Detection and Recognition confidences update in a multi-sensor pedestrian tracking system

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Abstract

We present in this paper a method for confidence updating in a multi-sensor pedestrian tracking system. We focus on the computing of detection and recognition confidence indicators according to the object detection and/or recognition probabilities provided by sensor modules. We propose to use the Transferable Belief Model in order to model and combine the sensor module outputs at different times. Since detection and recognition processes are not really independent, we propose to use the cautious rule to combine the belief functions. We propose a track confidences updating algorithm and its interesting behavior is shown on synthetic data.

Keywords: data fusion, multi-target tracking, belief updating, detection confidence, recognition confidence.

1 Introduction

We propose in this paper a loosely coupled fusion method based on the tracking process were observations (objects detected at a time t) are provided by different sensors (physical and logical) and are fused with maintained tracks. This approach is generic, sensor failure tolerant and allows different sensor configurations. We focus in this paper on the method computing a detection and recognition confidence according to the probabilities of object detection and/or pedestrian recognition provided by sensor modules. The inputs/outputs of the modules are normalized probability values, but we prefer to use the term “confidence” instead of “probability”, because we’re using non Bayesian methods to calculate and update them.

We consider in this paper the problem of confidence updating in a multi-sensor pedestrian tracking system. The tracking module consists in update pedestrian-tracks taking advantage of temporal redundant data coming from sensors. The tracking module can maintain, initialize and delete tracks decreasing the number of false alarms coming from detection process. This module is a part of an ADAS (Advanced Driving Assistance System) in pre-crash situation. The confidence evaluation is very important since the ADAS can perform autonomous braking or maneuvering in case of unavoidable collision.

The paper is organized as follow: section 2 presents an overview of the system and related works. We focus on the management of uncertainty and the confidence assessment. To do that, we propose to use the Transferable Belief Model (TBM) in order to model and combine the knowledge about pedestrian detection and recognition. Section 3 reminds the principle of belief functions and the combination operators used in our aggregation algorithm. The algorithm computing and updating the confidence values in a generic tracking module is then described in sections 4 and 5. Results presented in section 6 illustrate the evolution in time of recognition and detection confidence regarding different factors: the performance of sensors modules, the quality of extracted information (detection and recognition) and the frequency of data. Conclusion and perspectives will be proposed in the last section.

2 Overview

2.1 Related works

In the large multi-target tracking literature [1][2], we can find a lot of methods to compute and update the score of each track. The score evaluation depends of the association method between the current observation and the tracks coming from previous observations. The counting value is an example representing only the temporal persistence of the track. Other methods, such as score of Sittler [3] based on a likelihood ratio and hypothesis' probability computed with Bayesian rule [4] proposes to include the performance of the detection in the track score. These indicators are well formalized but not well adapted to the problem of heterogeneous observations coming from multi-sensor system.

Indeed, the problem of pedestrian detection can be decomposed in two parts: the detection of obstacles and their identification as pedestrians. According to the sensor ability the level of detection and recognition will be different. For example [5] proposes obstacle detection and obstacle identification with multilayer Lidar sensor; [6] propose stereo-vision obstacle detection with disparity analysis and SVM based pedestrian classification, [7] gives pedestrian classification results from monocular vision with AdaBoost algorithm: these are examples of mono-sensor systems. The combination of information coming from different sensors has the advantage of increasing the information reliability and reducing the influence of failing information. In the IV (Intelligent Vehicles) applications, obstacle detection is often based on sequential architecture: Radar/Lidar detection module gives the ROI (Region of Interest) to the image classifier [8][9]. The fusion methods proposed in these projects are strongly coupled. Two confidence factors are computed in SAVE-U system [8]: a track confidence and a recognition confidence. However, the recognition value takes the last result of classification without being updated with the history. We argue that recognition indicators could be updated according to the tracking. So we propose to formalize this approach.

2.2 System architecture

Independent sensor modules analyze data provided by each sensor to give lists of detected objects (Figure 1). Each object is described by its position, position error, dimension, dimension error, and some scores representing the detection probability at time t_k: $P_{d,k}$ (probability of object's existence) and/or the recognition probability $P_{r,k}$ (probability of being a pedestrian).

The sensors are not synchronized, nor are the outputs of the modules. Thus a multiplexer sends any ready object list to a generic fusion and tracking module to combine it with the existing track list, tacking into consideration the vehicle proprioceptive data (read and filtered inside the same module) and the performance of each detection module (stored in a configuration file with other tuning parameters). Latency problem is solved by a time indexed buffer of observations and state vectors as in [10]. The buffer size depends on the maximum acceptable observation delay.

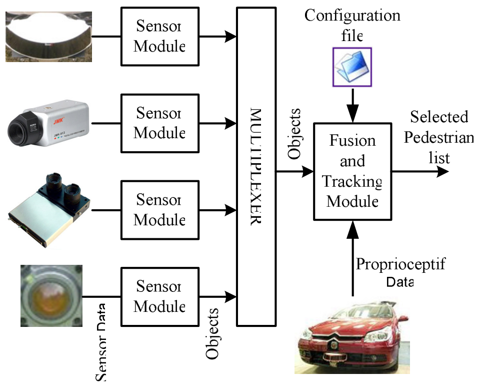

Figure 1: Example of the pedestrian's tracking system architecture

The fusion and tracking module updates all tracks information such as track's state and track's detection and recognition indicators. The object to track association is beyond the scope of this article and supposed done.

Before starting with the confidence update method we remind in the following section the TBM principle and notation.

3 TBM principle and notation

The transferable belief model TBM is a model to represent quantified beliefs based on belief functions (Smets [11]). It has the advantage of being able to explicitly represent uncertainty on an event. It takes into account what remains unknown and represents perfectly what is already known.

3.1 Knowledge representation

Let Ω be a finite set of all possible solution of a problem. Ω is called the frame of discernment (also called state space); it's composed of mutually exclusive elements. The knowledge held by a rational agent can be quantified by a belief function defined from the power set 2^Ω to [0,1]. Belief functions can be expressed in several forms: the basic belief assignment (BBA) m, the credibility function bel, the plausibility function pl, and the commonality function q which are in one-to-one correspondence. We recall that $m(A)$ quantifies the part of belief that is restricted to the proposition "the solution is in $A \subseteq \Omega$" and satisfies: $\sum_{A \subseteq \Omega} m(A) = 1$

Thus, a BBA can support a set $A \subseteq \Omega$ without supporting any sub-proposition of A, which allows to account for partial knowledge.

Smets introduced the notion of open world where Ω is not exhaustive; this is quantified by a non zero value of $m(\emptyset)$.

The other functions can be calculated from the BBA m using these formulas:

Credibility function: $bel^{\Omega}(A) = \sum_{\emptyset \neq B \subseteq A} m^{\Omega}(B)$

Plausibility function: $pl^{\Omega}(A) = \sum_{A \cap B \neq \emptyset} m^{\Omega}(B)$

Commonality function: $q^{\Omega}(A) = \sum_{B \supseteq A} m^{\Omega}(B)$

3.2 Information fusion

n distinct pieces of evidence defined over a common frame of discernment and quantified by BBAs $m_1^{\Omega} \cdots m_n^{\Omega}$, may be combined, using a suitable operator. The most common are the conjunctive and the disjunctive rules of combination defined, respectively as:

$$m^{\Omega}(A) = \sum_{A_1 \cap \cdots \cap A_n = A} m_1^{\Omega}(A_1) \times \cdots \times m_n^{\Omega}(A_n)$$

$$m^{\Omega}(A) = \sum_{A_1 \cup \cdots \cup A_n = A} m_1^{\Omega}(A_1) \times \cdots \times m_n^{\Omega}(A_n)$$

Obtained BBAs should be normalized in a closed world assumption.

The conjunctive and disjunctive rules of combination assume the independence of the data sources. In [12] and [13] Denoeux introduced the cautious rule of combination (denoted by $\oslash$) to combine dependent data. This rule has the advantage of combining dependent BBAs without increasing total belief: the combination of a BBA with itself will give the same BBA: $m = m \oslash m$ (idempotence property). The cautious rule of combination is based on combining conjunctively the minimum of the weighted function representing dependent BBAs.

3.3 Reliability and discounting factor

The reliability is the user opinion about the source [14]. The idea is to weight most heavily the opinions of the best source and conversely for the less reliable ones. The result is a discounting of the BBA m^{Ω} produced by the source into the new BBA $m^{\Omega,\alpha}$ where:

$$\begin{cases} m^{\Omega,\alpha}(A) = (1-\alpha) m^{\Omega}(A), \quad \forall A \subseteq \Omega, A \neq \Omega \\ m^{\Omega,\alpha}(\Omega) = \alpha + (1-\alpha) m^{\Omega}(\Omega) \end{cases}$$

The discounting factor (1-α) can be regarded as the degree of trust assigned to the sensor.

3.4 Decision making

The couple (credibility, plausibility) is approximated by a measurement of probability by redistribute the mass placed on each element of 2^{Ω}, different from singleton, to the elements which compose it. The probability resulting from this approximation is called pignistic probability *BetP*; it's used for decision making:

$$\forall \omega_i \in \Omega \;\Rightarrow\; BetP^{\Omega}(\omega_i) = \sum_{\omega_i \in A \subseteq \Omega} \frac{m^{\Omega}(A)}{|A|(1 - m^{\Omega}(\emptyset))}$$

4 Basic belief assignments for detection and recognition processes

4.1 Defining the frames of discernment

Before constructing any quantified description of belief with respect to the objects' detection and/or pedestrians' recognition, we must define a frame of discernment Ω on which beliefs will be allocated and updated.

For the objects detection problem, we can associate two general cases: object O and non object NO. The object can be a pedestrian or a non pedestrian object, but with no object identification, the frame of discernment of the object detection process is limited to: $\Omega_d = \{\mathrm{O}, \mathrm{NO}\}$. As an example, a disparity image analyzer of a stereo-vision system can have Ω_d as frame of discernment.

A mono-vision pedestrian recognition process based on an AdaBoost algorithm for example, gives the probability of detecting a pedestrian P or non pedestrian NP. The non pedestrian can be a non pedestrian object or a false alarm. Let $\Omega_{r1} = \{\mathrm{P}, \mathrm{NP}\}$ be the frame of discernment of this type of recognition processes.

Other recognition processes provide more detailed data. By analyzing data provided by a laser scanner for example, we can get detailed recognition data defined over the frame of discernment $\Omega_{r2} = \{\mathrm{PO}, \mathrm{NPO}, \mathrm{FA}\}$, where: PO denote a pedestrian object, NPO a non pedestrian object and FA a false alarm.

4.2 Basic belief assignment calculation

The outputs of the detection and the recognition processes are Bayesian probability functions. With no additional information, we have to build, based on these probabilities, the basic belief assignments $m_{d,k}^{\Omega_d}$ (BBA of the detection module defined over Ω_d at time t_k) and/or $m_{r1,k}^{\Omega_{r1}}$ (BBA of the recognition module defined over Ω_{r1} at time t_k) and/or $m_{r2,k}^{\Omega_{r2}}$ (BBA of the recognition module defined over Ω_{r2} at time t_k).

We used the inverse pignistic probability transform proposed by Sudano [15] to calculate belief functions from pignistic probabilities.

To simplify notations we dropped in this paper object's index because we have similar equations for all objects.

4.2.1 BBA of the detection process

Let $P_{d,k}$ be the probability function given by the detection process at time t_k: so we can have these values:

$P_{d,k}(\text{O}) = p_d$ then $P_{d,k}(\text{NO}) = 1 - p_d$

p_d represent the detection probability of an object.

To build the BBA of the detection module $m_{d,k}^{\Omega_d}$, we will calculate from the probability function the less informative BBA who regenerates the same probability function P_d as its pignistic probability $BetP_d$ (see Table1).

Table 1: the less informative BBA of the detection module

2^{Ω_d}	$BetP_{d,k} = P_{d,k}$	$m_{d,k}^{\Omega_d}$ (if $p_d \leq ½$)	$m_{d,k}^{\Omega_d}$ (if $p_d \geq ½$)
Ø		0	0
{O}	p_d	0	$2p_d$-1
{NO}	1-p_d	1-2p_d	0
Ω_d		2p_d	2-2p_d

The first column of Table1 shows the subsets of Ω; the second shows the initial probability distribution provided by the detection process, it's equal to the pignistic probability $BetP_{d,k}$ calculated from the BBA $m_{d,k}^{\Omega_d}$. The third and the fourth columns are the calculated BBA for the two cases of $p_d \leq ½$ and $p_d \geq ½$.

4.2.2 BBA of the recognition process

For the recognition process, we will describe the two cases already mentioned.

The first one is the case of the recognition process defined over $\Omega_{r1} = \{\text{P}, \text{NP}\}$. Let $P_{r1,k}$ be the probability function provided by this process at time t_k: so we can have these values:

$P_{r1,k}(\text{P}) = p_r$ then $P_{r1,k}(\text{NP}) = 1 - p_r$

p_r represent the recognition probability of an object.

As in the detection process, the same steps are used to calculate the BBA of this type of recognition module (see Table2); these steps give $m_{r1,k}^{\Omega_{r1}}$ as BBA defined over the frame of discernment $\Omega_{r1} = \{\text{P}, \text{NP}\}$ at time t_k.

Table 2: the less informative BBA of the recognition module defined over Ω_{r1}

2^{Ω_r}	$BetP_{r1,k}$ $=P_{r1,k}$	$m_{r1,k}^{\Omega_{r1}}$ (if $p_r \leq ½$)	$m_{r1,k}^{\Omega_{r1}}$ (if $p_r \geq ½$)
Ø		0	0
{P}	p_r	0	$2p_r$-1
{NP}	1-p_r	1-2p_r	0
Ω_{r1}		2p_r	2-2p_r

Table 3: the less informative BBA of the recognition module defined over Ω_{r2}

$2^{\Omega_{r2}}$	$P_{r2,k}$= $BetP_{r2}$	$m_{r2,k}^{\Omega_{r2}}$
Ø	0	0
{PO}	p_{po}	$p_{po} - (m_{r2,k}^{\Omega}(\{\text{PO}, \text{NPO}\}) + m_{r2,k}^{\Omega}(\{\text{PO}, \text{FA}\}))/2$
{NPO}	p_{npo}	$p_{npo} - (m_{r2,k}^{\Omega}(\{\text{PO}, \text{NPO}\}) + m_{r2,k}^{\Omega}(\{\text{NPO}, \text{FA}\}))/2$
{PO,NPO}	0	2(min(p_{po}, p_{npo})- $m_{r2,k}^{\Omega}(\Omega_{r2})/3$)
{FA}	p_{fa}	$p_{fa} - (m_{r2,k}^{\Omega}(\{\text{PO}, \text{FA}\}) + m_{r2,k}^{\Omega}(\{\text{NPO}, \text{FA}\}))/2$
{PO,FA}	0	2(min(p_{po}, p_{fa})- $m_{r2,k}^{\Omega}(\Omega_{r2})/3$)
{NPO,FA}	0	2(min(p_{npo}, p_{fa})- $m_{r2,k}^{\Omega}(\Omega_{r2})/3$)
Ω_{r2}	0	3 min(p_{po} , p_{npo} , p_{fa})

The second case is the case of the detection module defined over $\Omega = \{\text{PO}, \text{NPO}, \text{FA}\}$. Let $P_{r2,k}$ be its probability function at time t_k with:

$P_{r2,k}(\text{PO}) = P_{po}$

$P_{r2,k}(\text{NPO}) = P_{npo}$

$P_{r2,k}(\text{FA}) = P_{fa}$

With: $p_{po} + p_{npo} + p_{fa} = 1$

The same method is used to calculate the less informative BBA having $P_{r2,k}$ as its pignistic probability $BetP_{r2,k}$ (Table3)

4.3 Discounting BBAs

To take into account the reliability of a sensor and the performance of the detection and the recognition processes, discounting will be applied to the obtained BBAs. The detection process is characterized by its probability of false alarm P_{FA}, let $\alpha_d = 1 - P_{FA}$ be its discounting factor. The recognition process is characterized by its probability of false recognition P_{FR} so let $\alpha_r = 1 - P_{FR}$ be its discounting factor.

After the discounting stage, the obtained BBAs are denoted: $m_{r2,k}^{\Omega_{r2},\alpha_r}$, $m_{r1,k}^{\Omega_{r1},\alpha_r}$ and $m_{d,k}^{\Omega_d,\alpha_d}$

5 Score fusion and updating

The data fusion step will update the old tracks' scores (detection and recognition scores) with the new results of the detection and recognition processes. Depending on the sensor module structure, we can have the result of recognition, or detection or both.

5.1 Confidence update algorithm

The algorithm of track confidence updating with object features consists in:

- Transform the probabilities $P_{d,k}$ and $P_{r,k}$ of an object into basic belief assignment BBAs: $m_{d,k}^{\Omega_d}$ (BBA of the detection process defined over the detection state space Ω_d at time t_k) and $m_{r,k}^{\Omega_r}$ (BBA of the recognition process defined over the recognition state space Ω_r at time t_k)

- Transform the performance of the sensor module into discounting values: the probability of false alarm P_{FA} and the probability of recognition P_R of the sensor module transform the last BBAs into $m_{d,k}^{\Omega_d,\alpha_d}$ and $m_{r,k}^{\Omega_r,\alpha_r}$ where α_d and α_r are respectively the discounting factors of detection and recognition BBAs.

- Compute the combination of discounted BBAs: $m_{dr,k}^{\Omega}$

- Combine this result with the associated track belief function m_{k-1}^{Ω} to obtain m_k^{Ω}

- Estimate the track's detection and recognition confidence: $P_{d,k}$ and $P_{r,k}$

5.2 The common frame of discernment

To combine all BBAs we have to transform them to the same frame of discernment. Let $\Omega = \{\text{PO}, \text{NPO}, \text{FA}\}$ be a general frame. Ω can be considered as refinement of the two frames Ω_d and Ω_{r1}: in fact in $\Omega_d = \{\text{O}, \text{NO}\}$, the objects O can be divided into two sets: pedestrians objects PO and non pedestrian objects NPO, and non objects NO are false alarms FA. In $\Omega_{r1} = \{\text{P}, \text{NP}\}$, pedestrians P are pedestrian objects PO and non pedestrians NP can be non pedestrian objects NPO or false alarms FA.

Ω_{r2} is identical to Ω, so the BBA of the second recognition process $m_{r2,k}^{\Omega,\alpha_r}$ is already defined over $2^{\Omega} \equiv 2^{\Omega_{r2}}$, but not $m_{d,k}^{\Omega_d,\alpha_d}$ and $m_{r1,k}^{\Omega_{r1},\alpha_r}$ because they are defined respectively over 2^{Ω_d} and 2^{Ω_r}. To transform them to the new frame of discernment Ω, we have to do the refinement process, i.e. to move our belief on a subset of Ω_d (respectively Ω_r) to the corresponding subset of Ω, we get:

$$m_{d,k}^{\Omega}(\{\text{PO}, \text{NPO}\}) = m_{d,k}^{\Omega_d,\alpha_d}(\{\text{O}\})$$
$$m_{d,k}^{\Omega}(\{\text{FA}\}) = m_{d,k}^{\Omega_d,\alpha_d}(\{\text{NO}\})$$
$$m_{d,k}^{\Omega}(\Omega) = m_{d,k}^{\Omega_d,\alpha_d}(\Omega_d)$$
$$m_{r1,k}^{\Omega}(\{\text{PO}\}) = m_{r1,k}^{\Omega_{r1},\alpha_r}(\{\text{P}\})$$
$$m_{r1,k}^{\Omega}(\{\text{NPO}, \text{FA}\}) = m_{r1,k}^{\Omega_{r1},\alpha_r}(\{\text{NP}\})$$
$$m_{r1,k}^{\Omega}(\Omega) = m_{r1,k}^{\Omega_{r1},\alpha_r}(\Omega_{r1})$$

The three obtained BBAs $m_{r2,k}^{\Omega}$, $m_{d,k}^{\Omega}$ and $m_{r1,k}^{\Omega}$ are not independent, so we chose to combine them by the cautious rule of combination [12][13].

5.3 BBAs combination

The cautious combination of the two BBAs $m_{d,k}^{\Omega}$ and $m_{r1,k}^{\Omega}$ for example, denoted $m_{dr1,k}^{\Omega}$ can thus be computed as follows:

a. Compute the commonality functions $q_{d,k}^{\Omega}$ and $q_{r1,k}^{\Omega}$ of the two BBAs $m_{d,k}^{\Omega}$ and $m_{r1,k}^{\Omega}$

b. Compute the weight functions $w_{d,k}$ and $w_{r1,k}$ from $q_{d,k}$ and $q_{r1,k}$ using the formula: $w(A) = \prod_{B \supseteq A} q(B)^{(-1)^{|B|-|A|+1}}$

c. Compute the weight function $w_{dr1,k}$: $w_{dr1,k} = w_{d,k} \otimes w_{r1,k} = \min(w_{d,k}, w_{r1,k})$

d. Compute $m_{dr1,k}^{\Omega}$ by combining all $A^{w_{dr1,k}}$ conjunctively

5.4 Updating BBAs

Measurement noise are supposed time independent, so under the assumption of measurement independency the BBA result of the cautious combination $m_{dr1,k}^{\Omega}$ is combined with the track's BBAs m_{k-1}^{Ω} by the conjunctive rule of combination to get m_k^{Ω} the final result of BBA combination.

5.5 Detection and recognition confidences result

The pignistic probability (*BetP*) calculation gives the final result of detection and recognition confidences.

BetP should be calculated on the original frames of discernment Ω_d and Ω_r, so we have to do the inverse of the refinement process already done.

$$m_k^{\Omega_d}(\{O\}) = m_k^{\Omega}(\{PO\}) + m_k^{\Omega}(\{NPO\}) + m_k^{\Omega}(\{PO, NPO\})$$

$$m_k^{\Omega_d}(\{NO\}) = m_k^{\Omega}(\{FA\})$$

$$m_k^{\Omega_d}(\Omega_d) = m_k^{\Omega}(\{PO, FA\}) + m_k^{\Omega}(\{NPO, FA\}) + m_k^{\Omega}(\Omega)$$

$$m^{\Omega_r}(\{P\}) = m^{\Omega}(\{PO\})$$

$$m_k^{\Omega_r}(\{NP\}) = m_k^{\Omega}(\{NPO\}) + m_k^{\Omega}(\{FA\}) \; m_k^{\Omega}(\{NPO, FA\})$$

$$m_k^{\Omega_r}(\Omega_r) = m_k^{\Omega}(\{PO, NPO\}) + m_k^{\Omega}(\{PO, FA\}) + m_k^{\Omega}(\Omega)$$

The detection and the recognition probabilities ($P_{d,k}$ and $P_{r,k}$) of a track are:

$$P_{d,k} = BetP_{d,k}(\{O\}) = m_k^{\Omega_d}(\{O\}) + m_k^{\Omega_d}(\Omega_d)/2$$

$$P_{r,k} = BetP_{r,k}(\{P\}) = m_k^{\Omega_r}(\{P\}) + m_k^{\Omega_r}(\Omega_r)/2$$

The fusion module will provide these results as output, but will keep the original BBa m_k^{Ω} for the next updating stage at time t_{k+1}.

6 Results

All results are based on synthetic data covering most important and critical cases that show the advantage of the described fusion system and the advantage of using belief functions, especially in the situations where there is lake of information. Graphs show the evaluation of the detection and the recognition confidences with respect to the time i.e. to the sensor scanning cycle.

To compare the variation of the detection and the recognition track confidences with the corresponding object confidences, we're showing for the tracks the pignistic probability BetP (5.5) to have comparable variables.

To show the difference between the cautious and the conjunctive rule of combination in case of combining dependent data, we combined two BBAs: $m_{d,k}^{\Omega}$ and $m_{r2,k}^{\Omega}$ calculated from probabilities provided by detection and recognition processes provided by a sensor.

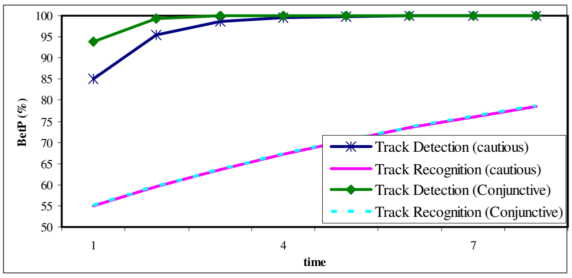

Figure 2: Comparison between the cautious and the conjunctive rules of combination

Figure 2 shows that the recognition process is not affected by the combination method because the detection BBA does not contain recognition data. But the difference is clear between the track detection results for the two methods: because of the dependent detection information in the two BBAs, the confidence result of the conjunctive combination will be highest than the cautious combination but erroneous.

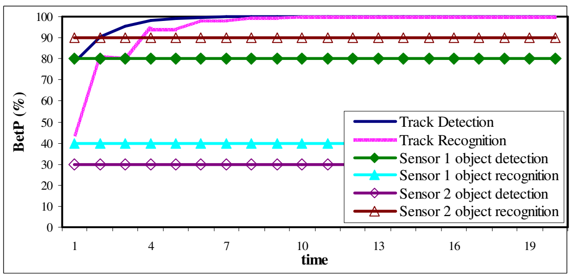

Figure 3: Track detection and recognition with two sensors

Figure 3 and Figure 4 show the sensors' reliability effects. With constant object detection and recognition, the more reliable sensor dominates: in Figure 3, the sensor 1 is reliable in detection with a probability of false detection of

20%, but not in recognition (80% false recognition) and the sensor 2 is reliable in recognition (20% false recognition) but not in detection (80% false detection): fusion results shows that the corresponding track is well detected and recognized. Figure 4 shows the inverse case.

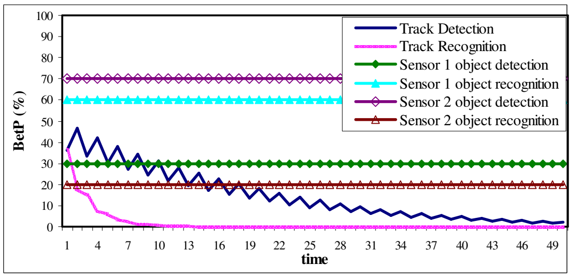

Figure 4: same as Figure.3 with different data

With no object detection information, Figure 5 shows that object recognition provides detection data in good recognition state (*BetP*>50%), but not in non recognition (*BetP*<50%).

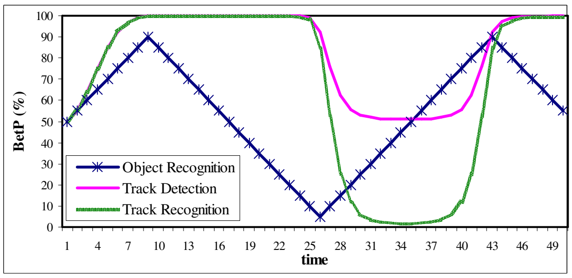

Figure 5: Track detection and recognition with variable object recognition and without object detection information

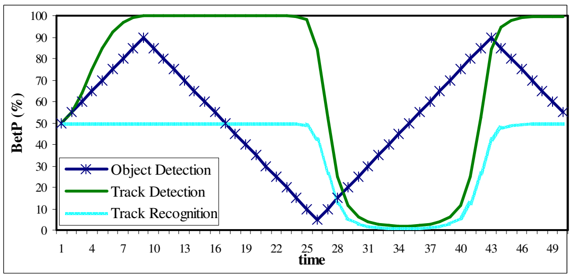

Figure 6: Track detection and recognition with variable object detection and without object recognition information

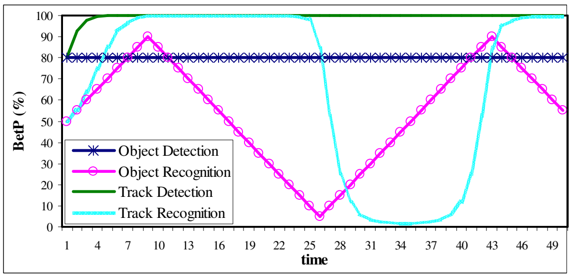

Figure 7: Track detection and recognition with variable object recognition and constant good object detection

The case is not the same with the lack of recognition information. Figure 6 shows that good detection (*BetP*>50%) can't provide recognition information because without recognition we can't distinguish between pedestrian object and non pedestrian object, non detection (*BetP*>50%) provide the recognition information: non pedestrian.

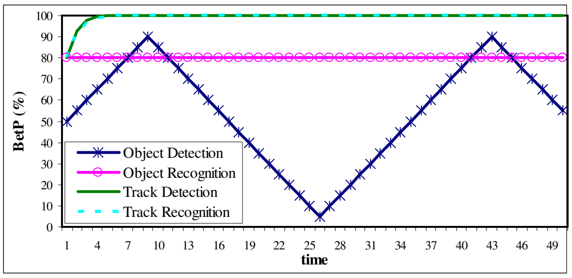

Figure 8: Track detection and recognition with variable object detection and constant good object recognition

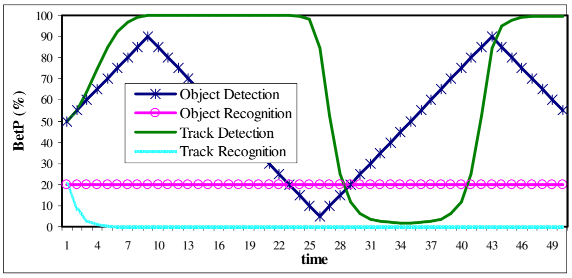

Figure 9: Track detection and recognition with variable object detection and constant low object recognition

Figure 7 shows that good object detection (80%) doesn't affect track recognition that remains variable with the object recognition.

Figure 8 shows that good object recognition (80%) means good track detection, even thaw if the object detection is variable.

Figure 9 shows that a low object recognition (20%) affects the track recognition but not the track detection.

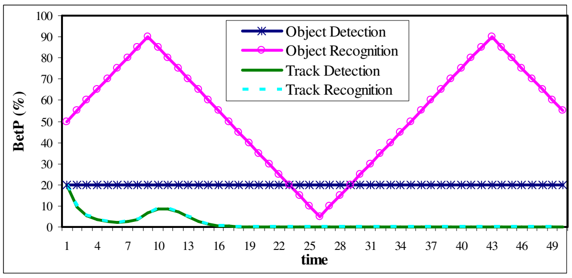

Figure 10: Track detection and recognition with variable object recognition and constant low object detection

Figure 10 shows that with low object detection information (20%) we can't get any track detection or track recognition information.

These results showed the advantage of using belief functions, especially in the situations where there is lake of information. The next step will be the implementation and the test of the system as an imbedded real time system in the experimental vehicle.

7 Conclusion

In this paper we have described a credibilistic approach to combine and update detection and recognition confidences in a multi-sensor pedestrian tracking system. We have showed that combining confidences should take into consideration the data dependency by using appropriate fusion operator. Results showed that our generic tracking and fusion module can profit of any existing object's confidence data (detection and/or recognition) to provide track's detection and recognition information by redistributing knowledge between the two confidences and taking into consideration sensors' reliabilities. These confidences are very important for any ADAS system in pre-crash situation since the ADAS can perform autonomous braking or maneuvering in case of unavoidable collision.

The future work concentrates on testing the system with real sensors data, and its implementation as a real time system in our laboratory platform CARMEN equipped with Lidar, radar and vision systems.

Acknowledgements

This work is a part of the project LOVe (Logiciel d'Observation des Vulnérables http://love.univ-bpclermont.fr/) and supported by the French ANR PREDIT.

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