

Methodologies and Techniques for Cognitive Automobile applications

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On behalf of the Intelligent Vehicle Team
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www.hds.utc.fr

Which title?

- ▶ *Environment for Cognitive automobile*
 - Better Title:
- ▶ *Methodologies and Techniques for Cognitive Automobile applications*
- ▶ Application oriented selection of methodologies and techniques
- ▶ Project oriented vision (French, German and European)

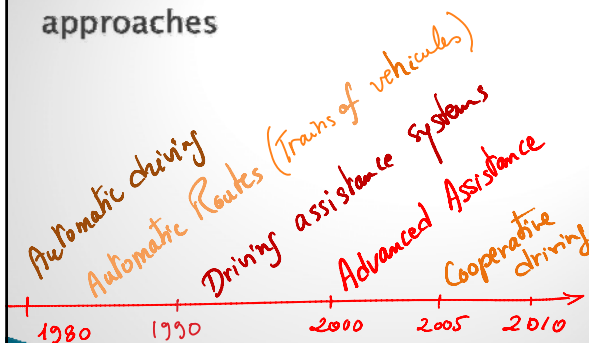
Automotive industry

- ▶ Situation in France:
 - 35 million vehicles
 - 4 million employments (direct or indirect)
 - Market in XXB€, £, \$
- ▶ Passionate relation with « my » car
 - Would my vehicle remain so dumb?
- ▶ Intelligent Transportation Systems
- ▶ IEEE ITS group, IEEE trans. For ITSC, trans. for Vehicular Technology

outline

- ▶ Orientations of research in automotive field
 - Automatic driving versus Advanced Driving Aid Systems
- ▶ Environment perception
 - Sensors, data fusion, etc.
- ▶ Driver behavior assessment
 - Driving situation awareness
- ▶ Cooperative cognition
 - Distributed approach

Evolution of "automation" approaches



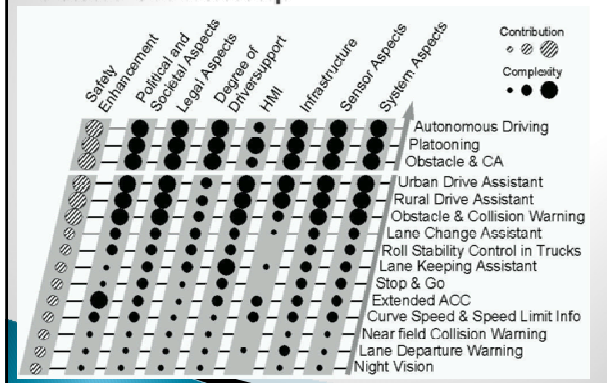
Automatic driving versus driving assistance

- ▶ « *An ultimate artificially designed cognitive system should include a human operator* »

Simon Haykin, McMaster Univ.
Dynamic Cognitive Systems Workshop,
Niagara-on-the-Lake,
May 26-29, 2008

- ▶ Research works nearly abandoned automatic driving for driving assistance
 - Do not replace driver, but assist him
- ▶ Introduction of ADAS
 - Advanced Driving Aid System

Adas Roadmap



Radar ACC



Figure 2: "Distronic" ACC radar for Mercedes (source: www.daimlerchrysler.de)



Figure 4: ITERIS "Auto-vue" Lane Warning system (source: www.iteris.com)



Figure 3: Night Vision system on Cadillac Deville (source: www.cadillac.com)

second generation ADAS

- ▶ **Semi-automatic parking**
 - helps the driver in penetrating into a parking slot in a parallel manoeuvre
 - by automatically acting on the steering wheel
 - driver is acting only on the pedal with the reverse gear inserted
 - In camera is controlling the motion of the vehicle
- ▶ **The pre-crash systems**
 - announced by Toyota and Honda
 - reduce the negative effects of an accident
 - acting on the pretensioner of the safety belts before the accident
 - occurs and to reinforce driver pressure on the brake pedal in case of an imminent collision.
- ▶ **Tendency**
 - introducing functions more directly related to safety than to comfort, such as ACC.

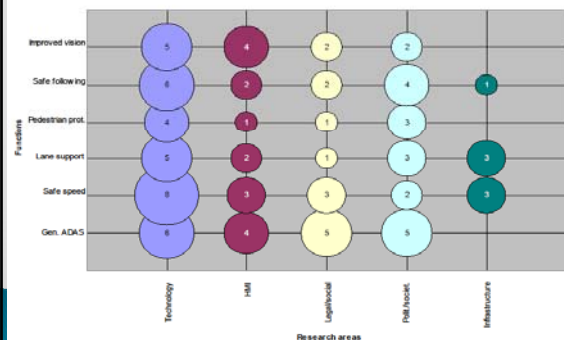
European research program Adase II

- ▶ **System Aspects**
 - To deal with complexity of the controller algorithms.
- ▶ **Sensor Aspects**
 - Key technologies to detect the environment and the surrounding traffic
 - Radar, lidar or video image processing
 - Data fusion
- ▶ **Infrastructure (incl. Communication v2i)**
 - Measure for street construction (e.g. brightness of lane markers)
 - Technical devices (e.g. light warning system)
 - Communication between infrastructure and vehicles
- ▶ **Communication v2v**
 - Vehicles network dimensioned to assistance system (e.g. concerning range).

Adase II

- ▶ HMI Aspects
 - The HMI gives the driver the feedback of the system activities or available information. Further aspects related to this topic are user acceptance and learn ability.
 - Technology roadmap ADASE 01.10.03
 - Deliverable D2D (Draft) Version 1.0 4
- ▶ Degree of Driver Assistance
 - The degree of driver assistance represents the different stages of driver support (e.g. information, warning, support, autonomous intervention). The more of the driving task is done by the system, the less the driver himself has to fulfill this task. This aspect is strictly connected with HMI, legal and system aspects.
- ▶ Legal Aspects
 - As some of the assistance systems can possibly overtake certain aspects of the control of the car, it becomes more and more necessary to think about the legal aspects concerning liability of the manufacturer, the car owner and the driver. The responsibility of the driver will be questioned depending on the degree of driver assistance.

EU integrated projects (700 M€)



ADAS usefulness assessment

➤ Impact on Driver behavior

Roadsense UE project

Objectives



Develop a **methodology** of assessing the **efficiency** of the new driving assistance systems
Multi-disciplinary work
 {Human Factors + Techno}

Develop **technological tools** to set up this methodology
 Definition of **DBITE**
 (Driver Behaviour Interface Test Equipment)

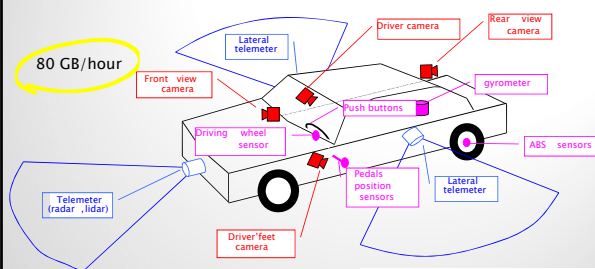
Metrics for driver behaviour

Table 1. Number of selected metrics

	NB of found metrics	NB of selected metrics	NB of selected metrics with target values
Lateral control	14	8	3
Visual scene management	7	5	5
Longitudinal control	3	2	0
Interactions with other vehicles	13	5	1
Situation awareness	16	7	6
Support of the system	24	16	6
Driver physiological status	5	0	0
total	82	45	21

- ▶ Among 82 metrics found in the literature, 45 have been selected for real road situations experiments
- ▶ Example:
 - Lateral control
 - ▶ Number of major line deviation
 - ▶ Steering wheel position variance
 - ▶ Steering wheel reversals rate
 - ▶ Time to Lane Crossing (TLC)

DBITE equipment



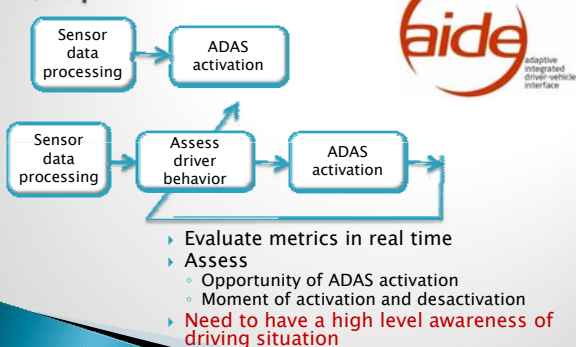
ADAS assessment

- ▶ Experiments with tens of drivers
 - With the new ADAS
 - Without the new ADAS
- ▶ Record all vehicle sensor data and videos during test sequence
- ▶ Post-synchronize data at 1 ms resolution
- ▶ Compute off-line all metrics
- ▶ Assess usefulness

Results

- ▶ Renault use case
 - ACC, Adaptive Cruise Control, radar to detect TTC and action on breaks
- ▶ Porsche use case
 - Night Vision System using a Head Up Display, *projected image overlays the real scene on widescreen*
- ▶ PSA Peugeot Citroën use case
 - Hypo vigilance detection camera

Following step: ADAS in closed loop



Data fusion for driving situation characterization

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Heudiasyc Lab – UTC (France)

Data fusion for driving situation characterization

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Experimental Vehicle :
STRADA

Telemeter

Cameras

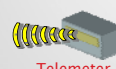


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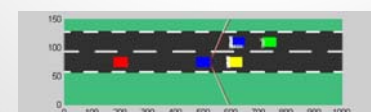
Overtaking sequence



Camera

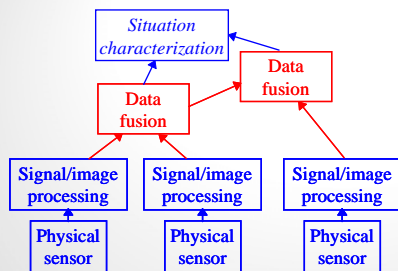


Telemeter



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Perception architecture



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For a particular application

- ▶ What objectives to reach?
- ▶ What information to get?
 - Front vehicle following: position and speed of the front vehicle (accuracy: position 20cm, speed 5km/h)
 - Overtaking assistance: existence of a rear left vehicle (no vehicle: 100%, a vehicle 90%)
- ▶ Characterization of the data:
 - accuracy, reliability, frequency, delay*

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Objectives

- ▶ take advantage of *redundancy* of data to increase the *accuracy* and the *reliability*
- ▶ take advantage of the *complementary* data to access to a higher level of interpretation

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Definition of accuracy

- ▶ Estimation of the difference between the measure m from the sensor and the real unknown value X to measure
- ▶ Ordered and continuous space of definition Ω



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Example

The distance between the experimental vehicle and the front vehicle (target) is $23m$ more or less $60cm$

This means :

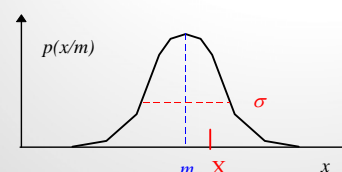
The real value X of the distance is in the interval $[22,4m ; 23,6m]$

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Accuracy modeled by probabilities

$p(x/m)$: probability that $X = x$, if the measure is m

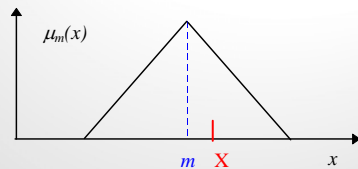
Gaussian distribution : mean m , variance σ^2



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Accuracy modeled by fuzzy sets

$\pi_m(x)$: possibility that $X = x$, if the measure is m
 The membership function $\mu_m(x) = \pi_m(x)$ is defined by an expert



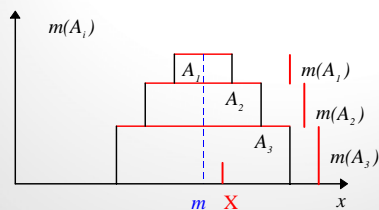
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Accuracy modeled by evidential theory

- ▶ The space of discernment is the set 2^Ω of the subsets A_i of Ω
- ▶ $m_m(A_i)$ is the evidence that X is in A_i if the measure is m

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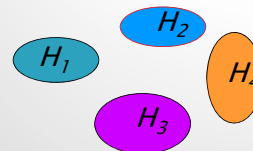
Accuracy modeled by evidential theory



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Definition of reliability

- ▶ Estimation of the confidence in an hypothesis H_i
- ▶ Discrete and non-ordered space of definition Ω



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Example

- ▶ H_1 : the target is a car
- ▶ H_2 : the target is a truck
- ▶ H_3 : the target is a motorbike
- ▶ H_4 : the target is a pedestrian

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Data processing

- ▶ Temporal data fusion
- ▶ Fusion of redundant data
- ▶ Fusion of complementary data
- ▶ Symbolic characterisation of the situations

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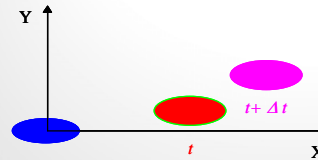
Temporal data fusion

- ▶ The experimental vehicle (EV) moves in the static environment
- ▶ Other vehicles around the experimental vehicle move too.
- ▶ The information, true at time t , becomes false at time $t + \Delta t$
- ▶ Need to time stamp the data (different delays and frequencies)

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Example of data evolution



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Data evolution

- ▶ Use of the model evolution (a priori knowledges)

$$v(t + \Delta t) = \gamma \Delta t + v(t)$$

$$x(t + \Delta t) = 1/2 \gamma \Delta t^2 + (v(t + \Delta t) - v(t)) \Delta t + x(t)$$

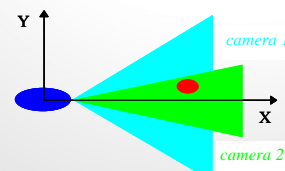
- ▶ Based on the Kalman filter
- ▶ Target following algorithm
 - line following
 - multi-vehicles following

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Fusion of redundant data

- ▶ Simultaneous observations of the same object
- ▶ Improve the accuracy
- ▶ Few redundant data because of the lack of sensors

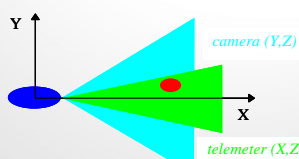


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Fusion of complementary data

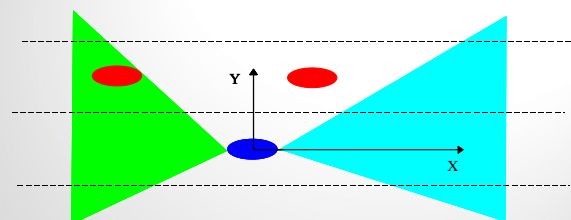
- ▶ Same object, different types of data
- ▶ Different objects
- ▶ Increase the knowledge on environment



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Fusion of complementary data

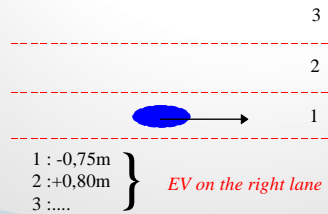


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Symbolic characterisation

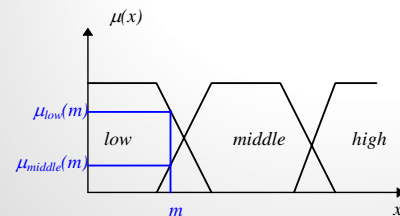
- Data interpretation
- Definition of the symbolic models
- Use of a priori knowledges



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The numeric/symbolic conversion



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maneuver recognition

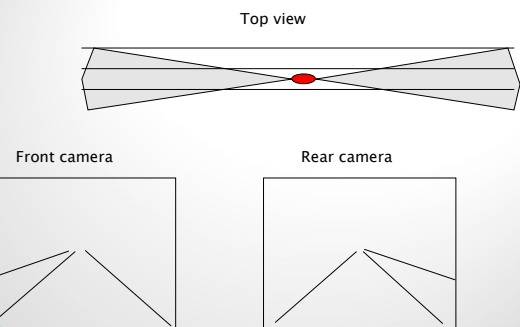
- Temporal sequence of situations
- Example of maneuver: the overtaking

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Overtaking

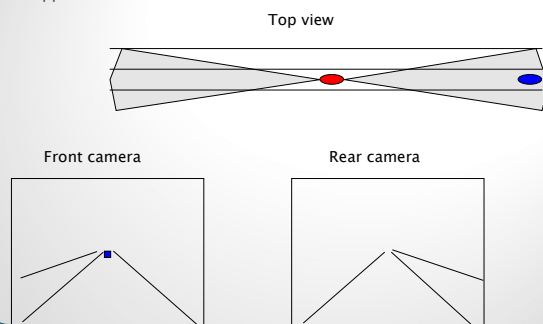
State :



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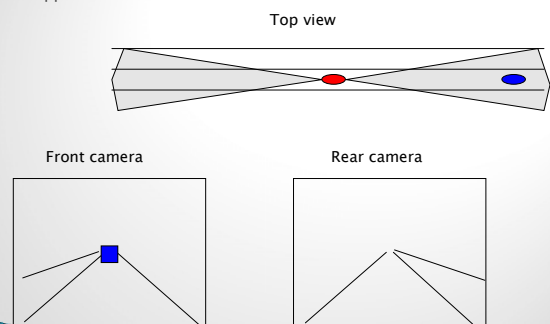
State : approach



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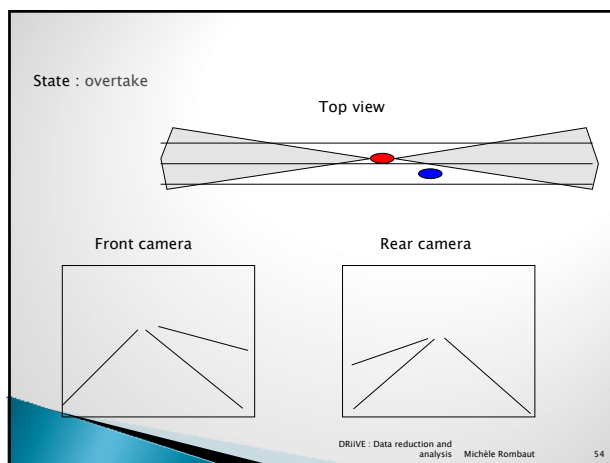
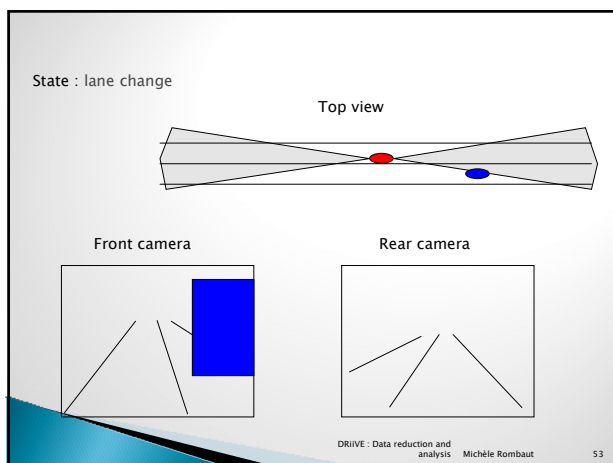
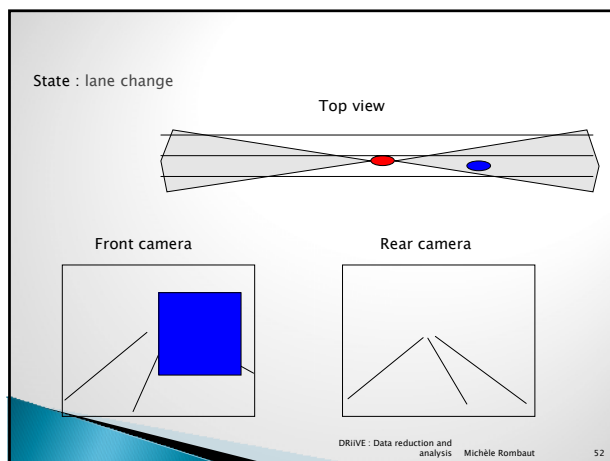
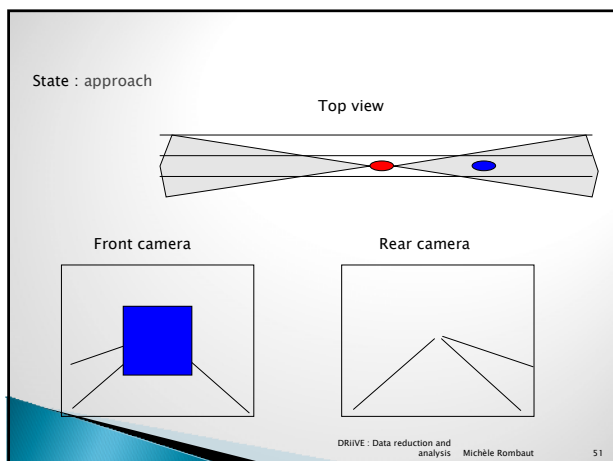
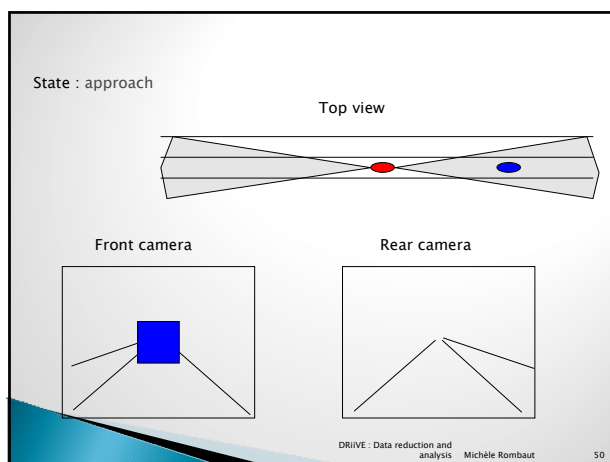
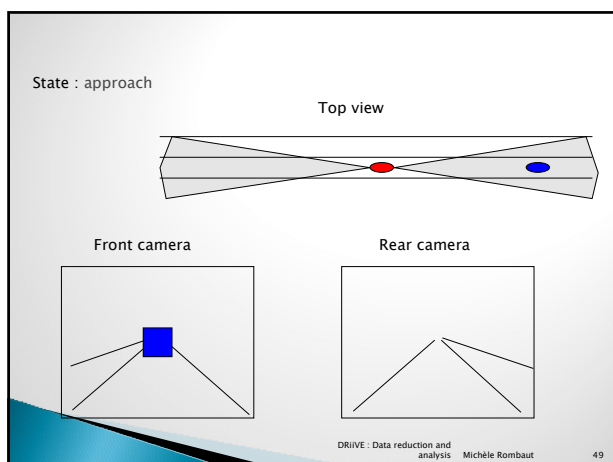
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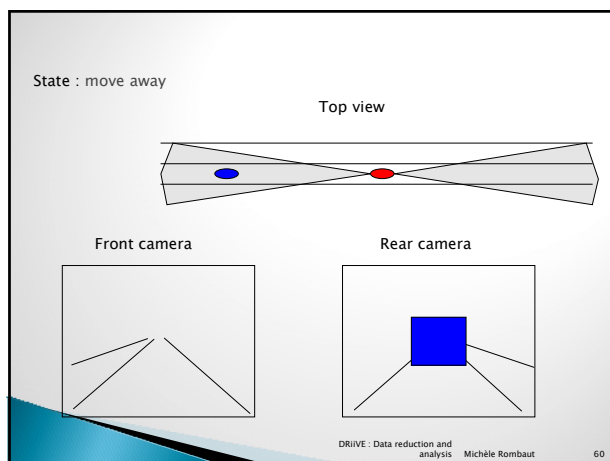
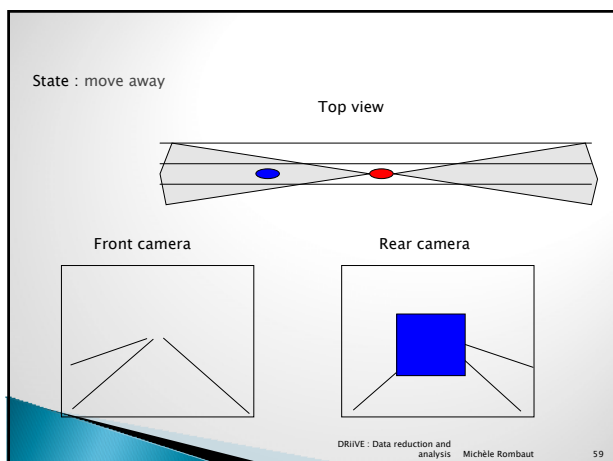
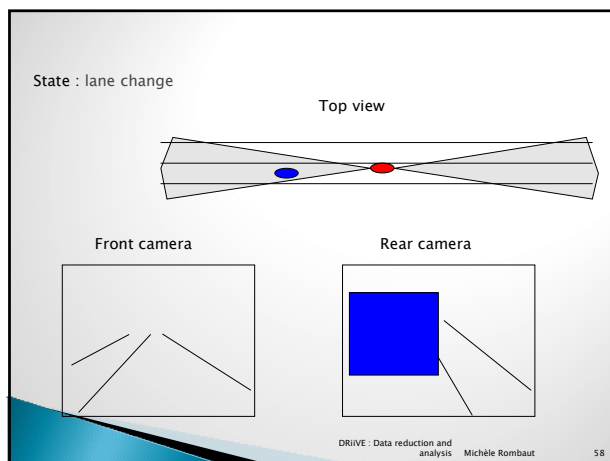
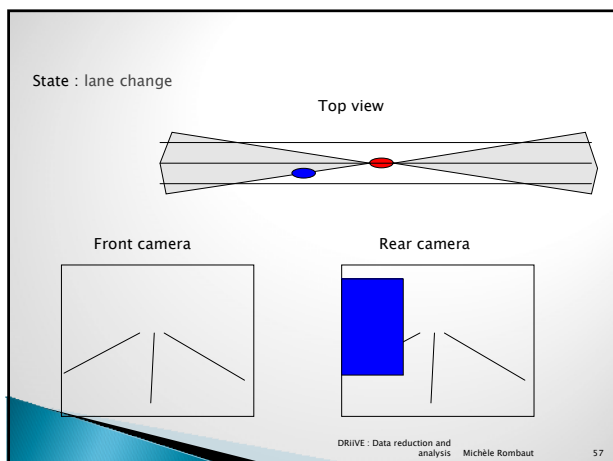
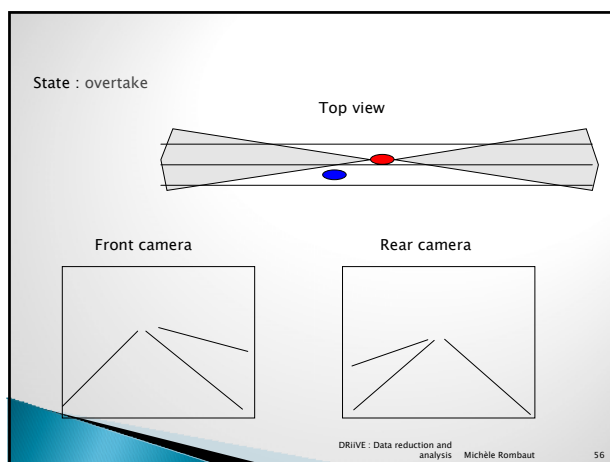
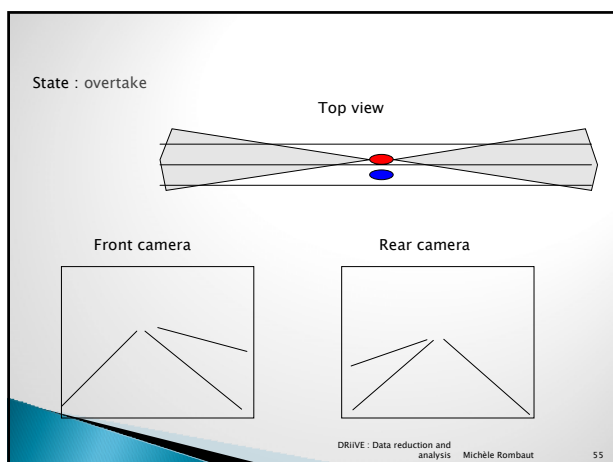
State : approach

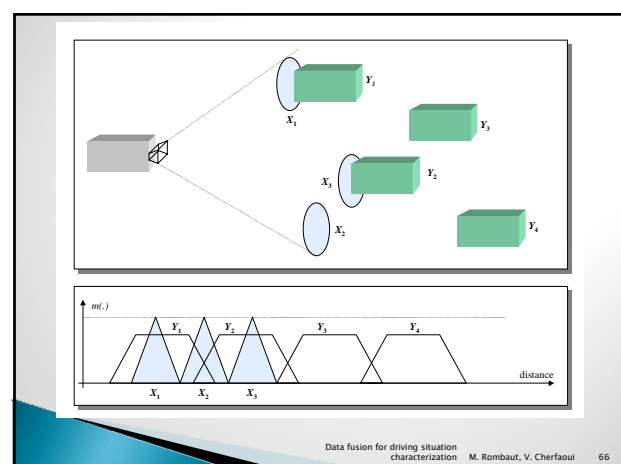
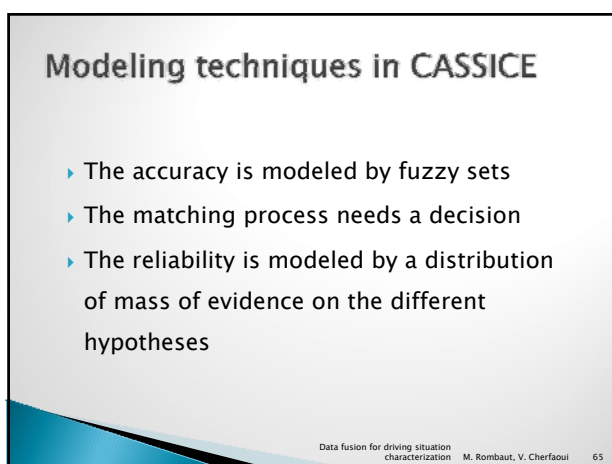
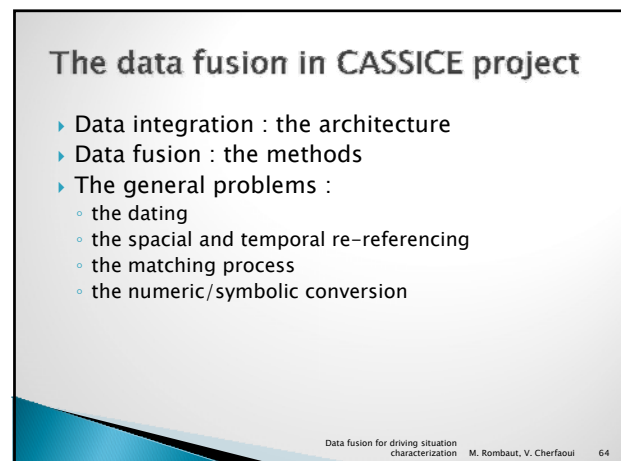
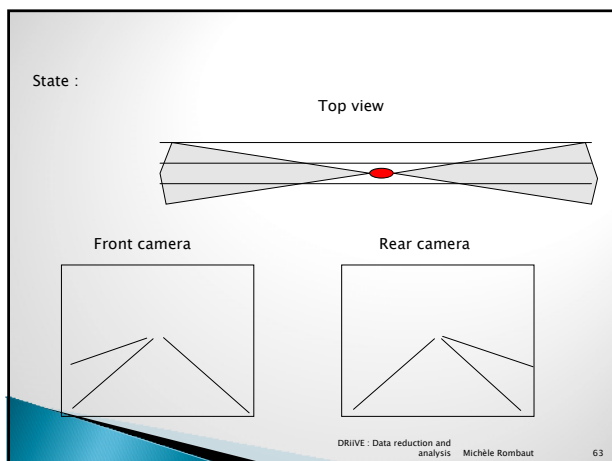
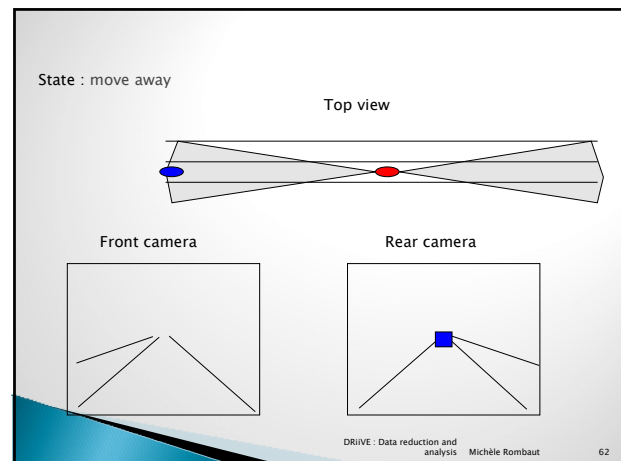
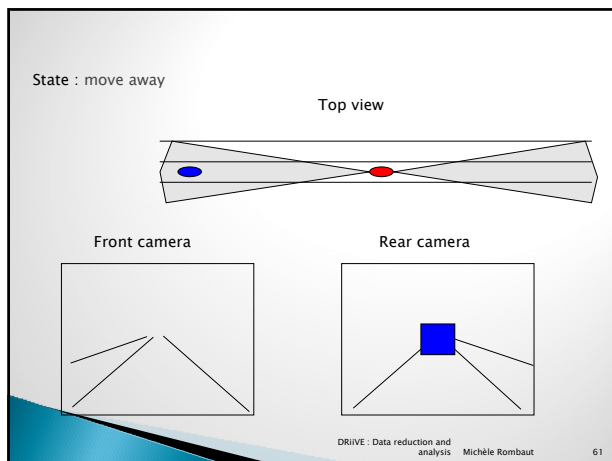


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General conclusions

- ▶ model the accuracy of the reports
- ▶ model the reliability of the reports and the decisions
- ▶ *one or several formalisms must be chosen in order to ease the data processing*
- ▶ define the fusion architecture
- ▶ the spatial and temporal re-referencing
- ▶ choose the matching algorithms
- ▶ choose the fusion algorithms

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High-level interpretations of driving situations

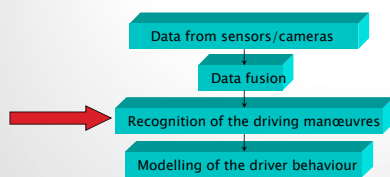


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Objectives



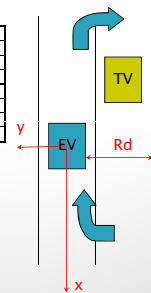
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Raw data

Time	X	Y	S	Teta	Acc	Phi	Rg	Rd
0.01	-32.00	0	15	0	0	0	-3.50	1.50
0.02	-31.85	0	15	0	0	0	-3.50	1.50
0.03	-31.70	0	15	0	0	0	-3.50	1.50
...
1.12	-15.52	-2.01	15	-9.91	0	3	-1.46	3.54
1.13	-15.37	-2.04	15	-9.68	0	3	-1.44	3.56
1.14	-15.22	-2.06	15	-9.46	0	3	-1.41	3.59

Data obtained from the experimental vehicle

Time	Clock (s)
Acc	Acceleration of EV relative to TV (meters/second)
Phi	Front wheel angle of EV (in degrees)
Rd	Position of EV against the right road side (meters)
Rg	Position of EV against the left road side (meters)
Teta	Angle of the target TV (degrees)
S	Speed of EV relative to TV (meters/second)
X	Position on the x's axis of TV against EV (meters)
Y	Position on the y's axis of TV against EV (meters)



Data fusion

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Recognition of the overtaking manoeuvre : 2 approaches

- ▶ Exhaustive generation of states, then choice of the best manoeuvre → IDRES approach
- ▶ contextual recognition of the overtaking manoeuvre → DSRC system

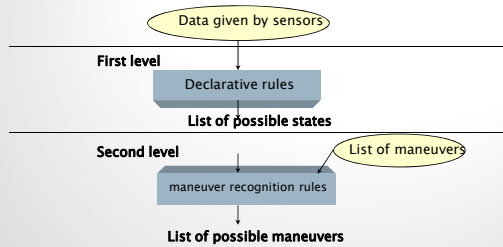
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States of the overtaking manoeuvre

1. Overtaking intention
2. Beginning of lane changing to the left
3. Crossing the left discontinuous line
4. End of lane changing to the left
5. Passing
6. End of Passing
7. Beginning of lane changing to the right
8. Crossing the right discontinuous line
9. End of lane changing to the right

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The IDRES approach



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The first level (declarative rules)

Rule Waiting_for_overtaking

If *EV and TV same lane* between times ?t1 and ?t2
EV behind TV between times ?t1 and ?t2

Then

State = "Waiting for overtaking" between times ?t1 and ?t2

Rule Overtaking_Intention

If *Fast coming from EV to TV* between times ?t1 and ?t2

Then

State = "Overtaking Intention" between times ?t1 and ?t2

Rule Crossing_left_line

If *Moving to the left* between times ?t1 and ?t2

Crossing the left discontinuous line between times ?t1 and ?t2

Then

State = "Crossing the left discontinuous line" between times ?t1 and ?t2

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Results obtained from the 1th level rules

Time	States
0.01 - 0.22	Waiting for overtaking Overtaking intent
0.22 - 0.58	Waiting for overtaking Overtaking intention Beginning of lane changing to the left
0.58 - 0.63	Waiting for overtaking Overtaking intention Beginning of lane changing to the left Crossing the left discontinuous line
...	...
2.15 - 2.22	Passing
2.22 - 2.23	Passing
2.23 - 2.51	End of passing

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2nd-level rules

Rule Begin_of_maneuver

If *A state S has been found between the time t1 and t2*

This state S is the first state of the maneuver M

The maneuver M has not still be recognized

Then

The maneuver M is in progress between the time t1 and t2 with the state S

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Results of the 2nd level rules

0.01 - 0.22	Waiting for overtaking	Normal overtaking
0.22 - 0.58	Overtaking intent	
0.22 - 0.58	Waiting for overtaking	
0.22 - 0.58	Overtaking intention	Normal overtaking
0.58 - 0.63	Beginning of lane changing to the left	
0.58 - 0.63	Waiting for overtaking	
0.58 - 0.63	Overtaking intention	
0.58 - 0.63	Beginning of lane changing to the left	Normal overtaking
0.58 - 0.63	Crossing the left discontinuous line	
...
2.15 - 2.22	Passing	Normal overtaking
2.22 - 2.23	Passing	Normal overtaking
2.23 - 2.51	End of passing	Normal overtaking

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First assessment

Advantages:

- exhaustive generation of states
- can easily recognize other kinds of maneuver

Drawbacks:

- recognition of the stages of the manoeuvre very closely related to low-level data -> many states may be recognized

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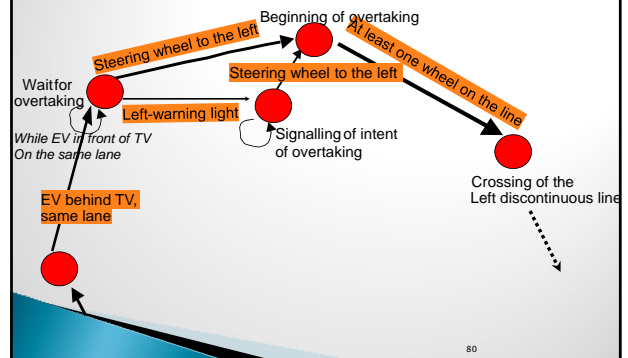
DSRC approach

- The overtaking manoeuvre may be seen as a succession of stages (or *states*)
 - wait for overtaking, beginning of changing lane, ..., passing, etc.
- The recognition of a stage requires that a certain state has been previously detected and that one or more actions have been performed

→ a graph of states

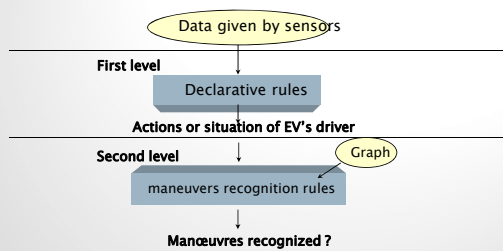
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Overtaking manoeuvre recognition graph



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The DSRC approach



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1st-level rules

- If, at time t , $\phi_i = 0.0$ and at time $t + 1$, $\phi_i = -3.0$ then consider that the user has turned its steering wheel to the left
- If, at time t , $\phi_i = 0.0$ and at time $t + 1$, $\phi_i = +3.0$ then consider that the user has turned its steering wheel to the right
- If, at time t , the equipped vehicle has a negative value for y then consider that it is behind the target vehicle
- If, at time t , y is in $[-1.00, +1.00]$ then both vehicles are on the same lane

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2nd level rules

- They are based upon the recognition of a graph
- If there exists a transition between 2 states E_i et E_j , and that its label is « action A », then we define the following rule :

If at time t , the state E_i is recognized, and the action A is detected **then** consider that the state E_j is recognized. E_j becomes the current state.

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2nd level rules

- ```
(defrule waiting_for_overtaking
 (same_lane ?t)
 (behind ?t)
 (rough_data (t ?t) (S ?vS))
 (test (>= ?vS 0))
 =>
 (assert (wait_for_overtaking ?t)))
```
- ```
(defrule signalling_intent_overtaking
  (left_warning_light ?t)
  ?t <- (wait_for_overtaking ?t)
  =>
  (retract ?t)
  (assert (signalling_intent_overtaking ?t)))
```

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First assessment

- ▶ Advantages
 - low cost : $\theta(n)$
 - permits to take into account the context/history of a situation
- ▶ Drawbacks
 - extension to other maneuvers : reuse of states?
 - Abort of the maneuver : how to recognize it?

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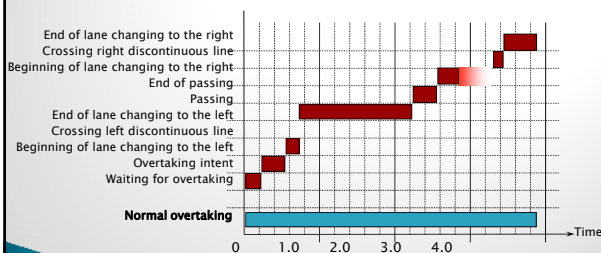
Results IDRES or DSRC ?

- Both approaches have to be more experimented on real data
- we have to experiment them with other maneuvers
- we have to handle the imprecision of real data that have consequences on
 - the states to generate in IDRES
 - the time at which the graph has to change its current state in DSRC, and the choice of the new state to recognize

→ Belief Petri nets

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IDRES Experimentation results

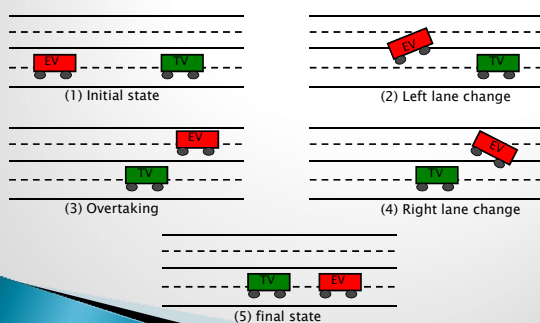


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High-level interpretations of driving situations

➤ Using Belief Petri net

High-level interpretations of driving situations



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Modelisation of the overtaking maneuver with a Petri net

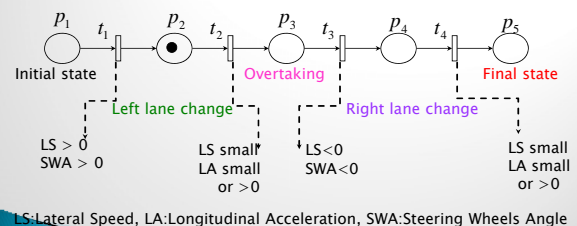
$PN = \langle P, T, R, M \rangle$

P: the set of places

M: the marking vector

T: the set of transitions

R: the vector of receptivity

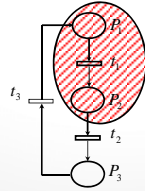
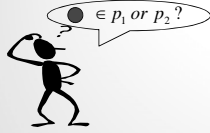


LS: Lateral Speed, LA: Longitudinal Acceleration, SWA: Steering Wheels Angle

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Problem

- State of the system **unknown**
- The transitions are uncertain



The theory of Petri net

+ The theory of evidence

The belief Petri net

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The belief Petri net

$$P = \{p_1, p_2, p_3\}$$

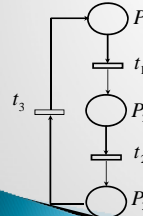
$$PN = \langle P, T, R, M \rangle$$

$$2^P = \{\{p_1\}, \{p_2\}, \{p_3\}, \{p_1, p_2\}, \{p_1, p_3\}, \{p_2, p_3\}, \{p_1, p_2, p_3\}\}$$

The new marking function

$$m^k : 2^P \rightarrow [0,1]$$

$$\sum_{A \subseteq P} m^k(A) = 1$$



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First step

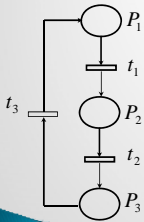
* The transitions are sure

$$R^k = [0,1,0]^T$$

* The initial state, at time k,

$$m^k(\{p_1, p_2\}) = 0.6, m^k(\{p_2, p_3\}) = 0.3,$$

$$m^k(\{p_1, p_2, p_3\}) = 0.1$$



$$\{p_1, p_2\} \xrightarrow{R^k = [0,1,0]^T} \{p_1, p_3\}$$

$$\{p_2, p_3\} \xrightarrow{R^k = [0,1,0]^T} \{p_3\}$$

$$\{p_1, p_2, p_3\} \xrightarrow{R^k = [0,1,0]^T} \{p_1, p_3\}$$

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Uncertain knowledge of transitions

The frame of discernment: $\Omega = \{0,1\}$

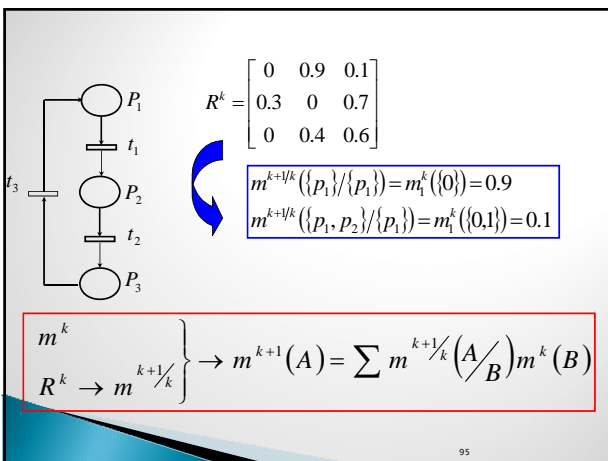
$$t_i \text{ is false} \rightarrow R_{i,1}^k = m_i^k(\{0\})$$

$$t_i \text{ is true} \rightarrow R_{i,2}^k = m_i^k(\{1\})$$

$$t_i \text{ is false or true} \rightarrow R_{i,3}^k = m_i^k(\{0,1\})$$

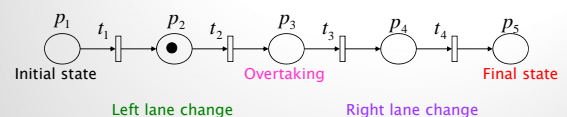
The vector of receptivity: $R^k = [R_{i,1}^k, R_{i,2}^k, R_{i,3}^k]_{i=1 \dots q}$

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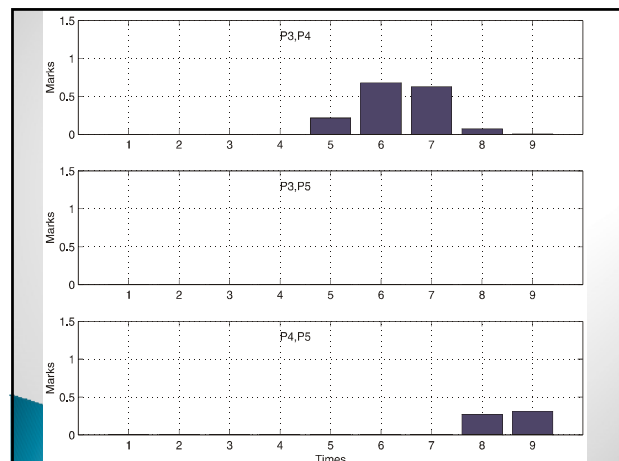
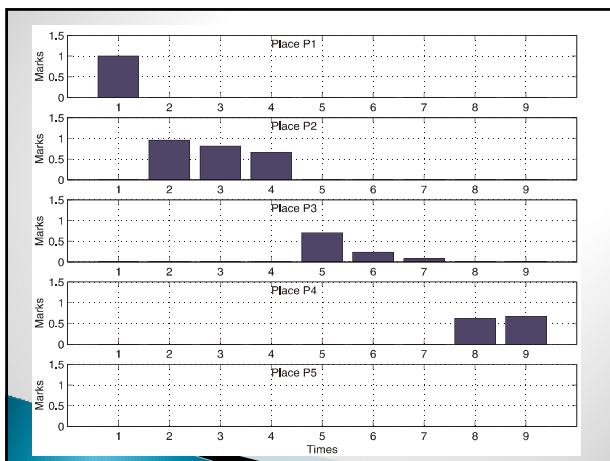


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Example of simulation



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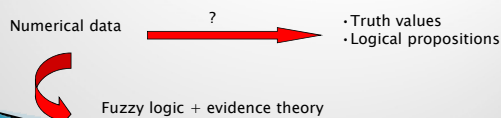
Conclusion

- Ignorance of the initial state
- Uncertain observations

Belief Petri net

Application:

- Driving assistance system
- Real measurements



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Real time implementation

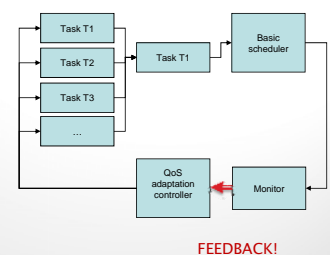
- » Cognitive software implementation?

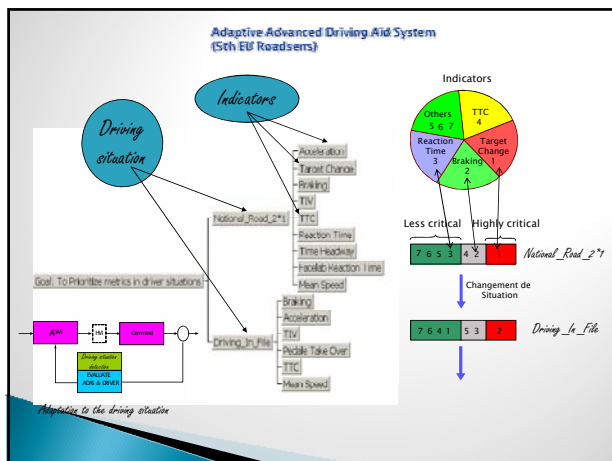
Processing needs

- 5 Pentium-4 PCs embedded in the car
 - Managing analyzing video streams
 - Computing metrics
 - Impossible to deploy on large scale
- Optimization efforts
 - Feedback real time scheduling
 - Compute only needed metrics according to driving situation

Dynamic modification of priorities according to criteria

- Compute task elicitation criteria
- Dynamically modify task priority
- Basic scheduler doesn't notice: task is scheduled





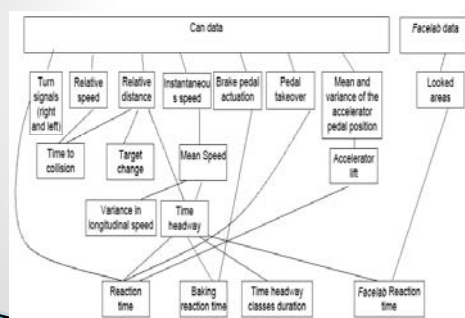
Priority Semantic

Principle:

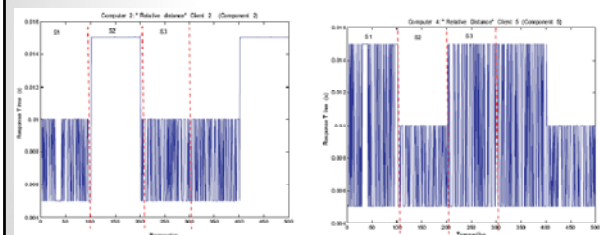
- Dynamically modify the task priority according to its computed results
- Example : compute the same metric (Human Factor) by two different methods (tasks)
 - Increase the priority of the task (method) that yields a 'better' result
 - Programmer provides code of both Tasks and their evaluation code
 - SCOOT-R middleware periodically invokes the evaluation and adjusts the task priorities

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Precedence rules

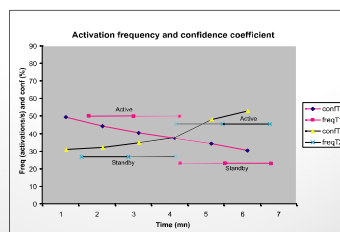


Results



Activation frequency wrt confidence coefficient

- Reducing computing resources need
- Down to 1.5 Pentium-4 PCs



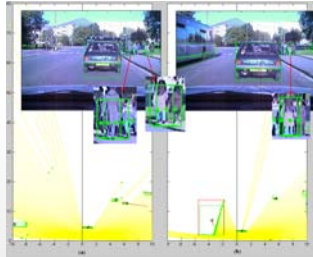
Pedestrian Detection

- LOVe project (French gov.)
- Multi-sensor approach
- Increase the detection reliability from 96% to 99%
- 20 partners, 20M€

-Véronique Cherfaoui, Philippe Bonnifait
-Heudiasyc Lab, Univ. Tech. Compiègne

Detection and tracking in driving situation

- › Laser-based perception
- › Cooperation with vision
- › Partially hidden objects
- › Road limits detection

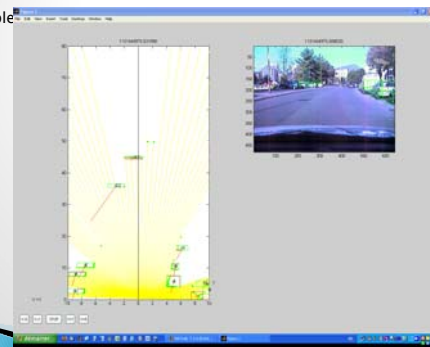


a) Pedestrians and car detection
b) Pedestrians, bus and car detection

[IV2007]

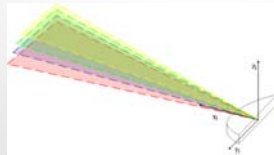
Detection and tracking in driving situation

- › Example



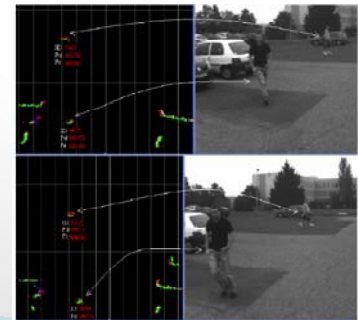
Detection and tracking in driving situation

- › Pedestrian detection (LOVe project)
- › Four planes laser scanner
- › Detection and recognition
- › Confidence indicators
 - Detection
 - Recognition
 - Tracking



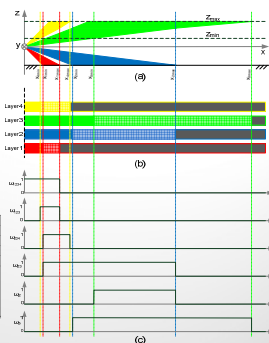
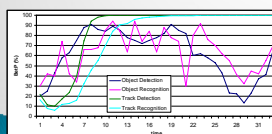
Detection and tracking in driving situation

- › Pedestrian detection (LOVe project)
- › Four planes laser scanner
- › Detection and recognition
- › Confidence indicators
 - Detection
 - Recognition
 - Tracking



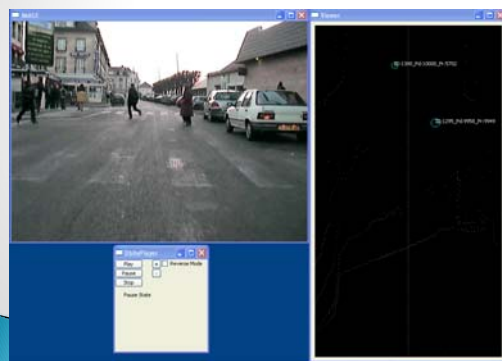
Detection and tracking in driving situation

- › Pedestrian detection (LOVe project)
- › Four planes laser scanner
- › Detection and recognition
- › Confidence indicators updating
 - Detection
 - Recognition
 - Tracking



Detection and tracking in driving situation

- › First experimentations

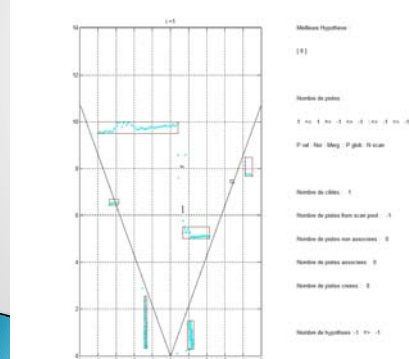


Data from Renault vehicle real sensors



Detection and tracking in driving situation

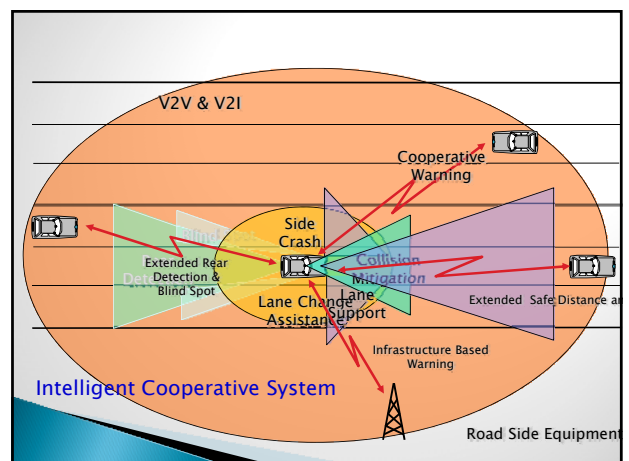
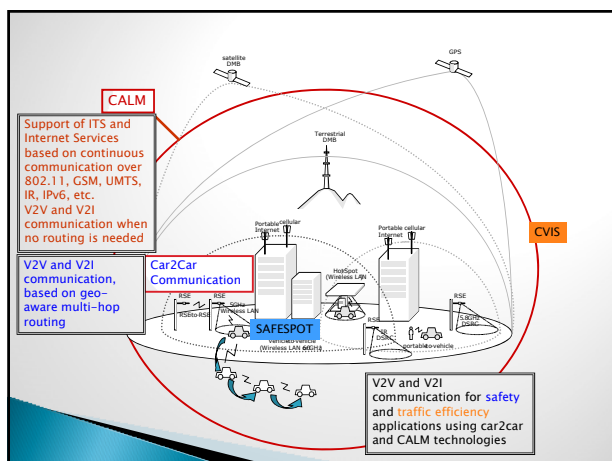
Example



Cooperative 'cognition'

- Vehicle to Vehicle and Vehicle to Infrastructure communication
- V. Cherfaoui, B. Ducourthial, M. Shawky, P. Bonnifait
- Heudiasyc Lab, Compiègne Univ. Of Technology


Bigger picture



SAFESPOT applications will allow the extension of the "Safety Margin" that is the time in which a potential accident is detected before it may occur (e.g. in static and dynamic black spots, in safety critical maneuvers)

Some typical use cases:

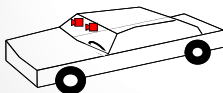
- Safe lane change maneuvers
- Road departure
- Cooperative situation awareness and extended collision warning
- Cooperative tunnel safety
- Road condition Information
- Cooperative maneuvering
- Predictive speed reduction



Cooperative approach

- ▶ Cooperate to better perceive
 - Loose cooperation
 - Receive information and update your Local Dynamic Map
 - Tight cooperation
 - Exchange information during the perception process
- ▶ Initiate cooperative behavior
 - Reduce speed for lane insertion
 - Reduce speed at intersection
- ▶ Distributed « cognition »?

Tight cooperative perception



Comparison of optic flows

- ▶ Compute pixels speed in both images sequences
- ▶ Aggregate intelligently
 - According to speed and "object" size
- ▶ Determine whether they belong to same object
- ▶ Match objects
- ▶ Stereo-compute distances
- ▶ Overall perception enhancement of 20%

LOOSE cooperation LOCAL DYNAMIC MAP SAFESPOT COOPERATIVE SYSTEMS FOR ROAD SAFETY

The target is the representation of vehicle's surroundings with all static and dynamic safety relevant elements

Com. nodes, fusion result

Temporary regional info

Landmarks for referencing

Map from provider

current view to be refined during the project

Vehicles

Road side unit

Ego Vehicle

Congestion

Tree

Fog

Accident

ITS in Europe Aalborg, June 20th 2007 Courtesy of Renault Information Society and Media 9

Data uncertainty management

- ▶ Goal :
 - managing **uncertainty** (or confidence) of redundant data
 - taking into account the **time management**.
- ▶ Ongoing works :
 - Data fusion approach with "**believe functions**" [Dempster-Schaefer, Smets]
 - believe functions model the uncertainty
 - conflict between 2 believe masses is quantified
 - decision tools : plausibility, credibility...
 - Each node combine with **aggregation** operators (conjunctive)
 - Attenuation is applied to aging data.

Redundant data management

- Using the uncertainty management from **redundant** messages in vehicular network in order to maintain a level of **confidence** in information
- Could be added in ad-hoc network protocol
- Could be applied to dynamic local map
- Could be used as one of security factors
- Managing obsolescence

Theory of evidence (Dempster, Schaefer)

Framework of hypothesis

$$\Theta = \{H_1, \dots, H_N\}$$

All possible hypothesis

$$2^\Theta = A / \{ A \subseteq \Theta \} = \{ \emptyset, H_1, \dots, H_N, H_1 \cup H_2, \dots, \Theta \}$$

Veracity of a hypothesis

$$m_\theta : 2^\Theta \rightarrow [0, 1]$$

Verifying the properties

$$i) m_\theta(\emptyset) = 0 \text{ (by)}$$

$$ii) \sum m_\theta(A) = 1$$

Focal elements

$$N_\theta = \{ A \in 2^\Theta / m_\theta(A) > 0 \}$$

Credibility and Plausibility

Credibility function (sum of veracities coming from different sources)

$$Cr_\theta : 2^\Theta \rightarrow [0, 1]$$

$$Cr_\theta(A) = \sum_{B \subseteq A} m_\theta(B)$$

Plausibility function (sum of no doubt)

$$Pl_\theta : 2^\Theta \rightarrow [0, 1] \text{ avec } Pl_\theta(A) = 1 - Cr_\theta(A)$$

$$Pl_\theta(A) = \sum_{A \cap B \neq \emptyset} m_\theta(B)$$

Dempster combination laws

Combine veracities from different sources for the same hypothesis

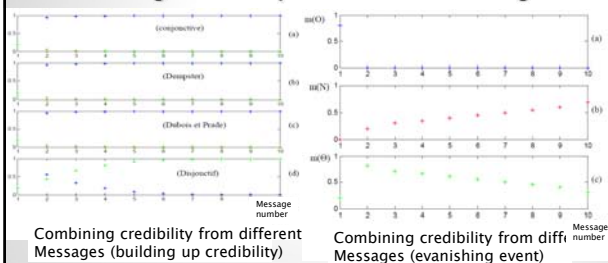
Conjunctive sum

$$m_\theta(A) = \sum_{A_i \cap B_j = A} m_\theta^i(A_i) \cdot m_\theta^j(B_j)$$

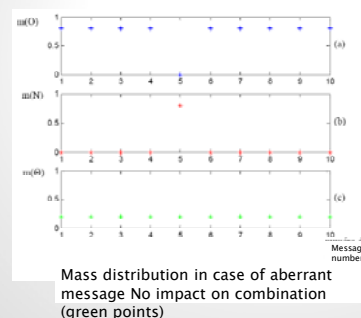
Disjunctive sum

$$m_\theta(A) = \sum_{A_i \cup B_j = A} m_\theta^i(A_i) \cdot m_\theta^j(B_j)$$

Combining credibility for different messages



Filtering capacity of aberrant message



Time management for messages

- All messages are time-stamped
 - Message end-of-life has to be managed
 - Binary threshold
 - Smooth impact (aging)
- Using the uncertainty techniques to **decrease** a message relevance in vehicular network
 - An old message (and its data) is better than no message (data) at all
 - Could be added in ad-hoc transmission protocol

Time decaying functions

Time decay functions

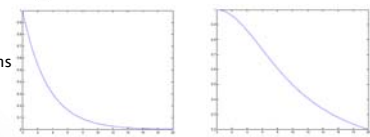
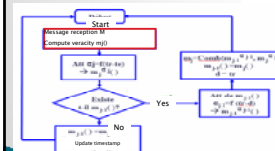


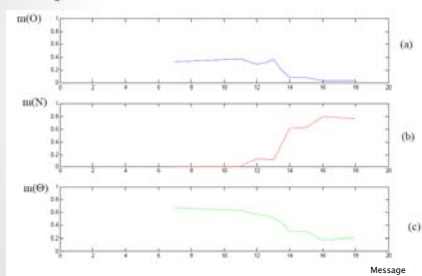
Fig 3-2: $\alpha = e^{-(t-t_0)/\tau}$

Fig 3-3: $\alpha = \frac{1}{0.01t + 1}$



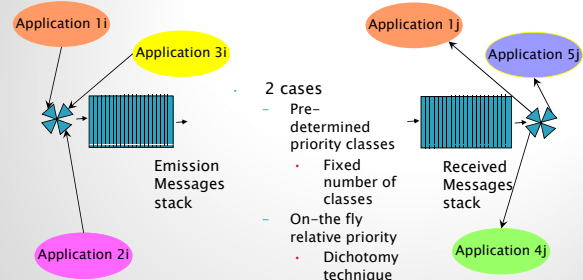
Combination process

Credibility combination with obsolescence



Event Credibility combination integrating obsolescence

Scheduling message stacks

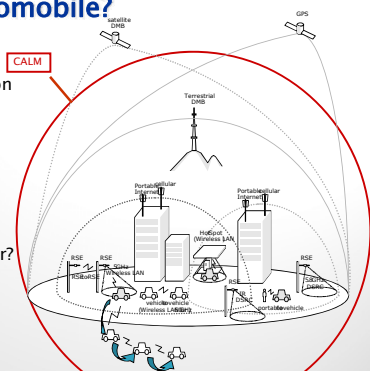


End to end messages priorities to avoid congestion

- Main constraint
 - No access to lower control layers
- Multi criteria communication optimization
 - Messages **priorities** (shared radio medium)
 - Higher priority of Alert and urgent messages
 - Bandwidth consumption
 - Adapt to exchanged messages **size** or to channel **occupation, road traffic** configuration
 - Adapt priorities of all comm. modules
- Feedback** to message emission scheduler
 - Periodically scan emission/reception stack
 - Reschedule by priority or by earliest deadline

Cognition Automobile?

- Distributed cognition versus supervised cognition?
- System of systems research program 2008-2012
- Would these techniques survive the scaling up factor?



Embedded computing in vehicle

- » – 20 % progress in embedded electronics per year since 2001
- Property verification to check safety and diagnosability aspects

Diagnosability assessment on functional/architectural level

M. Shawky, M. Khlif
Heudiasyc/CNRS/UTC

non-public presentation,
Project Confidential

28/05/2008

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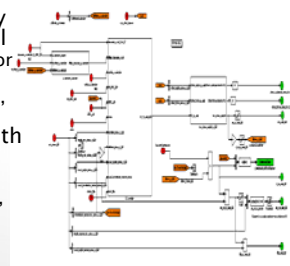
1

Embedded computing units

- » Comparable application
 - Avionics, but price / unit incomparable!
- » 60 ECUs (Electronic Control Units) on recent models
- » Whereas no overall design tools
- » Design approach quite empiric
- » Car manufacturers are just integrators
- » Few properties are checked during design process

Mixed functional and architectural model

- » Usually we have only the functional model
 - Formal or not, timed or not
 - Expressed in Simulink, matlab, etc.
- » Enrich this model with architectural information
 - I/O (linked to sensors, actuators)
 - Distribution on computing units
 - Communication between ECUs

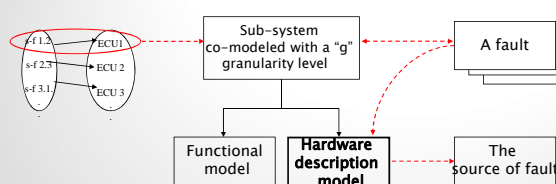


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3

Co-modeling granularity and supervision accuracy relationship

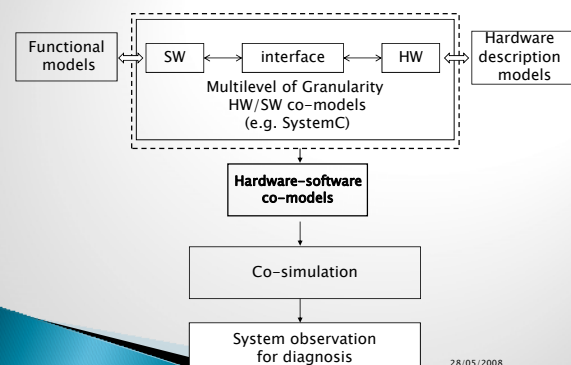


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HW/SW Co-modeling



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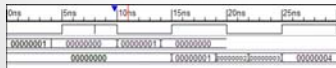
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Diagnosability metrics from system architecture viewpoint

- ▶ We started with
 - Degree of observability of
 - I/O, memory variables
 - Internal system state

- ▶ Other metrics should be added?

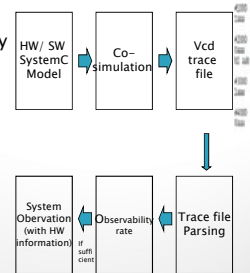


Observability rate = 1 - Occupation duration / Cycle duration

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6

Diagnosability & co-modelling

- ▶ Starting from simulink
- ▶ Convert to SystemC or any ADL (Architecture Description Language) to include architectural information
- ▶ Analyse the obtained model to assess the diagnosability metrics
 - Unwind the execution-operation
 - Associate to architecture modules
 - Compute the time slots to external access to I/Os
 - Compute « observability » degree



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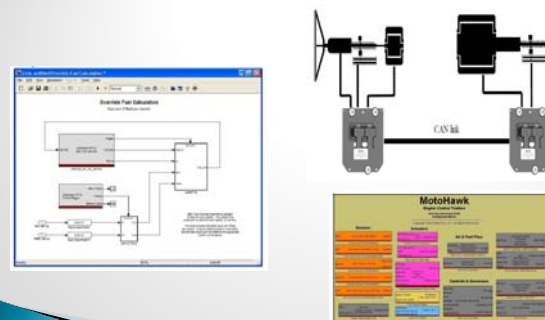
Assessment of results

- ▶ If observability degree not sufficient
 - Determine what are the additional I/O external cycles to add to observe
 - Needed I/O
 - Internal states
 - Memory variables
- ▶ Undergoing and future work
 - Determine the accessibility to I/O values by network
 - Define « reachability » degree via CAN network

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Platform



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9

Methodologies and Techniques for Cognitive Automobile applications

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University of Technology of Compiègne, France
Heudiasyc laboratory, Join Research Unit with CNRS
On behalf of the Intelligent Vehicle Team
Philippe Boninfaït, Ali Charara, Véronique Cherfaoui, Paul Crubillé, Gerald Dherbomez, Bertrand Ducourthial
www.hds.utc.fr