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An Evidential Fusion Architecture for Advanced Driver Assistance

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***Abstract*—In this paper, we deal with an original Advanced driver assistance system (ADAS) based on the use of omnidirectional vision and an evidential fusion architecture. The panoramic perception solution permits us to address efficiently the problem of close vehicles detection but also the monitoring side traffic system. The fusion and integration of this sensorial data stream is assumed by a credibilist architecture based on the Transferable Belief Model (TBM) of Smets. This paradigm permits the filtering of false alarms efficiently by an optimal management of the uncertainties estimation.**

I. Introduction

ADVANCED driver assistance systems (ADAS) support the driver's decision making to increase safety and comfort by providing an ergonomic display of the driving environment. The global goal of assistances is to manage as well as issue warning signals or even exert active control if conditions are dangerous. The major challenge is then to provide assistance to the driver, by extracting the relevant driving information with respect to the road. To do it, a large panel of perception solutions has been integrated into the vehicle, generally stemming from the sensors used for the autonomous navigation of mobile robots. The classical solution consists in combining telemetric sensors, like lidar, laser scanner [1] or ultrasonic sensors, and vision sensors [1][9]. These combinations have the advantage of treating data which are mainly complementary but also redundant. Some researches have therefore focused on multi-sensor fusion dedicated to the intelligent vehicle field. The aim of such a step is to provide a fused description of the traffic scene surrounding the vehicle, which is relevant for ADAS. Several categories of assistance functionally exist. The most generalized is the lane detection, such as lane departure warning system (LDWS), lane change assistance system (LCAS) or lane keeping system (LKS). We can observe that the major part of studies on lane detection address computer vision [3][9]. In connection with our work, the second preponderant function is the close vehicles detection, which is highly linked to the pattern recognition problematic. For real-time processing, the use of prior knowledge on potential vehicle locations is relatively common [14]. The last function we can note is the side traffic monitoring. The side obstacle detection method is generally similar to the front and rear vehicle detection methods [7], but can also consist of detecting vehicle wheels [13].

Our work deals with the two last functions. We propose an assistance system which can alert the driver to the non possible drive actions in connection with the vehicles situated around. It is based on a multi-target tracking and uses the complementary sensorial data stream provided by a laser SICK and an omnidirectional vision system located on the roof of the vehicle. The originality of our paradigm is linked at two points: (1) the use of an omnidirectional vision sensor and its associated vision target tracking (2) the evidential fusion architecture which permits the filtering of false alarms.

This paper is organized as follow: in the first part, we present our omnidirectional vision strategy. In the second part, we propose the telemetric algorithm vehicle detection. The third part deals with the description of the credibilist fusion architecture which sets off the warnings to the driver. In the last part, we discuss experimental results.

II. Sensor context

Our ADAS solution integrates two warning parts. Firstly, a detection of dangerous situations connected to road configurations (crossroads, reductions in traffic lanes, speed limits, etc.) by using a SIG system matched with a GPS differential localization. Secondly, the detection of dangers connected to the traffic lanes (immediate dangers) by analysis of the environment close to the vehicle. In this part, we detail only the perceptual solution deployed for immediate danger detection.

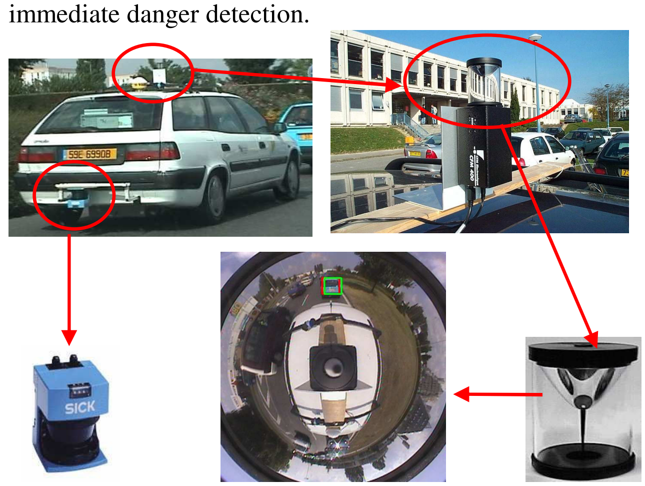

Fig. 1. The ADAS perception solution on the vehicle and an example of omnidirectionnal image.

The vision data stream is provided by an omnidirectional

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sensor composed of a camera and a hyperboloid mirror. This catadioptric sensor corresponds to the solution ACCOWLE (Fig. 1). We use a color camera SONY EVI 330 with a 768×576 resolution. This omnidirectional system is placed on the vehicle's roof. The telemetric data stream is provided by two SICK LMS 200 laser scanners placed on the rear and on the front of the vehicle (Fig. 1). They provide a 2D depth view of the scene by steps of 0.5 degree.

III. TARGET RECOGNITION - VISION TRACKING

To track a vehicle in our particular omnidirectional image, we have revisited the CAMShift paradigm [15]. We made this choice in connection with the drastic constraint of real time and non a priori knowledge of the considered targets. Various tracking algorithms have been proposed in the literature, including approaches using optical flow, templates and local features, Kalman filters, Haar wavelet, Gabor filter, scale invariant feature transform (SIFT) but none satisfy our constraints. The mean-shift algorithm was first adopted as an efficient tracking technique.

What is the general principle of the mean-shift estimator? The core of the mean-shift tracking algorithm is to compute the mean shift vector Δy recursively [14]. The current target centroid location vector y_j and the new target centroid location y_{j+1} are related through a translation:

$$\Delta y = y_{j+1} - y_j \qquad (1)$$

While a normal kernel was adopted [14], the new target centroid location is derived as:

$$y_{j+1} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \qquad (2)$$

where the set $\{x_i\}_{i=1..n}$ represents n pixel locations in the search window and wi the corresponding weight assigned to each pixel.

In order to find the candidate target whose density distribution is the most similar to the model, an appropriate distance metric to measure the similarity between two histogram distributions must be used. The Bhattacharyya coefficient is a near optimal choice and it's defined by:

$$\rho(y) \equiv \rho\left[p(y), q\right] = \sum_{i=1}^{m} \sqrt{p_u(y) q_u} \qquad (3)$$

where p and q indicate the target and model distributions respectively. To minimize the metric distance, the Bhattacharyya coefficient has to be maximized. The maximization of this coefficient is achieved by the mean-shift iterator, by computing a set of weights given [14] to each pixel in the search window. The new location of the target centre is obtained by insertion of these weights in (2).

The Continuously Adaptive Mean Shift (CAMShift) algorithm [15] is based on the mean-shift algorithm, a robust non-parametric iterative technique for finding the mode of probability distributions including rescaling. We have named in [11] the calculation of a CAMShift directly in an omnidirectional image "Omnicamshift". We have also applied some specificity linked to the sensor used (fast gyration …).

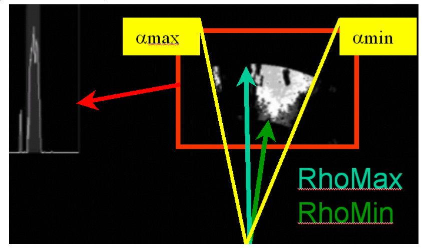

Fig. 2. Backprojection of OmniCAMShift

We track a vehicle in connection with its colorimetric model which is built with the significant classes of the histogram R, V, B of the vehicle in a polar area on the omnidirectional image. The first problem we solved is linked to the initialization of the vehicle histogram, i.e. the target model. To do it, we used the telemetric data stream to extract the angular sector interval (α_{min}, α_{max}) (Fig. 3) and the distance interval (φ_{min}, φ_{max}) to determine the polar area in the omnidirectional image which will provide the vehicle histogram. The angular interval (α_{min}, α_{max}) is directly used on the omnidirectional image; the distance interval (φ_{min}, φ_{max}) is transformed by the catadioptric sensor calibration in (φc_{min}, φc_{max}). The tracking step, i.e. the maximization of the Bhattacharyya coefficient, can begin with this window computing histogram. If the model (histogram) is not significant, the Bhattacharyya coefficient decreases and the track is lost.

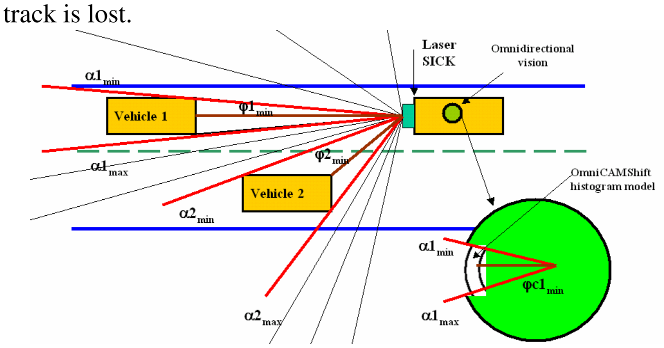

Fig. 3. Colorimetric model initialisation of the tracking vehicle based on laser scan detection.

IV. THE EVIDENTIAL FUSION ARCHITECTURE

A. Introduction

The aim of this part is:

- To get an estimation of the danger of each vehicle around us. To this end, we will manage three levels of danger: (1) green danger (the considered vehicle is not dangerous), (2) orange danger (the considered vehicle represents a lateral danger) and (3) red danger (the vehicle represents a rear or front danger).
- To get an estimation of the global risk situation in which our vehicle is (no danger, lateral danger: an overtaking should be prevented, rear danger: a brutal braking should be

avoided, etc.).

To reach this aim, we have developed an uncertainty propagation architecture from low level sensor data to high semantic levels (global risk situation). Our architecture is divided into five stages summarized in Fig. 4.

The telemetric data processing and those stemming from the omnidirectional vision respectively supply a set of segments (stage **E1-2**) and a set of omnidirectional images (stage **E1-1**). An uncertainty quantification is associated to each object. From these data, we extract objects of "vehicle" type (stage **E2**). An uncertainty about each vehicle is computed. This uncertainty takes into account in particular the uncertainties of the segments which compose the considered 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 next stage (**E4**) allows the possible danger situation in which the detected vehicles are situated to be characterized. Finally, the last stage (**E5**) enables us to determine if our vehicle is in danger, and, if so, what type of danger (lateral danger or/and rear danger or/and…).

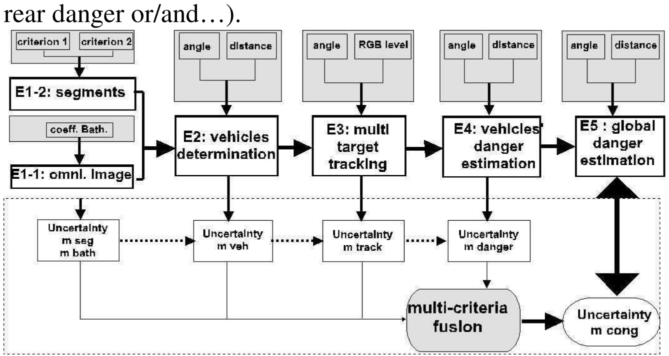

Fig. 4. Architecture of distribution of the uncertainties.

The key tool used in this data fusion and uncertainties propagation system is the Transferable Belief Model [12] (TBM of Smets), The TBM is a model to represent quantified beliefs based on the belief function theory developed by Shafer [2], but completely unrelated to any underlying probabilistic constraints as it is the case with the model of Dempster and with the hint model.

B. Stage E1-2: uncertainty of the telemetric segments

After a segmentation stage, the set of points given by the laser sensor provides a set of segments. To determine the uncertainty (i.e. the reliability) of each segment, two criteria are taken into account within the framework of the TBM.

Frame of discernment. For each detected segment, 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 Fig. 5. This figure shows that the greater this distance is, the more points on average are far from the segment. If this distance is high, we can say that the segment does not approximate the set of points well. As a result, we consider it rather unreliable.

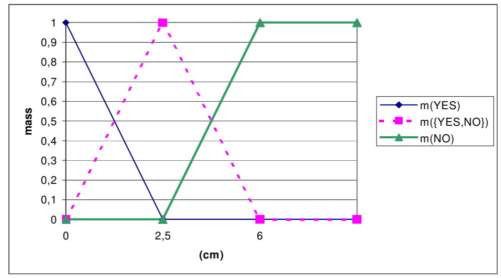

Fig. 5. Mass function m_1 of the first criterion

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 the two criteria. The fusion of the two criteria described previously allows us to obtain m_{seg}(YES), m_{seg}(NO) and $m_{seg}(\Theta_{seg})$ These three values allow to obtain a quantification of the segment's uncertainty. For example, if m_{seg}(NO) is high, it means that the segment is not reliable.

C. Stage E1-1 : uncertainty deduced from the omnidirectional images

To estimate the uncertainty linked to the omnidirectional vision tracking, we take into account the Bhattacharyya coefficient at time t (paragraph III).

D. Stage E2: uncertainty of the detected vehicles

The aim of the next stage **E2** is to manage "vehicle" objects and to compute an uncertainty about each of these vehicles.

Detection of vehicles. After a stage of fusion which associates the close co-linear or perpendicular segments, we are able to detect vehicles by performing an identification with the two possible signatures of vehicles. Every vehicle can be identified by two different signatures:

- A straight line, when the perpendicular of the segment passes through the point of emission of the laser beam.
- Two perpendicular straight lines in the other cases.

Frame of discernment. For each detected vehicle, 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 vehicle primitive, 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. This gives the mass function m_a
- The uncertainty m_{seg} of the segment(s) which compose

the vehicle. For example, a vehicle composed of two unreliable segments will be considered as unreliable.

- The uncertainty deduced from the Bhattacharyya coefficient corresponding to the vehicle, denoted by the mass function m_{bhat} computed on paragraph III-C.

We can note that these mass functions m_{seg} and m_{bath} allow to propagate the uncertainties computed at the previous level **E1** to this level **E2.**

The three previous mass functions m_a, m_{seg} and m_{bhat} are merged to obtain a mass m_{veh} quantifying the uncertainty of the detected vehicle: $m_{veh} = m_a \cap m_{seg} \cap m_{bhat}$, where $\cap$ is the fusion operator of Smets.

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 reliability of the segments which compose the vehicle.

E. Stage E3: 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. We have developed a prediction system based on an extrapolation of the azimuth angle curves of the vehicle primitives: we generate a predictive observation vector composed of angles obtained according to the vehicle cinematic [5].

For example, if we examine the evolution of the vehicle angles Θ1, Θ2 and Θ3 (fig. 6), we can compute a prediction Θ4p. If a matching is done between Θ4p and an observation angle, the track is propagated [5].

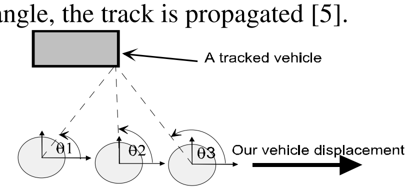

Fig. 6. Evolution of a tracked vehicle angles.

At this level, the problem is to match the *p* angular observations obtained at the acquisition *t* with the *q* predictions computed from the last observations. To reach this aim, we use the algorithm developed by Gruyer [6] and based on the Dempster-Shafer theory in the framework of “extended open word” [17].

This method allow us to manage the notion of appearance or disappearance of tracks, that is to say vehicles :

- If an observed vehicle cannot be matched, it is a new vehicle and a track can be initialized.
- If a prediction cannot be matched with an observation, 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) Initialization 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’s initial uncertainty is $m_{track\ 0} = m_{veh}$.

2) Propagation of a track: as soon as a track is initialized, its uncertainty is updated at every new acquisition according to three criteria: the uncertainty of the track at time *t*-1 $m_{track\ t\text{-}1}$, the uncertainty of the vehicle primitive m_{veh} and the uncertainty of the matching m_{app}. These three masses are merged to obtain a mass $m_{track\ t} = m_{track\ t\text{-}1} \cap m_{veh} \cap m_{app}$ quantifying the uncertainty of the track at time *t*.

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

$$m_2(\text{YES})=0,\ \ m_2(\text{NO})=0.2,\ \ m_2(\{\text{YES, NO}\})=0.8$$

This mass function m_2 is built to regularly increase the track uncertainty by attributing some mass on the “no” hypothesis. So, as long as the track uncertainty at time *t* $m_{track\ t}$ 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. Finally, if the track uncertainty is too strong, that is to say if $m_{track\ t}(\text{NO}) > m_{track\ t}(\text{YES})$, the track is definitively cancelled.

F. Stage E4: estimation of the danger of each vehicle

The next stage **E4** of our algorithm of estimation and propagation of uncertainties consists of characterizing 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 characterize three types of danger for every tracked vehicle.

- A “green” danger: the tracked vehicle does not represent a danger.
- An “orange” danger: the tracked vehicle is situated near the left or right side of our vehicle. It 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 tracked vehicle, we define a frame of difference Θ_{danger_t}={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 is, 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 closed 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.

The fusion of these two criteria provides a mass set m_{type} on the frame of discernment Θ_{danger_t}. The type of danger selected is the one which has the maximal pignistic probability [12].

As soon as the type of danger is determined, we compute its uncertainty m_{danger}. To this end, we take two uncertainties into account:

- The uncertainty $m_{track\ t}$ of the vehicle's track.
- The uncertainty of the danger represented by the mass function m_{type}

$m_{danger} = m_{track\ t} \cap m_{type}$

We can again note that this uncertainty is obtained notably by propagation of the low level uncertainties calculated previously.

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

G. Stage E5: estimation of the global danger around our vehicle

The last stage **E5** of our architecture is the determination of the global danger(s) around our vehicle. The aim is to warn the driver if he tries to execute a dangerous driving. We will determine the kind of traffic jam (congestion) around us and, for example, if there are cars on the left hand side, an overtaking should be considered as dangerous. An other example is front congestion: in this case, the driver should brake.

Frame of discernment. The frame of discernment Θ_{cong} is composed of five hypotheses: *Re* (a rear congestion), *Fr* (a front congestion), *Le* (a left congestion), *Ri* (a right congestion), *OK* (no dangerous congestion)

We can note that these five hypotheses are not mutually exclusive. For example, cars can be situated behind us and also in our left side. This is in contradiction with the TBM rules which impose that the hypotheses of the frame of discernment are mutually exclusive. But the aim of the stage is not to take a decision: we will only consider the masses of each hypotheses and union of hypotheses, and warn the driver according to these masses.

Criteria used. Two complementary criteria are used and applied to each tracked vehicle:

- Criterion 1: angle of vehicles. E.g., a vehicle located at 180 degrees will put some mass on the *Re* hypothesis, but only if this vehicle is near our car. This explains why a mass equal to 1 is attributed to the union of hypotheses {*Re*, *OK*} for this angle of 180. The second criterion described below will allow us to select the good hypothesis between *Re* and *OK*.
- Criterion 2: distance of vehicles. A tracked vehicle far from us will put some mass on the *OK* hypothesis. On the contrary, a close vehicle will put some mass on the union of hypothesis {*Re*, *Fr*, *Le*, *Ri*}: there is a danger, but this criterion cannot be more precise (the criterion 1 will determine the good case of danger).

Fusion of these criteria. It is performed in two steps.

First step. We fuse the two criteria described below for each tracked vehicle. The obtained mass set does not take into account the uncertainty of each tracked vehicle. To solve this problem, we perform a discounting operation [2] according to the pignistic probability of the YES hypothesis $m_{track\ t}$(YES). At the end of this step, we get m mass sets corresponding to the m tracked vehicles at time t. We have to fuse these m mass sets: it is the second step.

Second step. If we use the classical fusion operator of Smets to fuse these m mass sets, a high conflict will rapidly appear. For example, a left near vehicle puts mass on the *Le* hypothesis and another near and rear vehicle puts mass on the *Re* hypothesis; and the fusion of these two mass sets will generate conflict. So, in this case of left and rear conflicts, it seems natural to reject the conflict on the union of hypothesis {*Le*, *Re*}. This manner of fusion by rejecting the conflict on the union of hypotheses which generate it is in fact the fusion operator of Dubois and Prade [16]:

$$m(A)=\sum_{A\cap B=A} m_{S1}(A).m_{S2}(B)+\sum_{C\cup D=A;C\cap D=\varnothing} m_{S1}(C).m_{S2}(D)\quad \forall A\subseteq\Theta$$

$m(\varnothing)=0$

Let us consider the following example. We assume that two vehicles V1 and V2 are tracked. At the end of the first step of stage **E5**, our uncertainties propagation architecture gives us the following mass sets:

$m^{V1}(Le)=0{,}63$, $m^{V1}(Le \cup \text{OK})=0{,}27$, $m^{V1}(\Theta_{cong})=0{,}1$

$m^{V2}(Fr)=0{,}56$, $m^{V2}(Fr \cup \text{OK})=0{,}14$, $m^{V2}(\Theta_{cong})=0{,}3$

This means that vehicle V1 is considered to be a left danger and vehicle V2 a front danger (but this last piece of information is not very reliable since we have a mass of 0.3 on the ignorance Θ_{cong}.).

The fusion of these two mass sets with the Dubois and Prade operator provides the following results:

$m_{cong}(\text{OK})=0{,}27\times0{,}14=0{,}0378$

$m_{cong}(\Theta_{cong})=0{,}1\times0{,}3+0{,}1\times0{,}14+0{,}1\times0{,}56+0{,}63\times0{,}3+0{,}27\times0{,}3 = 0{,}37$

$m_{cong}(Le\cup F \cup\text{OK})=0{,}63\times0{,}14 + 0{,}56\times0{,}27=0{,}2394$

$m_{cong}(Le \cup Fr) = 0{,}63\times0{,}56 = 0{,}3528$

The maximal mass is $m_{cong}(Le \cup Fr)$: there are cars on our left and in front of us. The driver has to be careful if he wants to overtake or to accelerate. Nevertheless, we can note that this information is not very reliable (little mass of 0.35 and mass of 0.37 on the ignorance).

V. EXPERIMENTAL RESULTS

On Fig. 8, we show an example of tracking sequence.

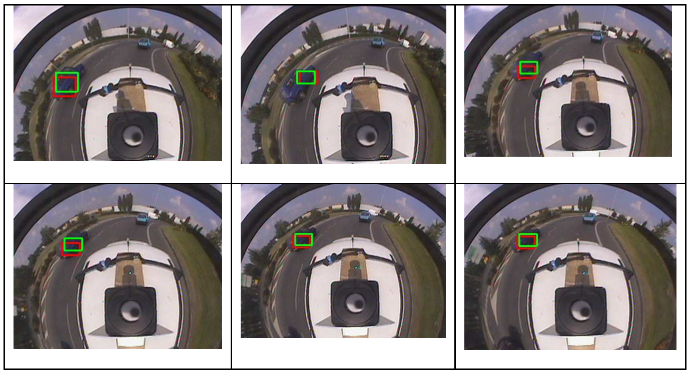

Fig. 8. A tracking sequence given by the omniCAMshift approach on a vehicle located on the left side.

On Fig. 9, we show the uncertainty evolution of a track corresponding to the vehicle number 3. The uncertainty initialization is made with the vehicle uncertainty. Then the vehicle is well tracked, except on acquisition number 5 where the car is lost. But the track is recovered on acquisition number 6. This shows the interest of our multi target tracking: we don't cancel a track immediately, but only when the mass of the NO hypothesis $m_{track\ t}(NO)$ is superior to the mass on the YES hypothesis $m_{track\ t}(YES)$. In this case, the track is too unreliable and we cancel it. This situation occurs on acquisition 14. Indeed, the track is not propagated since acquisition number 9 (the car has slowed down in order to turn), so $m_{track\ t}(NO)$ increases until it becomes superior to $m_{track\ t}(YES)$.

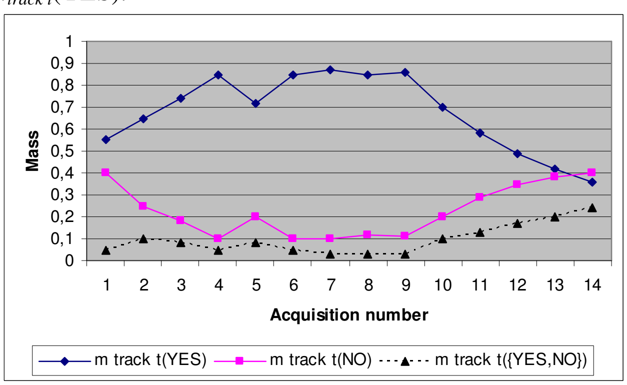

Fig. 9. The uncertainty evolution of vehicle number 3.

Let's talk about the danger represented by this vehicle at acquisition number 7. The track's uncertainty at this time is:

$m_{track\ t}(YES)=0{,}87 \quad m_{track\ t}(NO)=0{,}1 \quad m_{track\ t}(\Theta_{track})=0{,}03$

Besides, this vehicle is at 3.2 metres behind us. So it is considered to be a "red" danger according to this mass set:

$m_{type}(Red)=0{,}73 \quad m_{type}(\Theta_{danger\_t})=0{,}27$

Considering these two mass sets, this vehicle is labelled as a "red" danger with this uncertainty:

$m_{danger}(YES)=0{,}89 \; m_{danger}(NO)=0{,}02 \quad m_{danger}(\Theta_{danger})=0{,}08$

We can note that the reliability of this "red" danger is high (0,89). This results is coherent: the track's reliability is high (0,87) and the mass of the danger type is also high (0,73). This leads to a high reliability. So the driver should be careful.

VI. CONCLUSION AND PERSPECTIVES

In this article, we have proposed an original ADAS paradigm. The originality ensues from four points. First, the management of the vision stream by a catadioptric sensor. It allows the production of a panoramic perception of the road context on one acquisition. The second originality is linked to the omnidirectional dedicated treatment, the omniCAMshift. On the one hand, this algorithm addresses directly the target tracking on the omnidirectional image, and, on the other hand, it satisfies the real time constraint. The third point is linked to the combination of the complementary data which allows the obtainment of a highly semantic description of road context. The last contribution point, and probably the major one, is the TBM fusion architecture which permits the efficient management of the fusion of highly heterogeneous data on a given level on the one hand, and, on the other hand, the propagation of the uncertainties of several levels. This drastic computation of the uncertainties on the multi-criteria and multi-level fusion architecture permits the efficient filtering of the false alarms.

The combination of these four points produces a robust and reliable ADAS dedicated on the near danger estimation, that is to say on panoramic vehicle detection.

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