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A Data Fusion Architecture for the Dynamic Follow-up of Vehicles

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Abstract – **This article concerns road safety and driving assistance. To solve this problem, we propose a data fusion architecture based on the Dempster-Shafer theory. This multi-level approach allows the management of complementary and redundant data which come from two perception systems: an omnidirectional vision sensor and a laser telemeter. The originality of this architecture is its ability to manage and propagate uncertainties from low level data until an high level information of danger given to the driver. The first part concerns the data sensor The second part deals with the quantification of the uncertainties of the detected vehicles, followed by a determination of situations of danger and the evaluation of their level of dangerousness with the aim of supplying the driver with an indicator of global danger around the vehicle.**

I. INTRODUCTION

One of the pre-requisites in driving a car is to have a supply of reliable information to the driver about the state of neighbouring vehicles. For that purpose, an essential criterion is to be capable of situating one's own vehicle on the road and to envisage the location of the other vehicles on the same axis. At the moment, this characteristic still constitutes the object of research in numerous laboratories working on road safety. In spite of a great deal of research having ended in supposedly "reliable" solutions, it has to be remarked that very few car manufacturers have developed them to the point of integrating them into their marketed vehicles.

We can, nevertheless, notice that major constructors have proposed some solutions, but with particular conditions of use and on privileged axes of traffic: on highways where traffic lanes are separated and on which the road markings in are very well maintained. For example, we can quote the LDW system (Lane Departure Warning) proposed by the french car manufacturer Citroën as an option on certain vehicles, to alert the careless driver of a deliberate change of lane without having activated the indicators. This system is composed of three sets of two aligned infrared sensors located along the front side of the vehicle. During a sideways movement, these sensors detect the crossing of the white line and alert the driver to a change of lane in a reliable way. But the system must only be activated while travelling along a highway. Another LDW system developed by Volkswagen integrates cameras implanted in front of the vehicle which permanently analyse the trajectory. If this strays, a sound or sensory alert is sent to the driver.

Our solution integrates two essential parts which consist of the detection of situations connected with road configurations which could lead to a danger (crossroads, reductions in traffic lanes, speed limits, etc.) by using a SIG system matched with a GPS differential localisation (longitudinal detection). On the other hand, there is the detection of dangers connected to traffic lanes by analysis of the environment closed to the vehicle (lateral dangers).

This article constitutes a continuation in the work presented in [11] in which we explained the mechanisms of extraction and processing of the low level information.

In this article, we propose the parallel use of an omnidirectional sensor and a telemetric sensor. The first sensor is positioned on the roof of our experimental vehicle and allows an image of the road situation over 360 degrees to be attained in a single acquisition. The telemetric sensor is positioned behind the experimental vehicle to measure the distance of following vehicles. For the experimental results conducted in this project, we restricted the environment of use of our system to roadways with traffic in one direction only and with one, two or three lanes of the motorway type and urban ring-roads with contrasting markings on the ground. In the first part, we will briefly present the architecture of our experimental vehicle and we will show the various data processing phase resulting from both sensors (for more details, see [11]). In the second part, we will detail the data fusion module and multi target tracking module, both based on the Transferable Belief Model [12], a variant of the Dempster Shafer theory [2]. In particular, we will focus on the data uncertainty treatment.

II. DATA SENSOR AND PROCESSING

II.1 Sensors

The first sensor which composes our perception system is an omnidirectional sensor from the Japanese company ACCOWLE. It consists of an hyperbolic convex mirror and a CCD SONY EVI 330 camera (colour camera 768×576). It is schematised in figure 1 and photographed in figure 2. It is installed on the vehicle's roof (figure 3).

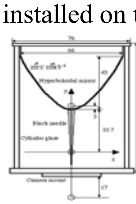


Fig. 1. Sensor characteristic

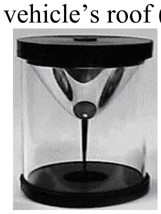


Fig 2. The Accowle hyperbolic sensor

Fig 3. Sensor configuration

The telemeter is installed behind the vehicle (fig. 4) because of problems of safety. It can be installed at the front, but only if the laws in force permit it. The system used is a laser telemeter SICK LMS 200, from which a 180 degrees 2D depth view of the scene can be obtained, by steps of 0,5°.

Fig.4. The laser telemeter and its installation of the vehicle.

II.2 Data processing

II.2.1 Omnidirectional images

The image obtained with the hyperbolic sensor is not totally exploitable. Indeed, it is easy to notice that, in omnidirectional images, the most outer zone corresponds to a part of the image not reflected by the hyperbolic mirror, thus not reflecting the scene around the vehicle. Also, the central zone of the image corresponds to the reflection of the camera and the black part to the lens of the sensor. The elimination of these image parts enables to gain more than 40% in processing time.

Then, the omnidirectionnal image is interpolated in the form of a classic 2D image in order to use operators of classic image processing.

II.2.2 Improvement of omnidirectional processing

The detection of vehicles by omnidirectional vision goes through two stages. The first stage consists of determining the zone identifying the road in every "sub-image", the second stage allows objects on the road to be segmented, with the aim of extracting vehicles.

■ *Algorithm of research for zone representing the road*

The algorithm of research for the zone representing the road is made according to several criteria:

- the detection of the edge of the road defined by white lines or projections of shadow,
- the colour of the road established by searching for limit threshold in various spaces of colour,
- final shape of the detected zone.

This algorithm is executed at initialisation of the process of vehicle detection and during the loss of the detection of the road zone in the image sequence. The first stage of our algorithm consists of approximating points characterising the edges of road (right-hand side, left-hand side) by a linear interpolation. "Candidate" points arise out of a search for peaks on five horizontal equidistant lines taken in the lower image. At the same time, the RGB image undergoes a transformation HSV (hue, saturation, value) and a transformation YCbCr (luminance, chrominance blue, chrominance reed) to associate homogeneous zones.

The combination of both processes allows a triangular closed shape to be identified, approximated by two straight lines and which informs us of the location of the experimental vehicle on the road (vehicle centred on the highway, vehicle on the left-hand side, vehicle on the right-hand side).

The following segmentation stage consists of identifying objects in the previous zone contrasting with the homogeneity of pixels. Our choice is the use of a modelling method based on the active contours, or “snakes”.

■ *Segmentation*

A snake [1] is an elasticised curve which can be modelled by a parametric shape normalised as follows:

$$\Omega : [0, 1] \rightarrow R^2$$
$$s \rightarrow v(s) = \{x(s), y(s)\}$$

where:

- s is the curvilinear abscissa or the parameter on the curve which belongs to the spatial domain Ω,
- $v(s)$ is the position vector of the point of contour which coordinates are $x(s)$ and $y(s)$
- $v(1)$ and $v(0)$ are the position vectors of the contour extremities

The total energy of the contour for which we try to minimize is represented by the following function [1].

$$E_{snake} = \int_0^1 E_{snake}(v(s))\, ds = \int_0^1 E_{int}(v(s)) + E_{ext}(v(s))\, ds$$

- E_{int} is the internal energy, it is intrinsic in the snake, it represents the rigidity and to the elasticity of the contour (curvature)
- E_{ext} is the external energy of the system, it represents gradients of the image.

Several resolution approaches exist. Let us quote the model of Amini[7], based on dynamic programming. William and Schah [5] proposed the algorithm Greedy. It was demonstrated in [10] that this algorithm turned out to be faster than those using variational calculation and dynamic programming. It is the approach which we adopted in our previous works [8]. In spite of the originality of this method, we did not obtain satisfactory results; we are thus directed to another method levy GVF (Gradient Vector Flow) [9].

■ *Initialisation of the detection process*

One of the major problems which exist when using active contours is their initialisation. Indeed, in the major part of the applications using this technique, the initialisation is done manually by asking the user to select points around the shape to be detected. These points will constitute the initial contour. In our project, we developed an algorithm of automatic initialisation, which consists of discovering homogeneous zones characterising the texture of vehicles on the road zone. This method is illustrated by figure 5, which represents an example of initialisation of the active GVF contours in an image extracted from our road sequence.

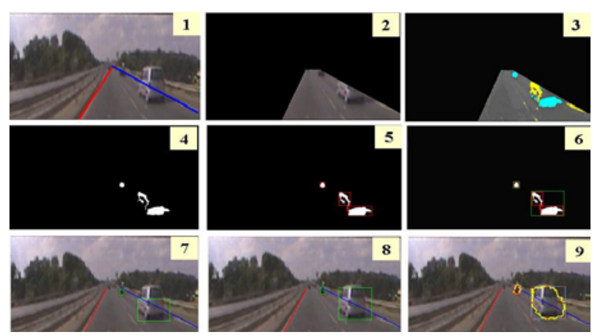


Fig.5. Example of the active contours initialisation

Figures numbered from 1 to 9 show the various stages of GVF snakes initialisation:

1. The figure 1 represents the initial image with the edges of road
2. Masking of zones situated outside of the road (outside of the triangle) (figure 2)
3. Transformation of the image obtained previously (stage 1) in the space YCbCr (figure 3)
4. Filtering of the zones obtained (figure 4)
5. Grouping of the homogeneous zones (figure 5 and 6)
6. Increase of the square size with frame detected zones (figure 7 and 8)

7. Search for initial points of the "snake" (figure 9)

II.2.3 Telemetric Data

The data resulting from an acquisition with the SICK LMS 200 are characterised by a pair of data (ρ_i,θ_i) expressing the polar coordinates of each point in the laser telemeter centre coordinate system. The following figure illustrates a road scene in a car park where vehicles were stationary. A first stage of grouping has been made to associate the points to a single object.

The various stages for the identification of vehicles consist of segmenting the groupings of points to filter out the inappropriate segments, and a final stage of fusion is needed to associate the close co-linear or perpendicular segments**.**

- From these associations of segments, we be able to detect vehicles by performing an identification with the possible signatures of vehicles.

III. DETERMINATION OF THE DETECTED VEHICLES UNCERTAINTY

III.1 Introduction

To the aim of obtaining a quantification of the uncertainty of the danger level in which our experimental vehicle is found, we developed an uncertainty propagation architecture from the low level sensors data to the higher levels. Our architecture is divided into four stages summarized in fig. 6.

The telemetric data processing and those stemming from the omnidirectional vision respectively supply a set of segments (stage **E1-2**) and a set of active contours (stage **E1-1**). An uncertainty quantification is associated to each object (segments and snakes). From these segments and these snakes, we extract objects of the "vehicle" type (stage **E2**). An uncertainty about each vehicle is computed. This uncertainty takes into account in particular the uncertainties of the segments and of the snake which compose the concerned vehicle by a propagation mechanism which will be described in the next paragraphs. To quantify the evolution of the uncertainty of each detected vehicle more finely, we integrate an algorithm of multi-target tracking into stage **E3** (tracks being vehicles detected). The final stage (**E4**) allows the possible danger situation in which our car is situated to be characterised.

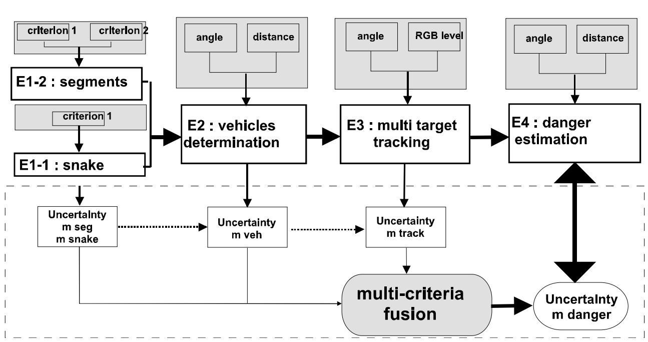


Fig. 6. Architecture of distribution of the uncertainties.

The key tool used in this data fusion and uncertainties propagation system is the Transferable Belief Model [12] (TBM of Smets), a non-probabilistic variant of the Dempster Shafer theory [2].

III.2 Uncertainty of the telemetric segments

To determine the uncertainty of each segment found by the telemetric sensor, two criteria are taken into account and they are then merged within the framework of the TBM.

■ *Frame of discernment:*

Our frame of discernment Θ_{seg} is composed of the two hypotheses YES and NO corresponding respectively to the two assertions "Yes, the segment exists" and "No, the segment does not exist": Θ_{seg}={YES, NO}

■ *Criterion 1: average distance of the points from the segment which contains them*

Experimentally, we determined the mass function m_1 shown in figure 7.

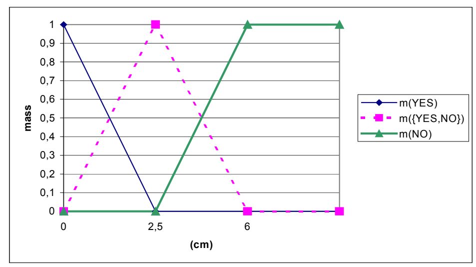


Fig. 7. Mass function of the first criterion

The figure 8 shows that the greater this distance is, the more points on average are far from the segment. If the distance is high, we can say that the segment does not well approximate the set of points. As a result, we consider it rather unreliable.

■ *Criterion 2: number of points of the segment*

This criterion can only discriminate when the segment contains very few points. In that case, it can be considered unreliable.

■ *Fusion of both criteria*

We tested these criteria on a set of fifty significant experimental readings. We particularly observed the value of the conflict. It turned out that conflict is weak in almost every case (average conflict: 0.13). This proves that our criteria are relevant and consensual.

Finally, the fusion of both criteria described previously allows us to obtain m_{seg}(YES), m_{seg}(NO) and m_{seg}(Θ_{seg}) These three values allow us to obtain a quantification of the uncertainty on the considered segment. For example, if m_{seg}(NO) is high, it means that the segment is not reliable.

III.3 Uncertainty of the active contours

■ *Frame of discernment:*

We are still working in a binary frame of discernment consisting of both hypotheses YES and NO corresponding respectively to both assertions "Yes, the active contour exists" and "No, the active contour does not exist ".

$$\Theta_{snake}=\{YES, NO\}$$

■ *Criterion used*

To characterise the uncertainty of a snake, we use the redundancy of the data, by confirmation of a snake detection by the laser telemeter. Indeed, a detection of a snake confirmed by a telemetric segment is more reliable than detection realised only by omnidirectional vision.

So, for an unconfirmed snake by telemetric detection, the function mass m_{snake} characterising its uncertainty was experimentally fixed in:

- m_{snake}(YES)=0.2
- $m_{snake}(\Theta_{snake})$=0.8
- m_{snake}(NO)=0

On the other hand, for a snake to which we were able to associate a telemetric measure, the function mass m_{snake} is equal to:

- m_{snake}(YES)=0.8
- $m_{snake}(\Theta_{snake})$=0.2
- m_{snake}(NO)=0

III.4 Uncertainty of the vehicles

- *Frame of discernment:*

Our frame of discernment Θ_{veh} is composed of two hypotheses YES and NO which correspond respectively to the two assertions "Yes, the vehicle exists" and "No, the vehicle does not exist": Θ_{veh}={YES, NO}

- *Criteria used:*

To determine the uncertainty of a primitive of vehicle type, we take into account three criteria:

- the angle between the two segments which compose the vehicle. A vehicle normally consists of two segments at 90 degrees, except when the vehicle is seen from the front or from the back. The more the angle varies from 90 degrees, the less likely it is that we are in the presence of a vehicle. The mass function of this criterion is given by m_a
- the uncertainty of the segment(s) which compose the vehicle. Indeed, if a vehicle is compose of two unreliable segments, then this vehicle will not be reliable.
  Let be m_{seg}^{S1} and m_{seg}^{S2} the respective uncertainties of two segments *S1* and *S2* which compose a vehicle. The mass function of this criterion is then given by $m_i = m_{seg}^{S1} \cap m_{seg}^{S2}$, where $\cap$ represents the Smets fusion operator [12]. We can note that this mass function allows us to propagate the uncertainties computed at the previous level **E1** to this level **E2**
- the uncertainty of the snake corresponding to the vehicle, denoted by the mass function m_{snake} computed on paragraph III-3

The three previous function masses m_a, m_i, m_{snake} are merged to obtain a mass m_{veh} quantifying the uncertainty of the detected vehicle: $m_{veh} = m_a \cap m_i \cap m_{snake}$

So, at the end of this step, we have a list of vehicle primitives with an associated uncertainty for each vehicle through the set mass m_{veh}. This uncertainty includes the uncertainty about the type of the primitive and the uncertainty about the existence (the reliability) of the segments and of the snake which compose it.

IV. MULTI-TARGET TRACKING AND ESTIMATION OF THE DANGER

IV.1 Multi target tracking.

Our method is based on a tracking of vehicle primitives: we propagate the matchings made at an acquisition *n* on an acquisition *n*+1. Our algorithm is based on a prediction-observation paradigm. So we have developed a prediction system based on a linear extrapolation of the azimuth angle curves of the vehicle primitives (on experimental results, we can note that the angles variation is locally linear): we generate a predictive observation vector composed of angles got by linear extrapolation (figure 9). For example, if we examine the evolution of the vehicle angles Θ1, Θ2 and Θ3 (figure 8), we remark that the curve can be extrapolated in order to have a prediction $\Theta4_p$. If a matching is done between $\Theta4_p$ and an angle observation, the track is propagated.

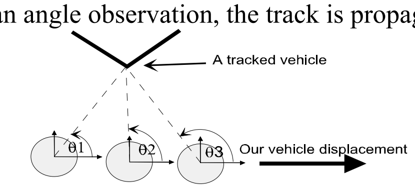


Figure 8: evolution of vehicle angles.

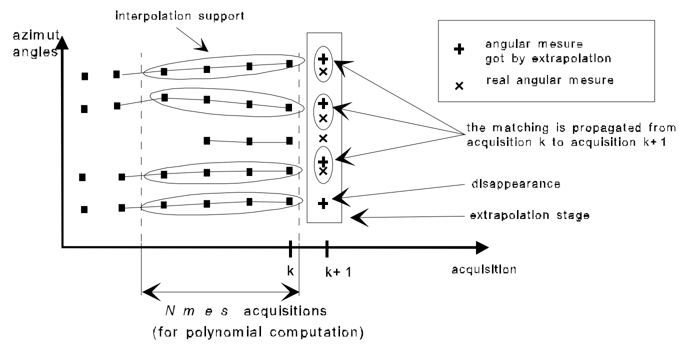


Figure 9: principle of angular measures extrapolation.

At this level, the problem is to match for each type of primitive the *p* angular observations obtained at the acquisition *t* with the *q* predictions. These *q* predictions are computed from the *Nmes* last observations. To reach this aim, we use the Dempster-Shafer theory in the framework of *extended open word* [3] because of the introduction in the frame of discernment of an element noted * which represents all the hypothesis which are not modelled in the frame of discernment. This will allow us to manage the notion of appearance or disappearance of tracks, that is to say vehicles.

For each prediction *Qj* ($j \in [1,q]$), we apply the following algorithm.

- The frame of discernment Θ*j* is composed of:
  - the *p* observations represented by the hypotheses *Pi* (*Pi* means “the prediction *Qj* is matched with the observation *Pi*”)
  - and the element * which means “the prediction *Qj* cannot be matched with one of the *p* observations”.

  So: $\Theta = \{P_1, P_2, \ldots P_p, *\}$
- The matching criteria are:
  - the angular difference between an observation and a prediction (mass function m_a, figure 10)
  - the difference of tint RGB between an observation and a prediction (mass function m_{RGB})

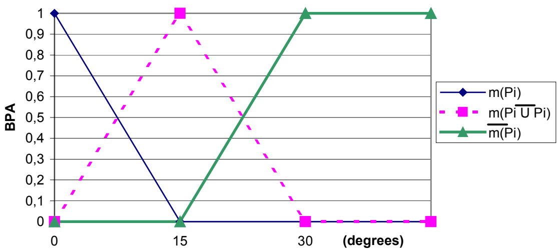


Figure 10: BPA of the matching criterion ma

- For each observation *Pi*, we compute :
  - $m_i(P_i)$ the mass associated with the proposition "the observation *Pi* is matched with the prediction *Qj*".
  - $m_i(\overline{P}_i)$ the mass associated with the proposition "*Pi* is not matched with *Qj*".
  - $m_i(\Theta_i)$ the mass represented the ignorance concerning the observation *Pi*.
  - This mass function m_i comes from the fusion of m_a and m_{RGB} : $m_i = m_a \cap m_{RGB}$

After the treatment of all the *Pi* observations, we have *p* triplets :

$$
\begin{array}{lll}
m_1(P_1) & m_1(\overline{P}_1) & m_1(\Theta_1) \\
m_2(P_2) & m_2(\overline{P}_2) & m_2(\Theta_2) \\
\ldots & & \\
m_p(P_p) & m_p(\overline{P}_p) & m_p(\Theta_p)
\end{array}
$$

We fuse these triplets and we get $m_{match}(P_1)$, $m_{match}(P_2)$,…, $m_{match}(Pp)$, $m_{match}(*)$ and $m_{match}(\Theta)$ by using the condensed formulas obtained by Gruyer in [4]:

  - $m_{app}(P_i)$ is the mass associated with the proposition «the observation P_i can be match with the prediction *Qj* ».
  - $m_{app}(*)$ is the mass associated with the proposition « the prediction Q_j cannot be matched with one of the observations P_i ».
  - $m_{app}(\Theta)$ is the mass of the proposition «we know nothing about the matching of the prediction Q_j».

- The final decision is the one which has the maximal mass.

Finally, we can note that this matching method enables us to easily manage vehicle appearances and disappearances:

- If an element *Pi* cannot be matched, *Pi* is an appeared vehicle and a track can be initialized.
- If a prediction *Qj* is matched with *, the vehicle is temporarily or definitively lost.

After this stage, we have to update the track uncertainty at time *t* denoted by the mass function $m_{track\ t}$ defined on the frame of discernment Θ_{track} composed of the two hypotheses "yes" and "no" corresponding to the assertions "Yes, the track exists" and "no, the track does not exist".

We can distinguish three situations:

1) Initialisation of a track: this case corresponds to the appearance of a new vehicle near our vehicle, that is to say the case where an observation is matched with no prediction. This track initial uncertainty is $m_{track\ 0} = m_{veh}$.

2) Propagation of a track: as soon as a track is initialised, its uncertainty is updated in every new acquisition by means of three criteria: the uncertainty of the track at time t-1 $m_{track\ t-1}$, the uncertainty of the vehicle primitive m_{veh} and the uncertainty of the matching m_{app}. The previous three masses are merged to obtain a mass $m_{track\ t} = m_{track\ t-1} \cap m_{véh} \cap m_{app}$ quantifying the uncertainty of the track at time *t*. As long as this uncertainty remains weak, the track is propagated. This means that we do not immediately abandon a track as soon as it is no longer propagated. We can thus take momentary eclipses of vehicles into account.

3) Non-propagation of a track: if a prediction is matched with no observation, the uncertainty of the track increases. This uncertainty is updated by merging two criteria: the uncertainty of the track at time *t*-1 $m_{track\ t-1}$ and a predefined mass function m_2:

$$m_2(\text{yes})=0,\ m_2(\text{no})=0.2,\ m_2(\{\text{yes, no}\})=0.8$$

This mass function m_2 is built to regularly increase the track uncertainty by attributing some mass on the "no" hypothesis. If this track uncertainty at time t $m_{track\ t}$ is too strong, the track is definitively cancelled.

IV.2 Estimation of the danger

The final stage of our algorithm of estimation and propagation of uncertainties consists of characterising the level of danger represented by each of the vehicles bordering our vehicle and computing this danger uncertainty.

To estimate the type of danger and its uncertainty, we first determine the type of danger and, secondly, its uncertainty.

To determine the type of danger, we have to characterise three types of situation for every vehicle tracked.

- A "green" danger: the tracked vehicle does not represent a danger.
- An "orange" danger: the tracked vehicle is situated near the side of our vehicle. This can represent a danger if our vehicle wants to overtake or seeks to pull back in after overtaking.
- A "red" danger: the vehicle is situated too close to the rear or the front of our vehicle. Safe distances are no longer respected, there is a danger, for example in the case of sudden braking of this vehicle.

So, for every vehicle tracked, we define a frame of difference Θ_{danger} = {GREEN, ORANGE, RED}. To determine the type of danger, we consider the two following criteria:

- *Criterion 1*: distance between our vehicle and another vehicle. The closer a vehicle is to our vehicle, the greater the danger, in particular if the vehicle is situated in front or to the rear.
- *Criterion 2:* angle between our vehicle and the tracked vehicle. For example, if this angle is close to 0 degree or to 180 degrees, we can be in the presence of a red danger, but only if the distance between us and the vehicle is small.

As soon as the type of danger is determined, it is necessary to calculate its uncertainty. To this end, we take two types of uncertainties into account:

- The uncertainty of the track corresponding to the vehicle tracked. This uncertainty is represented by the mass function $m_{track\ t}$
- The uncertainty of the danger represented by the mass function m_{type}

This uncertainty is obtained notably by propagation of the low level uncertainties calculated previously (figure 11).

So, each vehicle around us is characterised by a danger (green, orange, red) with an associated uncertainty through a mass set m_{danger} on a binary frame of discernment Θ_{danger}={YES, NO}.

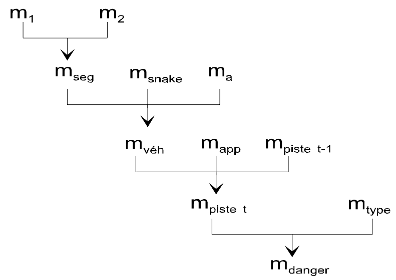
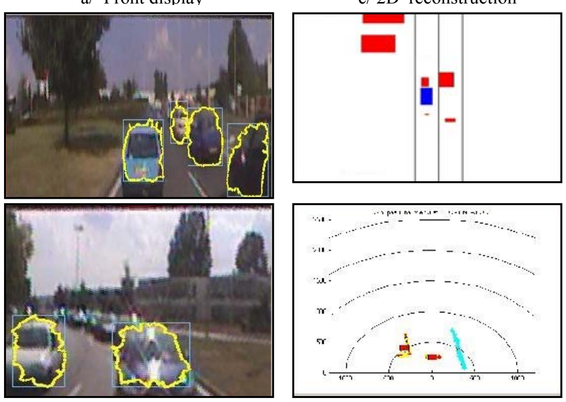


Fig. 11. Propagation of the uncertainties from low level to compute the danger uncertainty

V. Experimental results

All the results obtained by our experiment of cooperation for the assistance to driving are illustrated by figure 12. This figure shows the results obtained by telemetric acquisitions and from actual omnidirectional images.

a/ Front display c/ 2D reconstruction



b/ Behind display d/ Detection by telemetry

Fig. 12. Results of a detection of the surrounding vehicles

In the example of the figure 12, two vehicles situated behind our vehicle are detected by the laser telemeter. The first vehicle is situated at a distance of 3 metres and the second at a distance of 5 metres.

These vehicles are detected by the omnidirectional vision among which the one is partially detected. So, four vehicles situated in front are detected by the vision. For the fusion of both types of detection, that of the back is precise (estimated error is weak), that made by the active contours is less precise where from the thickness of the "red square". In this situation, the detected vehicles are too close and the distances of safety are not respected, it brings to the ignition of the alarm of "orange" level.

VI. Conclusion and perspectives

In this article we have shown an extension to what is currently on offer by car manufacturers in their new systems of assistance to driving (systems which have been marketed for two years). Indeed, the various solutions which we described in our introduction show the usefulness of these systems for the lane following in traffic, but in no case do they take account of surrounding vehicles. In our system, we have suggested extending the use of the LDW systems by combining them with the immediate road configuration (number of traffic lanes + immediate traffic), the main and original sensor being used based on omnidirectional vision which has the added advantage of showing the road in one view over 360 degrees. This information, combined with the telemetry laser, allows the information sensor to be considered supplementary, or even redundant . The use of the theory of evidence for the fusion of multi-criteria data has allowed the process of identification of the immediate danger to become reliable.

In our future work, we should, at the low processing level, apply Gradient Vector Flow (GVF) analytical methods of pressure to identify the place where the initial points of the active contour in the following image have to be positioned in a surer and more restrictive way. Indeed, at present, between two successive images, a rather imprecise algorithm is used to increase the future active contour which historically surrounds the vehicle. Also, the choice of the suitability of the fusion criteria could be revised with the aim of improving the management of the alarms. At the moment we have to envisage three cases of well identified figures but, according to the precision of the criteria, these solutions could be increased to better discern all the risk situations.

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