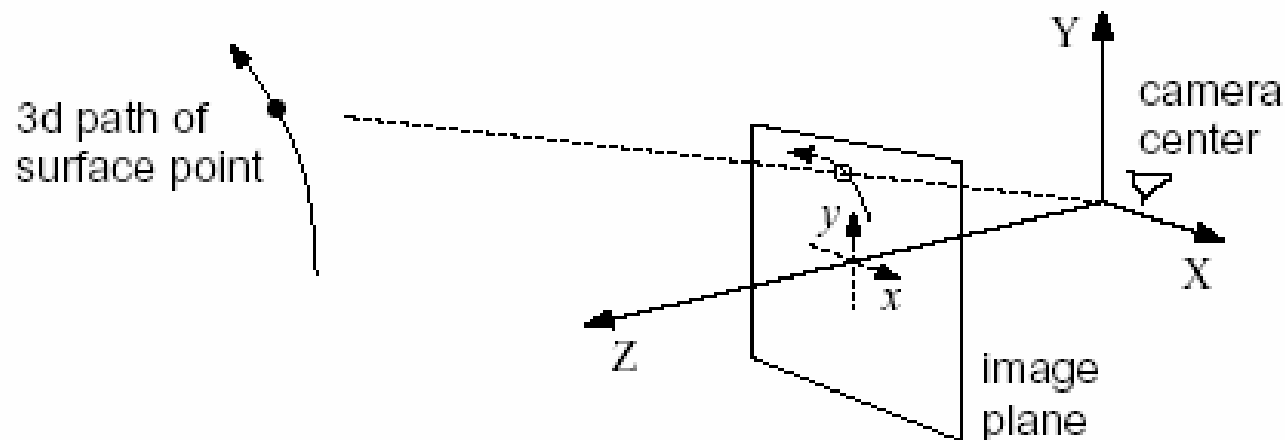
Rotation



Rotation+Translation  
of the camera

# 3D Velocity and 2D Velocity

- Motion equation if the camera moves...
  - $\mathbf{u} \in \mathbf{R}^2$  : image motion
  - $\mathbf{T} \in \mathbf{R}^3$  : translation of the camera
  - $\mathbf{\Omega} \in \mathbf{R}^3$  : rotation of the camera



$$\mathbf{u}(x, y) = p(x, y) \mathbf{A}(x, y) \mathbf{T} + \mathbf{B}(x, y) \mathbf{\Omega}$$

$$\mathbf{A}(x, y) = \begin{bmatrix} -f & 0 & x \\ 0 & -f & y \end{bmatrix} \quad p(x, y) = 1/Z(x, y)$$

$$\mathbf{B}(x, y) = \begin{bmatrix} (xy)/f & -(f + x^2/f) & y \\ f + y^2/f & -(xy)/f & -x \end{bmatrix}$$

# Image velocity in case of plains

- Image points belong to plain objects in 3D space

$$u_h = \frac{1}{fd}(a_1x^2 + a_2xy + a_3fx + a_4fy + a_5f^2)$$
$$u_v = \frac{1}{fd}(a_1xy + a_2y^2 + a_6fy + a_7fx + a_8f^2).$$

$$a_1 = -d\Omega_y + T_z n_x,$$

$$a_3 = T_z n_z - T_x n_x,$$

$$a_5 = -d\Omega_y - T_x n_z,$$

$$a_7 = -d\Omega_z - T_y n_x,$$

$$a_2 = d\Omega_x + T_z n_y,$$

$$a_4 = d\Omega_z - T_x n_y,$$

$$a_6 = T_z n_z - T_y n_y,$$

$$a_8 = d\Omega_x - T_y n_z.$$

- The main task is to find, by optimization, the best  $a_i$  parameters fitting to observations.

# Optical Flow Estimation

- Optical flow is an estimation of motion field
- Optical flow strongly correlates to the projection of real 3D motion
- Calculation is based on intensity conservation:

$$f(x, y, t) = f(x + u_v, y + u_h, t + 1)$$

- Several approaches are available:

- Block matching
- Horn and Schunk
- Lucas and Kanade
- ...

# Independent Motion Detection

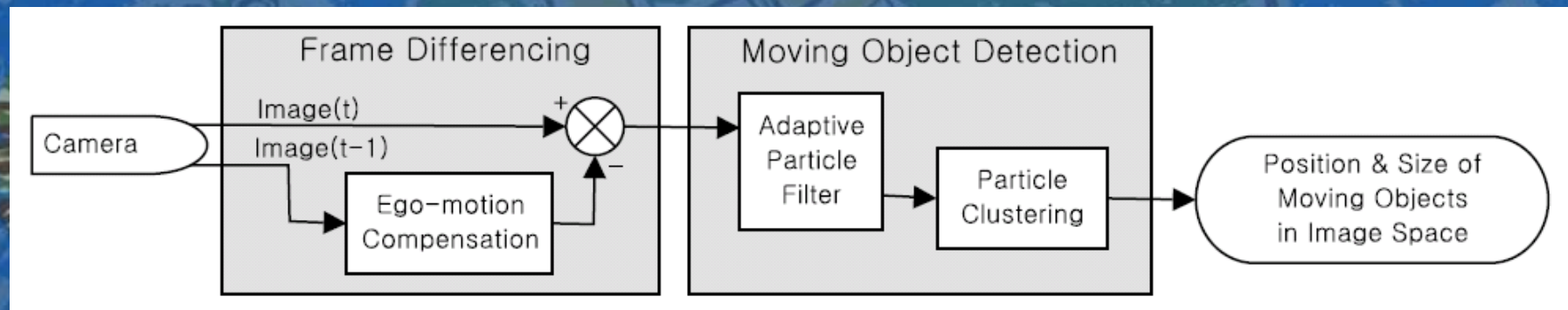
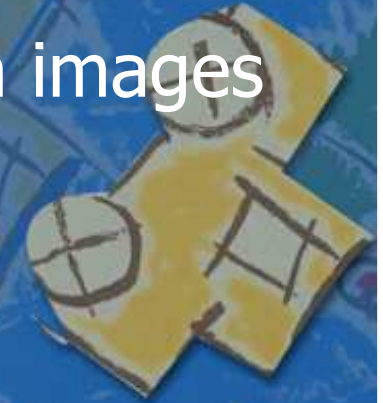
- It can be done with a single camera
- Assuming majority principle:
  - Some image model is assumed
  - Most points are “normal” background points
  - Outliers belong to independently moving objects (foreground points)





# Ego-motion removal

1. Find correspondence of image points in consecutive frames
2. Find the proper transformation between images (affine, perspective or linear models)
3. Apply transformation and make frame differencing



# Compensated image difference

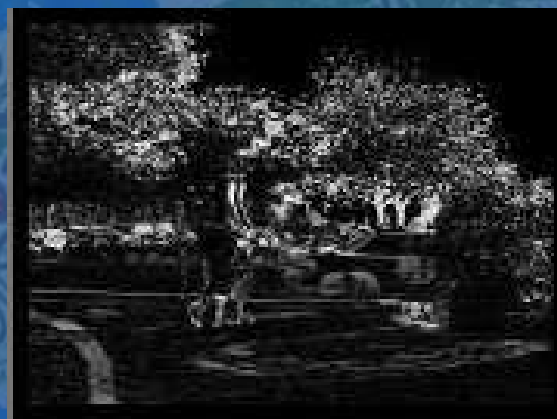


Frame t

Frame t+1

Normal difference

Compensated difference





# Object tracking

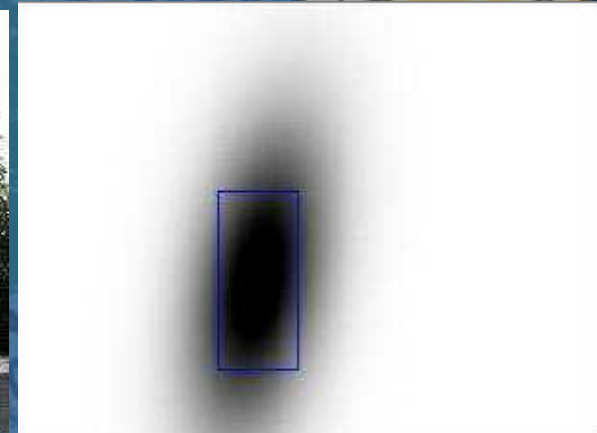
- Compensated difference image contains too much noise
- Particle/object tracking applied to find relevant moving points/objects



Input frame



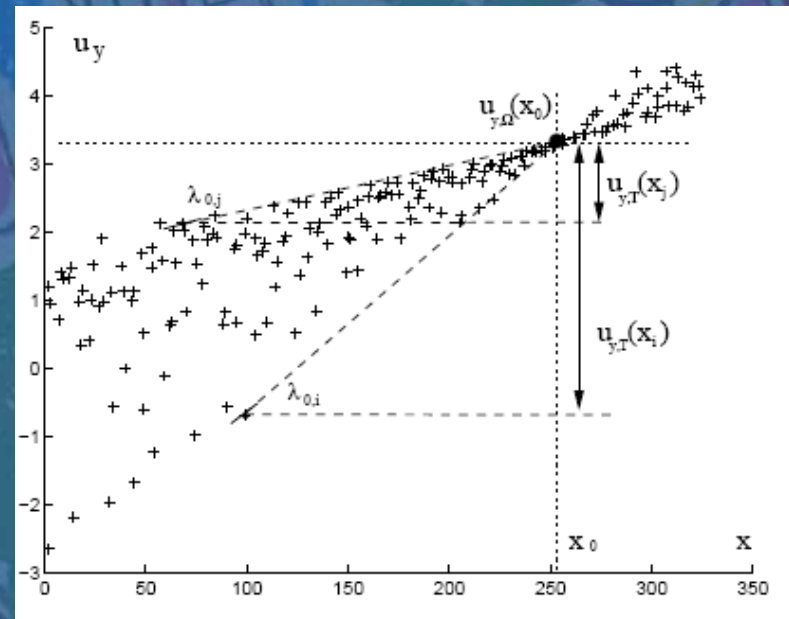
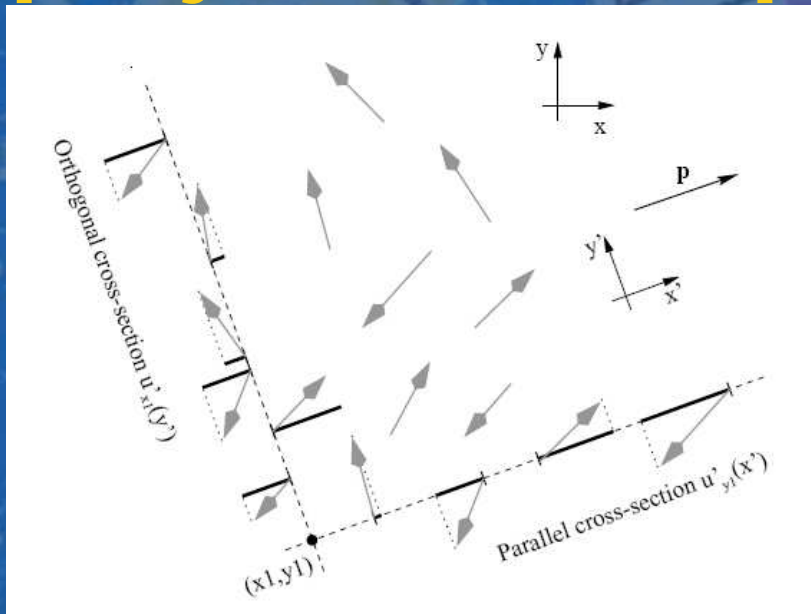
Particles tracked



Gaussian fitted

Boyoon Jung and Gaurav S. Sukhatme, Detecting Moving Objects using a Single Camera on a Mobile Robot in an Outdoor Environment, 8<sup>th</sup> Conf. on Intelligent Autonomous Systems, 2004

# Motion detection from the projection of optical flow vectors



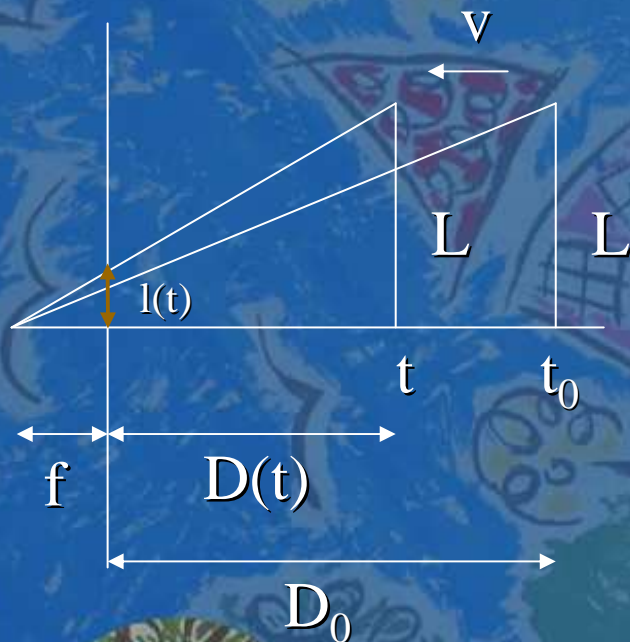
$$\forall x : \begin{cases} x \leq x_0 : & u_y(x) \leq u_{y,\Omega}(x_0) = u_y(x_0) \\ x \geq x_0 : & u_y(x) \geq u_{y,\Omega}(x_0) = u_y(x_0) \end{cases}$$

Drawback: needs large number of vectors

Sándor Fejes and Larry S. Davis: Detection of Independent Motion Using Directional Motion Estimation, Computer Vision and Image Understanding, Volume 74, Issue 2, 1999, Pages 101-120



# Simple Collision Detection



- Object of height  $L$  moves with constant velocity  $v$
- The image of the object has size  $l(t)$
- It will crash with the camera at time:
  - $D(t) = D_0 - vt = 0$
  - Time to Collide:  $\tau = D_0/v$

$$l(t) = \frac{fL}{D(t)}$$

$$l'(t) = fL \frac{v}{D^2(t)}$$

$$\tau = \frac{l(t)}{l'(t)}$$

**But what is the height of objects?  
(systems should not warn on patterns of the road surface)**

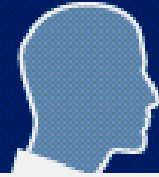
# Environment Discovery and Recognition

Image object classification based on segmentation:

1. Oversegmentation of image
2. Generating feature descriptors for image segments
3. Classification of segments



# Humans vs. Machines



„The best of both worlds“

Driver-vehicle-environment triangle

Human strengths	Strengths of technical systems
- Flexibility to respond to the situation as required	- No susceptibility to fatigue, stress or distraction
- Rapid decision-making, even in highly complex situations	- Objective measuring and assessment of physical values such as distance and relative speed
- Forward-thinking responses	- Fast pre-programmed reactions with high level of precision
- Rapid interpretation of situations	- Precise and reliable repetition of pre-defined processes
- Strongly developed ability to improvise	
- Instantaneous ethical assessment of situations	

Source: BMW

# Potential Problems with DAS

- Complexity of cockpit and handling
- Negative effect on driving skills
- Excessive reliance on ADAS
- Decreasing general driver alertness and systems imperfection can increase risks





# Conclusions

- Human errors can be reduced significantly
- Knowledge of human behaviour and psychology is necessary
- Wide diversity of solutions exists
- Intelligent systems: Understanding of complex traffic environment and situation is necessary



# Images, graphs and information originate from:

- Urmsom, C. et al. Tartan Racing: A Multi-Modal Approach to the DARPA Urban Challenge, *April 13, 2007*
- Sándor Fejes and Larry S. Davis: Detection of Independent Motion Using Directional Motion Estimation, *Computer Vision and Image Understanding, Volume 74, Issue 2, 1999, Pages 101-120*
- Boyoon Jung and Gaurav S. Sukhatme, Detecting Moving Objects using a Single Camera on a Mobile Robot in an Outdoor Environment, *8th Conf. on Intelligent Autonomous Systems, 2004*
- Tarak Gandhi and Mohan M. Trivedi: Pedestrian Collision Avoidance Systems: A Survey of Computer Vision Based Recent Studies, *IEEE International Transportation Systems Conf., 2006*
- W. Uhler, H.-J. Mathony, and P. Knoll, "Driver assistance systems for safety and comfort," Robert Bosch GmbH, Driver Assistance Systems, Leonberg, EU-Projekt EDEL im 5. Rahmenprogramm, edel-eu.org, 2003.
- BMW Group driver assistance systems. BMW Group publications, 2008
- F. Küçükay & J. Bergholz, Driver Assistant Systems, Institute of Automotive Engineering, TU Braunschweig, 2004
- GLOBAL STATUS REPORT ON ROAD SAFETY, Department of Violence & Injury Prevention & Disability (VIP), WHO, 2009
- Maria Staubach, Factors correlated with traffic accidents as a basis for evaluating Advanced Driver Assistance Systems, *Accident Analysis and Prevention 41 (2009) 1025–1033*
- Karel A. Brookhuis, Dick de Waard and Wiel H. Janssen, Behavioural impacts of Advanced Driver Assistance Systems—an overview, *EJTIR, 1, no. 3 (2001), pp. 245 – 253*
- Hucker Zsolt, Classification of traffic images, Diploma Thesis, University of Pannonia, 2009



# Abstract

- Driver Assistance Systems (DAS) are becoming very popular in today's commercial vehicles. Comfort, safety and environmental considerations require the effective use of a great variety of sensors and signal processing technologies. In the lecture an overview is given about the different DAS applications including the theoretical background of video based systems. Camera-independent motion detection and obstacle detection, as the basis of several functions, are also discussed.