Conflict Management in Multi-sensor Dempster-Shafer Fusion for Speed Limit Determination

Jérémie Daniel and Jean-Philippe Lauffenburger

Abstract—This paper deals with a Speed Limit Determination Advanced Driver Assistance System (ADAS) performing the combination of a navigation system and a Speed Limit Sign Recognition System (SLSR). The present strategy is based on a multi-level data fusion using the Evidence theory. In a first step, the sensor reliabilities are estimated using indicators provided by the sources. Simultaneously, a multi-criterion fusion is processed on attributes extracted from the navigation system to detect its potential erroneous data and define the best navigation limit speed candidate. The second fusion level - the multi-sensor fusion - considers the navigation and the camera-based SLSR to be independent and specialized. In addition, the conflict is interpreted as an additional source of information for the final speed limit definition. The benefits of the proposed solution are shown through simulations and real experiments.

I. INTRODUCTION

Using a single sensor does not allow the characterization of the sensor information (inaccuracy level, reality, etc.) and, at the same time, the determination of the global driving situation (road context, vehicle configuration, etc.). Nevertheless, to be effective, the next generation of ADAS will have to deal with both tasks. They will consequently have to combine information coming from multiple sensors. This represents a challenging task as sensors may provide heterogeneous, inaccurate or erroneous information. These imperfections have to be integrated during the combination to provide coherent information. Data fusion techniques, and especially the Evidence Theory, are well suited for this purpose [1], [2]. Indeed, Evidence Theory is efficient for uncertain, imprecise and incomplete information combination. Moreover, if the conflict and ignorance can be modeled, this theory can also consider singletons and unions of propositions contrary to Bayesian approaches for example.

The present document focuses on Speed Limit Assistants (SLAs). Originally, these systems were only based on an SLSR processed over camera images, i.e. on a sensor which is subject to inaccuracies and false detection [3]. To overcome these limitations, a new generation of SLAs has emerged: multiple-sensor-based SLAs which usually refer to the combination of an SLSR with a Geographical Information System (GIS) as they are complementary. Among the different techniques which can be used for their information combination, the focus is put here on Evidence Theory-based solutions.

This formalism was employed by [4] who proposed to use contextual information to characterize the quality of the vision and the navigation information. However, this contextual information is obtained using the vision system. The sources are consequently no longer independent as vision is used to define the confidence given to navigation. [5] and [6] proposed a different approach in which the GIS information is processed through a first step of combination. The latter is composed of simple weighted sum combinations of several criteria corresponding to digital map database attributes (in/out of city driving, presence of crossings, etc.). These attributes are of great help, on the one hand in the description of the current road context, and on the other hand to characterize the reliability of the GIS. However, these approaches are based on weighted sums which do not allow the correct detection of the GIS incoherences and inaccuracies. In addition, this solution is limited by the strategy adopted for the multi-sensor fusion, which in [5] favours vision information in any case.

To overcome these limitations, the present SLA is based on a new multi-level Data Fusion approach. The first level - the multi-criterion fusion - consists in the determination of reliable navigation information while the second step - the multi-sensor fusion - fuses both sensors to define the final speed limit and its global level of integrity. The main benefits of the multi-criterion fusion consists in the consideration of the GIS reliability (quality of the positioning, the localization and the digital map database) in its basic belief assignment (bba). In addition, this fusion level also helps to detect the GIS false information and to determine the appropriate navigation speed more efficiently. On the other hand, the multi-sensor fusion strategy, based on Rombaud’s bba model [7], considers the sensors as independent, specialized sources [8]. The conflict which may eventually be generated during this fusion step is considered here as an additional source of information. This allows the SLA to stay undecided regarding the current situation, and so avoids providing the Driver with false information. These benefits are depicted through simulations and real-time tests.

After an introduction to the Belief Theory in Section.II, Section.III describes the strategy adopted for its application to speed limit determination. Section.IV then presents the results obtained with the system developed. Finally, Section.V concludes this paper.

II. THEORETICAL BACKGROUND

A. Evidence Theory Basics

The Evidence Theory has been introduced by Dempster [1] and mathematically formalized by Shafer [2]. This theory is based on the modelling of the belief level in a defined event through mass functions defined on subsets (singletons and/or
unions). This section only presents the basic elements of this theory. More information is available in [2].

Let $\Theta$ be the discernment frame of all the solutions (or hypotheses) $H_j$, $j = 1, 2, \ldots, k$ with $k$ the number of possible hypotheses of the considered problem. $\Theta$ is said to be exhaustive and all the hypotheses are exclusive in the close world assumption. The corresponding referential subset, a power set $2^\Theta$ of $2^k$ propositions $A$ of $\Theta$ is such that:

$$2^\Theta = \{ A / A \subseteq \Theta \} = \{ \emptyset, H_1, \ldots, H_k, H_1 \cup H_2, \ldots, \Theta \} \quad (1)$$

“$\emptyset$” represents the impossible hypothesis which usually characterizes the conflict between sources, and “$\Theta$” is the ignorance (i.e. the union of all the hypotheses $H_j$). The referential subset defines all the solutions which can arise regarding the hypotheses of the discernment frame. The veracity of a proposition $A$ of $2^\Theta$ is characterized by its bba or mass $m$ defined as follows:

$$m : 2^\Theta \rightarrow [0, 1], \quad \sum_{A \subseteq 2^\Theta} m(A) = 1 \quad (2)$$

$$A \subseteq 2^\Theta, m(A) \neq 0 \Rightarrow A \text{ is a focal element}$$

The Combination is the core of the fusion as it gathers and regroups the different information of the sources $S_j$. The most common combination operator, also considered here, is the Dempster conjunctive operator $\oplus$. It is associative and commutative, so does not force the definition of a fusion order over the $p$ sources:

$$m_{1 \ldots p} (H) = m_{S_1} (H_1) \oplus m_{S_2} (H_2) \oplus \ldots \oplus m_{S_p} (H_p)$$

$$= \sum_{H_1 \cap \ldots \cap H_k = H} \prod_{j=1}^{p} m_{S_j} (H_j). \quad (3)$$

Finally, the selection of the most relevant hypothesis $H$ regarding the discernment frame is usually based on the maximum of Belief ($Bel$), on the maximum of Plausibility ($Pl$) or on the maximum of pignistic probability ($BetP$):

$$H = \arg \max_{1 \leq j \leq k} Bel (H_j) = \arg \max_{1 \leq j \leq k} \sum_{A \supseteq H_j} m(A)$$

$$H = \arg \max_{1 \leq j \leq k} Pl (H_j) = \arg \max_{1 \leq j \leq k} \sum_{A \supseteq H_j \neq \emptyset} m(A)$$

$$H = \arg \max_{1 \leq j \leq k} BetP (H_j) = \arg \max_{1 \leq j \leq k} \sum_{A \subseteq H_j \cap \Theta} \frac{1}{|A|} m(A) \quad (4)$$

B. Specialized Sources and Non-overlapping bba Model

A specialized source is a source which can only give information about one specific proposition ($H_j$) of the discernment frame. The specialized source can only say that “It is this proposition”, “It is not this proposition” and “I do not know” respectively denoted $1 \ H_j$, $\overline{1} \ H_j$ and $\Theta$. Based on this statement, several models are available for bba [8]. Among them, the model initiated by Rombaut is particularly interesting as it is based on the following condition [7]: “A source cannot simultaneously affect mass on the hypothesis and its complementary, thus giving antagonistic information”. This does not allow the generation of belief mass over $H_j$ and $\overline{1} \ H_j$ simultaneously. A classic representation of this model is shown in Fig.1. This model is defined by three parameters:

- The reliability variable $R_v$ used to perform the bba. This indicator describes the reliability of a given sensor information. For the vision system, this variable is defined regarding the percentage in the SLSR detected speed while the navigation variable is defined regarding the accuracy of the positioning, localization and digital map database [9].

- The bba model describing their evolution w.r.t. $R_v$. Among the different solutions such as quadratic polynomials, Gaussian curves, etc. (cf. [10]), linear expressions have been considered here, as presented in Fig.1.

- The boundary value $\tau$ which defines the limit between the belief in $H_j$ and $\overline{1} \ H_j$. If $\tau < 0.5$, the estimation is said to be optimistic; on the contrary, if $\tau > 0.5$ the estimation is said to be pessimistic. Finally, if $\tau = 0.5$ the estimation is said to be neutral.

C. Multi-sensor Combination

Here, the focus is on combination rules defined for specialized sensors which may have different points of view, i.e. give opinion on different hypotheses $H_j$ which can be

![Fig. 1. Basic Belief Assignment Model](image-url)
any speed of the discernment frame. They are consequently characterized by masses on their hypothesis \( m_j(H_j) \), on their complementary hypothesis \( m_j(\overline{H_j}) \) and on the ignorance \( m_j(\Theta) \). Considering these elements, the results of the multi-sensor combination are presented in Table I for \( p \) sensors and generalized in (5) with \( \alpha_j = (1 - m_a(H_a)) \), \( \beta_j = (1 - m_b(H_b)) \) and \( \gamma_j = (m_a(\overline{H_a})) \) [8].

\[
m_{1...p}(H_j) = m_j(H_j) \prod_{a=1}^{p} \alpha_a + m_j(\Theta) \prod_{a=1}^{p} \gamma_a
\]

\[
m_{1...p}(H_j \cup \ldots \cup H_l) = m_j(\Theta) m_l(\Theta) \prod_{a=1}^{p} \gamma_a
\]

and for union combinations of 2 to \( p-1 \) hypotheses:

\[
m_{1...p}(H_j \cup \ldots \cup H_l) = m_j(\Theta) \ldots m_l(\Theta) \prod_{a=1}^{p} \gamma_a
\]

\[
m_{1...p}(\overline{H_j}) = m_j(\overline{H_j}) \prod_{a=1}^{p} m_a(\Theta)
\]

\[
m_{1...p}(\Theta) = \prod_{a=1}^{p} m_a(\Theta)
\]

\[
m_{1...p}(\Theta) = 1 - \left[ \prod_{a=1}^{p} \alpha_a + \sum_{a=1}^{p} m_a(H_a) \prod_{b=1}^{p} \beta_b - \prod_{a=1}^{p} \gamma_a \right]
\]

(5)

III. APPLICATION TO THE COMBINATION OF VISION AND NAVIGATION INFORMATION

A. Multi-level Fusion for SLAs

The fusion strategy using the Dempster-Shafer Theory is based on the diagram presented in Fig.2. This figure shows a two-level fusion. The first step consists in the local processing of the sensor data (information from the camera and from the navigation system processed independently). i.e. the determination of each sensor speed and its related belief/confidence mass. For the vision, it consists in the reliability estimation of the information provided by the SLSR algorithm. On the opposite, the GIS presents a more complex structure: it consists in a complete fusion step based on digital map attributes here, named criteria. This multi-criterion fusion helps to determine the best navigation speed as well as its belief mass w.r.t. the contextual information provided by the GIS digital map database. Indeed, this approach used in [10] and [11] for different applications, here helps to characterize a set of potential speeds, as each criterion gives relevant information about the road context or the reliability of the GIS. The combination of these criteria then allows the determination of the global road context (urban driving, highway driving, etc.), thus determines the appropriate speed out of the set of possible ones regarding this context. The multi-criterion fusion is processed sequentially over each of the speed candidates. The final navigation speed is then the one with the belief maximum. This multi-criterion fusion consequently confirms or infirms the GIS speed extracted directly from the database when available, thus detects its incoherences. More details about this approach can be found in [9].

The second fusion level is dedicated to the multi-sensor fusion, i.e. the fusion of the information from vision and from navigation. The strategy adopted for this fusion level is based on the consideration that each sensor is independent and specialized for one speed. Two speed limits are determined and provided to the Driver: the raw speed limit based on the direct combination results using the Dempster operator which considers the conflict as an additional source of information for the limit speed determination, and the conflict redistributed speed limit which is obtained after the redistribution of the conflict using the Florea operator [12].

B. Combining Sensor Data

The application of Rombout’s model (cf. Fig.1) to the present context results in the equations presented in (6) with \( m_j(H_j), m_j(\overline{H_j}) \) and \( m_j(\Theta) \) respectively corresponding to the belief masses on the speed \( H_j \), on the complementary speed and on the ignorance for source \( j \). \( \alpha_j \) values have been determined empirically.

\[
m_j(H_j) = \begin{cases} 0 & R_v \in [0, \tau] \\ \left( \frac{\alpha_j}{\tau} \right) R_v - \frac{\alpha_j \tau}{1 - \tau} & \quad R_v \in [\tau, 1] \end{cases}
\]

\[
m_j(\overline{H_j}) = \begin{cases} -\frac{\alpha_j R_v + \alpha_j}{\tau} & R_v \in [0, \tau] \\ 0 & \quad R_v \in [\tau, 1] \end{cases}
\]

\[
m_j(\Theta) = \begin{cases} \frac{\alpha_j}{\tau} R_v + (1 - \alpha_j) & R_v \in [0, \tau] \\ -\frac{\alpha_j}{\tau} R_v + \frac{1 - (1 - \alpha_j) \tau}{1 - \tau} & \quad R_v \in [\tau, 1] \end{cases}
\]

(6)

As the considered SLA fuses information from a navigation and a vision system, the number of sources is equal to 2. The discernment frame is then considered to be only composed of both sensor speeds such as:

\[
\Theta = \{ H_v, H_n \} \\
2^\Theta = \{ \emptyset, H_v, H_n, \Theta \}
\]

(7)
with $H_v$ the vision speed and $H_n$ the navigation speed. This greatly simplifies the multi-sensor fusion equations presented in (5) into:

$$
\begin{align*}
    m_v(H_v) &= m_v(H_v) (1 - m_v(H_n)) + m_v(\emptyset)m_n(\Theta) \\
    m_v(H_n) &= m_n(H_n) (1 - m_v(H_v)) + m_v(\emptyset)m_v(\Theta) \\
    m_v(\emptyset) &= m_v(H_v)m_n(H_n) + m_v(\Theta)m_n(H_n) \\
    m_n(H) &= (1 - m_v(\Theta))(1 - m_v(H)) - m_v(\emptyset)m_n(\Theta) \\
    m_n(\Theta) &= m_v(\emptyset)m_n(\Theta) \\
    m_n(\emptyset) &= m_v(H)v_n(H_n) + m_v(\Theta)v_n(H_n) \\
\end{align*}
$$

(8)

Note that, as the discernment frame $\Theta$ is supposed to be exhaustive and as there are only two sources, $m_v(\Theta)$ and $m_v(H_v)$ are directly integrated into $m_v(H_n)$ and $m_v(\Theta)$. Finally, the specific case in which both sensors are specialized in the same speed $H_v$, thus based on the discernment frame $\Theta = \{H_v, \Theta\}$, results in the consideration of the combination rules used for specialized sources on the same hypothesis [9]. Equation (8) is then transformed into (9):

$$
\begin{align*}
    m_v(H) &= (1 - m_v(\Theta))(1 - m_v(H)) - m_v(\emptyset)m_n(\Theta) \\
    m_v(\Theta) &= m_v(\emptyset)m_n(\Theta) \\
    m_v(\emptyset) &= m_v(H)m_n(H) + m_v(\Theta)v_n(H) \\
\end{align*}
$$

(9)

C. Conflict Management and Final Decision

As sources can give opinions on different speeds, conflict may be generated during the multi-sensor fusion. The comparison of a raw and conflict-redistributed fusion is proposed in the present paper:

1) Raw Multi-sensor Fusion: The conflict can be interpreted as a piece of information related to the unreliability of the sources, to the non-exhaustiveness of the discernment frame or to a discordance between sensor data. In these particular cases, for safety reasons, no decision can be taken as one cannot take the risk to select a speed on which the belief is not high enough. The first speed information provided by the present SLA is consequently the speed with the belief maximum (Bel) considering a minimum threshold of 0.5. This speed corresponds to pragmatic and safe information based on the results of the combination step with no conflict redistribution. If both speeds have a belief which lies under the threshold, the speed considered is undefined:

$$
H_{raw} = \left\{ \arg\max \{\text{Bel}(H_v) \geq 0.5, \text{Bel}(H_n) \geq 0.5 \}, \text{undefined} \right\}
$$

(10)

2) Conflict Redistributed Multi-sensor Fusion: Commonly, the conflict is redistributed using the Dempster redistribution operator [11]. However, this operator is not adapted to the current situation as it redistributes the conflict which may be generated by a few sensors only, over all the masses (even the ignorance). To overcome this problem, Florea’s redistribution operator [12], named Proportional Conflict Redistribution (PCR), has been chosen:

$$
\begin{align*}
    m_{PCR}(H_j) &= m_v(H_j) + \\
    &\sum_{H_k \in \Theta \setminus \{H_j\}} \frac{m_j(H_j)^2 m_n(H_k)}{m_j(H_j) + m_n(H_k)} \\
\end{align*}
$$

(11)

with $m_v(H_j)$ the mass on hypothesis $H_j$ after the conjunctive combination, and $m_{PCR}(H_j)$ the mass on hypothesis $H_j$ after the conflict redistribution. The application of the PCR obviously involves $m(\emptyset) = 0$ and higher masses on the sensors speeds. Considering this point, the Decision step is based on the maximum of Belief over the navigation and vision masses after the PCR with no threshold:

$$
H_{red} = \arg \max_{1 \leq j \leq k} \text{Bel}(H_j) = \arg \max \{\text{Bel}(H_v), \text{Bel}(H_n)\}
$$

(12)

This maybe interesting information about the current speed limit, as it is based on the redistribution of the conflict over its generators. Indeed, sources which generate a high conflict have usually strong beliefs in their propositions. These beliefs are greatly reduced after the combination due to the conflict generation. The use of this redistribution operator can therefore involve a re-appearance of the strong beliefs which caused the conflict while preserving the other information obtained from the combination (ignorance, etc.). Contrary to the raw final speed, this speed is only an indication about the possible limit speed.

IV. EXPERIMENTAL RESULTS

A. Multi-sensor Fusion Simulations

The benefits of the proposed multi-sensor fusion are shown through a comparison with the solution presented in [5]. The latter consisted in trying to find a navigation speed (focal speed of the multi-criterion fusion) matching the vision speed, thus giving more weight to the vision information. In addition, the conflict was automatically redistributed using the Dempster operator. Contrary to this, the new approach considers the raw information of the sensors even if they are not in agreement, and so gives equal importance to both sensors. Then, the conflict is considered as an additional source of information for the final speed limit determination. The considered discernment frame is the following one:

$$
\Theta = \{5, 10, 20, 30, 45, 50, 60, 70, 80, 90, 100, 110, 120, 130, \text{unlimited} \}
$$

(13)

1) Sensor in Agreement: Consider the information provided by the sensors to be as presented in Table II, which corresponds to a case in which the sensors are in agreement. The results of the multi-sensor fusion are given in Fig.3. This figure clearly shows that for both multi-sensor approaches, fusion results in a strong belief in 50 km h\(^{-1}\). This is quite obvious as both sensors opt for this speed. Nevertheless, a few differences can already be stressed: the multi-level approach only generates mass on the speed and on the ignorance when both sensors are in agreement contrary to

\[\text{As there are only two possible speeds, the union of these speeds obviously corresponds to the ignorance (} H_v \cup H_n = \Theta).\]
the approach described in [5] which generates a small belief mass on the speed complementary (50). Then, remember that the proposed approach provides two speed limits to the Driver: the speed limit obtained from the raw multi-sensor fusion and an indicative speed limit obtained after the conflict redistribution using Florea’s operator. As there is no conflict generation, the latter has no impact, so that the fusion with conflict redistribution gives the same results as the raw fusion.

2) Conflict Between Sensors: Now consider a second configuration, presented in Table III, in which vision does not give the same speed as navigation. Both combination results are presented in Fig.4. This figure shows the combined belief masses on the vision speed (110km.h⁻¹), the navigation speed (50km.h⁻¹), the ignorance and the conflict. It is clear that the approach described in [5] has a strong belief in the vision speed (0.85). This is mainly due to the matching of a navigation focal speed with the vision speed. Indeed, in this case, the navigation and the vision speeds are different, the system therefore looks for a focal element of the navigation which is equal to the speed defined by the vision. Since 110km.h⁻¹ selected by the vision is a focal element of 50km.h⁻¹ (cf. [9]), the multi-sensor fusion is then processed with the navigation masses related to 110km.h⁻¹.

Contrary to this, the multi-level approach generates small beliefs in both navigation and vision speeds (respectively 0.13 and 0.27). As sensors disagree, there is a high conflict (0.54), which means that sensors provide contradictory data (considering the exhaustiveness of the discernment frame). In this particular case, before conflict management, the multi-level approach is not able to take a decision based on the raw fusion. In fact, as mentioned in Section III-C, the raw fusion Decision is based on the selection of the speed with belief maximum considering a minimal threshold of 0.5. Here, none of the speeds has a belief higher than 0.5. Consequently, the final speed is undefined, which represents a safe decision regarding the context.

Contrary to the previous test, the conflict redistribution, using Florea’s operator, involves an increase in each sensor belief, which are then close and respectively equal to 0.5 and 0.43, without modifying the ignorance. This is coherent regarding their initial belief (cf. Table III) contrary to the approach presented in [5] which completely overestimates the belief in the vision speed. Finally, considering the decision strategy adopted for the conflict redistributed fusion (cf. III-C), 110km.h⁻¹ is considered as the final speed limit. Nevertheless, as their belief masses are close, the decision is not obvious.

B. Real-time Tests

This section is dedicated to the description of real-time results obtained with the multi-level SLA. These experiments were carried out using a test car equipped with a camera and an SLSR coupled to a GIS. Fig.5 presents a snapshot of the SLA providing the following data (from top to bottom):

- Information provided by the SLSR.
- Information provided by the navigation system with the results of the multi-criterion fusion in the two last rows.

<table>
<thead>
<tr>
<th>Sensor Speed</th>
<th>Sensor Masses</th>
</tr>
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<tbody>
<tr>
<td>Vision speed = 110</td>
<td>( m_v(110) = 0.80 )</td>
</tr>
<tr>
<td></td>
<td>( m_v(100) = 0.00 )</td>
</tr>
<tr>
<td></td>
<td>( m_v(\Theta) = 0.20 )</td>
</tr>
</tbody>
</table>

| Navigation speed = 50 | \( m_n(50) = 0.67 \) |
|                       | \( m_n(50) = 0.00 \) |
|                       | \( m_n(\Theta) = 0.33 \) |

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**Table II**

Vision Information to be Fused with Coherent Navigation Information

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| Navigation speed = 50 | \( m_n(50) = 0.67 \) |
|                       | \( m_n(50) = 0.00 \) |
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**Table III**

Vision Information to be Fused with Coherent Navigation Information

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</tr>
</tbody>
</table>

| Navigation speed = 50 | \( m_n(50) = 0.67 \) |
|                       | \( m_n(50) = 0.00 \) |
|                       | \( m_n(\Theta) = 0.33 \) |
The multi-sensor fusion results composed of the raw fusion results, the conflict level and the conflict redistributed fusion results.

A graphical representation of the raw fusion results in the middle between the vision speed on the left and the navigation speed on the right.

A graphical representation of the conflict redistributed fusion results with the fused speed in the middle, the vision speed on the left and the navigation speed on the right.

In Fig.5, the vehicle is driving on a European highway limited to \(110\, \text{km.h}^{-1}\). This road context is confirmed by the multi-criterion fusion which chooses \(110\, \text{km.h}^{-1}\) for the navigation speed. Then, as the traffic sign detected by the SLSR indicates \(50\, \text{km.h}^{-1}\), the sensors are in conflict. In this figure, it can be seen that the confidence in the vision speed and in the navigation speed is high (respectively 0.96 and 0.81), the raw fusion is consequently subject to a high conflict of 0.68 which is too high for the raw fusion to give a final speed limit. The latter is then undefined (998) which is a safe decision regarding the level of confidence of each sensor. Contrary to this, the indicative speed limit given after conflict redistribution using Florea’s operator is \(110\, \text{km.h}^{-1}\) with a confidence of \((0.66)\). This speed reveals that the initial belief of the navigation information was stronger than the vision information belief. The conflict redistributed approach thus results in a speed which corresponds to the real one \((110\, \text{km.h}^{-1})\).

V. CONCLUSION

This paper has presented a new approach to the combination of information from a navigation system and a vision system for Speed Limit Determination. A Dempster-Shafer multi-level data fusion composed of a multi-criterion fusion and a multi-sensor fusion has been proposed. The latter, based on the consideration of each sensor as an independent and specialized source, is the core of this document. The benefits of the proposed approach are double: first, contrary to conventional approaches, the source independences are guaranteed. On the other hand, the consideration of the conflict as an additional source of information for the decision step, allows the Speed Limit Assistant to stay undecided about the final speed limit. This avoids the selection of a final speed in which confidence is low. These benefits have been highlighted in the comparisons of this multi-level Speed Limit Assistant with a conventional approach.

REFERENCES