HYBRID PHYSICS-INFORMED ARTIFICIAL INTELLIGENCE FOR DRIVING ASSISTANCE. APPLICATION TO PREVENTIVE AUTOMATED CRUISE CONTROL

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INTRODUCTION

A significant part of driver assistance systems (ADAS) is made up of so-called reactive systems: they are triggered at the last moment to manage an emergency situation in driver's place. The most telling example currently is Automatic Emergency Braking (AEB). Vehicle has sensors for perception, artificial intelligence for pattern and situation recognition, and it drives vehicle during the emergency situation much better than an ordinary driver. In fact, standard driver very rarely experiences emergency situations, and as a result, he/she generally detects them a little late, and above all, does not know what to do to solve problem, or even acts in a counterproductive way. increasing probability and severity of accidents. In this type of situation, we can almost certainly say that 'the machine is superior to human driver.

Under the pressure of “autonomous vehicle” development, we are also seeing the appearance of ADAS allowing delegation of certain driving tasks in normal conditions (outside of any emergency situation).

This is the case for example of:

. Lane Keeping, which brings vehicle back to the center of its lane by acting on the steering wheel

. ACC (Automatic Cruise Control) which can automatically manage interdistances

We can clearly see the difference between the first type of driving assistance, which consists in implementing quick reflexes adapted to the vehicle to avoid or moderate the accident, and the second type, which consists in finally applying supposed "precautionary rules" to minimize chances of being surprised. But goals are not really based on road safety research results : is center of the lane always the safest place ? It should be checked in road safety studies.

Driving assistance outside of any emergency situation are called partial delegations of the driving task, and are labelled in terms of performance, according to their level of autonomy (level 1 to level 5) and their scope of application , from a very specific case “e.g. on motorway in traffic jams” to the general case of driving in all weathers and all road traffic in town, on roads, and on motorways. This remark is important, a "level 2" in any driving condition can be more complex to achieve than a "level 5" in a very controlled case with a very restricted scope of application.

We have been working on the subject of driving assistance in normal operation (excluding emergency situations) for more than 20 years, and believe that this part of driving assistance is likely to produce a significant leap in road safety. Observation on which we started in 2001 is that an 18-year-old driver has better eyes and better reflexes than a 60-year-old driver, but costs insurers 3 to 4 times more [Kell2006], even 12 times more in some countries. Analysis of this phenomenon shows that experienced driver does not rely on super-reflexes (which he/she no longer has) to manage road safety: he/she applies a priori rules of prudence allowing to better anticipate, and so not end up in an emergency situation if possible. If we partially automate driving with this idea of anticipation, we come across, for example, management of interdistances and lane keeping presented above. Our work was to generalize this anticipation approach.

This led us to formally ask the question “*what does it mean to drive well, outside of any emergency situation?*” ". This question was initially asked by insurers and driving psychologists [Ban2021], and it is now coming to car manufacturers to offer non-emergency driving assistance systems, right up to autonomous vehicles.

We came up with the idea of reformulating this question from perspective of prudence and have chosen to estimate in real time level of caution (or prudence) of a driving behavior regarding context. Notion of context is essential and is used to define prudence [ICRP2018] as '*the adequacy of the behavior to the context, without necessarily knowing the whole context or all the possible consequences of a behavior*'. We have been working on this approach since 2001 through numerous collaborative research programs [Brunet2010]. The approach seems to us to be more operational than that consisting in seeking to know the whole context and knowing how to predict consequences of any action, an approach which is somewhat the philosophy of a lot of work on autonomous vehicle. Unfortunately, this last solution obviously leads to vehicles overloaded with sensors and to road infrastructures that are overpriced (since we have to know everything), and to increasing on-board computing power (since we have to understand everything) , putting the fruits of this work out of the market because it is too expensive. Such an approach can only be applied to public transport systems, since the purchase or rental of such a vehicle is not an option. It is still necessary that the flow of people transported make it possible to make investment profitable over an acceptable period, which is not yet the case to date.

Our original way of asking the question has given rise over the past twenty years to iterative development of an AI called SafetyNex, for monitoring driving behavior in regard of context, of which we have already published theoretical applications to resolution of several recurring problems in the automotive sector [Brunet2018].

NB: we can broadly link our approach to functional safety, but only for the specific part of "road safety" [Julien2016]. Similarly, we have been able to develop applications for the world of insurance [Yah2016] which are currently being deployed operationally.

We present in this paper the hybrid architecture of this AI, and AI techniques used, main automotive functions that can be built using this AI, and real driving results in piloting a preventive ACC, on a STELLANTIS vehicle in 2022.

CAUTION (OR PRUDENCE) AND RISK IN ROAD SAFETY: THEORY OF RISK

Prudence consists, as mentioned above, in acting in anticipation of potential surprises, without knowing everything about context. From this definition, we define the notion of risk as being lack of prudence. Note that with this definition, risk is absolutely not a probability of accident. It so happens that researcher Frank E. Bird has developed a theory of risk that is completely compatible with our definition [Bird1996]. This allows us to rely on theoretical bases that we apply to the particular case of road safety.

We therefore use the concept of 'risk triangle':

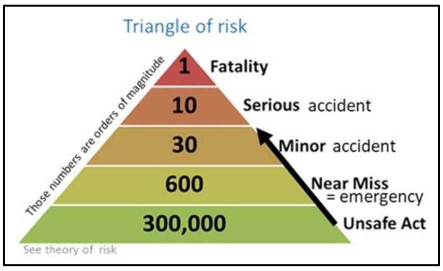

Fig.1

We show above this triangle of risk with numbers of occurrences which are good in orders of magnitude. Of course, precise frequencies of occurrence vary depending on use case.

We define on the triangle of risks the notion of 'unsafe act': driver commits an imprudence, and as the triangle shows, this does not lead to consequences most of the time (*). But rarely, this recklessness leads to Near-Miss situation, or emergency situation, for which accident is avoided most often. Finally, some accidents occur, of which a small part is serious and an even smaller part is fatal.

Level of prudence (or caution) estimated by our AI can be considered in a way as a "distance" to the risk triangle, with entry into the triangle (unsafe act) when prudence score is too low (or when ‘lack of prudence’, called ‘risk’, is too high). We will explain calculation of risk later, but from now on, on this graph, we can define two levels of anticipation:

. detection of entry into risk triangle, and action for a rapid exit: ‘undo unsafe act’. It is indeed still a question of anticipation because we are not yet in an emergency situation, but it is possible that we will find ourselves there if we do nothing.

. continuous monitoring of the value of risk so as never to enter, when possible, into risk triangle. To do this, we define a maximum authorized risk (lower than the high risk which corresponds to entering triangle). This risk is referred to below as ‘risk target’. If we manage not to exceed risk target, then we do not enter into risk triangle and we do not commit an unsafe act. This is the second level of anticipation. Note : conditions on real roads may be complex, and sometimes it is not possible to avoid entring triangle. E.g. : vehicle should slow down to stay prudent but a crazy vehicle appeared behind and may hit rear of the car if braking is done at right level. The idea is to be aware of it and if obliged to enter triangle, then find a quick way to exit.

RISK CALCULATION, CANDIDATE METHODS, AI METHOD SELECTED

. Disqualification of geotagged statistics and probabilities : the so-called black spots

Even if we have taken precaution of defining notion of risk, and of showing that it does not coincide with notion of probability, it is clear that the word ‘risk’ implicitly covers a notion of 'chance', and that temptation to modeling this by probabilities is great for engineers. The difficulty of using probabilities to help a driver results from the fact that, at the local level, observed frequencies of accidents do not make it possible to estimate probabilities. E.g., take the case of a section of road where no accident has been measured in recent years (observed frequency = zero). Who would dare to say that probability of an accident on this section is nil? (crash not possible). At most, we can say that probability is 'low'. In the same way, if we take a national road which has had a serious accident on a section in the last 5 years (definition of 'black spot’), we see that this place has seen tens or even hundreds of million accident-free vehicles. We can then say that a black spot is a mostly very safe area, which is quite paradoxical.

And observed frequency is of the order of magnitude of 10^{-8}.

We then have a zero observed frequency which intuitively corresponds to a very low probability, to be compared to a very low observed frequency which also intuitively corresponds to a very low probability. This information is not predictive at the local level. It cannot help driver to better anticipate.

Theoretical basis behind this uselessness is that road accidents are very rare: in the OECD, we see 1 accident on average every 100,000 km, and 3 deaths every billion km. From a statistical point of view, at local level, we are therefore still in the case of 'insufficient data' [Royal2004], so that accident observations prove nothing and have no predictive power at local level (i.e. « here » and « now »).

. Disqualification of deep learning and machine learning in general

When talking about AI, deep learning naturally appears as a candidate method. The interest being that one can build a function without modeling it explicitly, by only having examples of occurence of function calculation result. This skill is called supervised learning, and these occurences of function are called 'learning examples'.

In the case of risk level, or prudence level, arguments disqualifying deep learning are:

. intrinsic mathematical inadequacy: a neural network shows in its calculations linear combinations which constitute inputs of non-linear functions F called activation functions. However, a linear combination is a calculation that natively proposes notion of ‘counterbalance’: ‘*if I am bad on certain criteria and good on others, it is possible that I am average overall*’. This obviously depends on coefficients of the linear combination, which are modified iteratively by learning process.

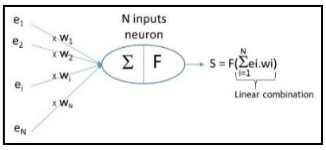

Fig.2

What goes into the function F is the scalar product of the input and synaptic point vectors.

And even in the case of Convolution Neural Networks (CNN) [Saks2018], convolution product between two vectors of the signal vector space e and h is written as a linear combination:

$$\boxed{S(i) = \underbrace{\sum_{k} h(i).e(k-i)}_{\text{Linear combination}}}$$

Fig.3

Note: We may notice that this convolution product is also written as a cross-correlation product which is the scalar product in the vector space of signals [Jutt1018] (functional equivalent in this vectorial space of the usual scalar product). We can also consider convolutions as the integration in neural network of filters classically applied in pre-processing.

But unfortunately concerning notion of risk (or prudence), it is quite rare that counterbalance makes sense: if I am very cautious on nine criteria but very risky on the tenth criterion, it is a safe bet that I am overall very risky. Of course, deep learning can in theory achieve this type of function, since multilayer neural networks, under certain conditions concerning their activation function, are 'universal approximants' [Hanin2019]. But we can then understand that learning such functions will naturally be complex and will require a large base of examples. However, on notion of risk in road safety, there is no large-scale resolved database.

Arguments disqualifying general machine learning (not just deep learning) are:

. fundamental inadequacy: the very notion of risk as described by Frank E. Bird's risk triangle makes supervised learning impossible: out of 300,000 unsafe acts, we get only 600 emergency situations result. However, these unsafe acts leading to near-misses will be 'identical' to others from point of view of what is measurable. We will then have same entry several times with desired exit "no near-miss" the vast majority of the time, and "near-miss" in a very small number of cases. Supervised learning cannot work under these conditions.

. insufficient data: Let's fancy that : *'I came to see you by passing all STOP signs without even slowing down, and I had no accident or quasi accident (we can see that it is possible), should I launch a learning?'* The answer is no. This is also unfortunately what some drivers do: they commit incautious acts but do not have an accident or even a bad surprise, and they take on bad habits in terms of road safety.

For all these reasons, deep learning (and machine learning in general) turned out not to be a good candidate.

. Qualification of knowledge-based systems

Prudence and good driving on road are explicit knowledges transmitted in high school and in driving schools. We have seen previously that we do not really have access to risk databases, on the other hand, we are lucky to have access to explicit knowledge [Roberts2001].

Since notion of prudence corresponds to explicit knowledge, we have oriented our development of risk assessment towards knowledge-based systems [Kraso2016].

Development of such a system required an operation to collect expertise from road safety experts from 19 countries. The main difficulty of this knowledge extraction is that experts do not know how to directly formulate their expertise, they need to be solicited by use-cases on which they give a diagnosis accompanied by the reasoning which led them there. It is a particular type of extraction of expertise [Diana2016], which is particularly time-consuming.

In addition to these collections of expertise (multi-country and multi-expert), we studied technical reports on road risk written by technical centers and research centers for road infrastructure equipment, as for example in France. SETRA [Setra2009] that is now renamed as CEREMA.

We converged on the use of notion of disruption on a pathway' proposed by researchers in road safety equipment [Lechner 2010]. This formalism makes it possible to judge inadequacy of an approach trajectory to a singularity on a route (examples for static part of context: an intersection, a bend, a roundabout, a school zone, a pedestrian crossing, a level crossing, narrowing of the lane/road, modification of speed limit, etc.).

In addition, we have carried out interviews with qualified public transport drivers on their rules of use which minimize their problems on road, and we have analyzed driving guides for the attention of public transport drivers in around twenty countries, and in particular in the USA where they are particularly detailed [Handbook2019].

Similarly, we collaborated with car drivers (endurance rally) to understand their way of reading difficulty on the road. Even if their performance is far from that of average driver, their expertise in reading difficulties is nevertheless very predictive of a driver's ability to remain cautious.

Last, we have compiled rules of caution contained in driving licenses manuals throughout the world, and in particular in the OECD countries which present these rules quite explicitly [HighwayCode2007].

VALIDATION OF KNOWLEDGE

Knowledge validation is a key element for this type of system. We were lucky to have more than 50 experts, spread over 19 countries.

We first had cross-assessments carried out on the same use cases by all experts. Expert reports that did not lead to a consensus were presented to all experts who clarified and modified their judgments. Most often, divergent expertise came from a misunderstanding of the use case. For example, the case of roundabout has shown that their characteristics in the cities of Trouville in France, and Tokyo in Japan, are so different that they are actually different use cases. Similarly, we were able to show the existence of road signs closely linked to a geographical area that only drivers in this area know how to interpret, which may have led experts to disagree. Let us cite, for example, the case of a traffic light accompanied by a STOP sign which is specific to a region of Germany. No one knows what to do with such road signs except the Germans in this area.

Once all the experts had converged on a large number of use cases, we took cases in new places, we formally applied gathered expertise, and asked experts in parallel to give their opinion. . Of course, we could see ruptures in the monotony of their reasoning and even questioning of the applicability of their expertise under certain conditions.

We spent 15 years between the start of collection of expertise and validation by the group of experts. This research spanned 12 collaborative research programs.

MATHEMATICAL REPRESENTATION OF KNOWLEDGE

Once knowledge is considered valid and stable (tested globally), a method of mathematical representation must be chosen. In the 1980s, expert systems generally used an ‘if…then…’ ‘logical rules’ formalism.

In the world of car driving, we are rarely in a canonical use case, real situation evolves continuously from one use case to another. Moreover, expertise of the experts is expressed quite naturally in a gradual manner: ‘more… and more…’. Example: when you cross a priority on the right, the more you keep legal speed limit (without slowing down), the greater the risk.

Furthermore, the expert appraisal showed that judgment of level of risk calls upon numerous criteria to be combined, each criterion being handled separately in a given logical atom. These criteria must be merged. These characteristics have oriented us towards the use of two mathematical theories to achieve this fusion with limited computational needs.

. fuzzy logic |Zadeh1996]

Fuzzy logic makes it possible to construct non-binary membership operators for sets which are then called “fuzzy sets”. These operators are continuous. This gives rise to notion of ‘membership degree to a fuzzy set’, this degree being able to vary between 0 and 1.

Such an operator can then be drawn as follows

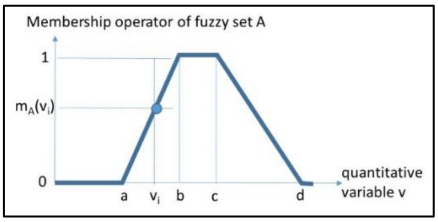

Fig.4

$m_A(v_i)$ is the membership degree of v_i to set A

We can define logical AND and logical OR:

$m_A(v_i)$ AND $m_B(v_i) = m_{A\cap B}(v_i) = \min(m_A(v_i), m_B(v_i))$

$m_A(v_i)$ OR $m_B(v_i) = m_{A\cup B}(v_i) = \max(m_A(v_i), m_B(v_i))$

From these two basic definitions, we can find the vast majority of properties of binary logic, with notable exception of:

. Exclusion of a truth and its opposite: $m_{non(A)}(v_i) = 1 - m_A(v_i)$, which is not zero in the general case.

We speak of this property of non-Aristotelian logic because a proposition can be both true and false with different degrees of truth (one being 1 minus the other).

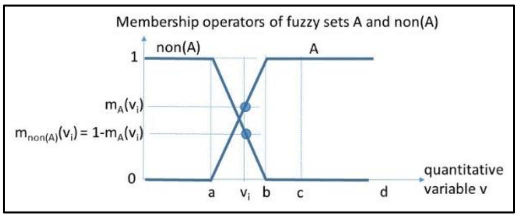

Fig.5

. their conjunction min(m, 1-m) takes its values in [0, 1]

. union of A and NON(A) does not shapes the universe: A and NON(A) are not a partition of the universe

We also define interesting notions such as ‘very(m)’, ‘a little(m)’, etc.

These elements make it possible to express very natural logical reasoning. In particular, one can easily express an atom of knowledge using a fuzzy logic operator.

Example: *“it is risky to drive too close to vehicle ahead”*

This proposition will first be reformulated as follows:

"the shorter the interdistance, the riskier the driving", which allows to build the following membership operator:

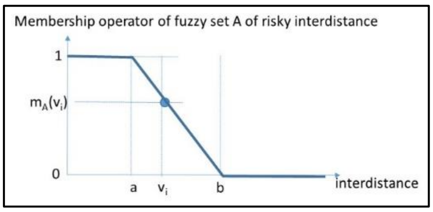

Fig.6

$m_A(v_i)$ is the membership degree of interdistance v_i to fuzzy set A of risky interdistances. Experts knowledge allows to shape the operator m_A and give values for a and b.

Note: we notice that modeling of knowledge atoms generally requires a reformulation in order to fit with the formalism of fuzzy sets.

Similarly, an imprecise datum which value is approximately v_i can be represented by an operator of membership to the fuzzy set of the numbers which are approximately vi :

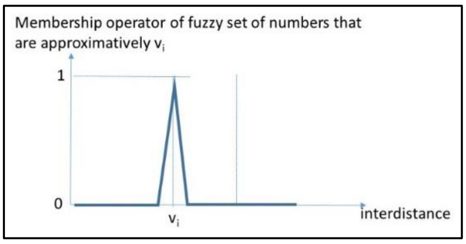

Fig.7

Width of this so-called hat-shaped operator depends on precision of data. It is noted that in the automotive sector, sensors can have different accuracies depending on price. It is quite easy to set up a system handling fuzzy logic to take this into account.

It then becomes possible to compare ‘imprecise data’ with a ‘concept’ by comparing fuzzy set operators.

For this, we can define notions of distance, similarity, etc. [Hamor2013].

We can also represent uncertainty attached to a fuzzy set operator as follows:

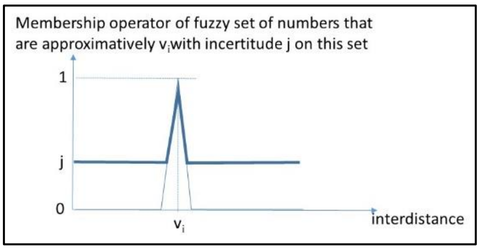

Fig.8

j is the level of uncertainty.

In this example, on a vehicle that does not have an interdistance measurement (frontal radar for example), we will set j to 1. Anf then interdistance will never be the riskier criteria and will not be taken into account. We see that this can be an elegant way of representing the absence of certain input data, either because corresponding sensor is not available on a vehicle range level, or because data is temporarily unavailable: sensor diagnosing its failure, asynchronous bus not supplying data for several frames, etc.

On a vehicle equipped with a radar, we will connect the value of interdistance with j to zero. If radar self-diagnosis indicates a possible malfunction, you can decide to set j to 0.5 for example.

This means that we are formally able to:

. create an AI that works with a variable amount of input data

. take into account self-diagnostics of sensors

All of these concepts also make it possible to mimic the way humans reason with non-monotonic logic and defeasible reasoning: “It has gained interest because it provides the basis for computational models inspired by the way humans reason” [Bench2007].

. possibility theory [Dubois2021]

Possibility theory is an alternative to probability theory for representing inaccuracies and uncertainties. This theory grafts very easily to fuzzy logic because it provides simple and efficient ways of comparing fuzzy membership operators.

In particular, the 'possibility index' expresses *'the possibility that imprecise data correspond to the concept of gradual knowledge'*.

For instance, we can define possibility index so that the set of interdistances equal to approximately v_i corresponds to concept of risky interdistance:

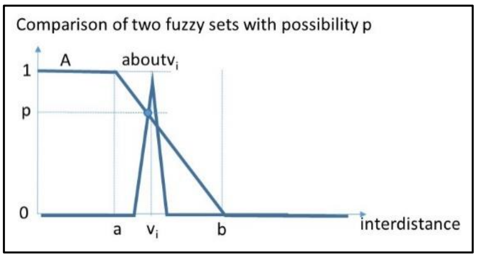

Fig.9

The possibility value p is the max of intersection between the membership operators of fuzzy sets A and aboutv_i

We can also define other indices such as ‘necessity’, for example. The possibility index is always greater than or equal to the probability. The interest is that it is calculated on operators of fuzzy sets representing existing gradual knowledge, and not on observations of frequency of occurrence which are not relevant at local level in road safety.

Similarly, possibility theory makes it possible to define a notion of non-interaction which is a generalization in gradual logic of logical independence. This makes it possible to manipulate atoms of knowledge group by group and only achieve the fusion at the end. In particular, this approach can be applied to fusion by combining possibility distributions by means of min functions on clusters of fuzzy sets [Benf2001]. Note that this approach is often applied to syntactic coding of the merging of the bases of classical logic using Hamming distance [Benf2002].

The strongest possibility index wins, and explains the cause of risk. AI is then by construction explanable since it explicitly manipulates knowledge: we then can say that it is a XAI (eXplanable Artifitial Intelligence) [Gunn2021].

It is important to note that this approach makes it possible to implicitly manipulate the combination of use cases, and meets following need:

. we know risk associated with behavior when approaching a roundabout

. we know risk associated with the same behavior when overtaking a biker

. we know risk associated with the same cornering behavior

This natively makes it possible to know risk associated with this behavior when overtaking a motorcyclist in a curve when approaching a roundabout.

. integration of physical knowledge

Physical knowledge is of two types:

a. knowledge of vehicle dynamics, mainly represented by Bode diagrams [DiStefano 2014]. Indeed, for certain applications, it is a question of piloting a vehicle, longitudinally in the case of ACC or globally in the case of autonomous vehicle. Car manufacturers have an deep knowledge of the dynamics of their vehicles, it would be inefficient not to take this into account. It is not a knowledge described in a logical way, but in an equational way (linear differential equations in first approximation, and studied in frequency space after Laplace transform).

We are currently testing a specific deep learning (DL) architecture to recalculate parameters of some fuzzy logic operators related to physics, we have integrated physics knowledge (differential equations Bode diagrams) in DL [Heng2019] for control applications (ACC and autonomous vehicle).

b. knowledge of experts on physics of road infrastructures [Gall2008] and practical consequences in terms of constraints on trajectories. Among other things, the impacts of mobilizable grip on road safety [Schae2005], the impacts of atmospheric visibility [Yah2003] (fog, rain, snow, etc.), on road safety, as well as knowledge concerning geometric elements of roadway which have a hierarchical impact on accidentology [Pemb2019], in particular in curves, where it is not simply a question of having the shortest radius of curvature to characterize difficulty: the evolution of radius of curvature , and its 'readability' under all visibility conditions must also be taken into account [PubRes2008].

. taking into account the characteristics of the driver:

Every driver has an almost unique prudence and risk footprint. If we calculate the histogram of the risk estimated by the method presented above, we obtain a profile that characterizes driver:

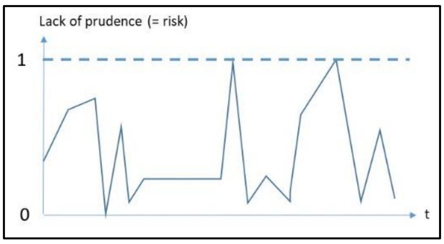

Fig.10

Histogram of this curve, in deciles, has the following shape:

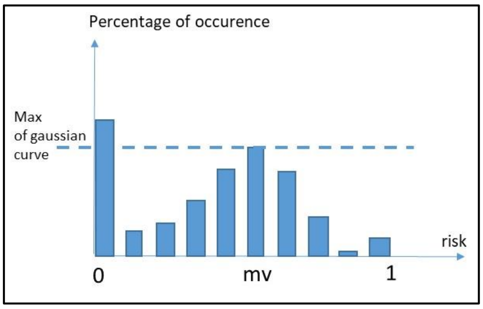

Fig.11

When developing a driving assistance system, whether it is an alert (cockpit application) which informs driver when he/she commits an 'unsafe act', or an ACC capable of regulating vehicle speed safely in traffic in all circumstances, it is important to characterize driver and take into account his/her way of taking risk. Indeed, even if it is imperative to limit risk to avoid 'unsafe acts' or at least to correct them very quickly, it is necessary to take into account the great disparity of drivers to prevent latter from switching off function. In this context, we carried out, on the one hand, risk profiles (histograms), and on the other hand, a vector quantification of vehicle control signals, using a modern version of neural gas [Qin2004], which makes it possible in particular to detect driving 'modes', used to make driving assistance adaptive (see applications chapter). We were able to show that profile (histogram) is very characteristic of driver. In particular, the graph above shows a bell curve identifiable as a Gaussian whose maximum likelihood mv, and standard deviation make it possible to calculate characteristics of driver.

ARCHITECTURE OF THE PRUDENCE AND RISK ESTIMATION AI

The complete architecture of this AI applied to real-time estimation of prudence and risk is:

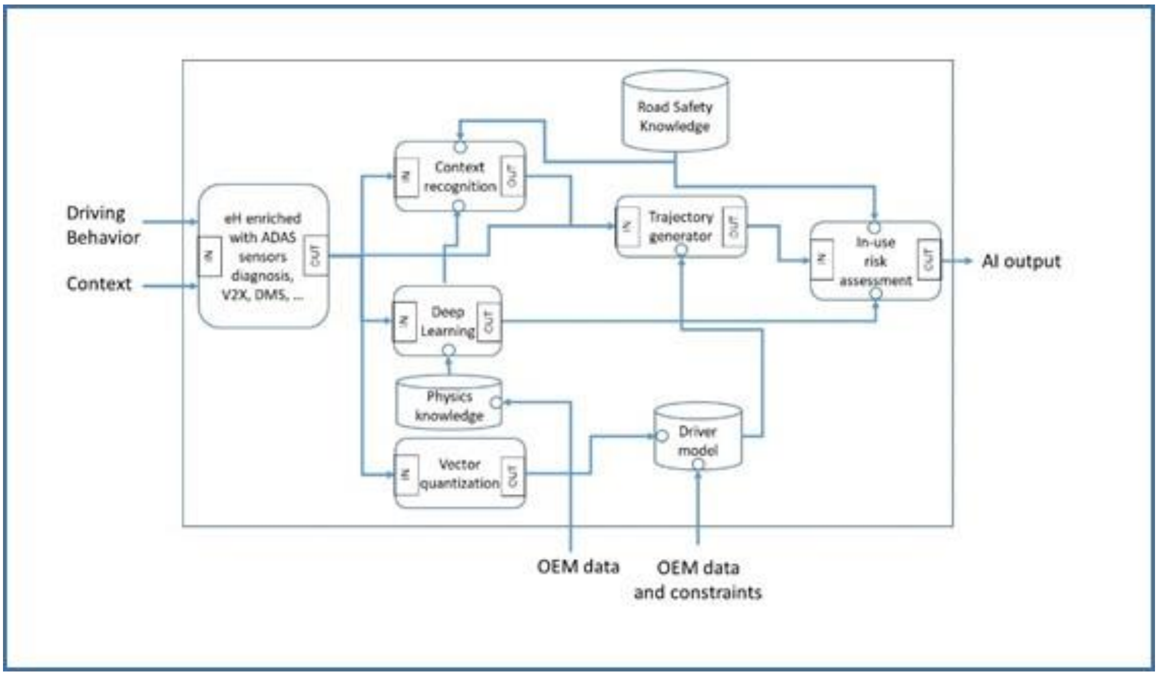

Fig.12

Driving behavior is described by variables containing location, kinematics and dynamics of the vehicle: geolocation and mapmatching, vehicle speed, yaw rate, acceleration vector, for example.

Context can be shared into two parts:

. Static context: shape, dimensions, and function of the elements of road infrastructure. This static input is in practice constituted by an electronic horizon reading a digital map in real time, and reporting all information concerning disruptions on the pathway (intersection, roundabout, pedestrian crossing, school zone, etc.). It is particularly important because 75% of road accidents can be explained by inappropriate driving behavior at road infrastructure [dataset2021]. This result is published by Great Britain known for developing quality infrastructures. We can use this percentage for OECD countries and consider that it is higher elsewhere.

. Dynamic context: interdistance, nature and location of other road users (vehicles, pedestrians, two-wheelers, etc.), mobilizable grip, atmospheric visibility, V2X hazard warning, Driver Monitoring System.

Context recognition uses explicit knowledge (example: an intersection with priority to the right) in the case of static context, when information is directly contained in map and read by electronic horizon. When data is implicitly contained in map but electronic horizon does not report it because no flag in the map references this context, then deep learning recognizes situation. For example, when driving on a priority road, a yellow sign indicates it in map, and electronic horizon brings it up. But where roads that intersect our electronic horizon have a stop sign, our electronic horizon does not have a yellow sign. Similarly, intersections are classified into categories, each of which corresponds, for road safety experts, to a clearly identified difficulty.

In the case of dynamic context crossed with static context, this systematically requires deep learning.

Trajectory generation is described in detail in specific case of ACC application in the applications chapter. In the case of manual driving, trajectory is that imposed by driver.

In addition to the fact that this AI is a XAI, OEM has very fine tuning inputs for behavior of the AI:

. vehicle physics data

. data and constraints on driver model in the case of ACC and the autonomous vehicle: among other things, the constraints are values of max acceleration, max deceleration, max jerk.

. risk target wich modulates with « one button » aggressiveness of an automated driving system

This allows each car manufacturer to tune their application exactly as they wish. This avoids the “black box effect”.

Real-time output of the AI provides, 20 times per second:

. instantaneous caution and risk values

. alerts on risk levels

. charts of iso-risk curves between present moment and the future when meeting of next rupture on the pathway: calculation of risk projected on electronic horizon (see safety coach chapter)

. explanatory data to know what generated the risk

AUTOMOTIVE APPLICATIONS

This chapter describes main applications of prudence or risk assessment in the automotive sector : ADAS and Autonomous Driving.

. Safety Score

The safety score is the recording along a journey of caution and risk data calculated 20 times per second in real time during trip. Risk histogram makes it possible to characterize the type of driver:

Beginner

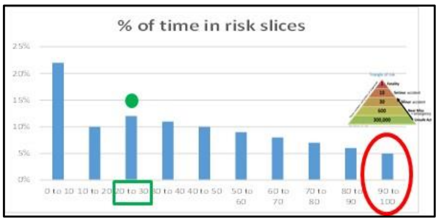

Fig.13

Gaussian curve is very flat (big standard deviation), maximum likehood is small (driver tries to regulate risk at low level), number of entering in triangle of risk (risk upper than 90%) is high: although driver tries to be careful, driver is risky.

Experienced driver

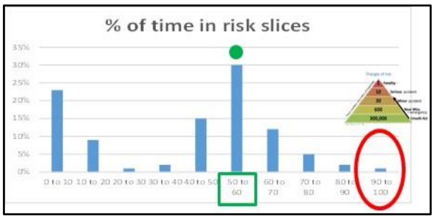

Fig.14

Experienced driver is much less often surprised, although he/she regulates his/her risk around a higher value. His/her level of expertise in driving most often allows him/her to reproduce his/her risk-taking identically, which leads to a tighter Gaussian. He/she rarely enters the risk triangle, which makes him/her a safe driver.

Pilot

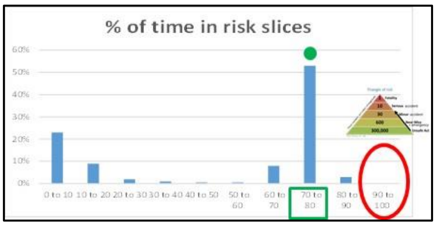

Fig15

Pilot knows exactly how to reproduce risk identically, standard deviation of Gaussian is almost zero, and despite the fact that risk is kept at a high level, he/she never enters the risk triangle. He/she is an expert.

This histogram can easily be interpreted automatically. For an OEM, this makes it possible to offer insurance companies an integrated measurement tool, particularly suitable for fleets that are always looking to lower their Total Cost of Ownership (TCO).

. Safety Coach / digital copilot

Since lack of caution (risk) is calculated 20 times per second while driving, this information can be used to help driver avoid emergency situations as much as possible [Yah2016]: for this, as soon as value of risk exceeds the threshold for entry into risk triangle (detection of an 'unsafe act'): a visual, audible or haptic interface informs driver who then becomes aware that it would be great to return to a safer driving behavior. In the aftermarket applications that deploy this solution for insurers and fleet managers, value of risk target is adjustable by driver: driver can thus choose when to be informed before entering risk triangle, which brings as we explained before a second level of anticipation.

As described previously, one of the outputs of our AI is an abacus of iso-risk curves between present position and the position of rupture on the pathway.

<u>Example of an abacus of iso-risk curves when approaching a STOP sign:</u>

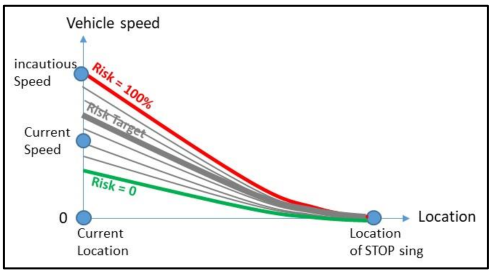

Fig.16

Ideally, driver should modulate vehicle speed to always stay between ‘risk = 0’ curve and ‘risk target’ curve. Each time he/she crosses 'risk target' curve, he/she can be informed.

We notice that if one drives at constant speed in this set of curves, one crosses all curves of the chart up to the 'risk = 100%' curve which one reaches before the location of STOP sign (anticipation), which corresponds to an increase in risk:

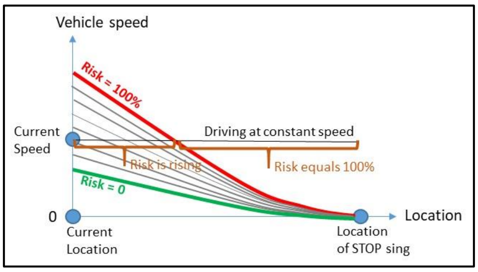

Fig.17

<u>Example of a rise in the risk curve when approaching a STOP sign for driving at constant speed:</u>

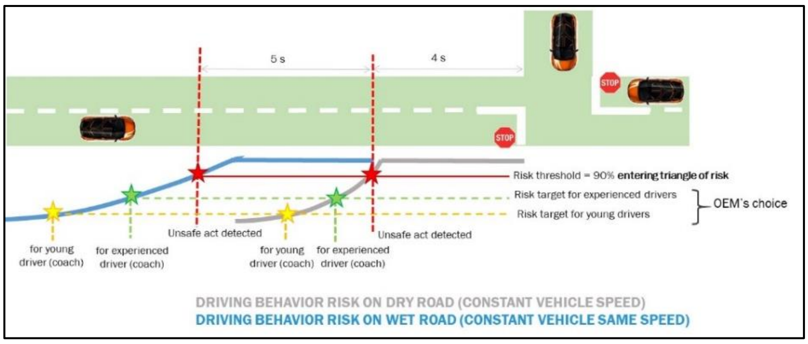

Fig.18

We can see in gray the curve of increase in risk of driving at constant speed as driver approaches (without slowing down) a STOP sign. This curve corresponds to a dry road case.

We can see in blue the curve of increase in risk of driving at the same constant speed as driver approaches STOP sign on wet surface.

We can see that entry into risk triangle (detection of an 'unsafe act') is later in the dry than in the wet, which is normal. We also see that we can select different 'risk target' values depending on type of driver to alert a novice driver earlier than an experienced driver.

This factual efficacy result corroborates results obtained by NEXYAD through a meta-analysis of scientific road safety publications. These publications show that at diruption points on a pathway, an increase in speed of 1Mph corresponds to an increase in accident frequency of 5% [Techrep2018], and this over a fairly large initial speed range.

We assume then, that when driver is alerted, driver slows down during two seconds with a deceleration of 0.15g (where g is gravity). Note: this assumption is realistic, but obviously everyone can reformulate their own assumption and calculate its impact on efficiency result. Braking during 2s at 0.15g leads to a speed reduction of 3m/s, that corresponds to 10.8 km/h or 6.75 Mph.

6.75 Mph multiplied by 5% equals to 34% of accident rate reduction. But to compare with the insurance experiment where only static context is used (75% of accident), we multiply 34% by 75% and it lead to an accident rate reduction by 25%.

So, theoretical estimation and practical observation coincide.

Main interest of such driving assistance for OEMs is reduction of Total Cost of Ownership (TCO). Indeed, a vehicle equipped with this ADAS will on average reduce number of accidents by at least 25%, thus eliminating part of risks for which insurer covers the vehicle. OEM can then negotiate with insurer to lower cost of insurance premiums. Integration of our AI does not change number of sensors, an then, it does not affect the cost of repairing claims, which allows insurer to lower its price, and this, contrary to road safety improvements obtained by adding expensive sensors: if there are fewer accidents but a higher repair cost in the event of an accident, insurance premium cannot go down.

We have implemented this application on DREAMOTOR1 vehicle (see http://dreamotor1.org), with an HMI allowing engineers who come into the vehicle to check that AI is working properly:

Fig. 19

On Fig.19, one can see that vehicle speed is 69km/h for a 70km/h speed limit, SafetyNex AI has detected a roundabout ahead and proposes to slow down to 32 km/h in 204m and current risk (lack of prudence) is 41 (and rising if we do not slow down approching roundabout. It also tells that just before roundabout there will be a reduction of speed limit from 70km/h to 50km/h. Cautious driver will follow advice and slightly slow down to 32 km/h. This HMI is not supposed to be a customer HMI, it pastes information for engineers who need to understand how it works and develop a customer function with it.

. Preventive ACC

Application in preventive ACC consists in using estimation of lack of prudence (called risk) linked only to longitudinal part of the driving behavior, depending on context.

From this assessment, we can then apply a very simple rule “if risk is too high, then slow down”. We detail this application made with STELLANTIS in the next chapter.

. **Self-Learning AD** for all infrastructures and all traffic conditions

Recent publications have proposed a so-called 'self-learning' approach to develop automatically, and by learning, an autonomous vehicle. In particular, the MOBILEYE company has proposed an interesting approach consisting in carrying out reinforcement learning based on compliance or non-compliance with few rules of caution [Shal2018].

This approach can obviously be generalized by using our prudence or risk assessment with a reinforcement learning process. We propose the following deep reinforcement learning [Mousa2018] architecture:

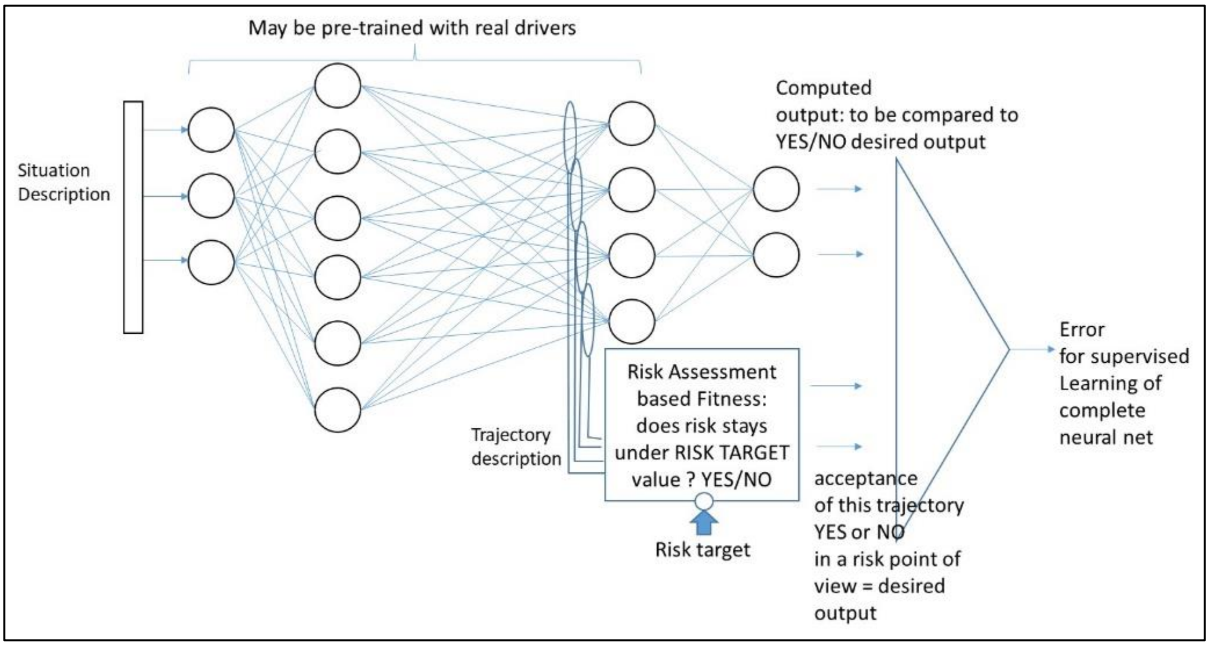

Fig.20

Note : number of neural layers may be bigger than on Fig. 20

Fitness function is performed by our prudence and risk assessment AI on trajectory (decelerations, accelerations, etc.) computed by left part of neural network. This left part can be pre-trained with human drivers: association between description of the situation and description of trajectory.

Risk assessment is carried out on trajectory and if risk remains permanently below risk target value, then trajectory is acceptable (YES), otherwise it is not acceptable (NO). This reinforcement ‘desired output’ is used for supervised learning of the full neural network. When error is minimized, trajectories are almost always acceptable and can be applied to autonomous vehicle.

In the rare cases where risk assessment shows an unacceptable risk, trajectory is not applied, it is replaced by a default security trajectory considered intrinsically pure, knowing reason of high risk (because our risk assessment AI is a XAI).

. **Level 3 and Level 4 AD certification** : in-use monitoring

The UNECE World Forum for Harmonization of Vehicle Regulations recently endorsed a framework on New Assessment Tes Methods" for Automated Driving (SAE L3 and above) [UNECE2022]. This framework will be used as basis for the coming activity on Regulation and Approval process from United Nations level. Similar approach has just been published in the European Regulation in summer 2022 [EUReg2022] dedicated to Automated Driving System approval using specifications on "in-service reporting". The following diagram summarizes this work :

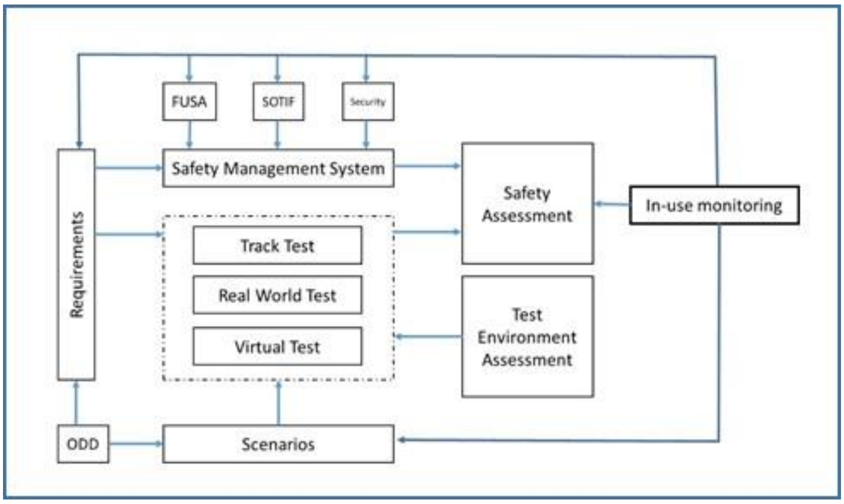

Fig. 21

It is obvious that the AI that we present here has its place in the so-called "in-use monitoring" component. Indeed, this AI monitors level of prudence in driving behavior in real time, and is then able to detect mismatches between driving behavior of Autonomous Driving system and context.

We recently proposed a specific implementation of this "in-use monitoring" [Yah2022], so as not only to detect driving behavior that is inappropriate to context, but also to inform autonomous driving system so that it can modify its decision in the event of behavior that significantly lowers caution rating (and increases risk rating), in real time. We explain how such an approach is likely to make autonomous driving system able to adjust to unpredictable road circumstances.

We use classic diagram of autonomous vehicle:

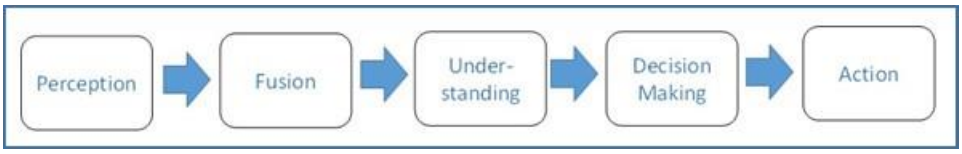

Fig.22

With such a scheme, we can imagine for instance that "understanding" stage has failed. Understanding becomes then Missunstanding, and “Decision making” stage leads to a “Wrong action” as shown below:

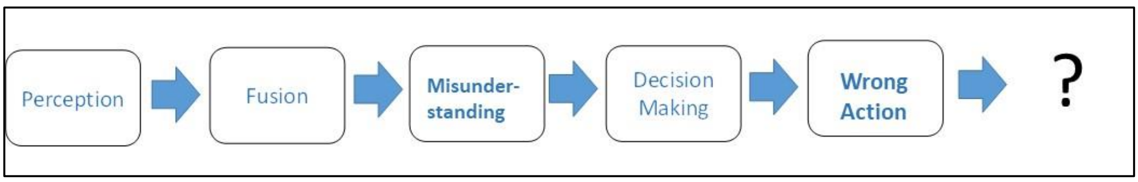

Fig. 23

We propose to integrate our “prudence assessment” (or “risk assessment”) AI in two places:

. before applying a decision, we can, in fast on-board simulation, calculate prudence and risk among possible trajectories, and choose the best decision according to this criterion.

. once decision has been applied, caution (or risk) of actual driving behavior is estimated in its context (in-use monitoring), and "Decision Making" stage is informed of this so that it can propose a alternative solution. In these alternative solutions, we may arrange typical trajectories for securing a vehicle in the event of failure of autonomous driving system.

We then obtain the figure:

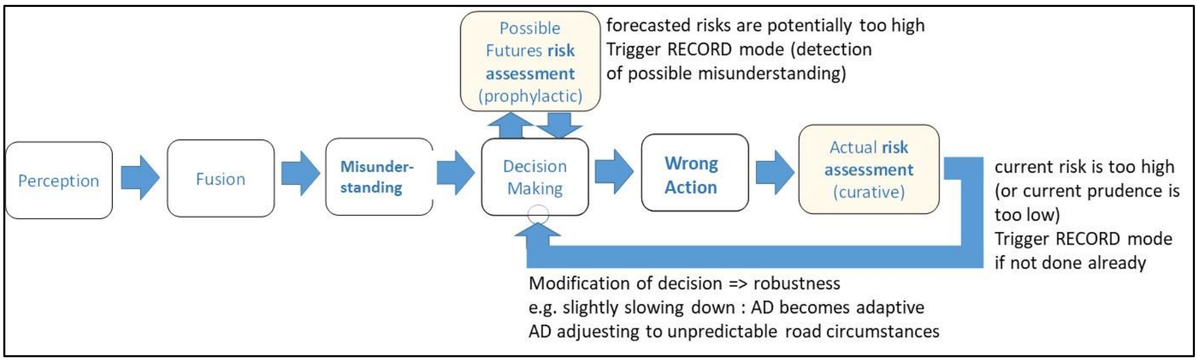

Fig. 24

Note: each time low prudence is detected, one can also save the use-case which will enrich database of examples for teams of engineers working on improving AD system.

RESULTS OF REAL EXPERIMENTATIONS FOR PREVENTIVE ACC WITH STELLANTIS

We had the opportunity to cooperate with STELLANTIS to integrate our AI into a Peugeot 308 “Predictive ACC – labcar vehicle in order to control the ACC in the simple way expressed in the ‘Automotive Applications’ chapter: “if risk is too high, then slow down”.

Vehicle is previously equiped with:

. a digital map

. an electronic horizon reading oncoming pathway (up to several km ahead) on a digital map

. a detection front camera indicating distance and nature of detected objects

. a frontal radar for measuring interdistance

. a measurement of dynamic and kinematic elements (accelerations, vehicle speed, yaw rate, etc.)

. signal from the blinker

Fig. 25 : STELLANTIS Peugeot 308 Lab Car

We have been able to show in practice that our formalism of iso-risk curve charts makes it possible to cope with all cases in a homogeneous way without ever breaking down use cases with "if then otherwise", and without ever using a complex servo-control law in every case.

Here are in particular our charts on some basic disruptions on pathway:

STOP sign

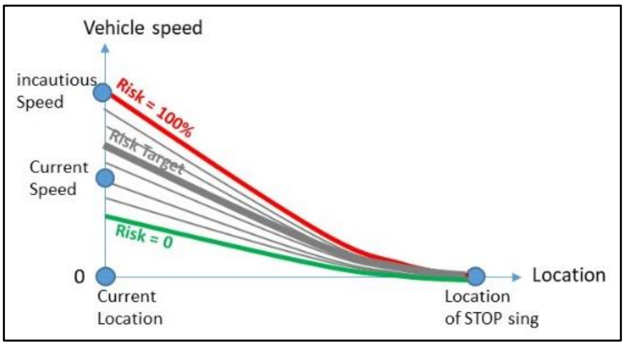

Fig. 26

On this figure, one can see that if driver stays at current speed, risk will rise and go upper risk target : those curves tell when and how to slow down.

Curve

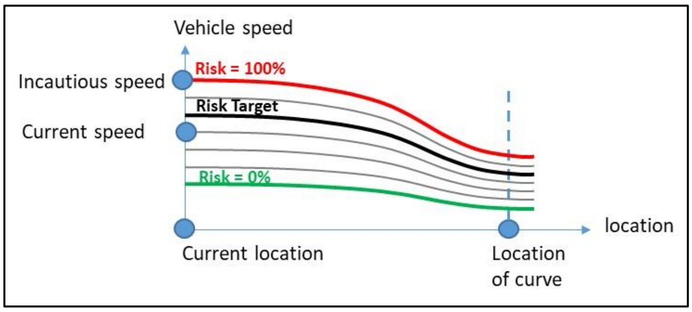

Fig. 27

Same than previous figure, if driver stays at current speed risk will be higher than risk target at curve location.

Interdistance

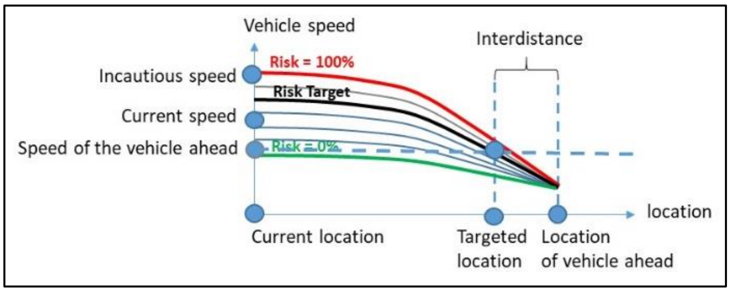

Fig. 28

One can see that interdistance (with a moving disruption on pathway) is easily represented with this formalism.

Trajectories (speed profiles of ACC) should stay beneath risk=0 curve and risk target curve.

NEXYAD allows OEM to introduce their own trajectories here if it wishes.

In the case of our experiment, we automatically generated trajectories with our AI as follows:

. compliance with OEM constraints: max acceleration, max deceleration, max jerk

. containment of trajectory in order to remain permanently below risk target value (chosen by OEM and modifiable interactively from HMI developed by STELLANTIS)

. tangential arrival with zero speed derivative at risk target value on geolocation of rupture on the pathway

. maximization under these constraints of surface under the curve (to avoid trivial solutions which consist of driving extremely slowly)

This leads to a trajectory (a speed profile) as follows (case of interdistance): Generated vehicle speed profile is the curve in blue.

Example 1

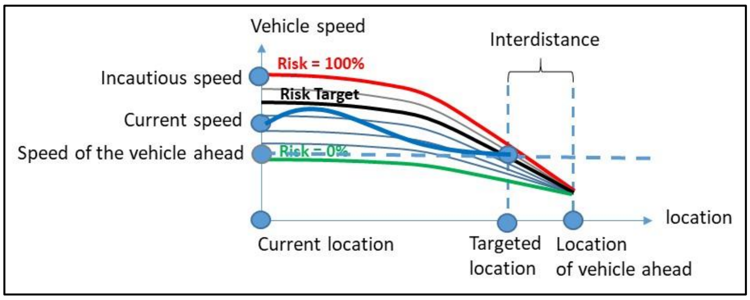

Fig. 29

Example 2

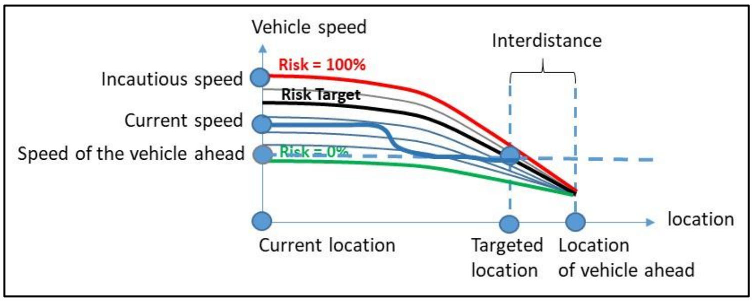

Fig. 30

Exemple 3

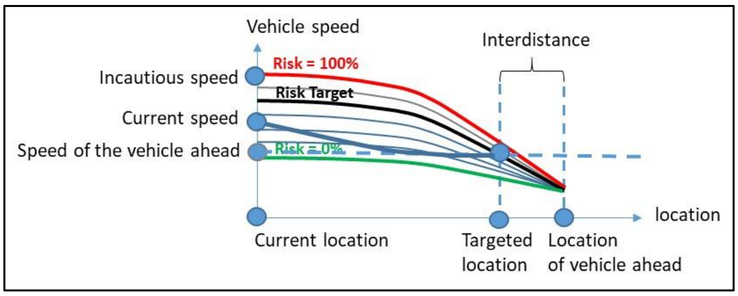

Fig. 31

The difference between these three speed profiles comes from constraint values imposed by OEM, which thus has a powerful tool for parameterizing ACC, so as to keep its identity of comfort and sportiness, while guaranteeing a level of prudence. (which is also chosen by OEM). Depending on constraints parameters in the hands of the OEM, one can imagine hundreds of solutions.

In a qualitative point of view, main characteristics of this solution on the STELLANTIS vehicle are:

. humanized automated driving: there is no impression of being driven by a robot

. validation of good responsiveness of system in complex real situations

. very easy to adjust level of prudence or risk and then aggressiveness of ACC by simply varying the value of risk target on the HMI (one button fine tuning).

Here is a cumulative stats results from real driving on the STELLANTIS vehicle Peugeot 308 LabCar. Use-case is «*appoaching roundabout* » :

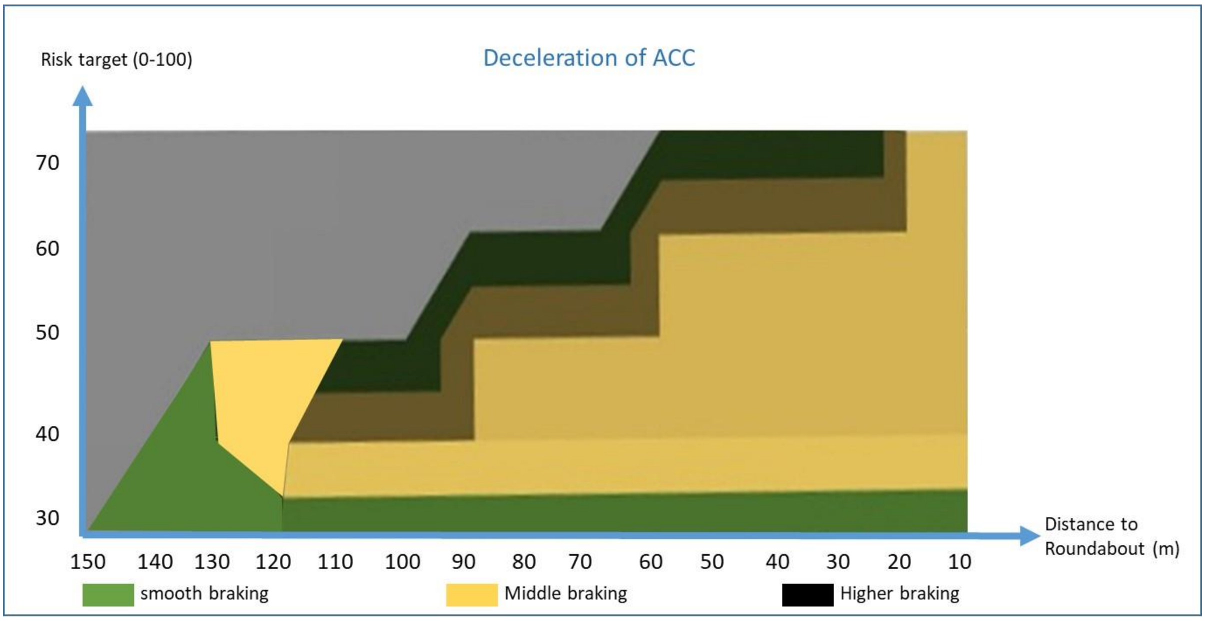

Fig. 32

One can see that risk target value modifies distance where braking is applied : for a small risk target, SafetyNex leads to an early and smooth braking and for a high risk target, it leads to a later and higher braking which is logic. Note : higher value of deceleration is a tuning parameter.

And on figure 33, we paste vehicle speed achieved by ACC for three values of risk target, on a pathway of 9km around STELLANTIS in Velizy (France).

One can clearly see that speed modulation is directly impacted by risk target value in a very logical way.

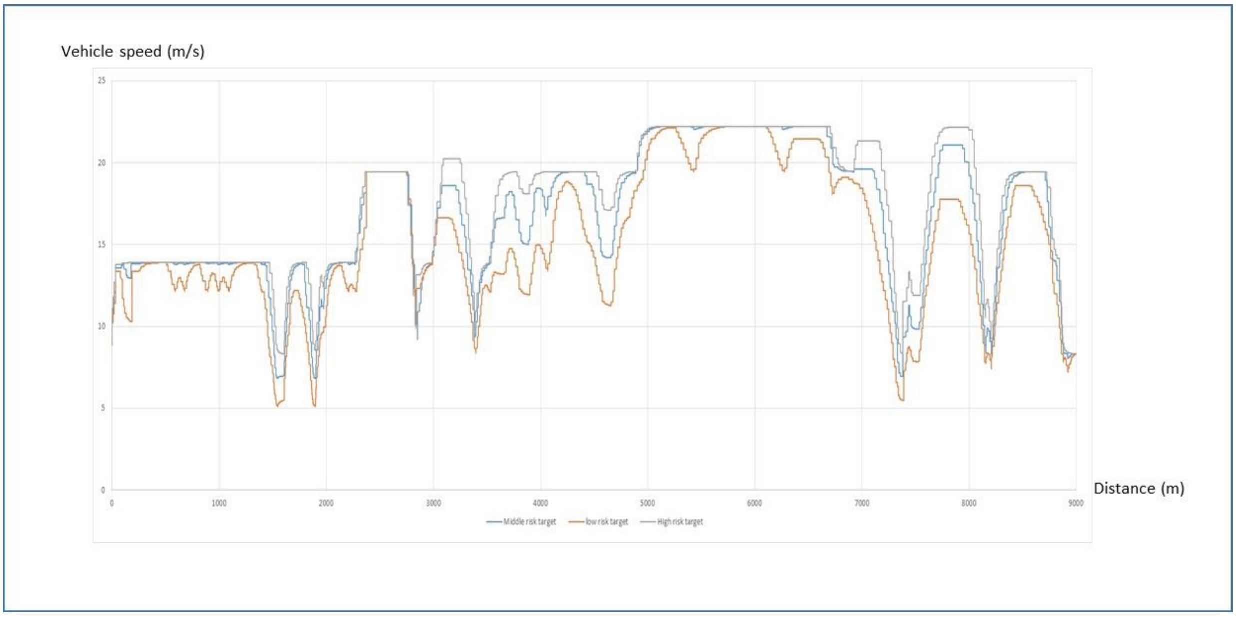

Fig. 33

OEM can tune ACC in a consistant and safe way, with one button which is risk target value.

CONCLUSION

We presented a road safety approach based on notions of prudence and risk, and we described a an AI that implements these concepts (IA SafetyNex).

This AI has the following characteristics:

. It is an XAI (eXplanable Artificial Intelligence): it provides reason for its decisions, in real time

. It is mainly based on knowledge (extracted from international experts over fifteen years). Knowledge representation and logical reasoning techniques are: fuzzy logic and possibility theory.

. It uses other AI techniques, in particular Deep Learning and neural gases, to calculate tuning parameters and adapt AI to vehicle and to driver.

. It is applicable to many automotive applications:

. Safety Score

. Safety Coach / Digital Copilot

. Preventive ACC

. Self-learning AD

. Level 3 and level 4 in-use monitoring, required for certification

. adaptive AD that can adjust to unpredictable road circumstances

. validated by road safety experts during 12 collaborative research programs, by insurers who have observed 25% fewer accidents thanks to a minimalist implementation of a safety coach, and by STELLANTIS on a preventive ACC project.

. It allows a generalization of the self-learning approach proposed by Mobile Eye to develop autonomous vehicles using reinforcement learning.

. this AI is easily tunable by OEM (there is no black box effect), and even makes it possible to consider customizations that were previously too complex to achieve.

. in the particular case of ACC, this AI makes it very easy to obtain modulation of speed profile while driving on any type of infrastructure (city, road, motorway), by any type of road traffic. And speed modulation is easily adaptable to driver, to automobile brand's policy (in terms of driving dynamics, comfort, etc.), and to real needs for controlled aggressiveness in road traffic mixing human drivers with partial driving delegation systems.

We are currently working on a generalization of the iso-risk charts to the case of the autonomous vehicle: charts become in this case two-dimensional because they not only manage speed profile, but also direction of the vehicle.

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