

Navigation and Speed Signs Recognition Fusion for Enhanced Vehicle Location

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Abstract: This paper presents an approach that provides extended vehicle location information based on multi sensor data fusion. Firstly, the vehicle location, a recommended speed level referred to this location and a confidence level attached to this speed evaluation are determined thanks to the digital road map of a navigation system. At the same time, a speed sign recognition device based on image processing determines the legal speed limit and an associated confidence level of the detection. Because of the uncertainties and imprecision of both sensors, fusion using Belief Theory is performed between the data provided by each sources. By merging several criteria from the digital map with the traffic sign detection results, this approach allows on the one hand a reliable determination of the driving conditions and on the other hand the evaluation of the confidence level of the decision. Real experiment results from a driving situation in which both sources are in conflict illustrate the effectiveness of the approach.

1. INTRODUCTION

In the context of Advanced Driver Assistance Systems (ADAS) and Intelligent Autonomous Vehicles (IAV), navigation systems and more precisely the accurate location of a vehicle are often of the utmost importance. Classically, positioning systems relying on GNSS (Global Navigation Satellite-based Systems) like GPS, Glonass or Galiléo in the future are used in addition to Dead-Reckoning (DR) systems. The main drawback of GNSS-based absolute positioning systems is that their performances are directly linked to the visibility of the satellites. Nevertheless, satellite outages or multi-paths of the signals are common. In addition to these positioning solutions, location techniques often rely on the use of digital road maps contained by Geographical Information Systems (GIS). Once the absolute position of the vehicle is estimated using a GNSS-DR approach, mapmatching techniques (Zhao, 1997) are applied to locate the vehicle on the road network and determine the driving conditions with respect to attributes stored in the database. These attributes can represent for instance road signs, legal speed limits, road types or pedestrian crossings. This contextual information linked to the infrastructure and to the road geometry can lead to good anticipation capabilities of navigation-based ADAS (Bradai et al., 2006; Lauffenburger et al., 2007). Unfortunately, the digital map is a simplified representation of the real road network. In fact the road network is modelled by a succession of points (nodes) representing the centreline of the roads. This last aspect limits drastically the capabilities of a GIS.

Then, as no single sensor is able to provide accurate location information in every situation and at any time, defining precisely the driving conditions needs to deal with multiple sources of information. Thus, vehicle location always depends on the use of multiple sensors (Zhao, 1997; Zhao and Shibasaki, 2001) integrated via data fusion techniques. Extra sensors detecting for instance landmarks, road signs or obstacles can also constitute a source of information in the location process. Then, the idea relies on the confrontation of the information of all the sources (navigation system, cameras, DR...) in order to enhance the integrity of the global decision, i. e. the vehicle location. Commonly used extra exteroceptive sensors are for instance radars, lidars or cameras allowing for instance lane keeping applications (Polychronopoulos *et al.*, 2005).

This paper focuses on the determination of the vehicle's global driving conditions using GIS- and camera-based information. From the images of the driving scene obtained by the camera, the traffic signs are extracted and analysed in order to detect the potential speed limit signs (Moutarde et al., 2007). The corresponding speed limit and also a confidence parameter evaluating the quality of the detection are then provided. However, this technique suffers from incorrect diagnosis (due to detection difficulties) or from a lack of detection (related to the presence of an obstacle between the camera and the sign). On the other hand, GIS are not able to update dynamic changes in speed limitations on roads and may be subject to map matching based positioning errors. The solution proposed in this paper is the fusion of these results with location information provided by a navigation system. Here, the principle consists first to locate the vehicle on the digital map and to extract some roaddependant attributes from the map allowing the determination of a GIS-based recommended speed. Finally, using Belief Theory, the speed information defined by both sources (camera and GIS) are fused in order to obtain a reliable

decision on the driving situation and its corresponding confidence level.

The outline of the paper is as follows: section 2 gives a description of the fusion approach used for driving situations refinement. It also briefly introduces the concepts of Belief Theory used in this work. Section 3 describes the driving situation recognition technique using multi criteria fusion between a GIS and a camera. This section first introduces the different criteria retained for the fusion and then describes the fusion approach using Dempster-Shafer combination. Finally, section 4 presents some experimental results showing how the proposed solution can overcome conflicts between the considered sources.

2. PRINCIPLE OF THE METHOD

2.1 Global location using GIS and vision information

The problem often encountered in the development of ADAS concerns the precise characterization of the driving situations required to provide an appropriate aid to the driver. This is mainly due to the inaccuracy and the uncertainty of the various sensor data used to reach this objective.

The use of a navigation system can provide anticipatory information related to the environment of the vehicle. Nevertheless, such GIS can not be used as a standalone solution: the information contained in the digital map is only point-dependant and not contextual; during GPS outages, the evaluated vehicle location can suffer from inaccuracies; the database is not always up to date with respect to the constantly evolving driving infrastructure.

A camera-based system detecting the speed signs using image processing techniques can also help in the real-time identification of driving situations. Indeed, the regulation concerning the speed limits constitutes a good indicator to specify the situation in which the vehicle is. Here, the main idea is based on the fact that the legal velocities depend at the same time on the geographical contexts (urban, extra-urban zone...) and on the particular driving situations (highway entrance or exit, vicinity of a school...). Thus, the use of the speed limits can directly be exploited to extend the vehicle location process and define the driving conditions. This source of information could thus help to raise certain ambiguities related to the exclusive use of a GIS. However, such a device suffers from a limited detection range and can only detect clearly seen signs. Difficult external conditions (presence of dynamic or static obstacles like cars, trucks or trees in front of the equipped vehicle, rusted or mudded traffic signs...) can lead to a wrong or an impossible detection.

In this paper, the data provided by both sensors are fused in the context of Belief Theory (BT). The principle focuses on the determination of the authorized speed limit with respect to the considered situation, based on the speed sign detection of the a camera and heterogeneous criteria C_i (speed level, vehicle pose, driving area...) provided by the navigation system and its digital map database (cf. Fig. 1). Both sensors deliver a set of possible speed limits (*focal elements* in Fig. 1) and their associated confidence levels defining the reliability of each source of information. For the particular case of the navigation system, criteria C_i extracted from the database and informing about the driving situation and context are fused in order to obtain the confidence level of the GIS.

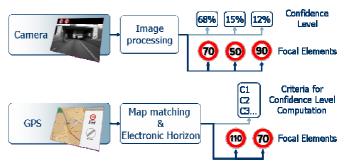


Fig. 1. Driving situation refinement approach

The joint use of these two information sources ensures a robust final decision, because of the redundancy and the complementarity of the data and allows raising ambiguities in the situation refinement (Darms and Winner, 2005).

2.2 Driving situations refinement in the framework of Belief Theory

The formalism of Belief Theory is particularly adapted to deal with uncertainties and inaccuracies on the one hand, and ambiguities and conflicts between information sources on the other hand. Moreover, the axiomatic relating to this theory applies ideally to classification or situations identification problems as it is the case in this application. Finally, it makes possible to take into account the ignorance in calculations. Within the framework of this application consisting in discriminating driving situations using different data sources, inaccuracies and uncertainties of the data have to be considered. Indeed, considering a GIS, many reasons can lead to a wrong location of the vehicle on the digital map describing the road network:

• vehicle positioning errors related to a bad reception of the satellite signals, to the multi-paths phenomenon affecting these signals, to the approximations carried out during the projection of the GPS coordinates in the local reference frame, on the reliability of the inertial sensors, etc.

• representation errors of the database (nodes and shape points only model the centreline of a road), modifications of the road network since the realization of the map, road network details not contained in the map, etc.

Concerning speed signs recognition, many factors mainly related to the driving context and the heterogeneity of the considered situations can lead to incorrect detections:

• high speed driving (for instance on motorway) makes the detection difficult because of a reduced measurement distance,

- presence of obstacles masking the traffic signs,
- dependency of speed limits with vehicle categories (cars, buses, trucks ...) and/or driving lanes,

• presence of several signs for a given situation (intersections, highways...),

• heterogeneity of signs to be considered.

Considering these points, Belief Theory is particularly adapted for this given application. Next section will introduce the concepts of this approach.

2.3 Belief Theory concepts

Belief Theory, also called Evidence Theory was introduced by Dempster (Dempster, 1967) and mathematically formalized by Shafer (Shafer, 1976). This theory can be seen as a generalization of the theory of probability. BT is based on the representation of the belief in an event. This modelling is carried out starting from *functions of mass* allowing a good representation of knowledge as well as an evaluation of the conflicts between the sources and of their respective reliability.

Belief Theory requires to define a state space D known as the *discernment frame*. This set is composed of the N possible solutions d_i (possible decisions) to a given problem.

$$D = \{d_1, d_2, ..., d_n\}$$
(1)

Based on the *discernment frame*, Belief Theory defines a *mass functions referential* corresponding to the set of all disjunctions of the decisions d_i denoted:

$$2^{D} = \{\emptyset, \{d_1\}, \{d_2\}, \{d_1 \cup d_2\}, \{d_3\}, \{d_1 \cup d_3\}, \{d_2 \cup d_3\}, \dots, D\}$$
(2)

This distribution represents the knowledge about the considered source of information. A mass function corresponds to the degree of belief that can be assigned to a given decision and is mathematically defined by a real number in the interval [0, 1]. Considering a source S_j , the respective mass function m_j satisfies:

$$\sum_{A \in 2^{D}} m_{j}(A) = 1 \tag{3}$$

The mass function $m_j(A)$ models the level of belief of the proposition A given by the source S_j . In general, the assumption of a *closed world* is made, meaning that decisions are exclusive and exhaustive (the *frame of discernment D* represents all the possible decisions). This is mathematically represented by:

$$m_i(\emptyset) = 0 \tag{4}$$

Each proposition A which satisfies $m_j(A) \succ 0$ is a *focal* element. In order to take account of the overall belief of A, the *belief function Bel()* is computed:

$$\forall A \in 2^{D}, Bel_{j}(A) = \sum_{\substack{B \subseteq A, B \neq \emptyset}} m_{j}(B)$$
 (5)

Belief Theory also defines a *plausibility function Pl()*:

$$\forall A \in 2^{D}, Pl_{j}(A) = \sum_{B \cap A \neq \emptyset} m_{j}(B) = 1 - Bel_{j}(\overline{A}) \quad (6)$$

The next section presents the use of Belief Theory for driving situations recognition using information provided by the GIS and a camera. The definition of the *discernment frame*, the identification of the respective criteria to be fused and finally the criteria fusion process are described.

3. DRIVING SITUATIONS RECOGNITION USING MULTI-CRITERIA FUSION

3.1 GIS-Based criteria selection

This part deals in particular with the identification of information (criteria) contained in the road network database or computed by the GIS that can be used for the assignment of the mass functions of the navigation system. The objective is to define, starting from the navigation system as a standalone sensor for situation refinement, a recommended peed level in relation to the identified driving situation, and a confidence level relating to this estimate. This confidence parameter related to the GIS is calculated based on several criteria contained in the digital map. It will then be exploited in the fusion process for the evaluation of the reliability of the decision and the management of conflict between the two considered sources.

Six criteria have been identified and retained for the assignment of the mass functions of the focal elements and for the calculation of the confidence level granted to the navigation:

• C_1 : confidence level of the positioning tool. The navigation system used in this application determines the vehicle pose using GPS data fused with odometric and inertial measures. It also computes the «Most Likely Candidate Probabiliy» defining the relevance level of the determined position,

• C_2 : the «ADAS Compliant Geometry» indicator identifies that the link representing the centreline of a road was generated in accordance (in terms of relative and absolute errors) to the requirements of evolved ADAS applications,

• C_3 : «Functional Class » of a road segment. In the digital database, the road network has been classified with respect to predetermined road levels. For instance, highways and european roads corresponds to Functional Class FC1 etc.,

• C_4 : Road type of the path computed by the navigation system,

• C_5 : observed driving situation and context (urban driving, junctions, ...),

• C_6 : activation/deactivation of the guidance mode of the GIS.

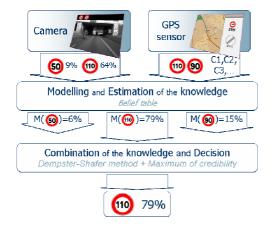
This strategy allows to adapt the belief functions with respect to the quality of the location. For instance, if the value of C_1 is high meaning that the vehicle's global location is accurate, a high value will be assigned to the mass function of the detected speed, corresponding to the vehicle location.

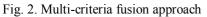
3.2 Vision-based criteria selection

The criterion extracted from the vision system is directly the speed limit identified by an image processing algorithm applied on the detected speed signs. This algorithm, developed by Valeo Driving Assistance also provides the level of confidence related to the performed detection (Moutarde *et al.*, 2007).

3.3 Multi-criteria fusion approach

Fig. 2 describes the fusion process developed in our application.





From the speeds determined by each system in an independent way, the fusion process initially identifies (in the modelling and estimation stage) the focal elements related to both sources (vision and navigation) as well as their associated mass functions. In a second time, the fusion is carried out using Dempster-Shafer combination rule (cf §3.4). Finally, a speed as well as an associated confidence index are obtained. The modelling and estimation of the knowledge consists in defining the mass functions of the criteria resulting from the navigation system and the camera. These functions are calculated for all possible speed limits. From the speed limits identified by both systems, one determines the possible speed limits, i. e. the focal elements. This step takes account of the possibility that one of the sources may provide erroneous and conflicting information. Finally, the resulting speed limit (after fusion) and its associated confidence level are used as a complementary element to enforce the vehicle location and precise the driving situation.

The *a priori* knowledge of the legal speed limits, their exhaustiveness and exclusiveness enable to easily define the framework of discernment. This framework represents the global set of the speed limits which can be determined by the sources. This framework was defined in order to model the speed limits imposed by the road regulation:

 $D = \{5, 10, 20, 30, 45, 50, 60, 70, 80, 90, 100, 110, 120, 130, 999\}$ (7)

The speed limits from 5 to 30km/h generally apply in restricted zones (school neighbourhood, car parks, etc.) but are of primary importance for our application. The value 999 has been considered in order to represent on the one hand unlimited driving situations (current for example in Germany) and on the other hand the transition between a limited to an unlimited section.

In order to determine the focal elements of each source based on this discernment frame, the possible detection errors have been considered. These mistakes can occur mainly in complex driving situations like for instance highway entrance/exit (combining several specific traffic signs) but also because of inaccurate vehicle location due for instance to the wrong selection of the candidate road during mapmatching.

The focal elements of the navigation system (see **Table 1**) were defined in order to represent the potential errors of the GIS. This approach takes account of the location errors, the inaccuracies in the digitalization of the map, the lack of attributes for a given road segment, the fact that the road database is not always up to date, etc.

Speed Limitation (km/h)	Focal elements (km/h)
5	50
10	50
20	50
30	50
45	30, 50
50	30, 70, 100, 110, 120, 130, 999
60	х
70	50, 80, 90
80	50, 60, 70, 90
90	50, 70
100	50, 70, 999
110	50, 70
120	50, 70, 999
130	50, 70
999	X

Table 1. Focal elements of the navigation system

The mass functions of the focal elements of the navigation system are computed using the following weighting equation applied to the 6 extracted criteria (C_1 to C_6):

$$m(SL_i) = \frac{\boldsymbol{\alpha}_1 C_1 + \boldsymbol{\alpha}_2 C_2 + \boldsymbol{\alpha}_3 C_3 + \boldsymbol{\alpha}_4 C_4 + \boldsymbol{\alpha}_5 C_5 + \boldsymbol{\alpha}_6 C_6}{\sum \boldsymbol{\alpha}_i}$$
(8)

where α_1 , α_2 , α_3 , α_4 , α_5 , α_6 are discounting coefficients assigned to the criteria with respect to their respective viability. The focal elements of the speed signs recognition device have been defined considering a wrong identification of the speed information (characters noted on the sign). When the speed sign can not be detected (for instance because of the presence of an obstacle), this device returns no speed limit to the fusion process. Because of the robustness of the detection system, this sensor provides only one focal element (i. e. the detected speed) and its associated confidence level. This confidence level corresponds to the mass function of the focal element. In order to take account of a wrong detection, an uncertainty growing with time has been assigned to this source. This uncertainty represents the possible ignorance of the detection system.

3.4 Criteria fusion

The fusion stage between the sources is based on the Dempster-Shafer conjunctive combination rule. This orthogonal combination reinforces the belief on events for which the sources are in agreement, and in contrary attenuates it when the sources are in conflict. In the hypothesis of a closed world, the relation $m(\emptyset) = 0$ must be satisfied (Bloch, 2003). If this is not the case, a normalization step is necessary in order to redistribute the conflict mass on all the other mass functions. The normalized representation of a mass function is defined by the following relation:

$$\begin{cases} m(A) = \frac{1}{1-k} \sum_{B_1 \cap \dots \cap B_m = A} \prod_{j=1}^m m_j (B_j), \text{ if } A \neq \emptyset \\ m(\emptyset) = 0 \end{cases}$$
(9)

where

 $k = \sum_{B_1 \, \cdots \, \cdots \, B_m = \emptyset} \prod_{j=1}^m m_j (B_j) \prec 1$

normalization factor.

After the combination step, a decision rule is applied in order to obtain the final speed limitation and the associated confidence level. Here, the considered method is the maximum of credibility consisting in retaining the most credible speed limit. A hypothesis is considered as credible if the confidence level is higher than a given threshold. In this application, this threshold has been fixed to 0.6.

4. EXPERIMENTAL RESULTS

The results presented in this section have been obtained with an instrumented demonstration vehicle from Valeo. This car integrates different ADAS mainly based on navigation information (Speed Limit Support, Navigation-based Advanced Front-Lighting System (Lauffenburger, 2007)). The prototyping platform that has been used to perform all computations and sensory acquisitions is ^{RT}MAPS (Nashashibi, 2000). The algorithm presented in this article has been tested in real-time conditions in different driving situations (highway, urban driving...). This section presents the results obtained in an ambiguous situation, i. e. when both sources are in conflict. Fig. 3 describes this situation and also shows the speed limits obtained with each source taken separately (respectively on the left/right hand side for the camera/navigation system) and the corresponding confidence levels.



Fig. 3. Driving situation and detection results

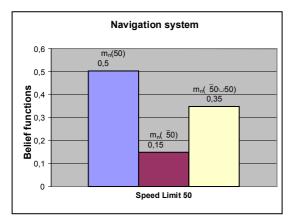
As can been seen in this figure the vehicle drives on a highway requiring a speed limitation of 110km/h as shown on the traffic sign. Nevertheless, using the information provided by the GIS, the navigation delivers a speed limit of 50km/h because of the extraction from the database of an attribute indicating an urban driving zone (criterion C_5). The discounting coefficients used for the computation of the mass functions were fixed to $\alpha_1=0.25$, $\alpha_2=0.5$, $\alpha_3=0.5$, $\alpha_4=1$, $\alpha_5=1$, α_6 =0.25. The mass functions of the resulting speed limit (50km/h) and of all the focal elements (cf. Table 2) obtained starting from equation (8) are respectively:

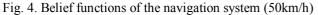
Table 2: Mass functions of the GIS for a speed of 50km/h

m(50) = 0.74	m(30) = 0.60	m(70) = 0.83
m(100) = 0.37	m(110) = 0.37	m(120) = 0.37
m(130) = 0.37	m(999) = 0.37	

The next step consists in computing, for the speed limit (SL) resulting from the navigation system and for each focal element, the belief functions $Bel(SL_i)$, $Bel(\overline{SL_i})$ and finally the belief function representing the ignorance level $Bel(S\overline{L_i} \cup SL_i)$. A value of 0.05 has been used for the representation of the ignorance of the navigation system. Considering 7 focal elements for the detected speed, the total ignorance of the GIS in this situation is of 0.35. Fig. 4 shows the belief functions obtained for the navigation system considering the identified speed limit of 50km/h. It can easily be seen that the detected driving situation using the navigation system is not reliable: the ignorance is high (0.35)and nearly equal to the belief function of the detected speed (0.5). In Fig. 3, the green square around the speed sign indicates that the speed recognition system detected the panel and identified the appropriate speed. The mass function of the vision system is equal to the confidence level directly computed by the image processing algorithm. For these results, an ignorance of 0.1 has been used based on the detection rate of the vision system. Finally, Fig. 5 presents the belief functions of the speed sign recognition process for the detected speed of 110km/h. Even if the belief in the detected speed is high (0.81), this is not sufficient to take an appropriate decision because of the high conflict (0.855) between both sources, showing that they provide ambiguous information.

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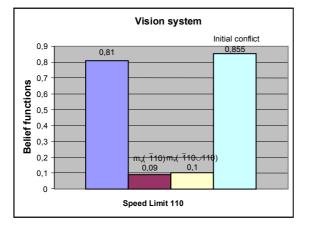


Fig. 5. Belief functions of the speed sign system (110km/h)

Applying the Dempster-Shafer combination rule and the maximum of credibility decision for the fusion of the sources leads to the result presented in Fig. 6. The maximum of credibility decision confirms the speed detected by the speed sign recognition system (110km/h) with a belief function (0.72) nearly equal to the one of the vision device (0.81). It can also be noted that this fusion causes a drop in the conflict factor from 0.86 to 0.3 showing that the fusion reduces the conflict between the sources.

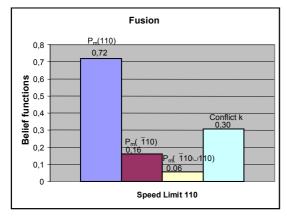


Fig. 6. Belief functions after combination and decision

5. CONCLUSION

This article has described an enhanced vehicle location method based on a multi-criteria fusion solution allowing to evaluate a confidence level of the driving situation recognition process. This approach is based on the fusion of a navigation system with a speed limit sign recognition device. The fusion considers several criteria from the digital map of the navigation system and the legal speed detected by the speed sign refinement system in order to define the appropriate driving conditions in terms of speed. The fusion, relying on Belief Theory because of the uncertainties and imprecision of both sources, also defines the confidence level of the fused information. Real experiments performed with an equipped demonstration car show the validity of this approach particularly when both sources are in conflict. The level of confidence of the estimation can be particularly interesting in ADAS applications requiring an integrity of the location function.

REFERENCES

- Bloch, I. (2003). Fusion d'Informations en Traitement du Signal et des Images, Traité IC2, série Traitement du signal et de l'image, Hermès Science Publications, Paris, ISBN 2-7462-0628-5.
- Darms, M. and H. Winner (2005). A Modular System Architecture for Sensor Data Processing of ADAS Applications. In: *IEEE Intelligent Transportation Systems*, Hannover, Germany, pp. 729-734.
- Dempster, A. P. (1967). Upper and Lower Probabilities Induced by a Multivalued Mapping, Anals of Mathematical Statistics, 38, pp. 325-339.
- Bradai, B., J. Ph. Lauffenburger, M. Basset, A. Herbin and J. Lelevé (2006). Commande prédictive d'éclairage automobile assisté par un système de navigation, In : Conférence Internationale Francophone d'Automatique (CIFA 2006), Bordeaux (France).
- Lauffenburger, J. Ph., B. Bradai, A. Herbin, M. Basset (2007). Navigation as a virtual sensor for enhanced lighting preview control. In: IEEE Intelligent Vehicles Symposium Proc., Istanbul (Turkey), pp. 1-6.
- Moutarde, F., A. Bargeton, A. Herbin and L. Chanussot (2007). Robust on-vehicle real-time visual detection of American and European speed limit signs, with a modular traffic signs recognition system. In: IEEE Intelligent Vehicles Symposium Proc., Istanbul (Turkey), pp. 1122-1126.
- Nashashibi, F., (2000). A framework for prototyping automotive multi-sensor applications. In: IEEE Intelligent Vehicles Symposium Proc., Dearborn (USA), October 3-5, pp. 99-103.
- Polychronopoulos, A., M. Tsogas, A. Amditis and A. Etemad (2005). Extended Path Prediction Using Camera and Map Data for Lane Keeping Support. In: IEEE Intelligent Transportation Systems ITS, pp. 166-171.
- Shafer, G. (1976). *A Mathematical Theory of Evidence*, Princeton University Press.
- Zhao Y. (1997), Vehicle location and navigation systems, Artech House.
- Zhao H., R. Shibasaki (2001). High accurate positioning and mapping in urban area using laser range scanner, In: IEEE Intelligent Vehicles Symposium Proc., Tokyo (Japan), May 13-17.