Future Challenges in Design Frameworks for Embedded Systems

Application to Intelligent Transportation Systems

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Meet the Expectations!

- Baby Girl iPad_ Magazine Confusion - YouTube [360p].mp4

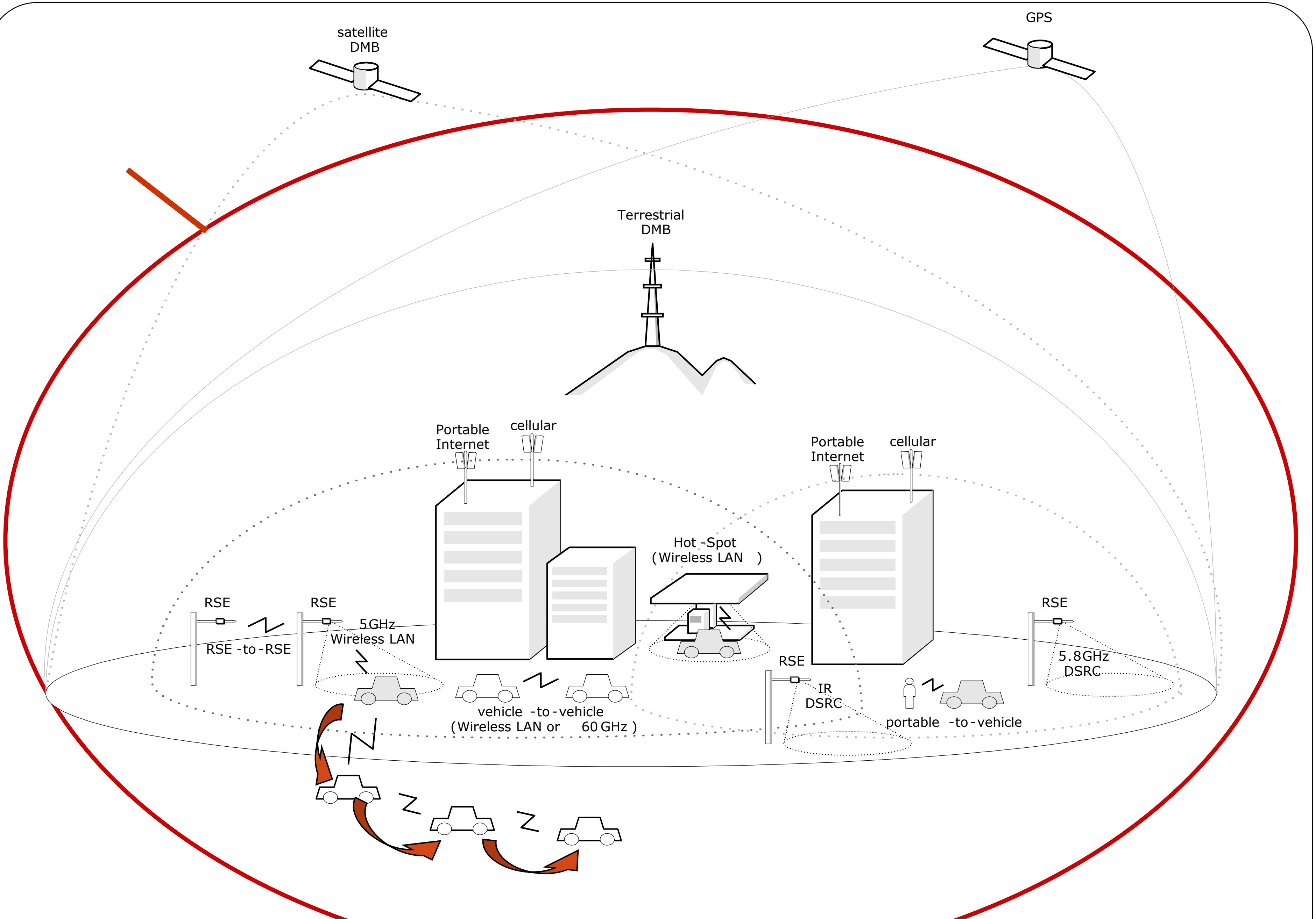
Dum systems no more tolerated!

- In the next 10 to 20 years
  - A ‘dum’ system will be considered dangerous
    - A car without pedestrian detection will no more be tolerated!
    - The same for obstacle detection with automatic breaking
  - So, no more:
    - dum vehicle!
    - Dum design tool!
    - Dum component!
    - Dum compiler!

Intelligent Transportation Systems

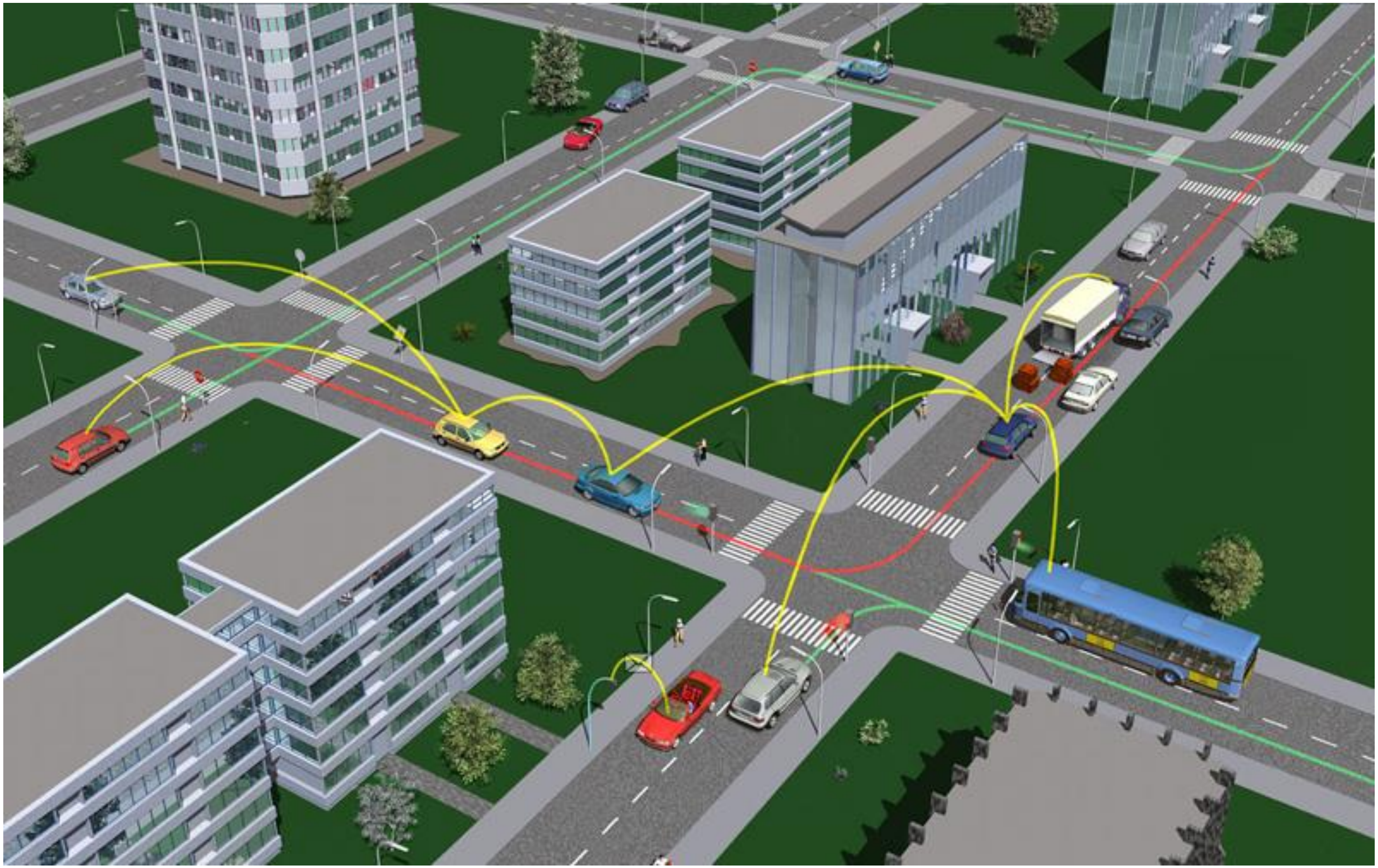
The bigger picture!


มักกะสัน
ดินแดง
อโศก
แว่นท็อปเจริญ
TOP CHAROEN OPTICAL
ISUZU
TAXI-METER
scotty_Graham

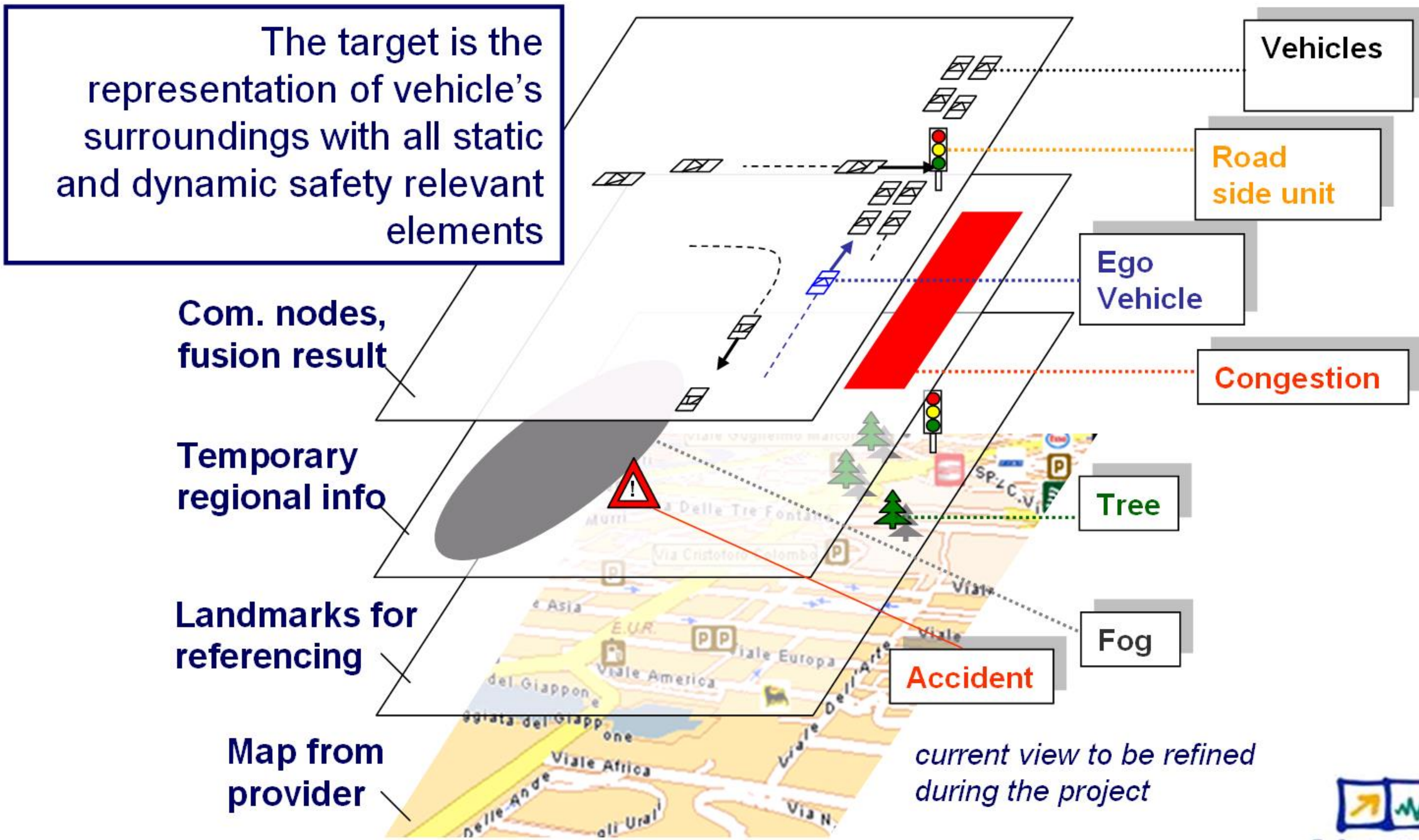


Courtesy of Fiat

Bigger picture, cooperate to drive better



LOCAL DYNAMIC MAP



current view to be refined during the project

Courtesy of Renault

Outline

- What do we mean by 'cognitive behavior' in ITS?
  - Recognition of Driving situation
- Environment perception
  - Sensors, data fusion, dealing with uncertainty, etc.
- 'Overcome uncertainty' or 'Live with uncertainty'
  - Distributed uncertainty management
- Redundancy; multi/many core opportunity

Cognitive car?

- ▶ BMW Automatic Driving - YouTube [720p].mp4

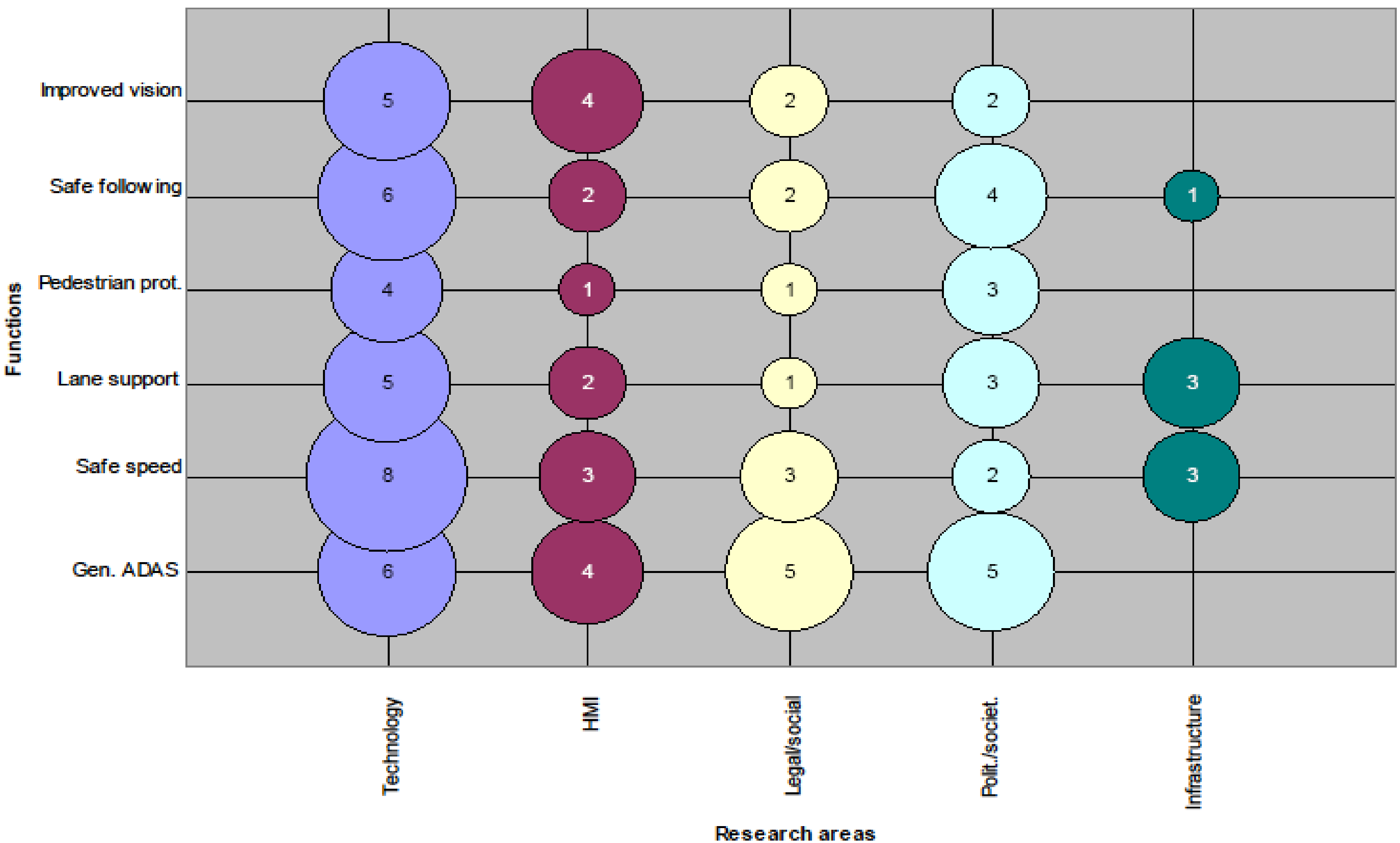
Lack of tools

- No programming framework today provides functional blocs for:
  - Pedestrian detection
- Or even
  - Pedestrian modeling for image processing toolbox
- Even if you find it
  - No easy way to integrate it in an embedded vehicle architecture
  - Probably not complying to Autosar
- What about much more complex functions like ‘cognitive functions’?

Cognitive functions

- Understanding
- Reasonning
- Double checking
- Downgraded operation

EU integrated projects (700 M€)



Driving situation characterization

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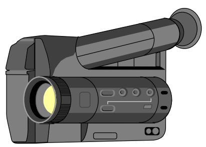
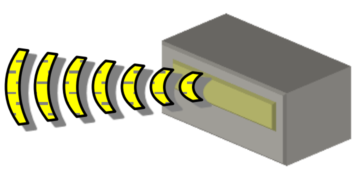
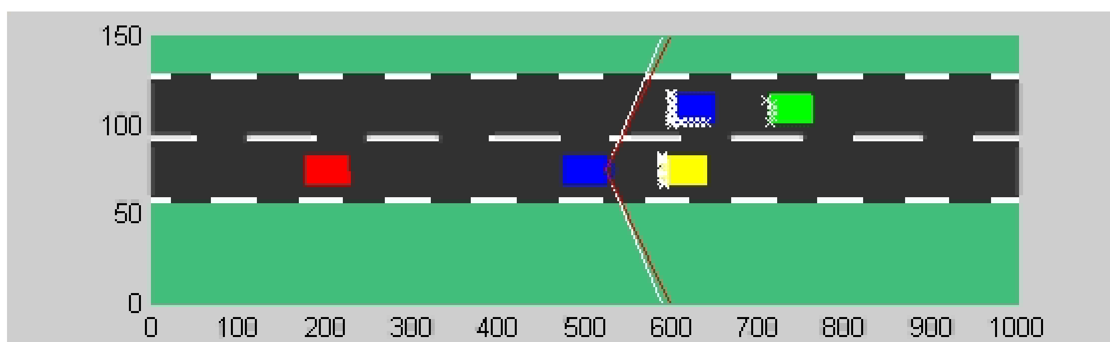
Overtaking sequence



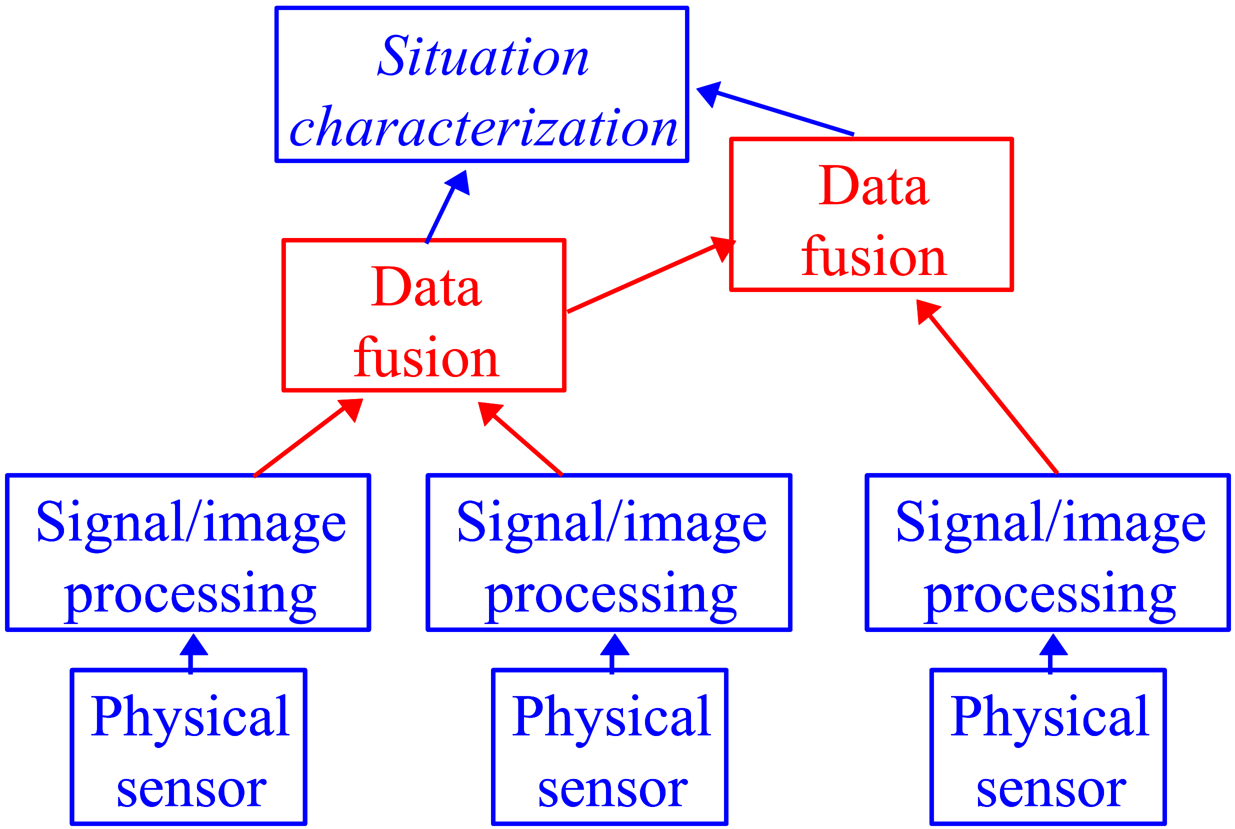
Camera



Telemeter



Perception architecture



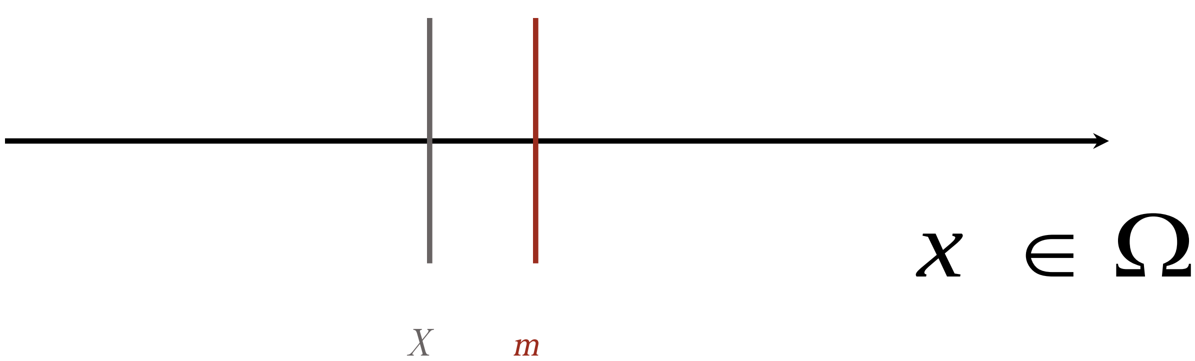
For a particular application

- 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

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



Example

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

This means :

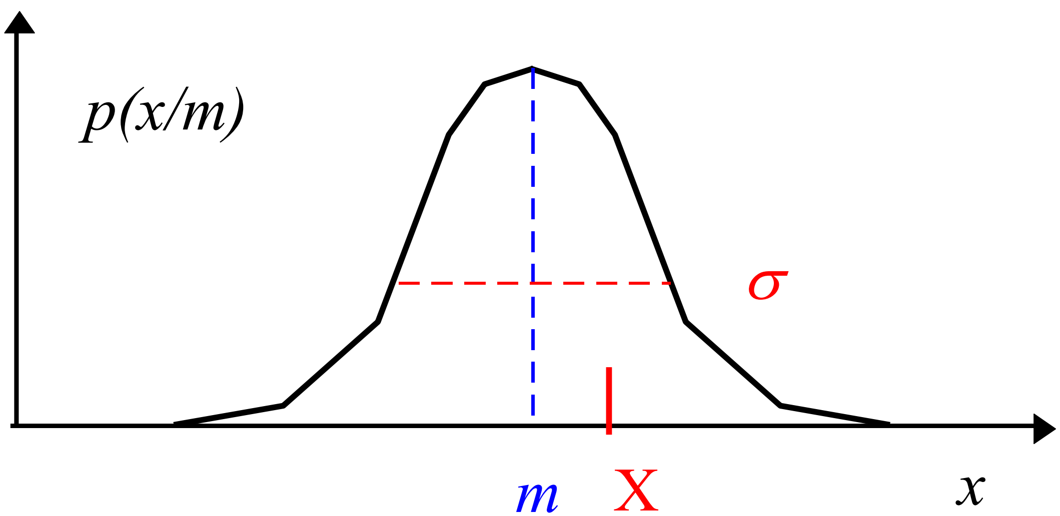
The real value X of the distance is in the interval

[22,4m ; 23,6m]

Accuracy modeled by probabilities

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

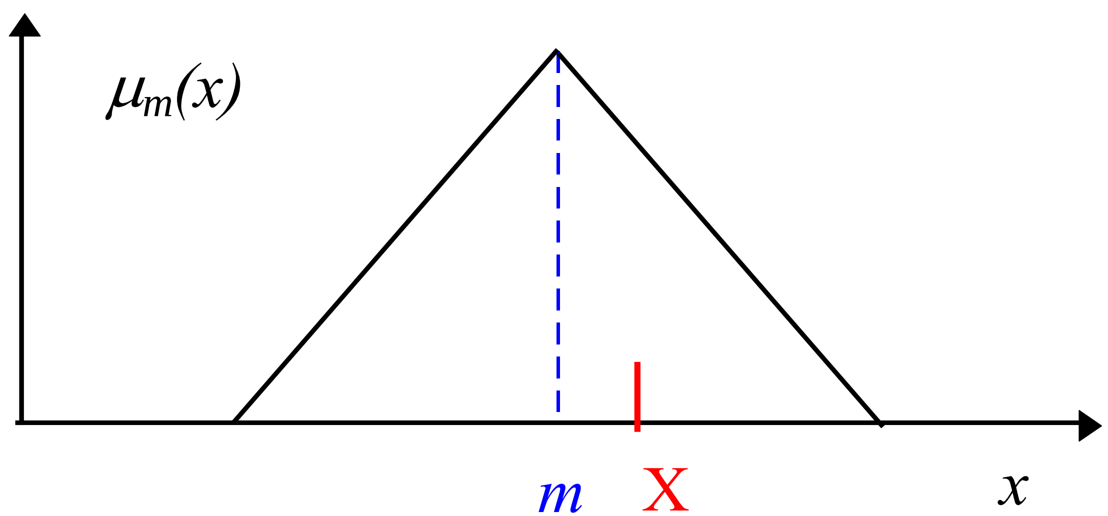
Gaussian distribution : mean m, variance σ^2



Accuracy modeled by fuzzy sets

$\pi_m(x)$: possibility that $X = x$, if the measure is m

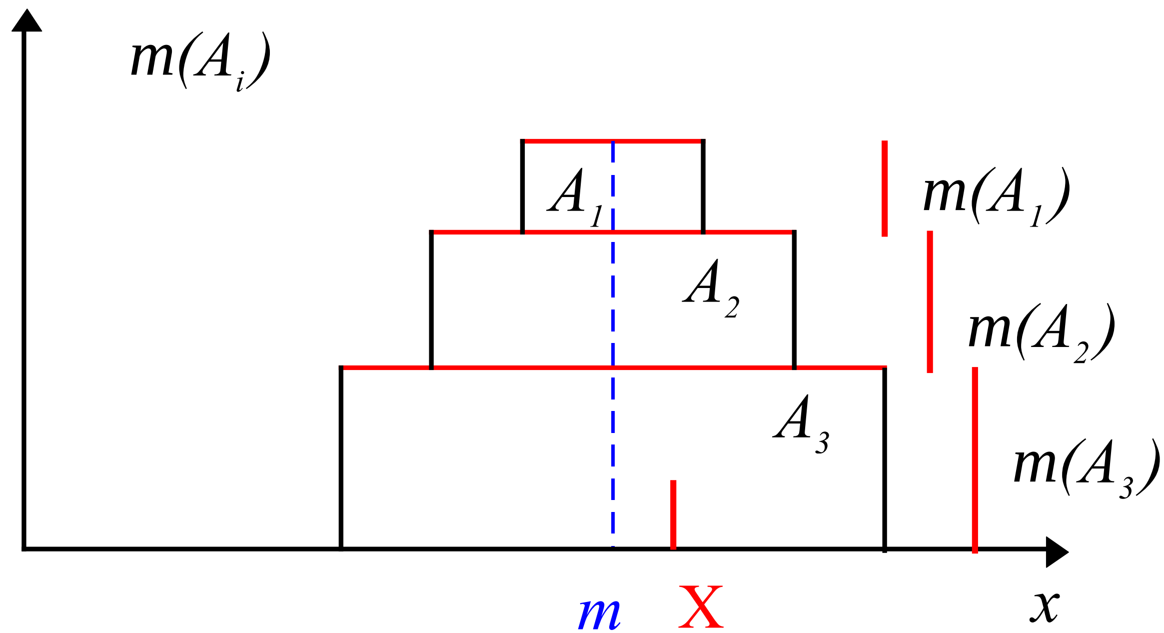
The membership function $\mu_m(x) = \pi_m(x)$ is defined by an expert



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

Accuracy modeled by evidential theory



What is the Theory of belief functions?

- A formal framework for representing and reasoning from partial (uncertain, imprecise) information. Also known as Dempster-Shafer theory or Evidence theory.
- Introduced by Dempster (1968) and Shafer (1976), further developed by Smets (Transferable Belief Model) in the 1980's and 1990's.
- A belief function may be viewed both as
  - a generalized set and
  - a non additive measure,

  and the theory includes extensions of probabilistic notions (conditioning, marginalization) and set-theoretic notions (intersection, union, inclusion, etc.).
- The theory of belief functions thus generalizes both the set-membership and probabilistic approaches to uncertain reasoning.

Mass functions
Definition

- Let Ω be a finite set of possible answers to some question: frame of discernment.
- A mass function on Ω is a function $m : 2^{\Omega} \rightarrow [0, 1]$ such that

$$\sum_{A \subseteq \Omega} m(A) = 1.$$

- The subsets A of Ω such that $m(A) > 0$ are called the focal elements of m.
- A mass function m is often used to model a piece of evidence about a variable X taking values in Ω.
- The quantity $m(A)$ can be interpreted as a measure of the belief that is committed exactly to the proposition $X \in A$.

Mass functions

Special cases

- Only one focal element:

$$m(A) = 1 \text{ for some } A \subseteq \Omega$$

  $\longrightarrow$ categorical mass function ($\sim$ set). Special case: $A = \Omega$, vacuous mass function, represents total ignorance.

- All focal elements are singletons:

$$m(A) > 0 \Rightarrow |A| = 1$$

  $\longrightarrow$ Bayesian mass function ($\sim$ probability mass function).

- A Dempster-Shafer mass function can thus be seen as
  - a generalized set;
  - a generalized probability distribution.

Example

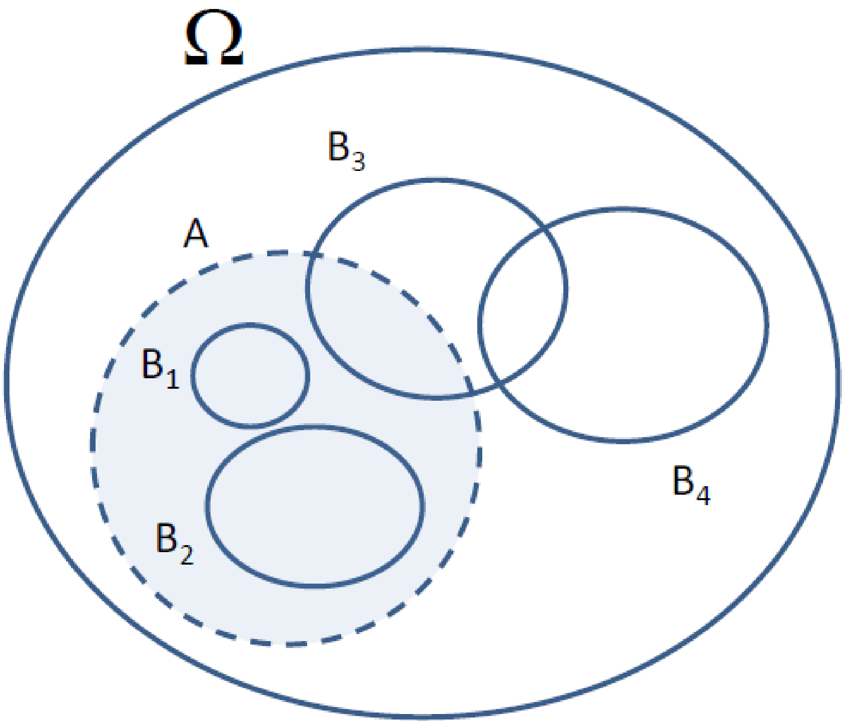
- A murder has been committed. There are three suspects: $\Omega = \{Peter, John, Mary\}$.
- A witness saw the murderer going away, but he is short-sighted and he only saw that it was a man. We know that the witness likes Irish pubs and is drunk 20 % of the time.
- This piece of evidence can be represented by

$$m(\{Peter, John\}) = 0.8,$$

$$m(\Omega) = 0.2$$

- The mass 0.2 is not committed to $\{Mary\}$, because the testimony does not accuse Mary at all!

Belief and plausibility functions
Definitions



$$bel(A) = \sum_{\emptyset \neq B \subseteq A} m(B)$$

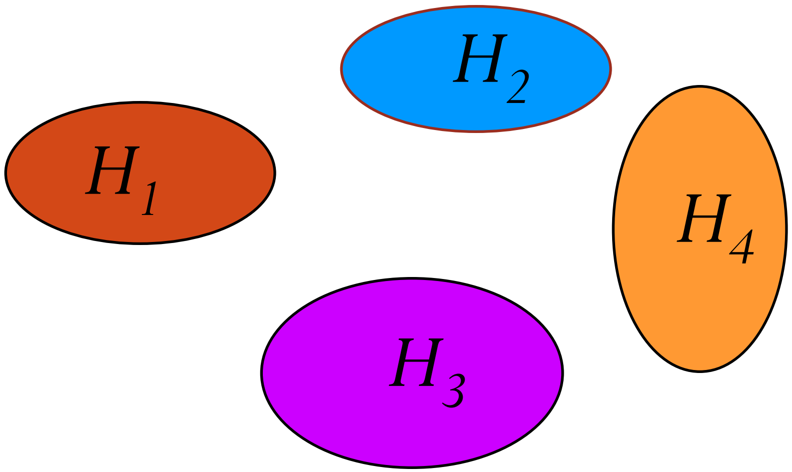
$$pl(A) = \sum_{B \cap A \neq \emptyset} m(B).$$

Belief and plausibility functions
Interpretation and special cases

- Interpretations:
  - $bel(A) =$ degree to which the evidence supports A.
  - $pl(A) =$ upper bound on the degree of support that could be assigned to A if more specific information became available ($\geq bel(A)$).
- Special cases:
  - If m is Bayesian, $bel = pl$ (probability measure).
  - If the focal elements are nested, pl is a possibility measure, and bel is the dual necessity measure.

Definition of reliability

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



- 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

Data processing sequence

1. Temporal data fusion
2. Fusion of redundant data
3. Fusion of complementary data
4. Symbolic characterisation of the situations

1- Temporal data fusion

- The experimental vehicle (EV) moves in a 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)

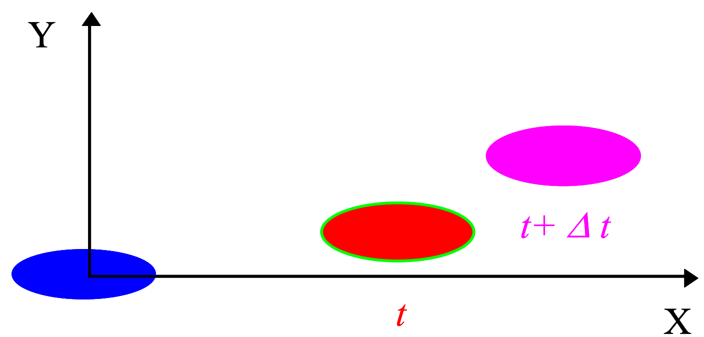
Data evolution

- Use of the model evolution (a priori knowledges)

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

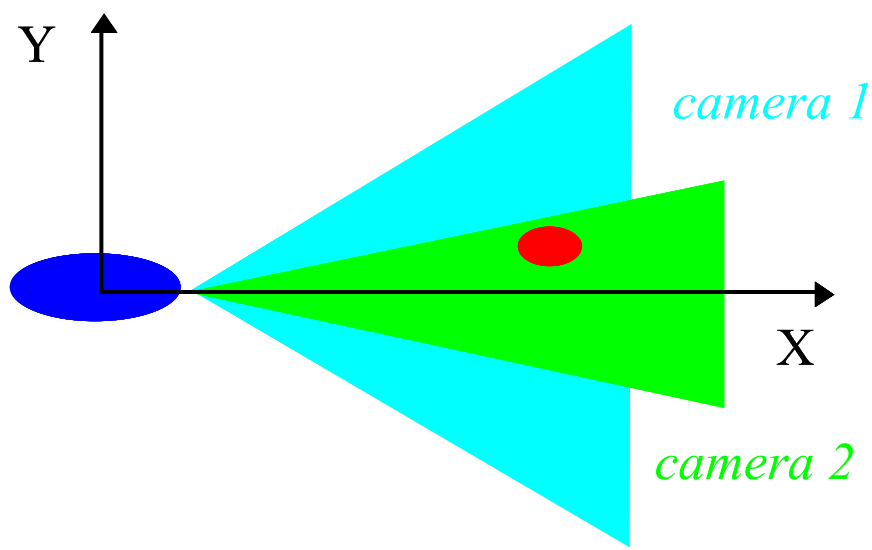
$$x\,(t + \Delta\, t) = 1/2\, \gamma\, \Delta\, t^2 + (v\,(t + \Delta\, t) - v\,(t))\, \Delta\, t + x\,(t)$$

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



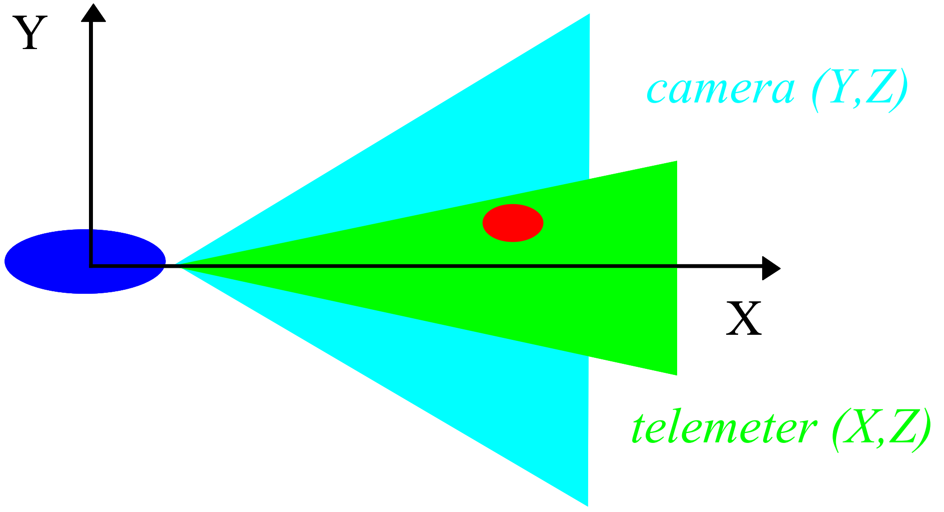
2- Fusion of redundant data

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

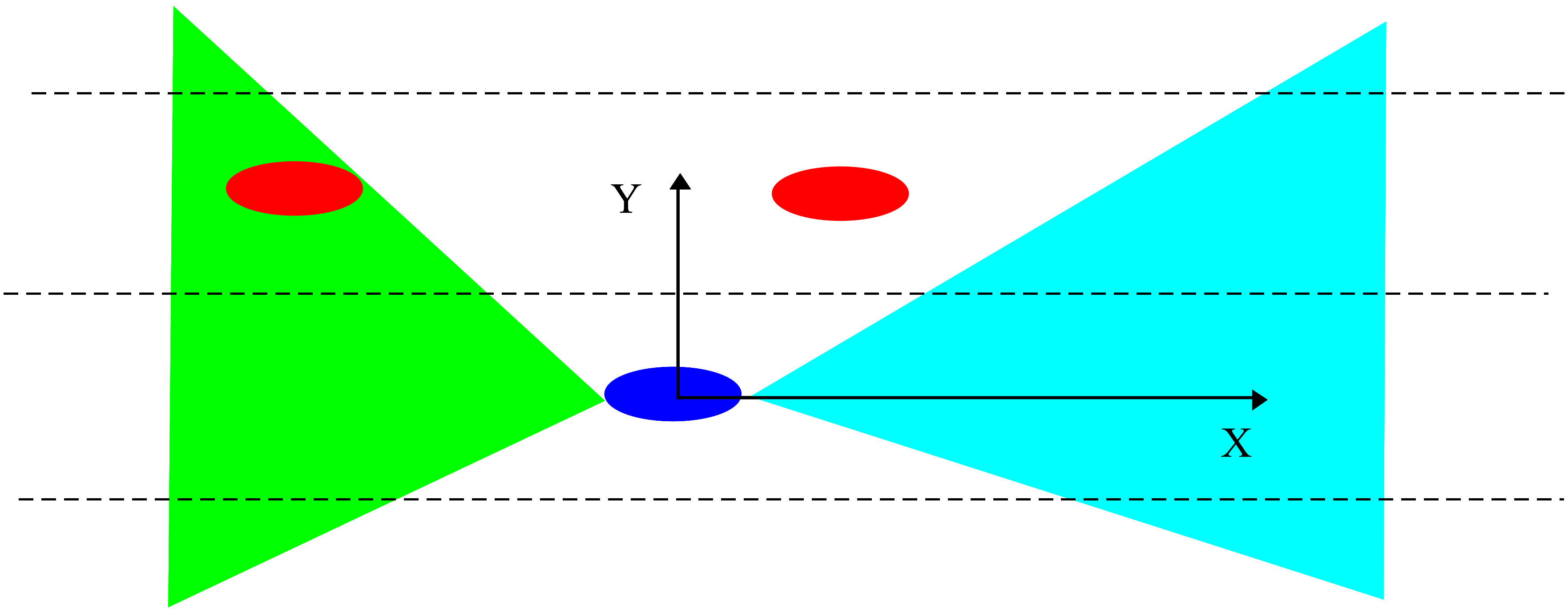


3- Fusion of complementary data

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

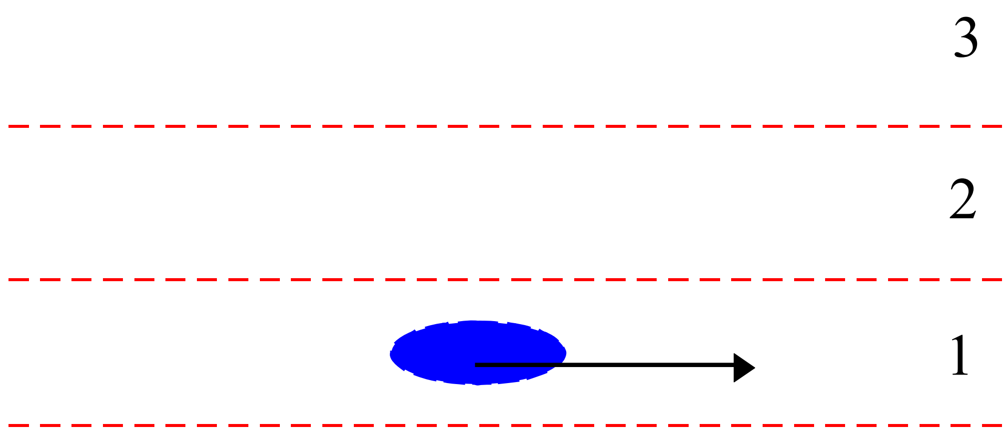


Fusion of complementary data



4- Symbolic characterisation

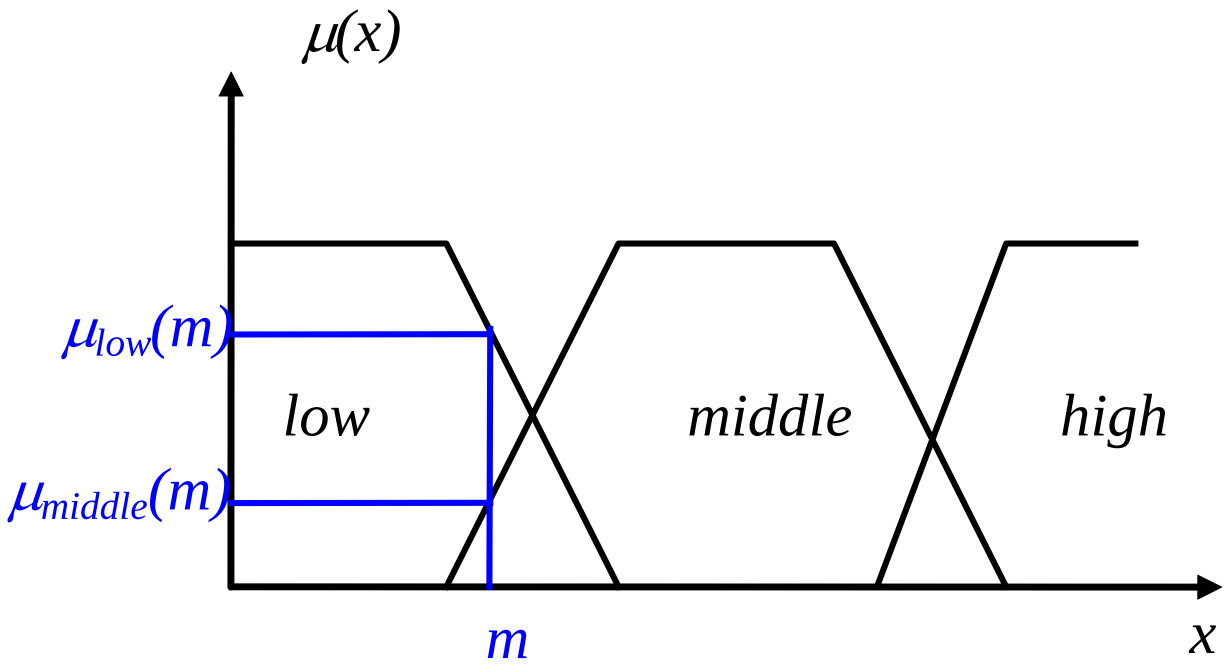
- Data interpretation
- Definition of the symbolic models
- Use of a priori knowledges



1 : -0,75m
2 :+0,80m
3 :....

EV on the right lane

The numeric/symbolic conversion



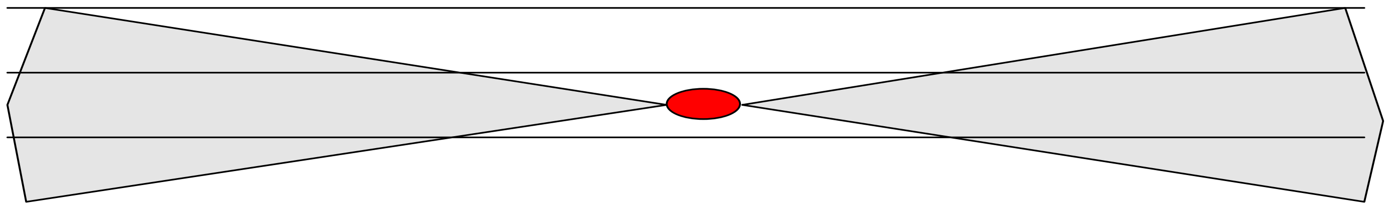
Maneuver recognition

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

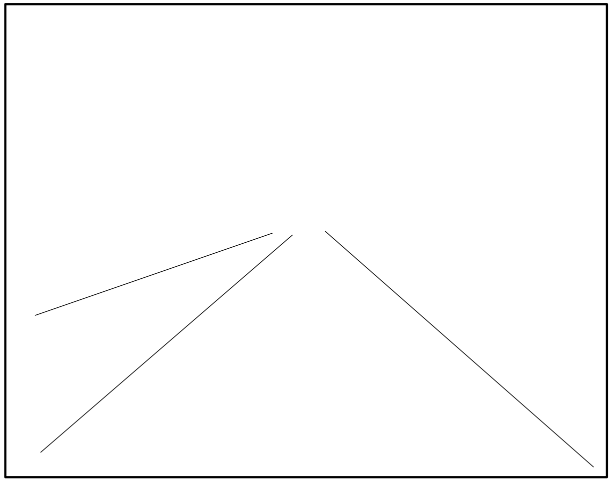
Overtaking

State :

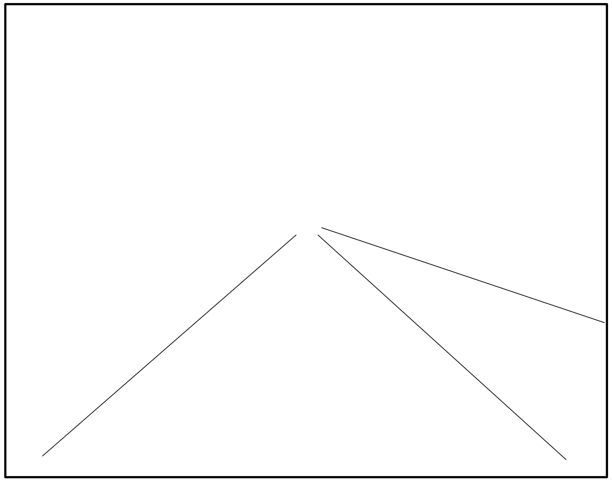
Top view



Front camera

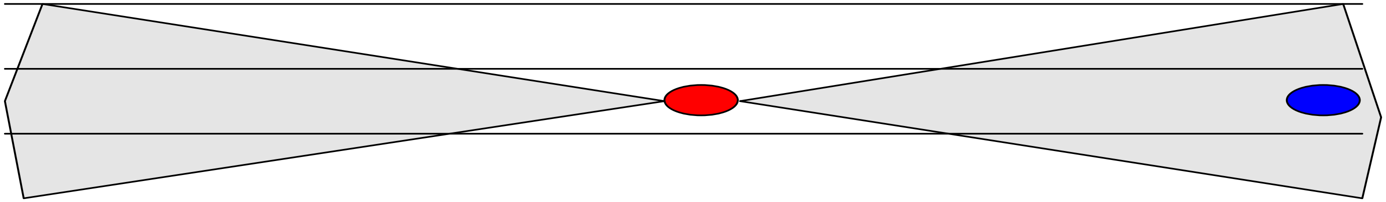


Rear camera

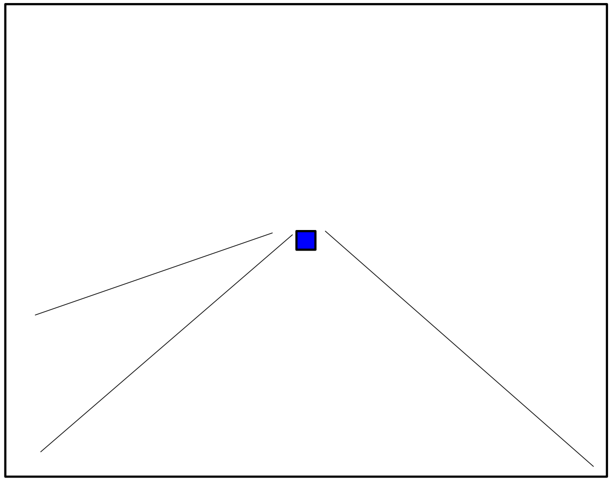


State : approach

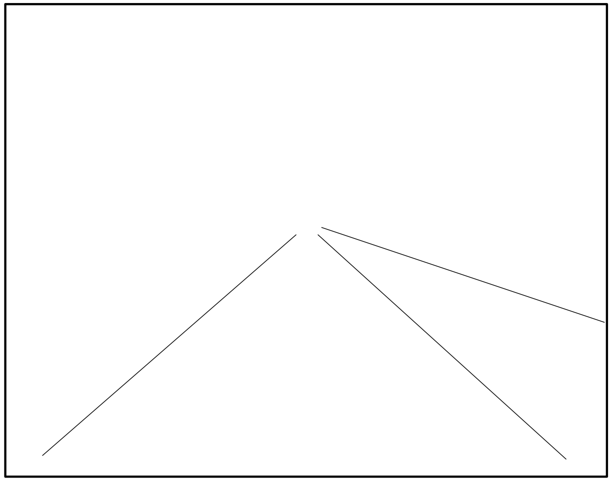
Top view



Front camera

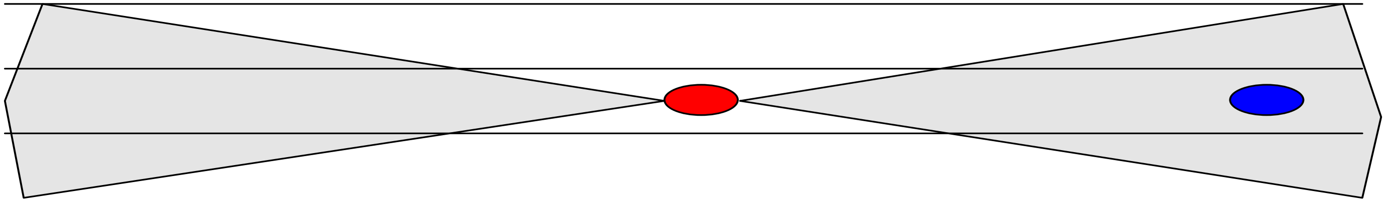


Rear camera



State : approach

Top view



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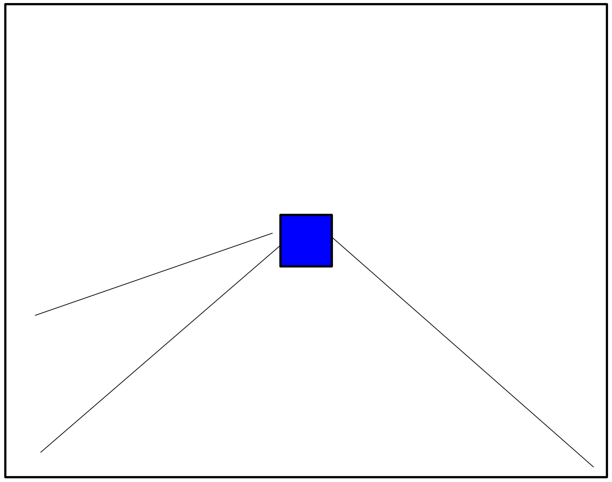
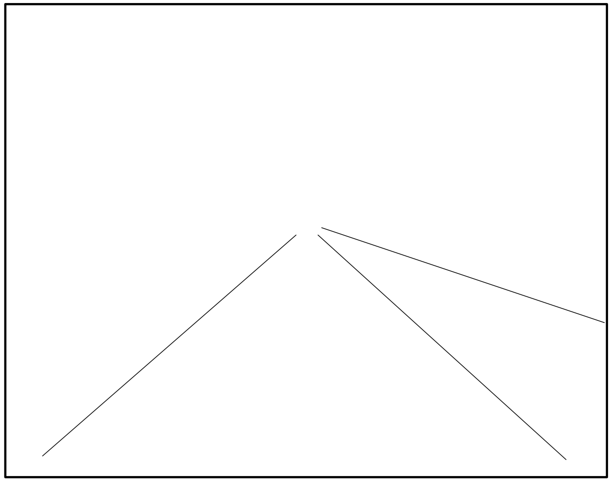
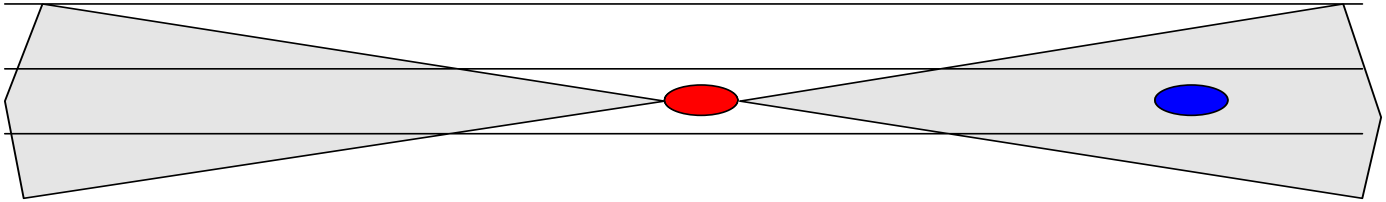


Rear camera



State : approach

Top view



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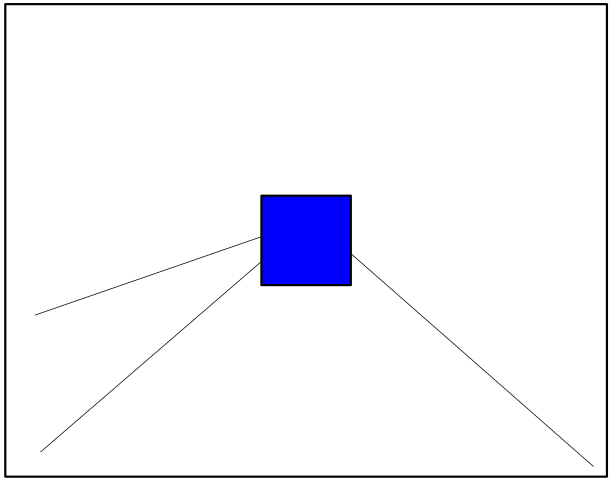
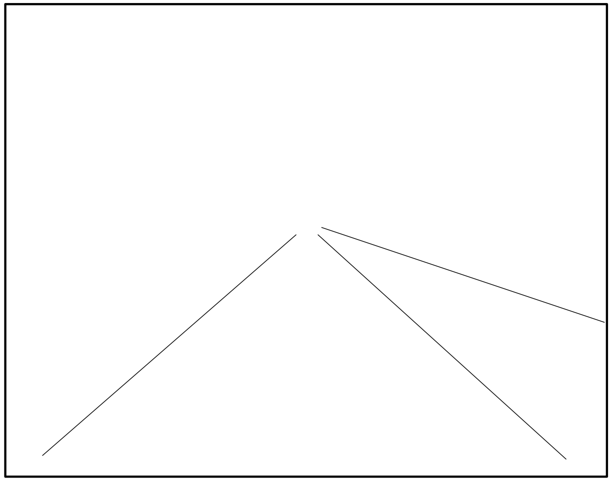
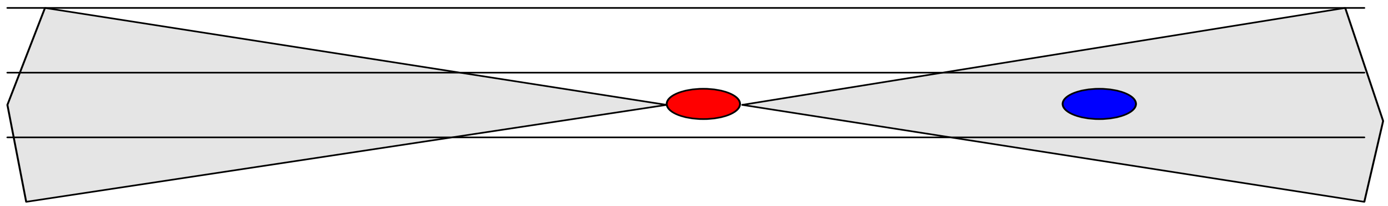


Rear camera

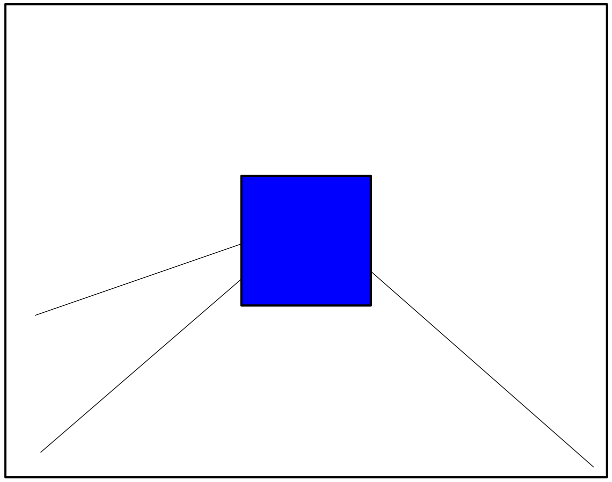


State : approach

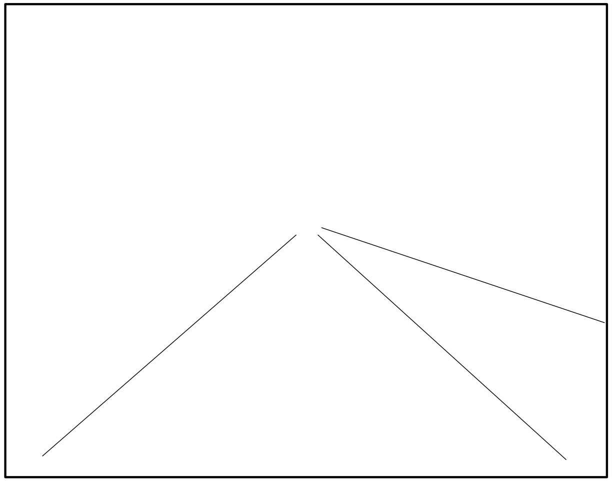
Top view



Front camera

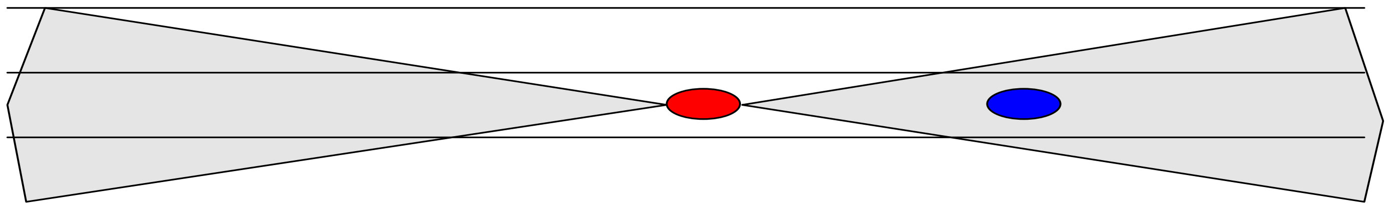


Rear camera

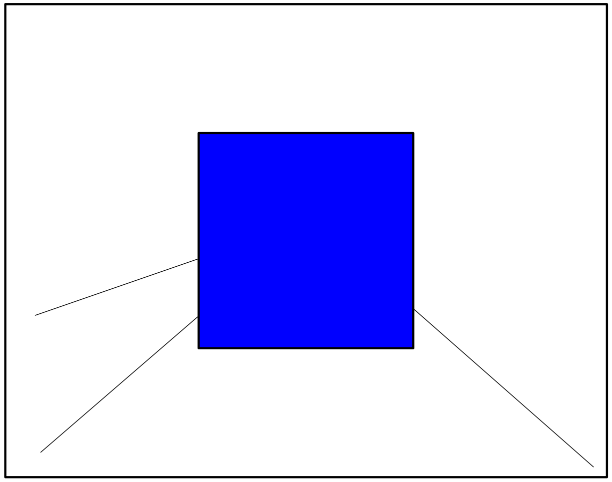


State : approach

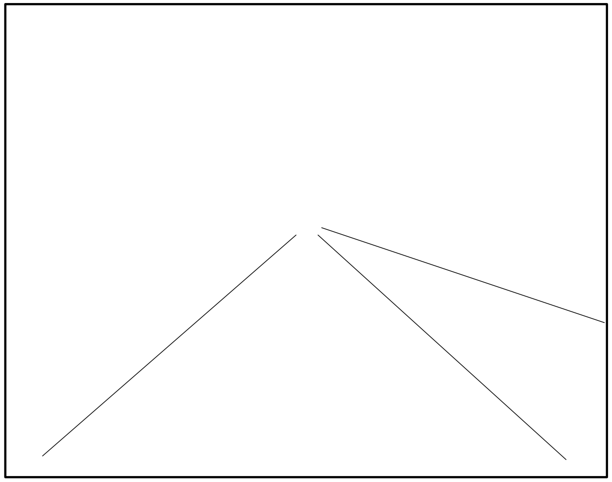
Top view



Front camera

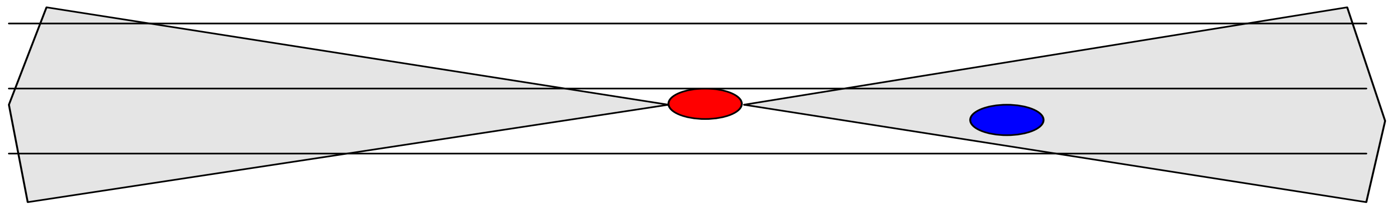


Rear camera

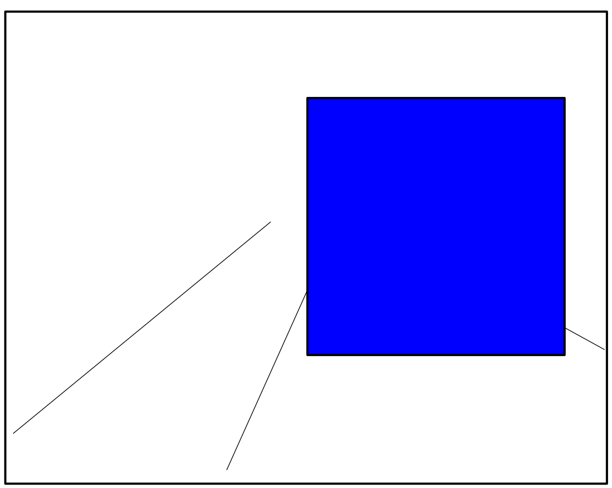


State : lane change

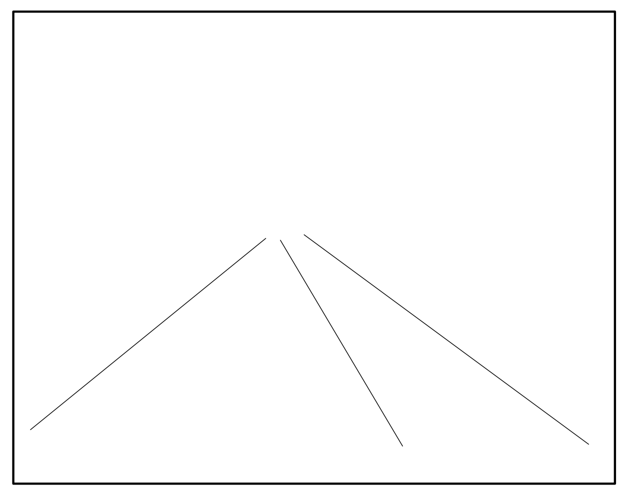
Top view



Front camera

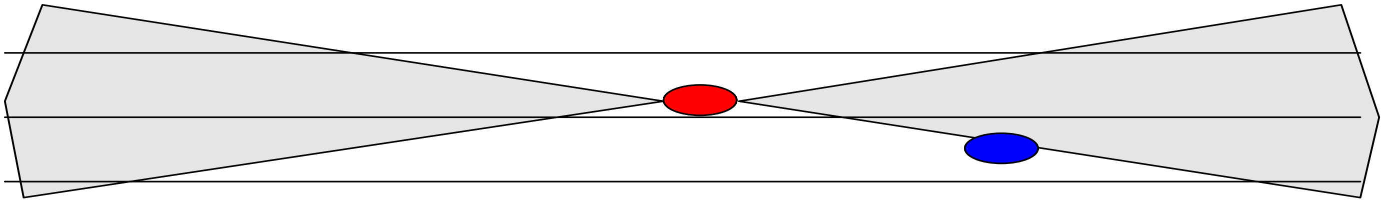


Rear camera

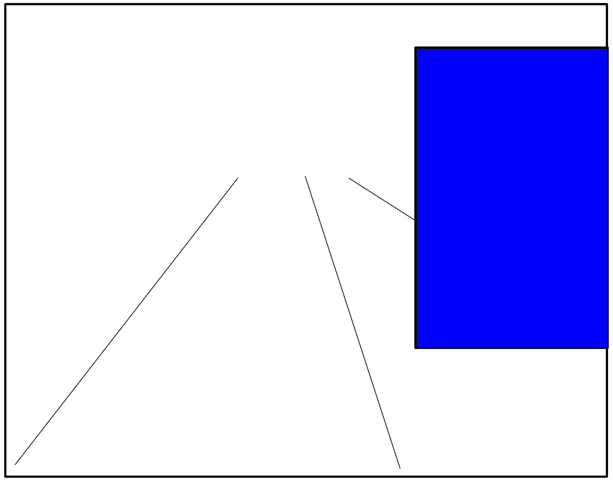


State : lane change

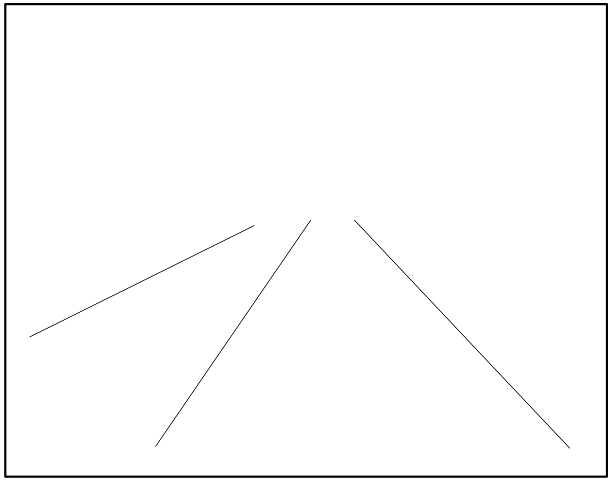
Top view



Front camera

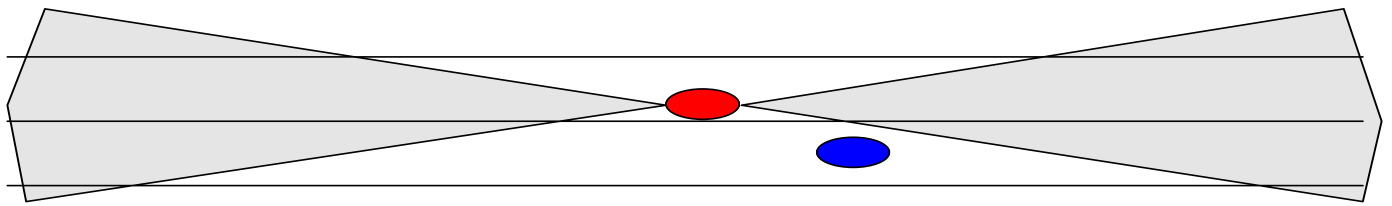


Rear camera

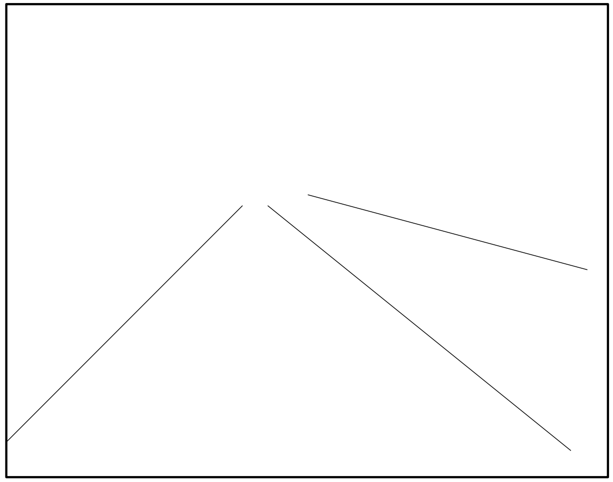


State : overtake

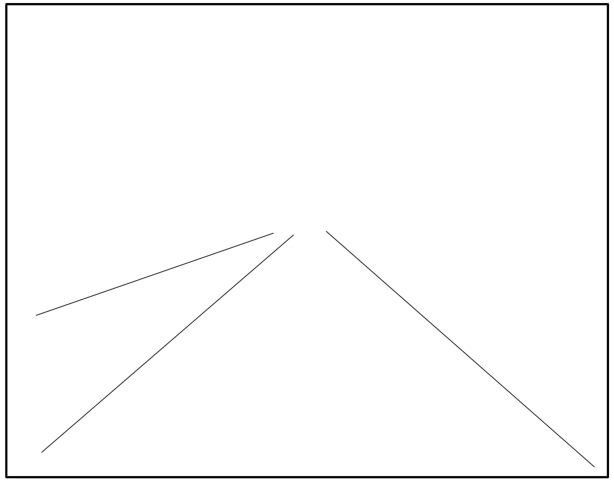
Top view



Front camera

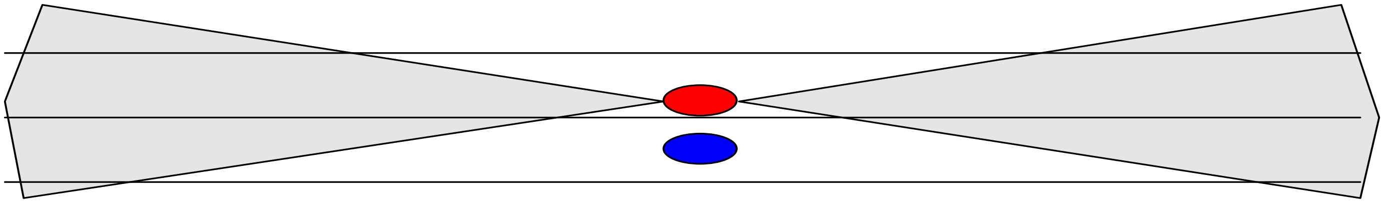


Rear camera

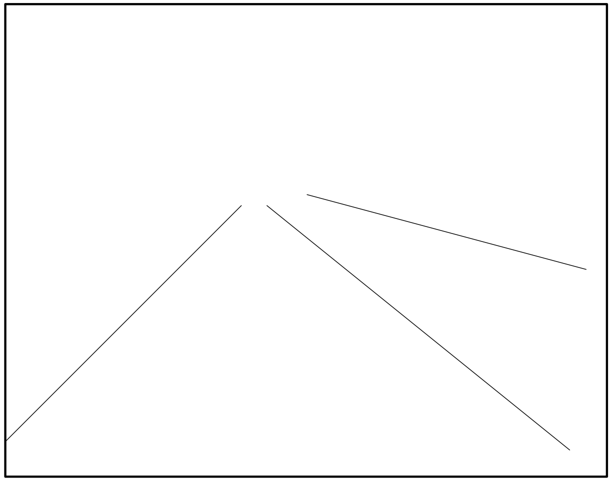


State : overtake

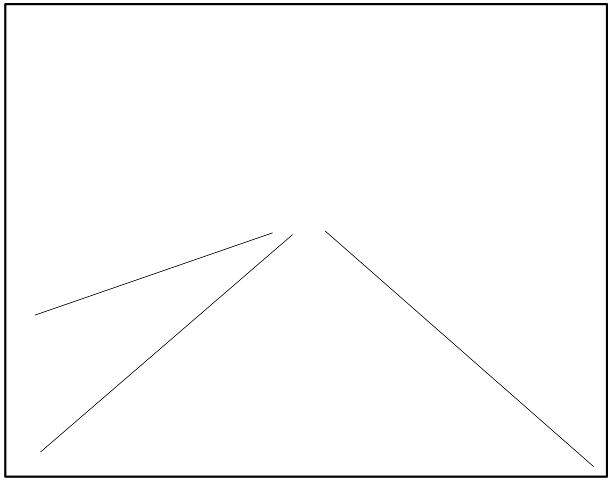
Top view



Front camera

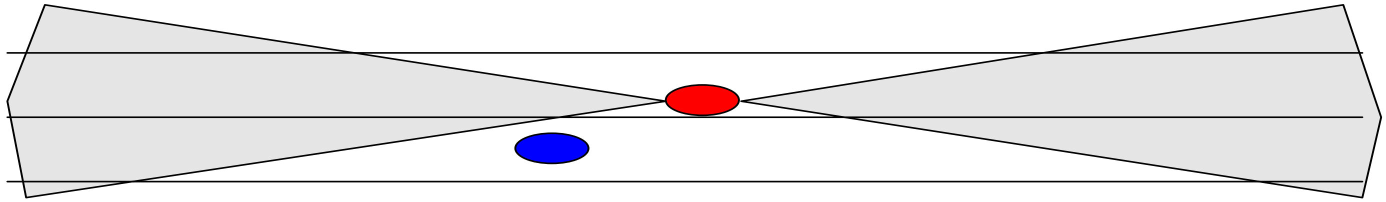


Rear camera

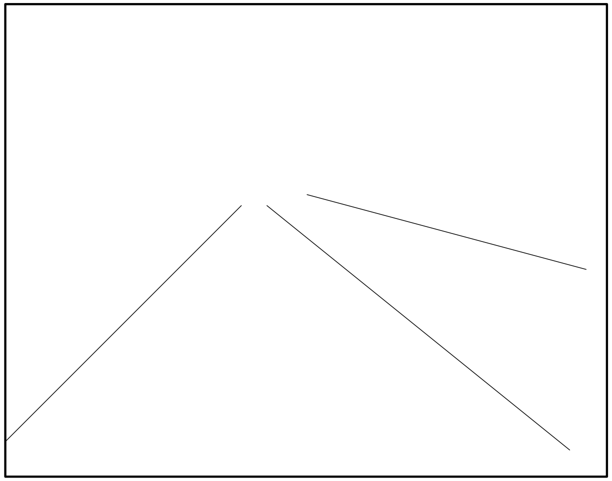


State : overtake

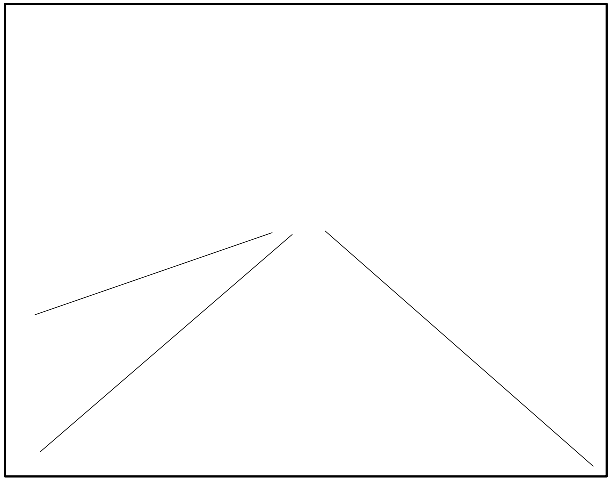
Top view



Front camera

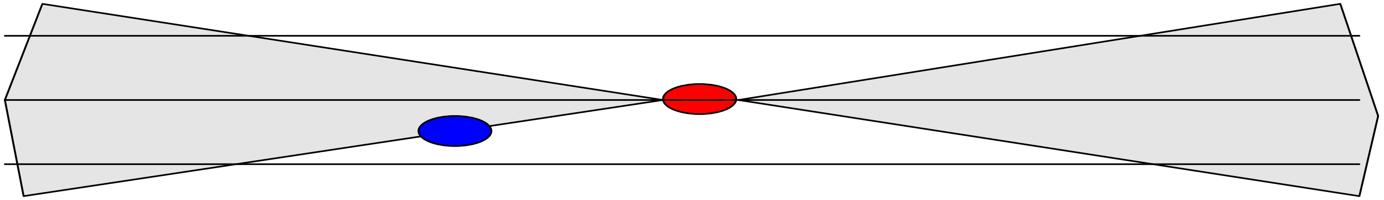


Rear camera

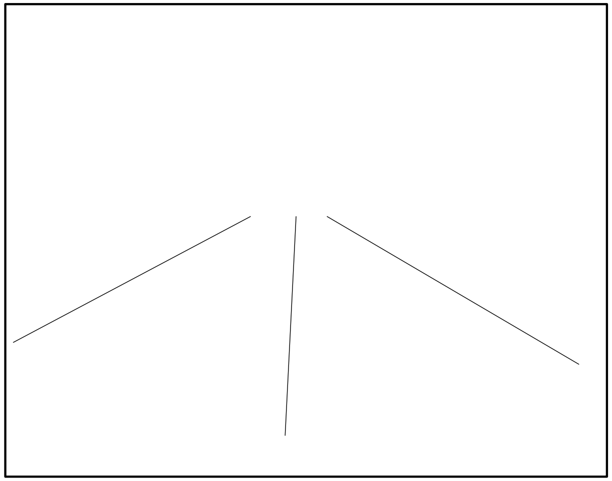


State : lane change

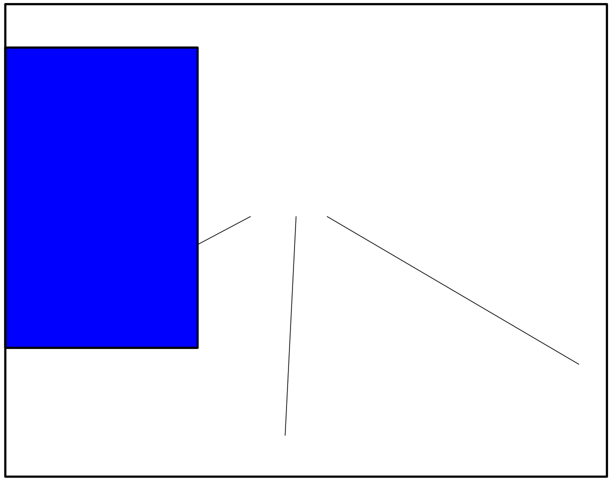
Top view



Front camera

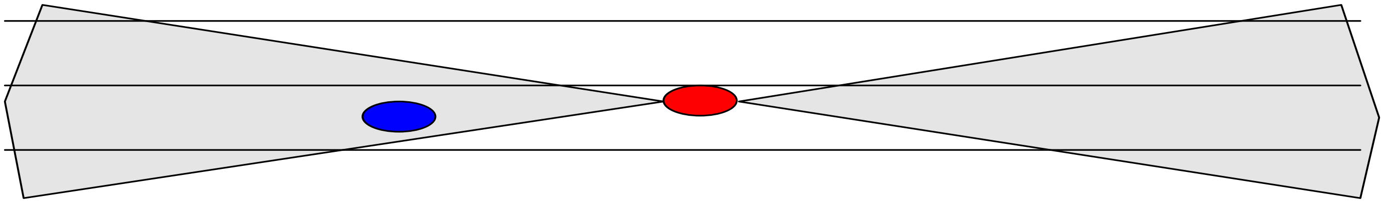


Rear camera

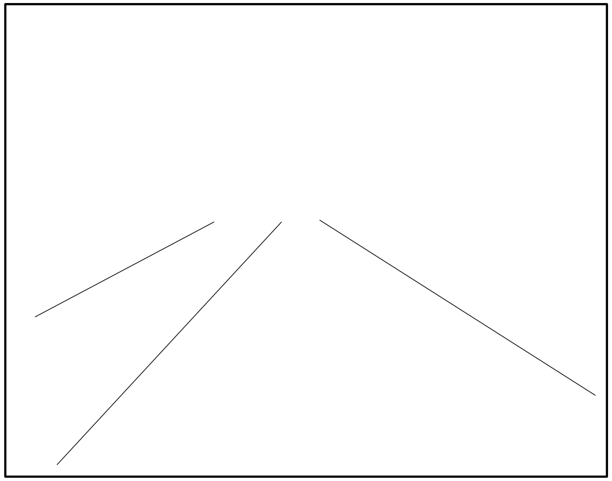


State : lane change

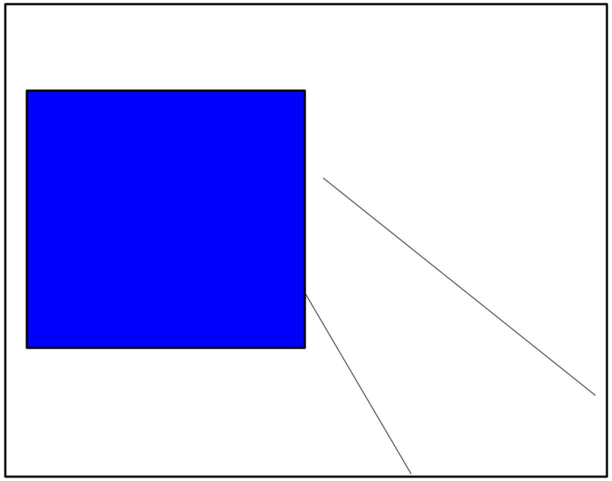
Top view



Front camera

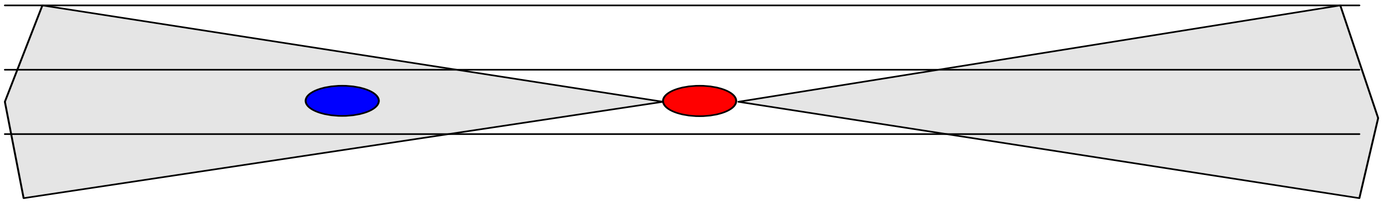


Rear camera

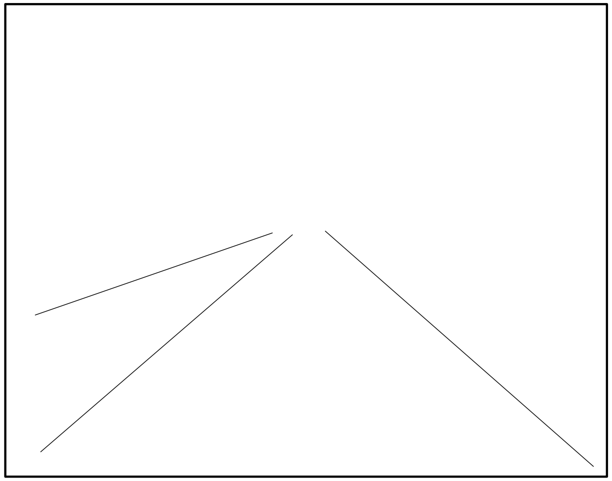


State : move away

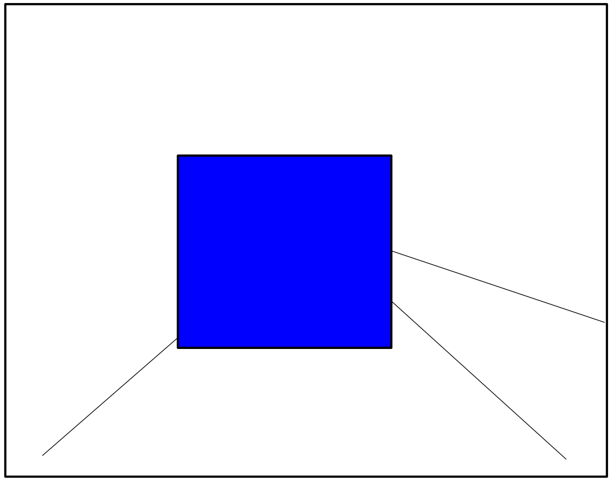
Top view



Front camera

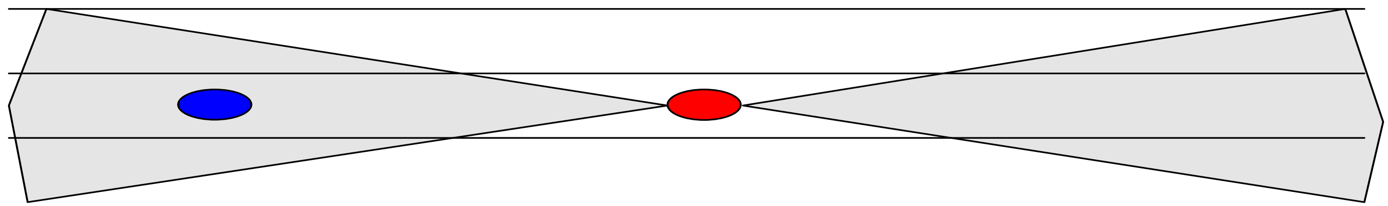


Rear camera

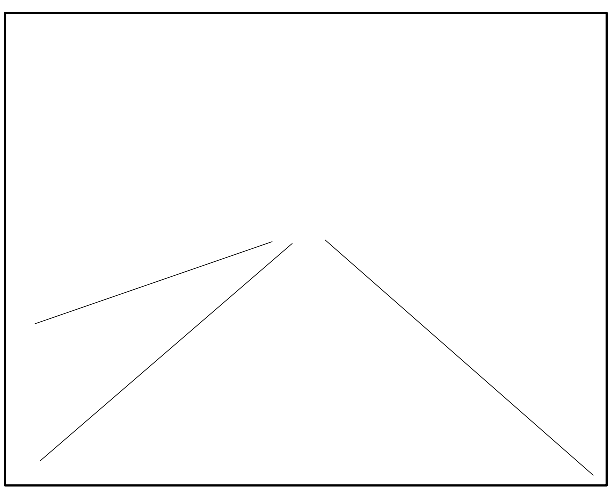


State : move away

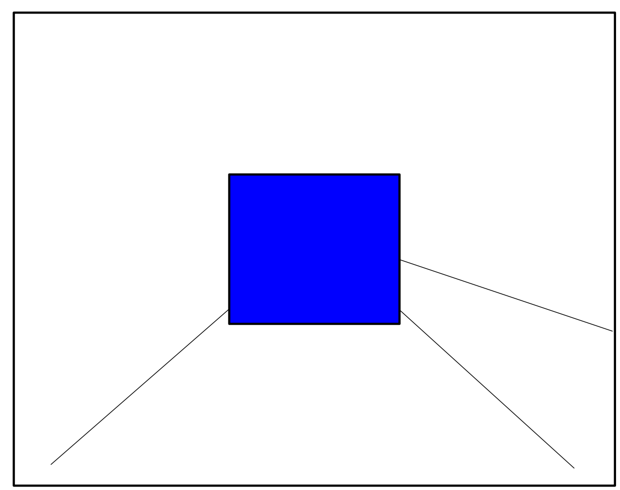
Top view



Front camera

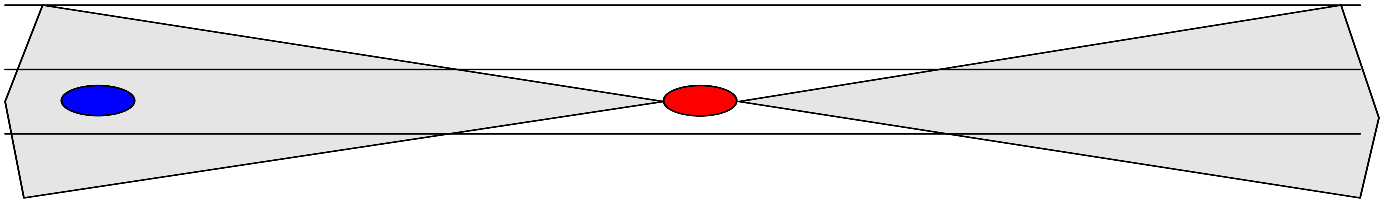


Rear camera

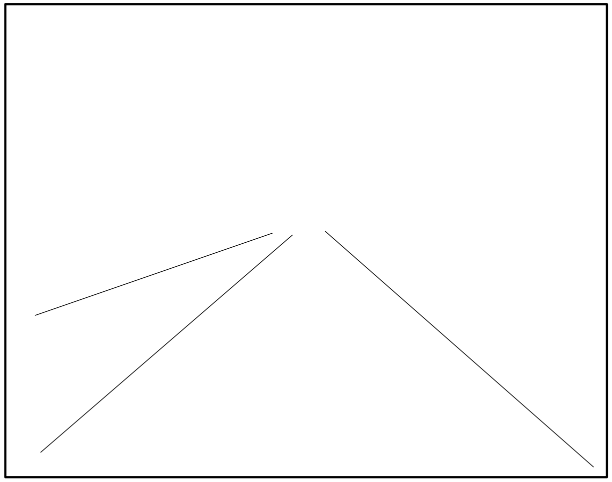


State : move away

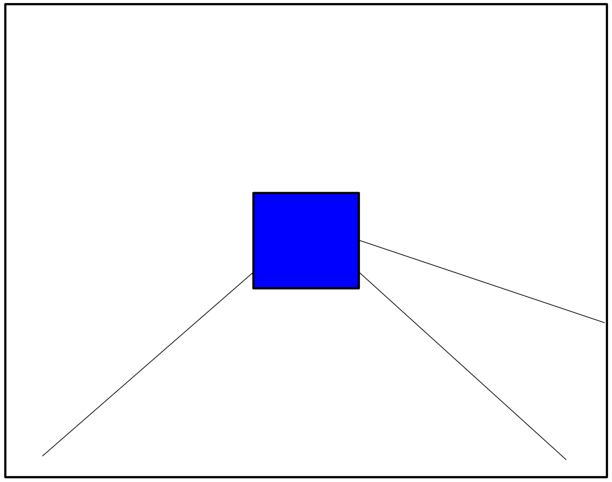
Top view



Front camera

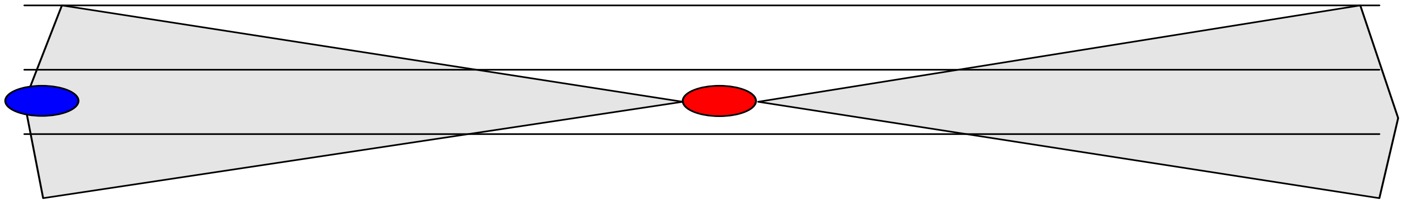


Rear camera

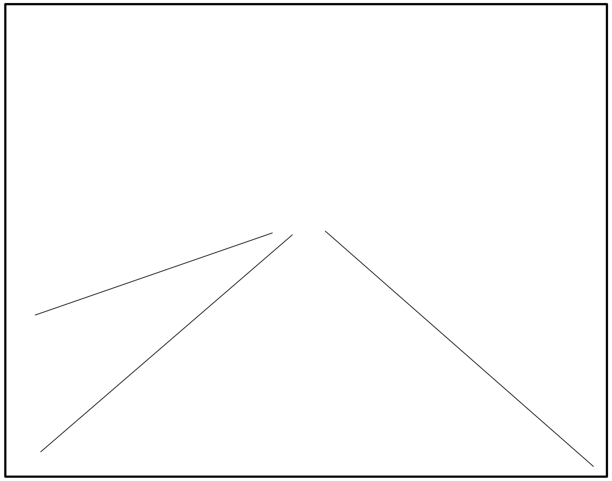


State : move away

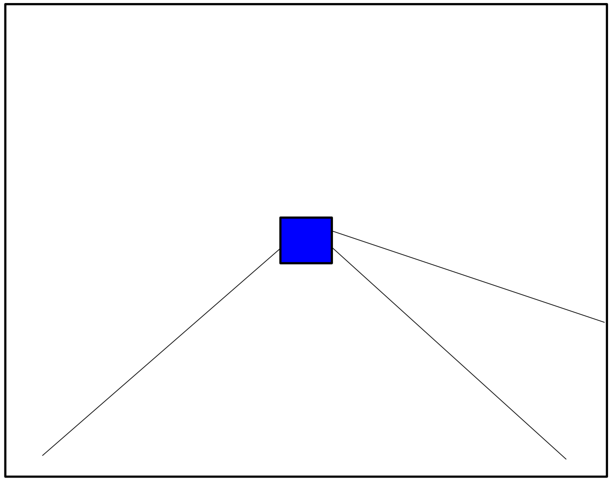
Top view



Front camera

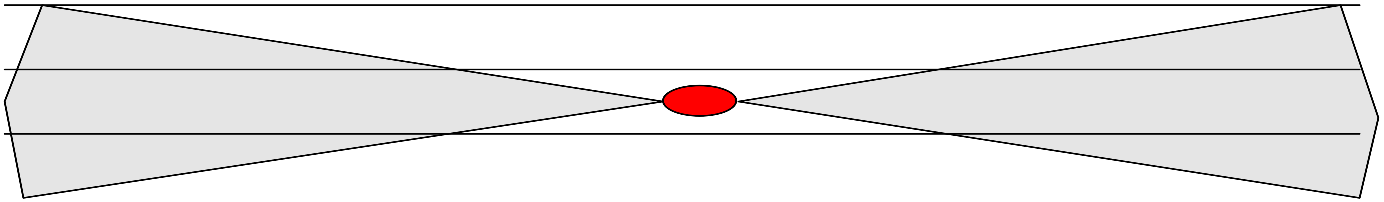


Rear camera

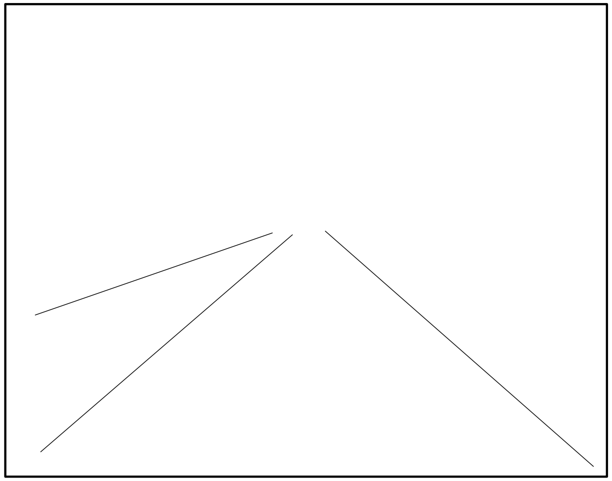


State :

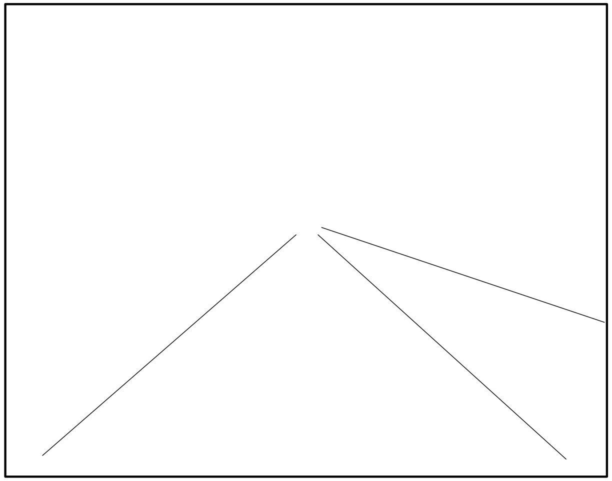
Top view



Front camera



Rear camera



High-level interpretations of driving situations

- Conclusions drawn from previous work
- Become Intermediate Data for the next step

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Jean-Marc NIGRO

Université de technologie de Troyes

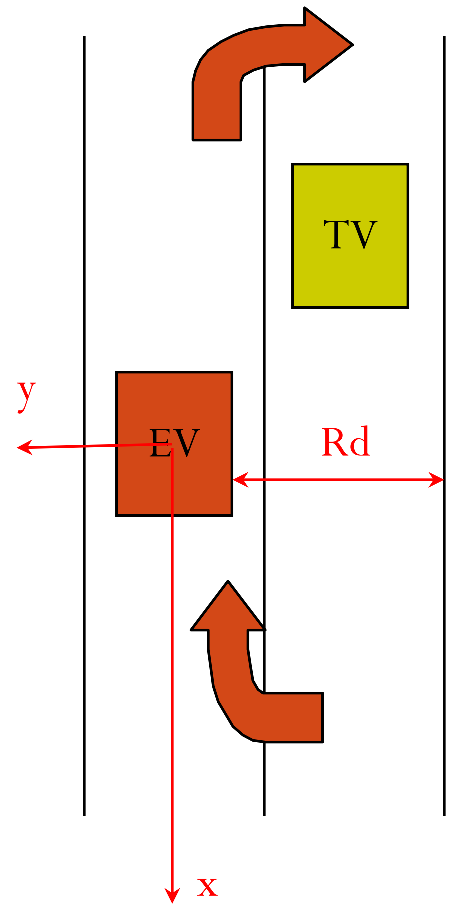
Laboratoire LM2S

TROYES – France

Raw data and intermediate 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

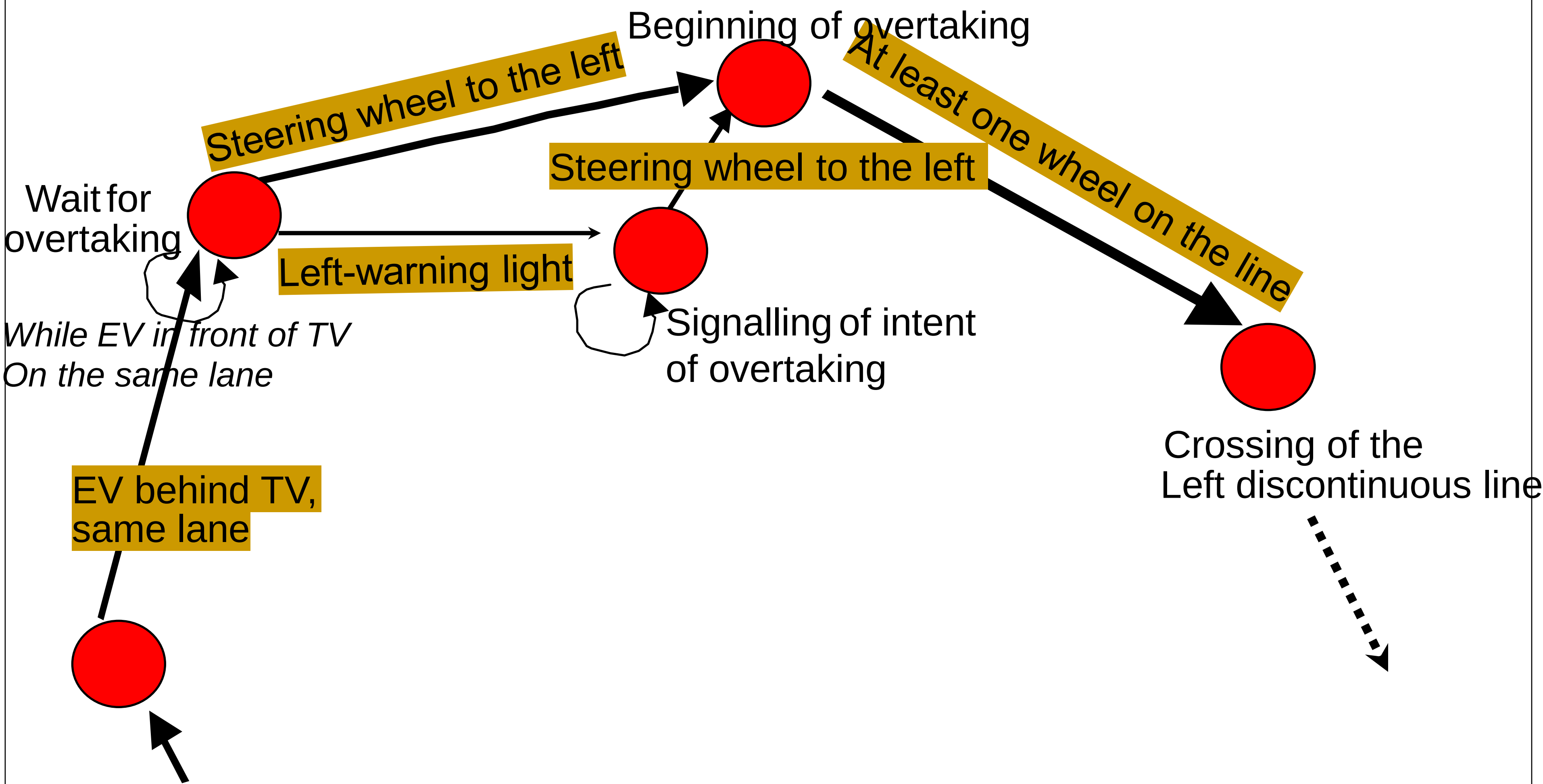
Data obtained from the experimental vehicle



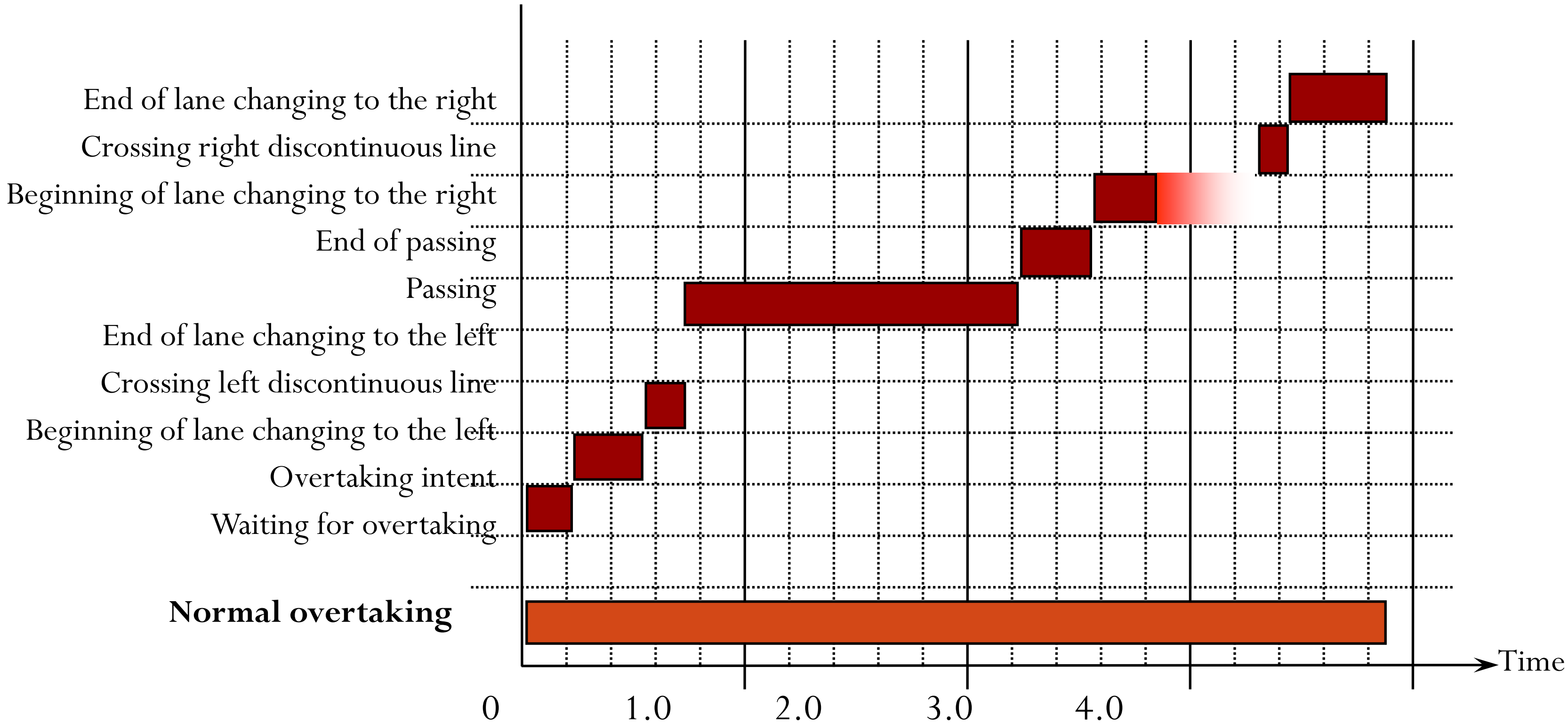
Time	Clock (s)
Acc	Acceleration of EV relative to TV (meters²/second)
Phi	Front wheel angle of EV (in degrees)
Rd	Position of EV against the right road side (meters)
Rg	Position of EV against the left road side (meters)
Teta	Angle of the target TV (degrees)
S	Speed of EV relative to TV (meters/second)
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's meaning

Overtaking maneuver recognition graph



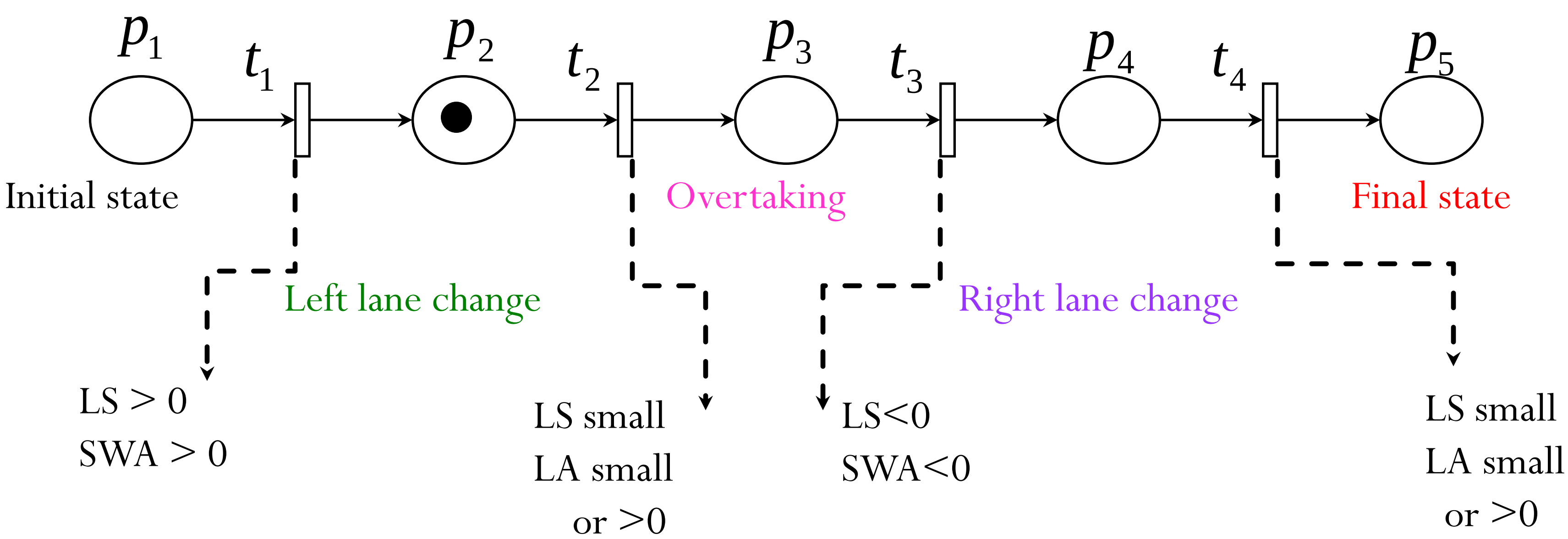
IDRES
Experimentation results



Modeling overtaking maneuver with a Petri net

PN = <P,T,R,M>

P: the set of places
T: the set of transitions
M: the marking vector
R: the vector of receptivity



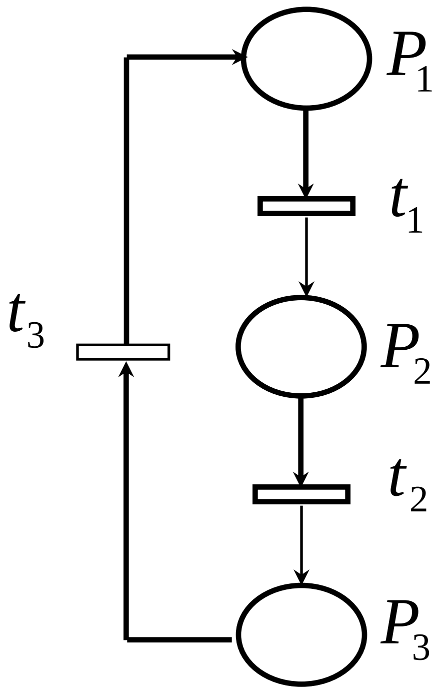
LS:Lateral Speed, LA:Longitudinal Acceleration, SWA:Steering Wheels Angle

The belief Petri net

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

PN = <P,T,R,M>

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



<u>The new marking function</u>

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

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

First step

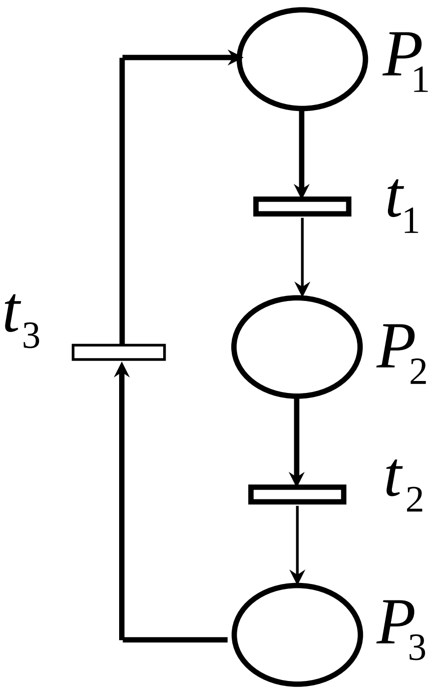
* The transitions are sure

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

* The initial state, at time k,

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

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



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

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

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

Uncertain knowledge of transitions

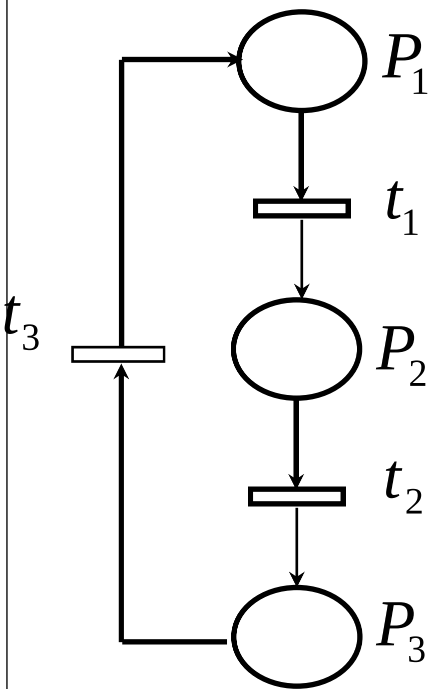
The frame of discernment: $\Omega = \{0,1\}$

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

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

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

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



$$R^k = \begin{bmatrix} 0 & 0.9 & 0.1 \\ 0.3 & 0 & 0.7 \\ 0 & 0.4 & 0.6 \end{bmatrix}$$

$$\boxed{\begin{array}{l} m^{k+1/k}\left(\{p_1\}/\{p_1\}\right) = m_1^k\left(\{0\}\right) = 0.9 \\ m^{k+1/k}\left(\{p_1, p_2\}/\{p_1\}\right) = m_1^k\left(\{0,1\}\right) = 0.1 \end{array}}$$

$$\boxed{\left.\begin{array}{l} m^k \\ \\ R^k \to m^{k+1/k} \end{array}\right\} \to m^{k+1}(A) = \sum m^{k+1/k}\left(A/B\right) m^k(B)}$$

Increasing complexity and tools

- $increasing\ cognition\ \propto 10 \times increasing\ complexity$
- $increasing\ complexity \propto 10 \times code\ size$
- $\therefore increasing\ cognition \propto 10 \times 10 \times code\ size$

- Lack of tools!
  - Currently, no programming tool provides uncertainty management
  - Fuzzy logic and Interval programming tools are insufficient

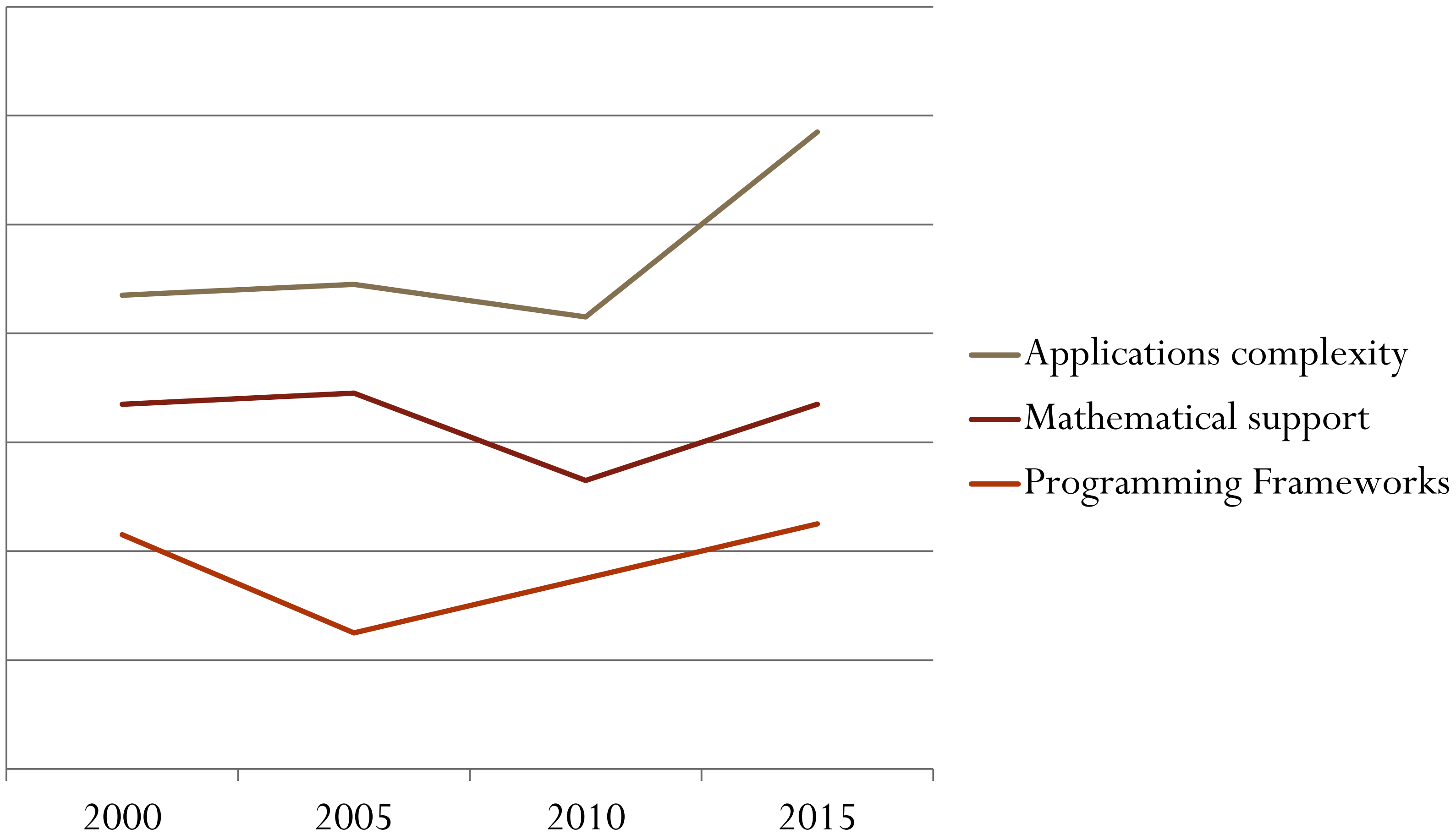
Programming with uncertainty management

- Example : Speed regulator

Usual programming	Programming with uncertainty management
IF (DISTANCE > 30) THEN	IF (bel(distance,30)>80%) AND pl(distance,30) < 20%) OR (….. AND….) OR (… AND….) OR (…. AND …) THEN

- It would better be integrated in a meta language, with automatic source code generation, all included in a single framework

Applications complexity versus tools



Dempster combination laws

Belief functions: canonical decompositions and combination rules. Frédéric Pichon, PhD. Thesis, March 2009

Combine veracities from different sources for the same hypothesis

Conjunctive sum

$$m_\Theta(A) = \sum_{A_i \cap B_j = A} m_\Theta^{S_1}(A_i) \cdot m_\Theta^{S_2}(B_j)$$

Disjunctive sum

$$m_\Theta(A) = \sum_{A_i \cup B_j = A} m_\Theta^{S_1}(A_i) \cdot m_\Theta^{S_2}(B_j)$$

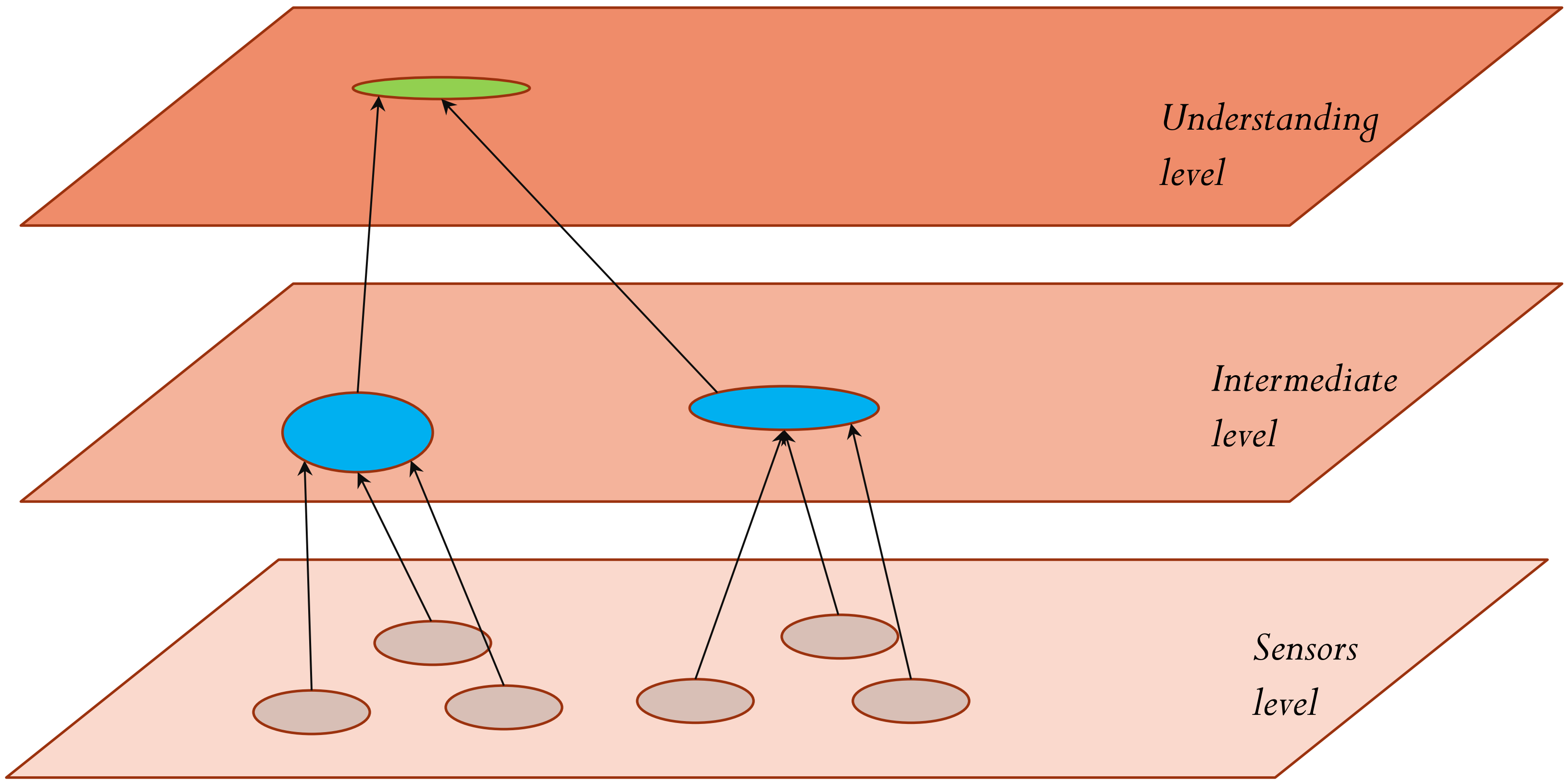
Critical systems Engineering and Uncertainty

Overcome uncertainty as used to do?

Overcome uncertainty

- Objective of Engineering today is to OVERCOME uncertainty
- What about ‘taking into account uncertainty’
  - Serious change in system design and programming paradigm
- Do we really have the choice?

Uncertainty: do we really have the choice?



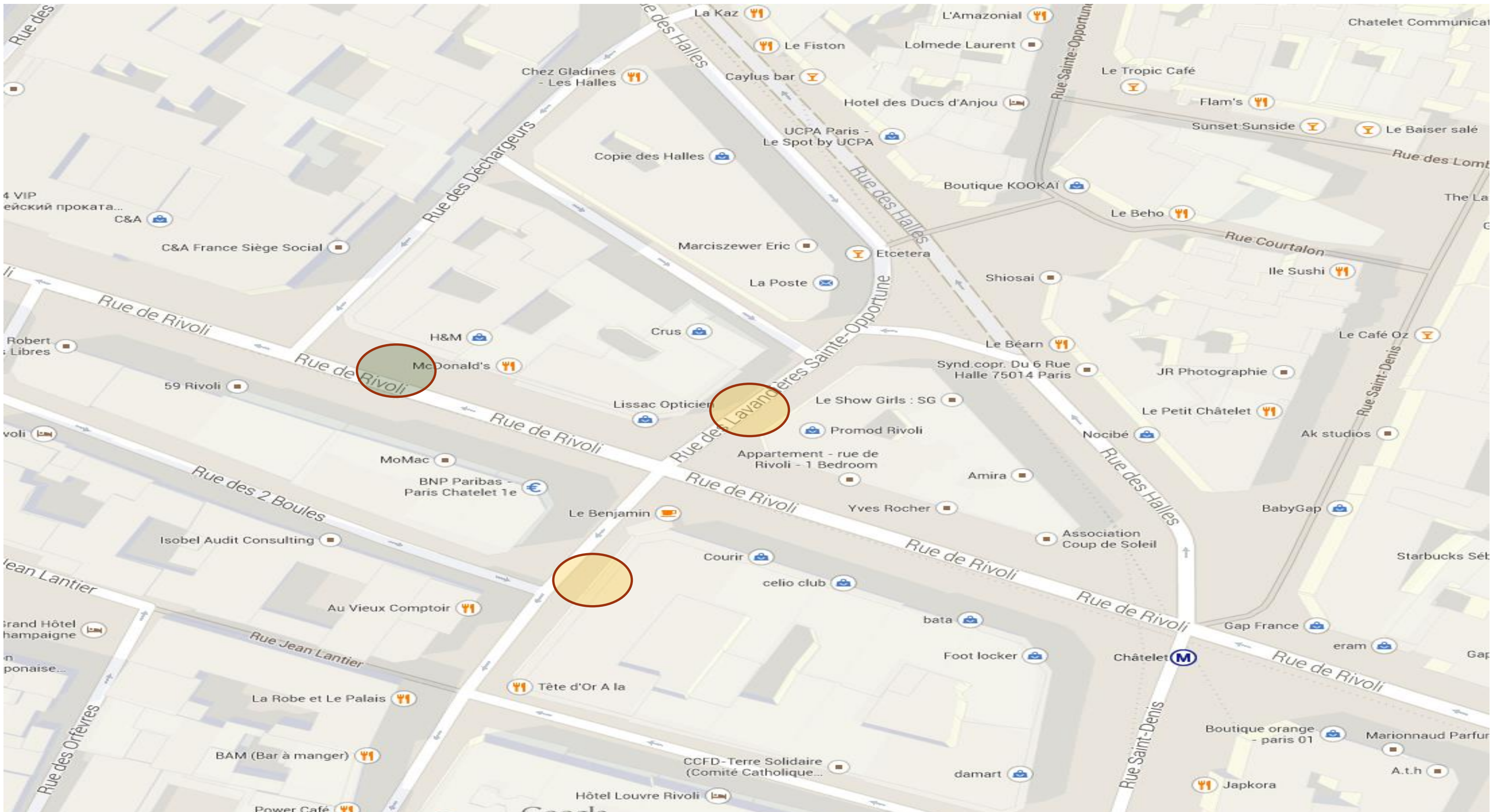
Embedded critical systems

- Astrium (EADS group) example
  - Interesting concepts
  - But how may I plug this stuff in the docking procedure of my spacecraft to the International Space Station (ISS)?
    - Centimetric, millisecond precision!

  - What are we comparing exactly?
    - Nominal operation
      - System behaves as modeled
    - or exceptional operation
      - $System\ behavior \neq model$
    - Which approach is more resilient?

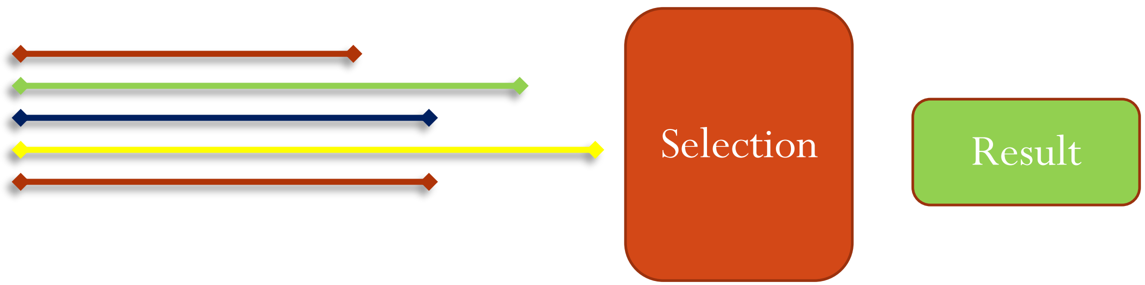
Redundancy and uncertainty

- Multi-track paradigm (example geolocation)



Multi track Paradigm & Framework

- Multi-track approach

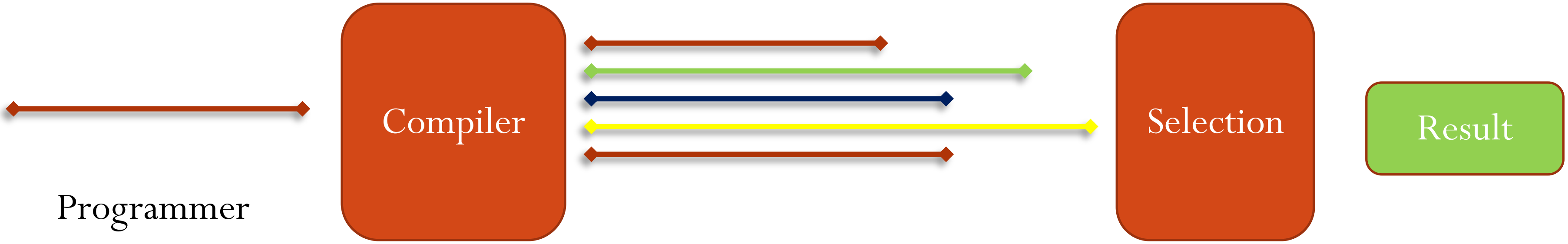


Programmer writes all alternative tracks code

Programmer writes selection function code

Multi track Paradigm & Framework

- Multi-track approach



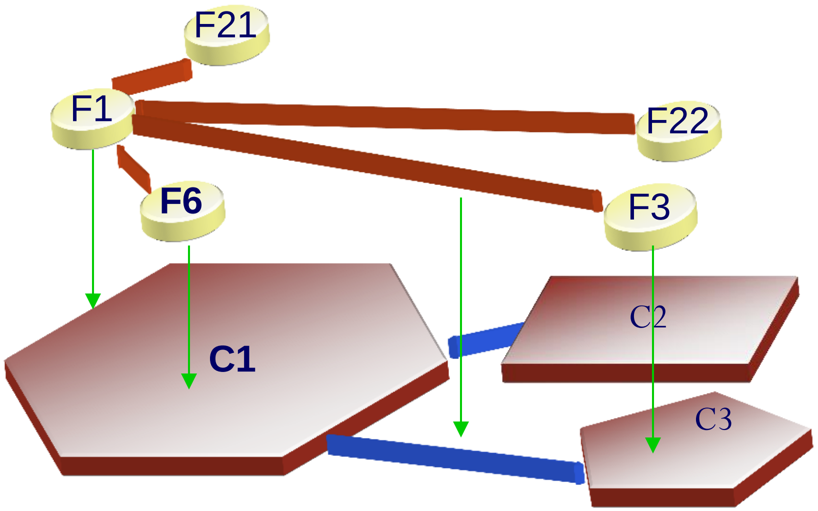
Programmer writes one instruction stream

Lack of tools, once more!

- No programming frameworks providing:
  - Programming just the track skeleton
  - Automatic generation of multi-track instances
  - Gathering all results
  - Comparing and deciding
- Quite a challenge to develop this framework!
  - How would a component look like in this case?
  - What would be the input?
  - Etc.

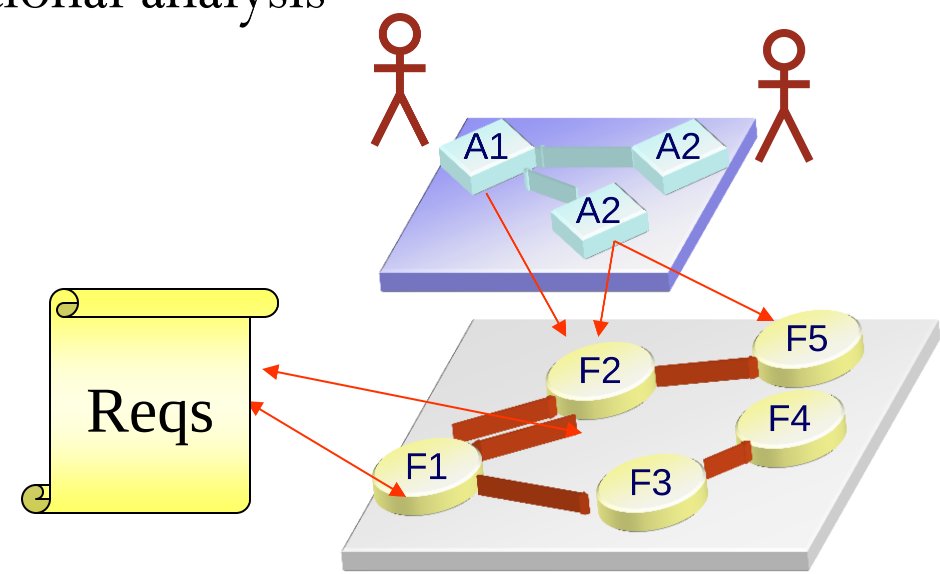
Functional approach: a major Key…

- To capture Need
  - (functional analysis, non-functional constraints allocation)
- To design Solution
  - (functions allocation to components)
- To ensure consistency between Need & Solution
  - (unique, consistent functional dataflow allocated)



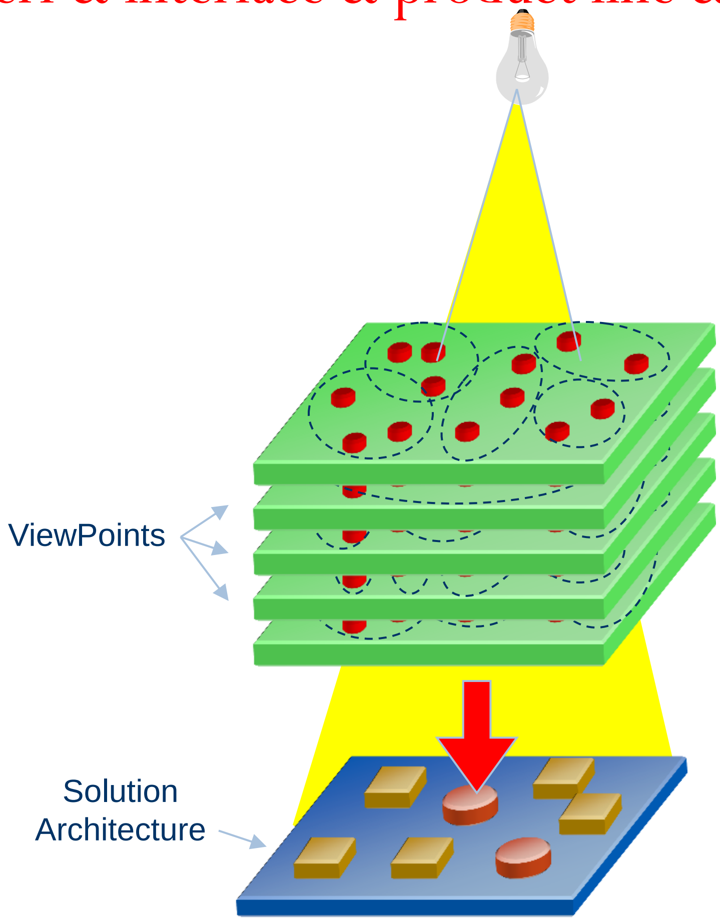
How to validate Need understanding

- Operational Analysis
  - (actors, tasks, roles, missions & goals)
- Including capture of non-functional constraints
- Functions traceability & justification Vs Requirements *<u>and</u>* operational analysis



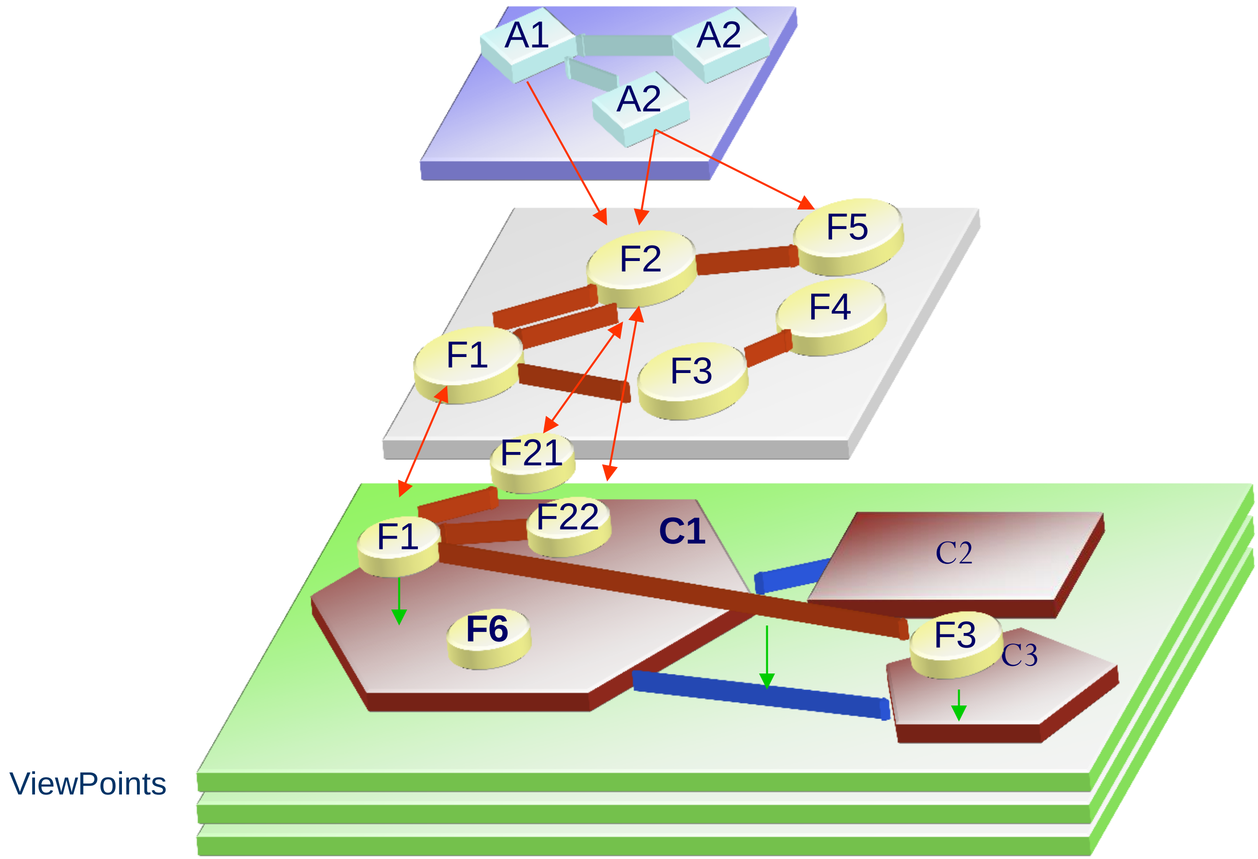
How to validate Solution /1

- Perform a multi-viewpoint trade-off Analysis
  - safety & perf & interface & product line & weight & cost &…

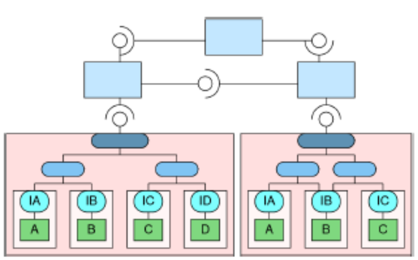


How to validate Solution /2

- Confront Components Architecture Vs Requirements and Need analysis
  - Operational, Functional, non-Functional



Summary: Steps & Models

- Operational Analysis
- Functional/NF Analysis
- Logical Architecture Viewpoints trade-off
- 

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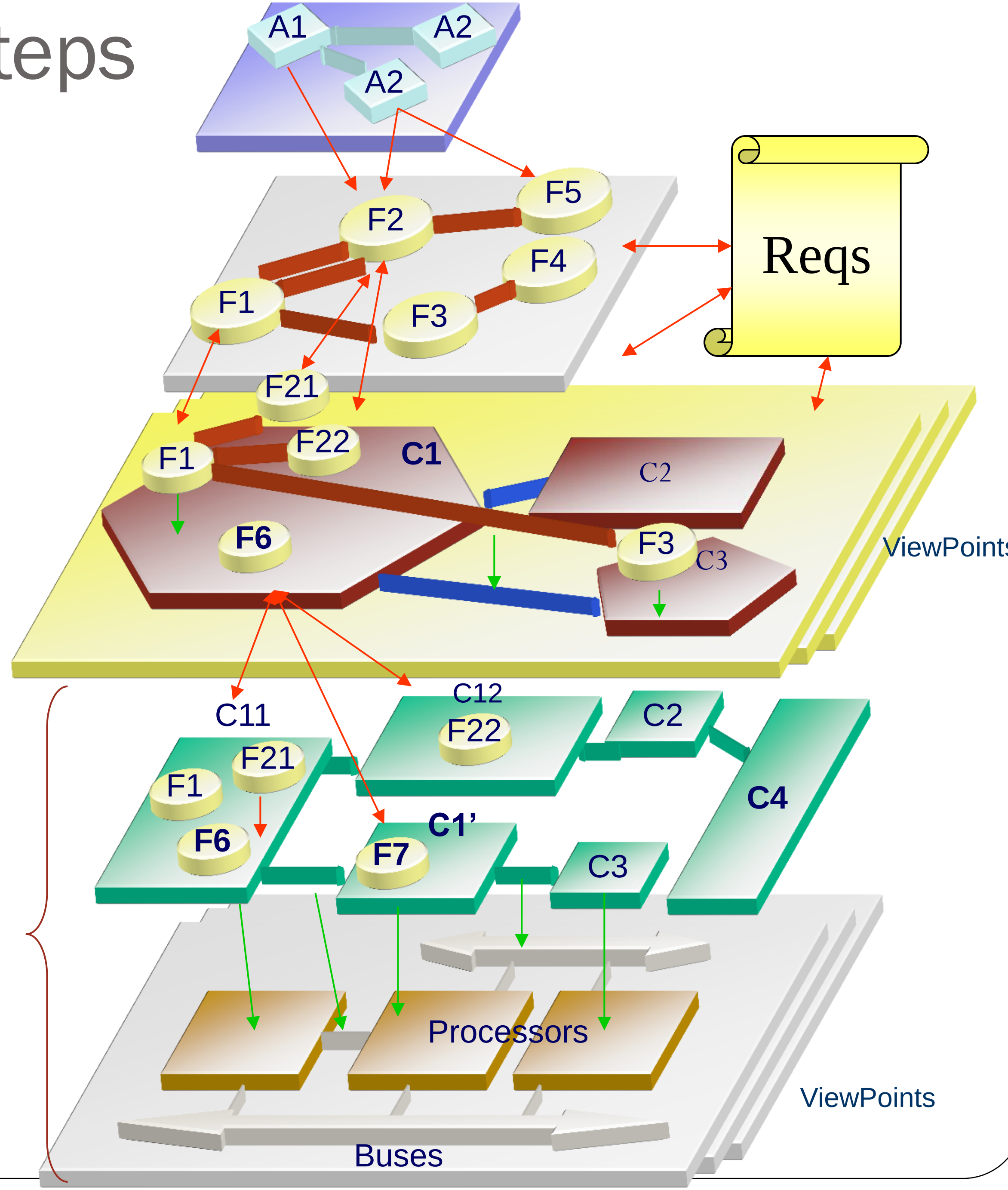
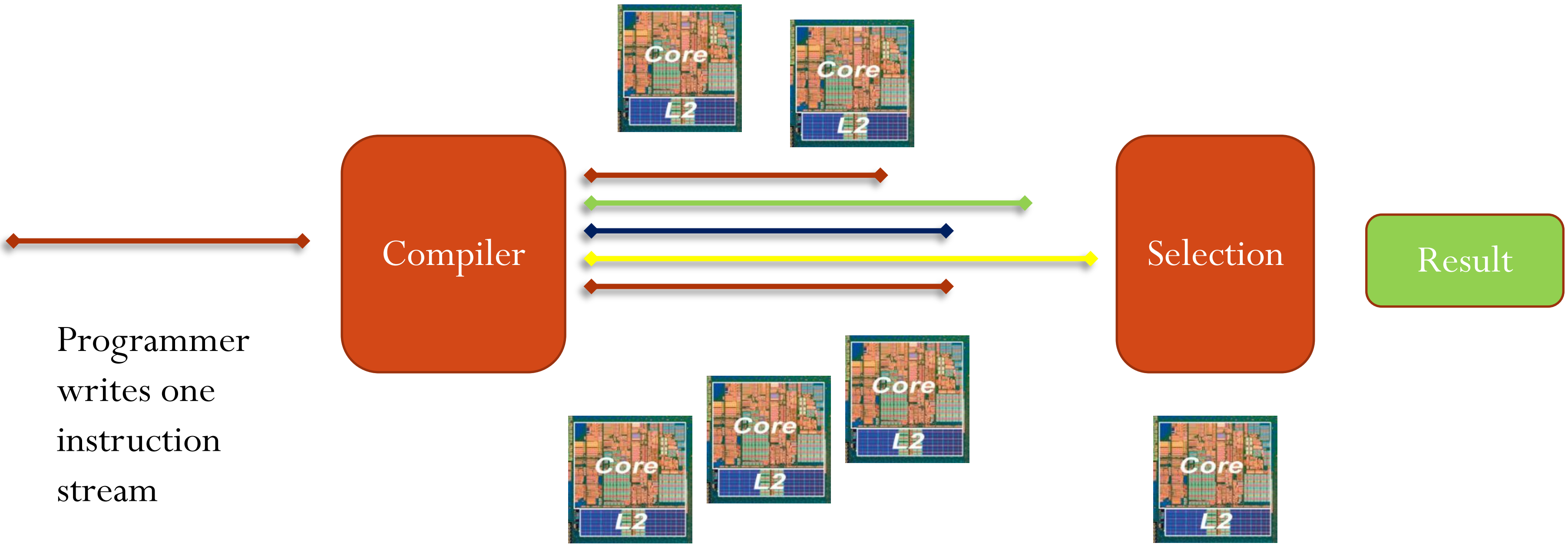


Redundancy and multi/many core processors

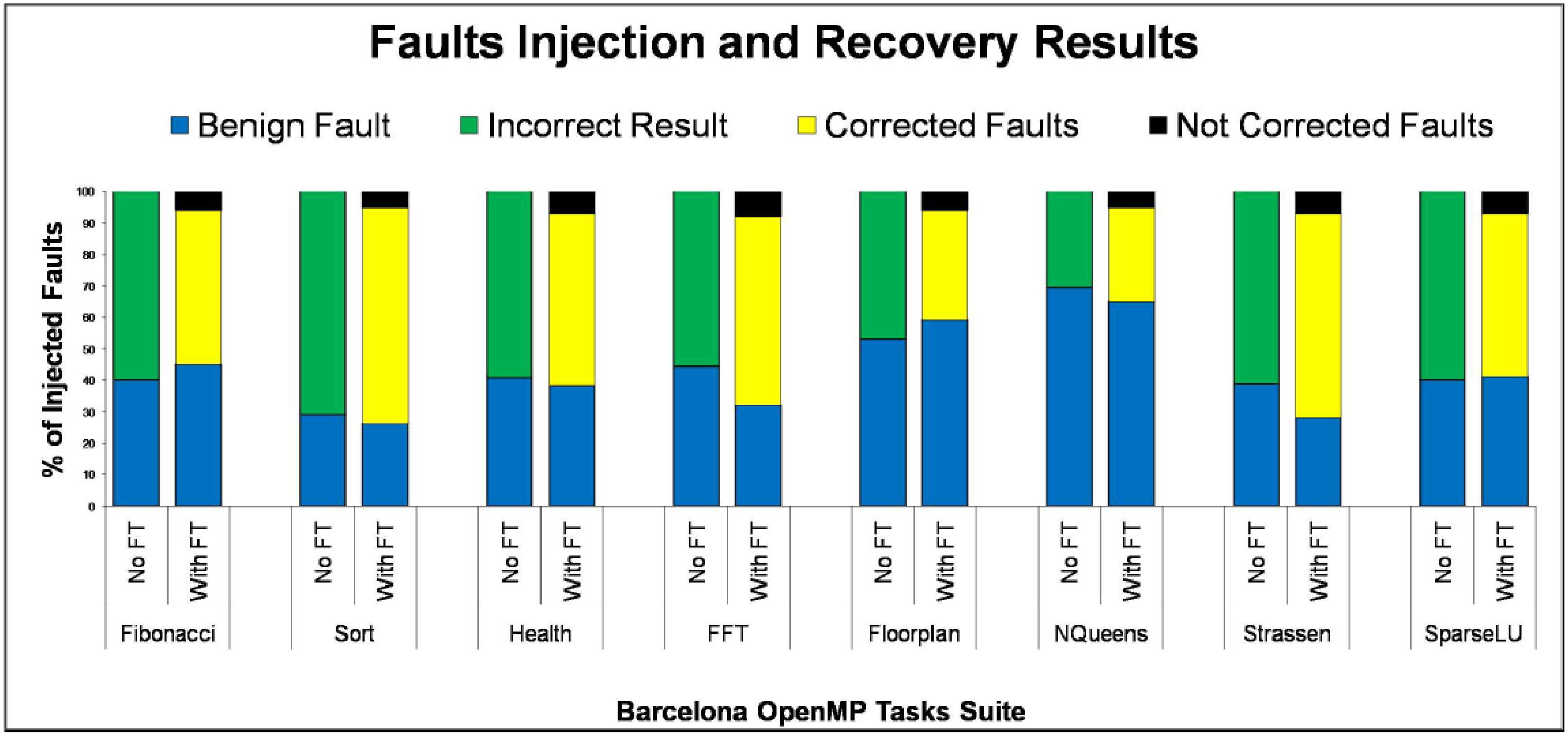
Towards automatic redundancy?

Smart Redundancy over multi/many core

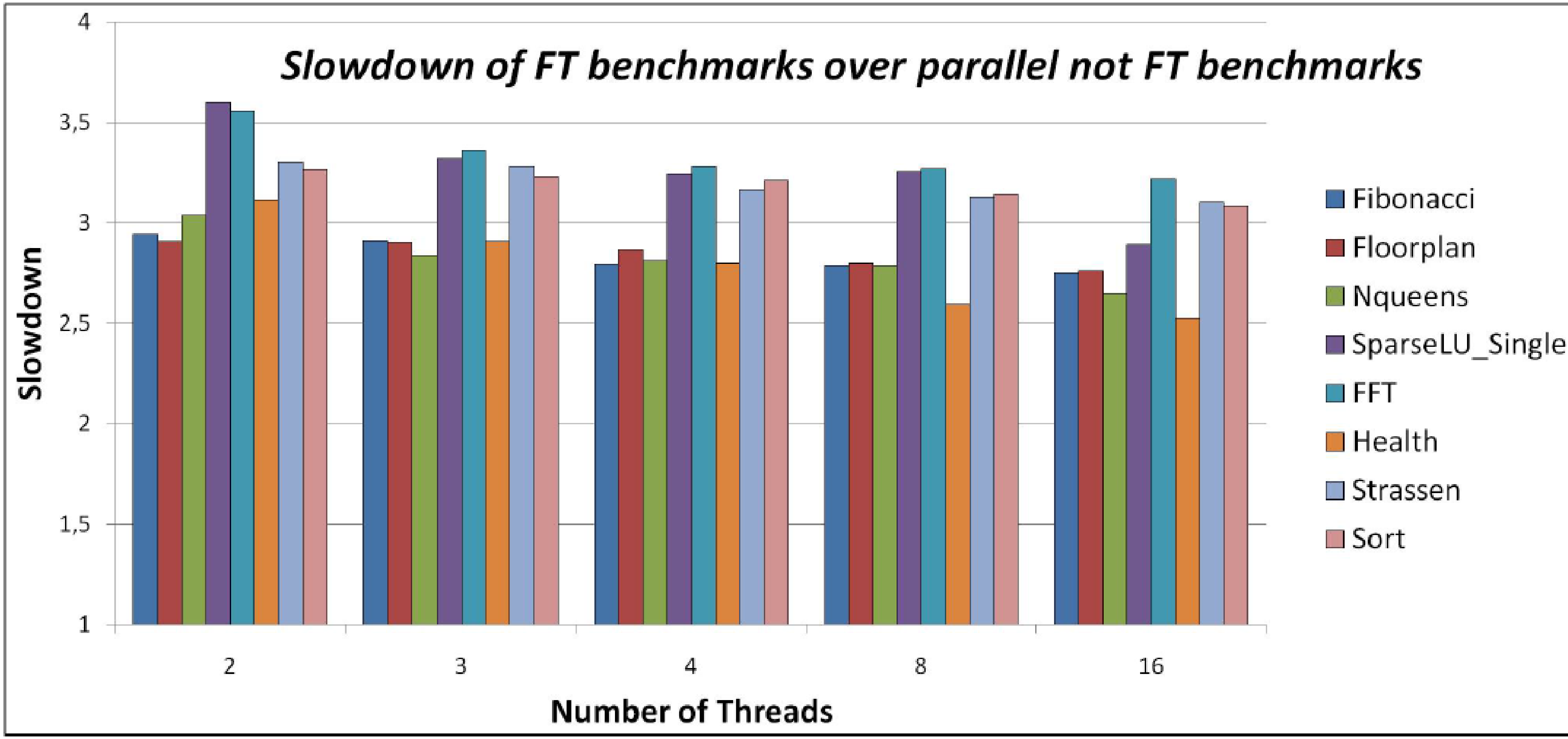


Automatic Redundancy Framework

- *Improving execution reliability of parallel applications on multi-core architectures*, O. Tahan, PhD. Thesis, December 2012

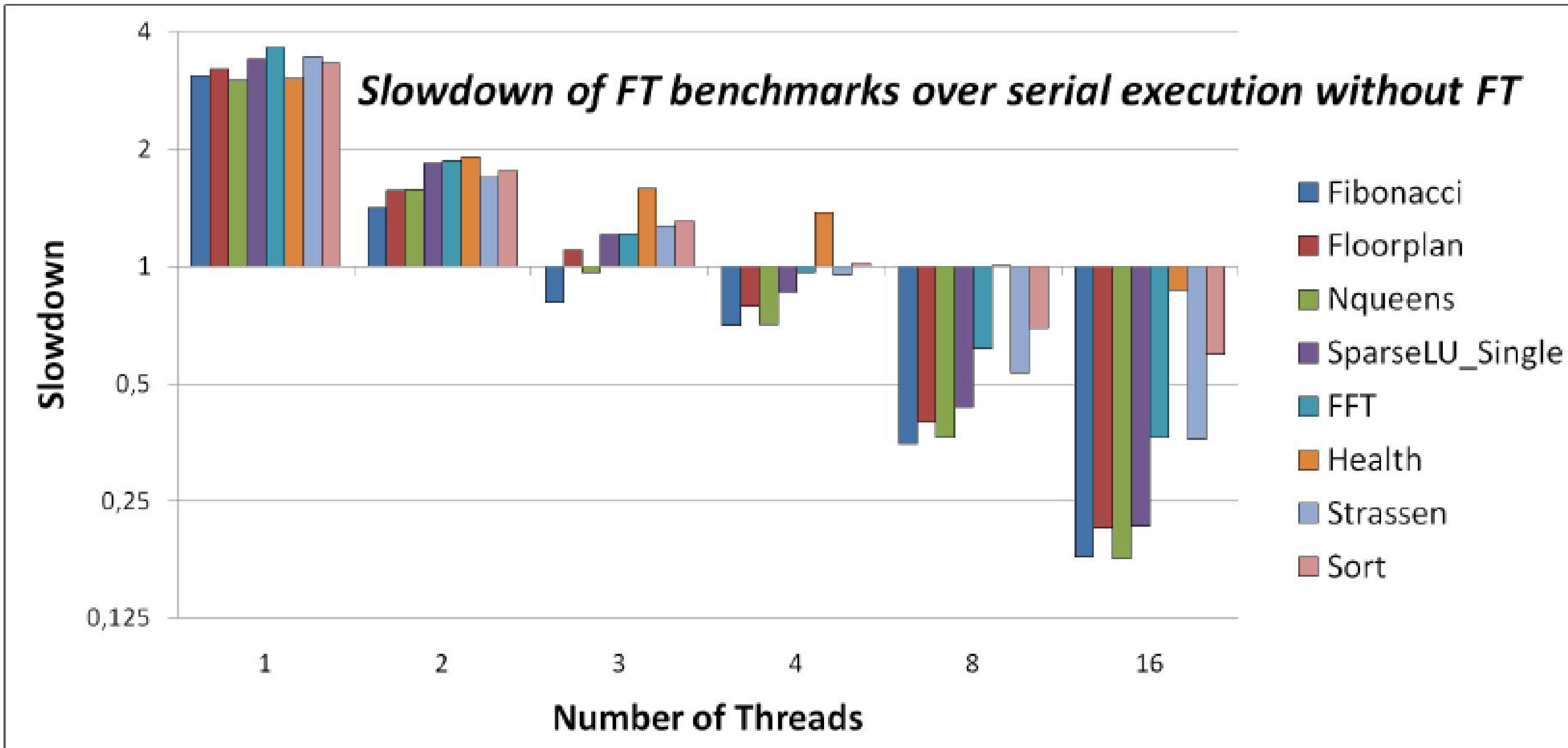


Redundancy Framework, Slowdown!

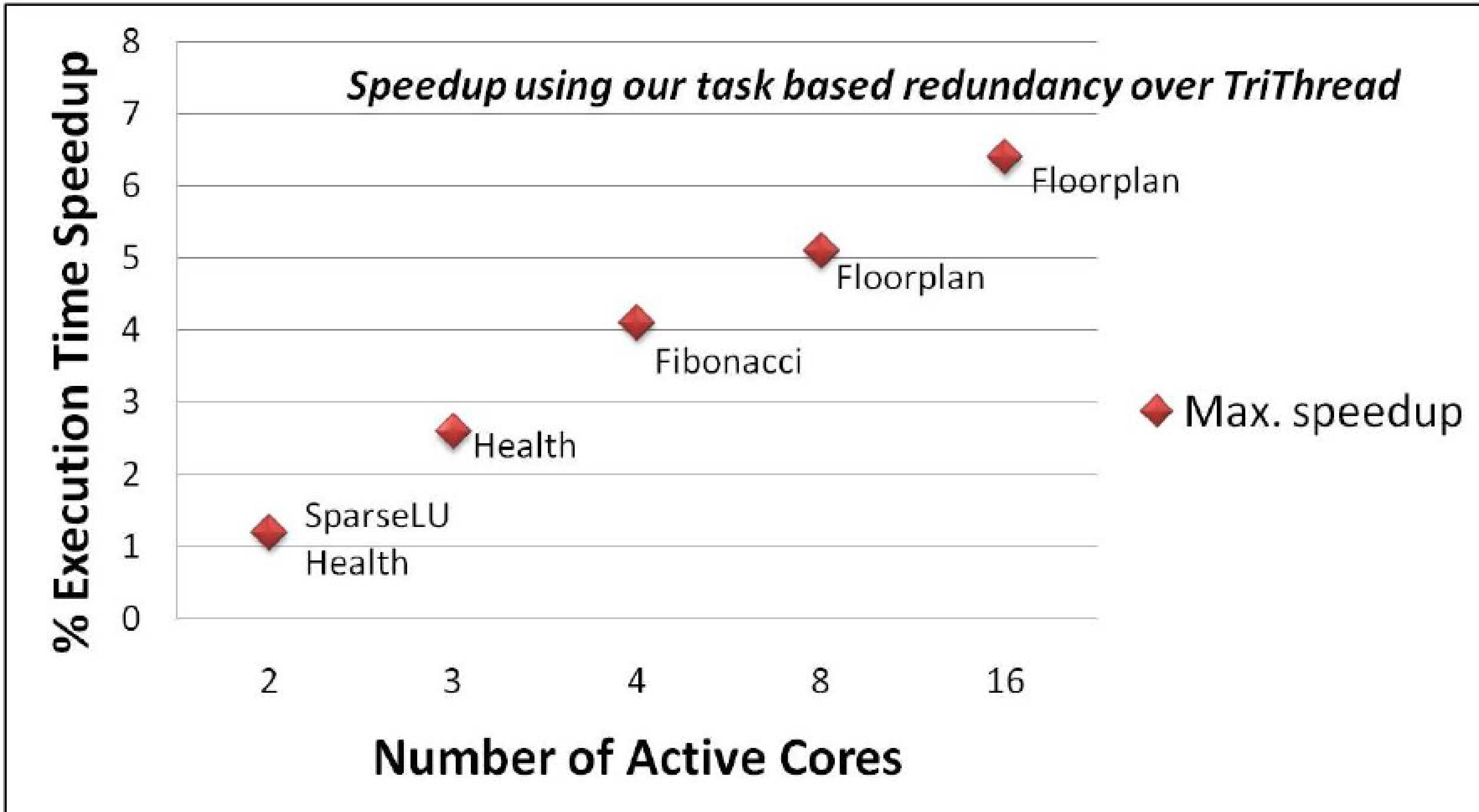


Benchmarks slowdowns vary between 2.53X and 3.22x on 16 cores

Redundancy Framework
but overall speedup wrt mono-core



Speed-up using ‘smart redundancy’



Tools for automatic redundancy

- From the fault tree analysis
- Automatically generate diagnosis models
- Check if architecture (hardware/software) are satisfying diagnosis model
- Automatically generate redundant software code

Conclusion

- ‘Overcome uncertainty’ or ‘manage uncertainty’
- Exact reasonning/programming
  - Versus
- Approximate reasonning/ « *programming?* »
- Automatic redundancy generation
  - Many core processors opportunity
- Lack of tools
  - In all your research works,
  - Please:
  - Think Algorithm but prototype a tool!