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Driving situation recognition with uncertainty management and rule-based systems

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Abstract

The recognition of a temporal sequence is a complex problem, especially in the framework of driving situations. However, this recognition is essential for the development of driving assistance systems. This paper presents a rule-based system that manages the real-time measurements got from sensors of an experimental vehicle, in order to determine the current possible maneuvers worked out by the driver. The particularity of the proposed system is that it manages the inaccuracy of the data and the uncertainty of the recognition, using fuzzy subsets and beliefs on hypotheses.

Keywords: Situation recognition; Evidence theory; Artificial intelligence

1. Introduction

Much research has been conducted in order to assist car drivers in their driving activity. That have led to the realization of different kinds of tools. It has been shown that in order to be useful, a driving assistance system has to take into account the driving context, and specially the maneuver worked out by the driver. The automatic acquisition of context and maneuver recognition is a particularly complex task, which is the goal of the CASSICE[1] project (Rombaut and Saad, 2000). The driving situations considered have to represent the context in which this activity takes place, in conjunction with the actions of the driver, namely his/her maneuvers performed.

The physical system is made up of an experimental vehicle equipped with sensors and a software to store and to exploit a database of driving situations. The software is made up of several layers, which go from the low-level processing of data (acquisition of data) to the construction of high-level descriptions of driving situations. The aim of this paper is to propose a method to recognize the maneuver performed by the driver according to raw data coming from the sensors of the experimental vehicle. In this paper, we are not concerned with other questions such as the equipment of the vehicle.

Section 2 presents the context of the "driving assistance", why it is important to study the drivers' behavior related to the maneuver they perform. The psychologist and engineering approaches are presented. In Section 3, the formal description of the maneuvers is detailed as well as the rule-based approach used for the maneuver recognition. Data used are assumed to be perfect and accurate. It will be illustrated with the description of an overtaking maneuver which is a typical example taken from an intelligent vehicle application (Blancard et al., 1994). Section 4 deals with the inaccuracy and uncertainty inside data, how we define the symbolic data using fuzzy subsets. Section 5 presents the modified rule-based systems dealing with uncertainty and inaccuracy. Finally, results will be presented in Section 6. They have been obtained from simulated data because the experimental vehicle has just been equipped. New experiments will begin soon with real data. In the follow-up, no distinction will be made between real and simulated data.

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[1] French acronym for symbolic characterization of driving situations.

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2. Context: the driving assistance

The study of the driver's activity represents an indepth qualitative investigation into driver behavior (Saad, 1997) in the context of the complex interactions at work in real situations. Research conducted at INRETS[2] on this topic relies on the observation of driver behaviors. The objectives are the following:

(1) understand the driver behavior in order to define rules of behavior,
(2) from these rules, build driving assistance systems taking into account the driving context and the driver's behavior,
(3) study the drivers' behavior modifications using the new driving assistance systems.

The investigations about the drivers' behavior are held by psychologists. The human driver is the center of interest of their research. In the CASSICE project, the objective is to recognize the current maneuver of the vehicle whoever is the driver and therefore his behavior. Our research relies on the research developed at INRETS.

2.1. Previous experiments for driver behavior study

At INRETS, experiments are realized using an equipped vehicle on an urban motorway, 21 km long, near Paris, France. The driving episodes are recorded with a video. Interviews conducted after the journey enable the driver to explain his/her strategies (Saad, 1993). In order to be able to learn knowledge about this kind of situation, grids of data are manually filled to detail the driving situations. These grids represent the infrastructure, the environment of the driver, in terms of traffic, and the actions of the driver (maneuver, action on the brake, etc.). An extract of this grid and the meaning of the columns are presented in Table 1. During all these experiments, we assume that only one vehicle preceding the subject on the road is of interest. The reason is that only pulling in and pulling out are considered. The number of occurrences of both actions is then computed in order to obtain the number of overtaking maneuvers.

2.2. Analysis

After the journeys and the interviews, the grids are analyzed. This work allows the psychologist to determine the strategies employed by the driver (the subject) during his/her activity, according to the kind of situation encountered and his/her intentions (ex: minimization of the number of maneuvers). The objective is to bring to the fore his/her tactic rules and strategic rules (Senach, 1999). An example of tactic rule is given below:

IN an orientation area on a 3-lane motorway,
IF the subject is on the middle lane
AND middle and right-lanes are orientation lanes,
AND the driver intends to go right
THEN he remains on the middle-lane.

2.3. The CASSICE project

The construction of driving situations and their analysis are very time-consuming tasks. One of the CASSICE project's objective is to automatically build the description of these situations. Automatically acquiring driving situations needs to respect the following main stages: acquire data from sensors, translate a numerical description into a significant representation allowing high-level requests, store the driving situation representations. The first stage has been presented in Shawky and Bonnifait (1999). The last one is in progress. In this paper, we were interested in the second stage. Its objective is to automatically construct a grid, such as the one presented in Section 2.1. We reasonably assume that particular data will continue being acquired manually: that is the case of the column "zone", for instance in Table 1. CASSICE is a big project broken in several varied tasks. All of these tasks are realized at the same time. That is the reason why the data used are simulated at the present time.

2.3.1. Input data

The recognition of the real-time maneuver needs to evaluate a lot of parameters that characterize the driving situation. In order to obtain these values, an experimental vehicle (EV: Experimental Vehicle) has been equipped and experiments have just begun with it. The input data we use are therefore generated by a simulator. During the simulation, as well as during the future real driving scenario, the acquired data, that will represent the same kind of data, are assumed to be provided by a vehicle moving on a straight urban motorway.

Our approach is illustrated throughout this paper by a typical example taken from an intelligent vehicle application (Fort et al., 1997). The goal is to detect and characterize an overtaking maneuver of a target vehicle (TV: Target Vehicle). We have used the simulated data presented in Table 2. Data used are related to the position of the EV on the motorway and towards the TV. It can be noticed that EV is the vehicle of the "Subject" whose behavior study is described in Section 2.1, and TV is the vehicle of the "Followed" driver.

[2] The French National Institut for transportation and Safety Research (http://www.inrets.fr).

Table 1
Example of grid detailing the maneuver

TimeCode	00:27:09	00:27:10	…	
Subject	1	1		Observed subject
NbL	2	2		Number of lanes
Zone	ZE	ZE		Kind of traffic zone (e.g. ZE = entry zone)
Sveh	118	115		Speed of subject
Star	131	130		Speed of the followed vehicle
BrS	0	0		Action on break by subject
BrA	0	0		Action on break by the followed vehicle
Dist	41	34		Distance covered
TIV	1.28	1.47		Time between before collision
Lane	2	3		Lane occupied by subject
ManS	6	6		Maneuver performed by subject
ManA	6	6		Maneuver performed by the followed vehicle
⋮				

Table 2
Example of simulated input data
Grid of measures

TimeCode	0.01	0.02	0.03	…	1.12	1.13	1.14
X	−32.00	−31.85	−31.70	…	−15.52	−15.37	−15.22
Y	0	0	0	…	−2.01	−2.04	−2.06
V	15	15	15	…	15	15	15
θ	0	0	0	…	−9.91	−9.68	−9.46
ϕ	0	0	0	…	3	3	3
Rg	−3.50	−3.50	−3.50	…	−1.46	−1.46	−1.46
Rd	1.50	1.50	1.50	…	3.54	3.54	3.54

Meaning of data

TimeCode	Clock(s)
X	Position on the x's axis of TV against EV (m)
Y	Position on the y's axis of TV against EV (m)
V	Speed of EV relative to TV (m/s)
θ	Angle of the target TV (deg)
ϕ	Front wheel angle of EV (deg)
Rg	Position of EV against the left road side (m)
Rd	Position of EV against the right road side (m)

By contrast with the manually acquired data of Table 1, simulated data, as well as the future real data, are time stamped and they refer to the center of the EV.

2.3.2. Method used

The maneuvers that have to be detected may be explained by a succession of stages, which may be described at different levels of description: pulling in, passing, pulling out, etc. The nature of the data at our disposal requires the recognition of certain moves of EV, or certain actions of its driver, for instance turning the wheel. Each of the actions can be recognized thanks to a subset of variables in Table 2. For instance, in order to recognize that EV gets closer to TV, one needs to consider the variations of variables X, Y over an interval of time. The approach chosen has naturally been the rule-based approach, which fully satisfies the requirement above.

3. Maneuver recognition

During his driving activity, the driver has the choice between different possible maneuvers. He can decide at a particular time to execute one of them, and to start the maneuver. Later, he can decide to change strategy, to give up the current maneuver to reach another one that seems better. The objective of the system we have to develop is to determine automatically at any time, the strategy of the driver, that means the possible maneuvers he has decided to execute.

In this section, we describe the logical representation of states and maneuvers, as well as the logical rule-based systems developed for this application.

3.1. Illustrating example

In order to illustrate our approach, the example of *overtaking maneuver* is used: on a highway composed of two one-way lanes, an experimental vehicle (EV) goes to the right lane. It catches a target vehicle (TV) going on the same lane with a lower speed. The EV is beginning an overtaking of the TV. It begins to go left for a lane changing, then goes straight forward. When TV is overtaken, it goes right to the right lane. This typical maneuver can be aborted at different places, for instance:

(1) during the left changing, the driver can choose to stay behind the TV, because he sees the next exit soon, and estimates the time of overtaking too long;
(2) on the left lane, the driver can choose to stay on this lane because there is a slow truck relatively close behind and he estimates that it is not necessary to change lanes twice.

3.2. Maneuvers and states

At a particular time t, the driver of the experimental vehicle (EV) performs a maneuver M and its real state s is one of the states that compose this maneuver. It is assumed that the set $\mathcal{M}$ of possible maneuvers M_i is known, as well as the description of each maneuver.

For the example described before, the set $\mathcal{M}$ is composed of three possible maneuvers:

$$\mathcal{M} = \{M_1, M_2, M_3\},$$

where M_1 is the complete overtaking maneuver; M_2 the aborted overtaking maneuver where EV stays on left lane; M_3 the aborted overtaking maneuver where EV stays behind TV.

A maneuver M_i is composed of an ordered sequence of n_{M_i} states s_i:

$$M_i = (s_1, s_2, \ldots, s_i, \ldots, s_{n_{M_i}}).$$

Table 3 presents the states of the three maneuvers described before.

Table 3
The sequence of states of the overtaking maneuver

Maneuver M_1	
s_1	Wait for overtaking
s_2	Beginning of changing lanes
s_3	Crossing of the discontinuous line on the left
s_4	End of changing lanes
s_5	Passing
s_6	End of passing
s_7	Beginning of changing lanes
s_8	Crossing of the discontinuous line on the right
s_9	End of changing lanes
Maneuver M_2	
s_1	Wait for overtaking
s_2	Beginning of changing lanes
s_3	Crossing of the discontinuous line on the left
s_4	End of changing lanes
s_5	Passing
s_6	End of passing
Maneuver M_3	
s_1	Wait for overtaking
s_2	Beginning of changing lanes
s_3	Return to right lane

With each transition between s_i and s_j is associated a logical condition $C_{i,j}$, that means that if the condition $C_{i,j}$ is true, it is possible but not sure the actual state s is s_j.

For instance, the condition $C_{5,6}$ between (s_5: *Passing*) and (s_6: *End of passing*) is:

(*EV on the left lane*) and (*TV on the right lane*) and (*TV behind EV*)

3.3. Evolution rule-based systems

The evolution of a dynamic system is usually represented by a model that allows to connect the states between two different times t_1 and t_2. The interest of the system community concerns both the analogical and sequential systems. In the first case, the evolution is modeled by differential equations, and in the second case, it is represented by a graph such as the largely used Petri net model (Courvoisier and Valette, 1992). In this paper, we focus only on the rule-based approach to model the sequential systems, mainly used in the artificial intelligence community. In this case, the system is modeled by a set of declarative rules.

The evolution rule presented in Table 4 corresponds to the classical one of the states charts, or Petri nets. The maneuver M is recognized when the last state s_{N_M} is reached.

The system rules consists in determining the states following the states previously reached, evaluating the truthfulness of their conditions and finely determining the new states reached according to these conditions. The rules are strongly dependent on the structure of the graph. The algorithm can be described as follows:

```
Loop
Determination of the next possible states
Evaluation of the conditions associated to these
states
Determination of the new states reached
End of loop
```

At any time, several possible maneuvers can be in progress with different levels of evolution. That means it

Table 4
Evolution rule

	Evolution rule
If	the states s_i and s_j are linked,
	s_i is already reached,
	$C_{i,j}$ is true,
Then	the state s_i is left and the state s_j is reached

is necessary to follow the evolution of several graphs associated with different maneuvers. A particular maneuver can be: *not attempted*, *in progress* (*what state*?), *finished*.

The previous loop algorithm must be extended as follows:

```
Loop
For each maneuver
If not attempted: Evaluation of the conditions
associated to the initial state
If in progress: Determination of the next possi-
ble states and Evaluation of the conditions
associated to these states
Determination of the new states reached
Qualification of the maneuver (not attempted, in
progress, finished)
End of loop
```

Two systems have been developed in the frame of the CASSICE project, the Intelligent Driving Recognition with Expert System (IDRES) and the Driving Situation ReCognition systems (DSRC).

The DSRC system has been developed in order to determine the state of a system following a particular maneuver (Loriette-Rougegrez et al., 2000). It is made up of two levels of rules. *The rules of the first level* have to validate the logical conditions making up the transitions in the graph. *The second level of rules* has to change the current state according to the valid transition. This formal model takes place between the *rule-based system* where no global representation of the system is used, and the *Petri net system* based on a strict representation of this dynamic system.

The IDRES system is developed in order to determine the maneuver followed into a set of possible maneuvers (Nigro and Loriette-Rougegrez, 1999). Several states may be found at any moment. The rules have to find among all the hypotheses generated, a consistent pattern of the a priori known sequence M, that corresponds to the sequences itemized in the system.

The complete system is composed of three levels:

(1) evaluation of the validity of all the conditions (made by DSRC),
(2) determination of the new current possible states using the validated conditions (made by DSRC),
(3) determination of the possible maneuvers (made by IDRES).

The logical functioning of IDRES and DSRC are presented in detail before taking into account the uncertainty of measurements.

3.4. The Driving Situation ReCognition systems

The recognition of a state inside a particular maneuver is directly related to the graph that represents it. Each state represents one stage of realization of the maneuver. Some situations are optional. For instance, during an overtaking, the driver may not use the turn signal. This peculiarity explains why a maneuver is not simply represented as a linear succession of states such as can be seen from Fig. 1. A maneuver has then been completely detected if the raw data acquired lead to go from the first state to the final state of the graph. The recognition is realized in batch mode. Nevertheless, DSRC has been conceived for a sequential processing of the data that should enable an easier adaptation of this system to a real-time processing.

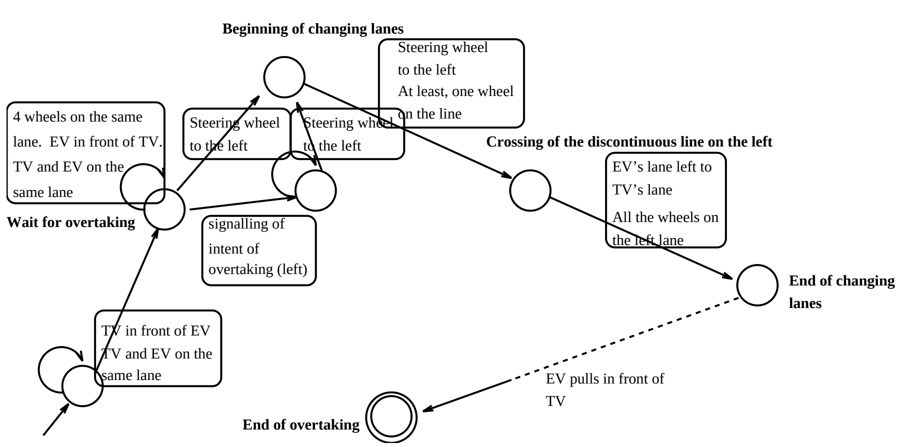

Fig. 1. Transitions and states making up the overtaking maneuver.

The transition between two states indicates which conditions have to be satisfied in order to change the current state. The conditions associated with each transition consist in a conjunction of tests about the current situation. They are represented at the symbolic level.

The first-level rules of DSRC have to control the truthfulness of the conditions that stamp the transitions of the graph. One such rule is represented in Table 5. This rule verifies, at each time point of the lines of Table 2, that the value of the variable Y indicates that both vehicles move on the same lane.

The second-level rules associate the validated transitions with the current state. If such an association is possible, the current state of the graph is changed (see Table 4). This kind of rule expresses the links between states. For instance, let us consider inside the graph of Fig. 1 the transition between the states *Wait for overtaking* and *Beginning of changing lanes*. The rule of Table 4 will enable the system to go from the first state to reach the second one if and only if the conditions associated with the transition between both states are validated. That is to say, *four wheels of EV are on the same lane*, *EV and TV are on the same lane*, and *EV is behind TV* are true.

3.5. The Intelligent Driving Recognition with Expert System

From states found by DSRC level, a set of decision-level rules has to select a sequence M of states. $M = \{s_1, s_2, s_3, \ldots, s_n\}$. This sequence is recognized when it matches with the different known sequences of states. For example, the simplest way to validate the M_3 maneuver would be to validate the three states which compose it ("*Wait for overtaking*", "*Beginning of changing lanes*", "*Return to right lane*") respecting this chronological order. Some sequence recognition rules are described with a textual syntax in Table 6.

The following principles have been adopted for the recognition of the sequence performed:

- it is necessary to respect the order of the states inside the sequence,
- some states inside a sequence may not be recognized,
- when the system is not able to detect a state at a given moment k, the concept of persistence of the previously detected state is used. This persistence is only valuable during a short interval of time.

Table 5
Same lane rule

	Rule Same_lane
If	Y between the right and left sides of the lane,
Then	condition "same lane" is true

Table 6
Example of sequence recognition rules

	Rule Begin_of_maneuver
If	A state s is found
	This state s is the first state of the sequence M
	The sequence M has not still been recognized
Then	The sequence M is in progress with the state s
	Rule Same_sequence_same_state
If	A state s is found
	This state s is included in sequence M
	The sequence M is in progress with the same state s
Then	The sequence M is in progress with the state s
	Rule Same_sequence_next_state
If	A state s_2 is found
	The sequence M is in progress with the state s_1
	The state s_1 precedes the state s_2 in the sequence M
Then	The sequence M is in progress with the state s_2

The rules of the decision level are developed independent of any application domains. They respect the three conditions described above. IDRES finds all possible a priori known sequences that may correspond to the real sequence of the dynamic system without determining the most relevant one.

4. Confidence evaluation of logical propositions

Because we have no information about the decision of the driver, the transition from one state to another one depends on different parameters that are measured on the vehicle and/or on the environment (static and dynamic) of the vehicle. The input data can be of different types such as the acceleration of EV, or the lateral speed, or the position of the vehicle on the lanes. Note that no temporal information is used, because the duration of each phase depends on the context of the maneuver (speed, length of TV, etc.) and cannot be easily evaluated.

The system described before has logical properties, meaning that its evolution is conditioned by logical values of the inputs. Sometimes the inputs are logical ones such as the blinker for instances (no blinker, right, left). But generally, the inputs are numerical ones. It is then necessary to turn the numerical values of the reports into logical values associated with a symbol. For instance, the speed of EV can be described by three linguistics terms such as low, middle, and high. The set of definition of the logical speed is then $\Omega_{\text{speed}} = \{\text{low}, \text{middle}, \text{high}\}$. Each linguistic term has to be described by an expert given the numerical limit between these symbols. The evaluation of the proposition associated with each term can be made by a set of rules such as the ones represented in Table 7.

Table 7
Numerical/symbolic conversion of the speed

If	$V < 10$ km/h then (relative speed is small) = TRUE
If	10 km/h $< V <$ 30 km/h then (relative speed is middle) = TRUE
If	30 km/h $< V <$ 50 km/h then (relative speed is high) = TRUE

In fact, the truth values of the logical data are usually not known with certainty, because of the limited precision and reliability of the sensors. For instance, during the state s_3 (*crossing of the discontinuous line on the left*), it is impossible to know precisely when this event occurs. So it cannot be sure to know the real state of EV as well as the real maneuver attempted by the driver.

We propose to model the confidence of the logical data by a belief function, as proposed by Dempster and Shafer in Shafer (1976). The transitions from the numerical values to the logical ones can be made using statistical measures as in Silverman (1988). In this paper, we propose to use expert knowledge about the dynamic system and we present an example.

4.1. Confidence in the inputs

The method is based on the evidence theory also named Dempster Shafer's theory (Shafer, 1976). This theory has yet been interpreted in the frame of propositional logic (Cholvy, 2000). We propose to introduce it inside of rules.

The problem is that the knowledge about the problem induces a basic belief assignment modeled by a distribution of mass of evidence m on the propositions A, subsets of the set $\Omega = \{H_i\}$ of hypotheses. A can be a singleton (or single) proposition such as $\{H_i\}$, but also a composed proposition such as $\{H_i, H_j\}$ for instance. The distribution of mass takes values in 2^Ω, the power set of Ω:

$$m : 2^\Omega \to [0, 1],$$
$$A \to m(A).$$

Some properties are attached to this distribution of mass:

$$m(\emptyset) = 0,$$

$$\sum_{A \subset \Omega} m(A) = 1.$$

The propositions of 2^Ω that have a mass not equal to zero are named *focal elements*. The value $m(A)$ represents the degree of evidential support that a specific element of Ω belongs to the set A, but not to a particular subset of A.

4.2. Example of the EV speed model

The speed of EV can be described by three linguistics terms such as low, middle, and high. The set of

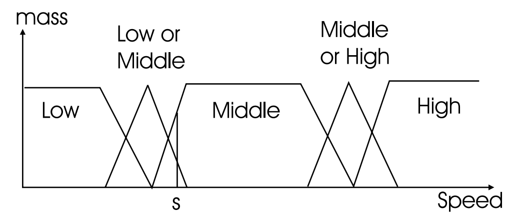

Fig. 2. Definition of the symbolic values of the speed.

definition of the logical speed is then $\Omega_{\text{speed}} = \{\text{low, middle, high}\}$. The distribution of mass of evidence is defined on $2^{\Omega_{\text{speed}}}$. Each term of $2^{\Omega_{\text{speed}}}$ can be represented in the numerical speed reference as a fuzzy set defined by an expert such as represented in Fig. 2.

On this example, the distribution of mass associated with the value s of the speed is then

$$m_s(\text{middle}) = 0.8,$$
$$m_s(\text{middle} \cup \text{low}) = 0.2.$$

It can be noted that all the propositions of 2^Ω are modeled by a fuzzy set such as (middle $\cup$ low).[3]

4.3. From the inputs to the conditions

The conditions of the first-level rules or of the transitions are generally a logic combination of the symbolic inputs. So a distribution of mass can be attached to each of them. For two logical propositions[4] A and B defined on $\Omega_A = \{A, \bar{A}\}$ and $\Omega_B = \{B, \bar{B}\}$, a distribution of mass m_A and m_B defined on 2^{Ω_A} and 2^{Ω_B} are attached. The evaluation of the confidence on the proposition $A \cap B$ is made by combining the distributions m_A and m_B on $2^{\Omega_A \times \Omega_B}$ using the conjunctive combination rules usually defined by

$$m_{1,2} = m_1 \oplus m_2,$$
$$m_{1,2}(U) = \sum_{V \cap W = U} m_1(V) \cdot m_2(W), \tag{1}$$

for $U, V, W \subset 2^\Omega = 2^{\Omega_A \times \Omega_B}$ the common space of discernment.

5. Confidence evaluation of states and maneuvers

We have described in Section 4 the tools we intend to use. Let us explain how they are applied inside DSRC then IDRES.

5.1. From input data to graph's states

The transformation of data is realized in three stages:

- from numerical input data, the confidence in the associated symbolic data is computed,

[3] The two principle logical operations are AND usually written $\cap$ and OR written $\cup$.

[4] $\bar{A}$ means A is FALSE and A means A is TRUE.

- the belief of conditions associated to transitions are computed,
- the uncertainty about conditions of transitions are propagated to the states.

5.1.1. From numerical input data to symbolic data

The truthfulness of each symbolic data depends on the value of the associated variable. The first-level rules presented in Section 3.4 have to first evaluate the belief about the symbolic data using fuzzy sets such as those presented in Section 4.2. In the example proposed in Section 3.2, the condition $C_{5,6}$ between (s_5: Passing) and (s_6: End of passing) is $C_{5,6} = H_1 \cap H_2$ where

H_1: (*EV on the left lane* and *TV on the right lane*),

H_2: (*TV behind EV*).

Using the numerical values described in Table 2, such as X (position of the x's axis of TV against EV) and Y (position on the y's axis of TV against EV), the two distributions of mass m_{H_1} and m_{H_2} concerning the propositions are evaluated. Numerical values examples are given in Section 6.

5.1.2. Belief conditions computation

Usually, the conditions of transitions are associated with more than one variable. We have to compute for each condition C a distribution of masses of evidence over $\{C, \bar{C}, C \cup \bar{C}\}$. This is made using the conjunctive combination-rule of Eq. (1). For instance, the combination of the distributions of mass m_{H_1} and m_{H_2} are described by:

$m_{H_1}(H_1)$	$m_{H_2}(H_2)$
$m_{H_1}(\overline{H_1})$	$m_{H_2}(\overline{H_2})$
$m_{H_1}(H_1 \cup \overline{H_1})$	$m_{H_2}(H_2 \cup \overline{H_2})$

We have now to compute $m_{C_{5,6}} = m_{H_1} \oplus m_{H_2}$ with $C_{5,6} = H_1 \cap H_2$. Table 8 gives the conjunctive combination of the propositions associated to the two distributions of mass. This table enables to evaluate the belief of the proposition, for instances:

$$m_{C_{5,6}}(C_{5,6}) = m_{H_1}(H_1) \times m_{H_2}(H_2),$$

$$\begin{aligned} m_{C_{5,6}}(\overline{C_{5,6}}) = {} & m_{H_1}(\overline{H_1}) \times m_{H_2}(\overline{H_2}) + m_{H_1}(H_1) \times m_{H_2}(\overline{H_2}) \\ & + m_{H_1}(\overline{H_1}) \times m_{H_2}(H_2) \\ & + m_{H_1}(\overline{H_1}) \times m_{H_2}(H_2 \cup \overline{H_2}) \\ & + m_{H_1}(H_1 \cup \overline{H_1}) \times m_{H_2}(\overline{H_2}), \end{aligned}$$

Table 8
Conjunctive combination of the propositions

	H_1	$\overline{H_1}$	$H_1 \cup \overline{H_1}$
H_2	$C_{5,6}$	$\overline{C_{5,6}}$	$C_{5,6} \cup \overline{C_{5,6}}$
$\overline{H_2}$	$\overline{C_{5,6}}$	$\overline{C_{5,6}}$	$\overline{C_{5,6}}$
$H_2 \cup \overline{H_2}$	$C_{5,6} \cup \overline{C_{5,6}}$	$\bar{C}_{5,6}$	$C_{5,6} \cup \overline{C_{5,6}}$

$$\begin{aligned} m_{C_{5,6}}(C_{5,6} \cup \overline{C_{5,6}}) = {} & m_{H_1}(H_1) \times m_{H_2}(H_2 \cup \overline{H_2}) \\ & + m_{H_1}(H_1 \cup \overline{H_1}) \times m_{H_2}(H_2) \\ & + m_{H_1}(H_1 \cup \overline{H_1}) \times m_{H_2}(H_2 \cup \overline{H_2}). \end{aligned}$$

5.1.3. From transitions to states

In order to recognize a maneuver, it is necessary to know at each time which state is validated. If we use a states recognition based upon a running of the graph, which is a normal utilization of a graph, the uncertainty upon transitions is propagating to the states. In our concern of coherence against the set of all the representations chosen in DSRC, ws associate with each state s too, a distribution of mass m_s over $\Omega_s = \{s, \bar{s}\}$.

By analogy with Petri nets (David and Alla, 1992), the evolution of the graph follows these rules:

- if the state is s_i and the condition $C_{i,j}$ is true, the state becomes s_j,
- if the state is s_i and the condition $C_{i,j}$ is false, the state stays s_i.

These rules can be translated into boolean equations

$$\begin{aligned} s_i^{k+1} &= (\overline{s_i^k \cap C_{i,j}}), \\ s_j^{k+1} &= s_i^k \cap C_{i,j}. \end{aligned} \tag{2}$$

The uncertainty upon transitions or states has seldom been considered until now. In Jarkass and Rombaut (1998a), the uncertainty is on the first state of the Petri net considered. In Jarkass and Rombaut (1998b), the uncertainty is related to each recognized state of Petri net at each time. This processing of the uncertainty maintains the main properties of the Petri nets such as the conservation of mass.

In the case of DSRC, the $C_{i,j}$ are associated with distributions of masses of evidence. For each state s_i is associated a distribution of mass m_{s_i} on $2^{\Omega_{s_i}} = \{s_i, \overline{s_i}, s_i \cup \overline{s_i}\}$ that models the confidence that the real state S is s_i. The aim is to compute the distributions $m_{s_i}^{k+1}$ and $m_{s_j}^{k+1}$ at time $k+1$ using the distributions $m_{s_i}^k$ at time k and the distributions $m_{C_{i,j}}$ about the conditions associated to the transitions between the s_i and s_j states. The boolean equations (2) are extended to give the tables of combination presented in Table 9.

The conjunctive combinations are made for each pair $(mk_{s_i}, C_{i,j})$. Sometimes two different conditions lead to define two distributions about the same state, for instance $C_{i,j}$ and $C_{k,j}$ give two different functions $m_{s_j}^{k+1}$. These functions are then combined using the conjunctive rule. If a conflict appears such as $m_{s_j}^{k+1}(s_j) \neq 0$ for the first function and $m_{s_j}^{k+1}(\overline{s_j}) \neq 0$ for the second function, a disjunctive rule of combination is used.

5.2. From states to maneuvers recognition

In order to evaluate the confidence in the realization of the maneuver represented by the sequence M, it is

Table 9
Tables of combination

	s_i	$\overline{s_i}$	$s_i \cup \overline{s_i}$
Computation of $m_{s_i}^{k+1}$			
$C_{i,j}$	$\overline{s_i}$	$\overline{s_i}$	$\overline{s_i}$
$\overline{C_{i,j}}$	s_i	$\overline{s_i}$	$s_i \cup \overline{s_i}$
$C_{i,j} \cup \bar{C}_{i,j}$	$s_i \cup \overline{s_i}$	$\overline{s_i}$	$s_i \cup \overline{s_i}$
Computation of $m_{s_j}^{k+1}$			
$C_{i,j}$	s_j	$s_j \cup \overline{s_j}$	$s_j \cup \overline{s_j}$
$\overline{C_{i,j}}$	$\overline{s_j}$	$s_j \cup \overline{s_j}$	$s_j \cup \overline{s_j}$
$C_{i,j} \cup \overline{C_{i,j}}$	$s_j \cup \overline{s_j}$	$s_j \cup \overline{s_j}$	$s_j \cup \overline{s_j}$

proposed to assign a mass m_M of belief for M on the power of the space

$$\Omega^M = \Omega_{s_1} \times \Omega_{s_2} \times \cdots \times \Omega_{s_i} \times \cdots \times \Omega_{s_n},$$

where s_i are the n states of the sequence M:

$$m_M : 2^{\Omega^M} \to [0, 1],$$

$$\Omega^M = \{M, \bar{M}\},$$

where the logical value $M = s_1 \cap s_2 \cap \cdots \cap s_i \cap \cdots \cap s_n$. When the mass of M is not equal to zero ($m_M(M) \neq 0$), the maneuver can be considered performed, that means all the states s_i of M have been reached during the realization of M.

In order to be combined, the mass of evidence m_{s_i} are extended to m'_{s_i} defined on the space 2^{Ω^M}:

$$m_{s_i}(s_i) = m'_{s_i}\left(s_i \cap \left(\bigcap_{j \neq i} \Omega_{s_j}\right)\right),$$

$$m_{s_i}(\overline{s_i}) = m'_{s_i}\left(\overline{s_i} \cap \left(\bigcap_{j \neq i} \Omega_{s_j}\right)\right),$$

$$m_{s_i}(\Omega_{s_i}) = m'_{s_i}\left(\bigcap_{j} \Omega_{s_j}\right).$$

The second rules level can be modified, taking into account the plausibility $Pl(s_i)$ of the states s_i of the sequence M such as represented in Table 10. We remember that the plausibility $Pl(A)$ of a proposition A of 2^Ω is defined by the relation

$$Pl(A) = \sum_{B/B \cap A \neq \emptyset} m(B)$$

and the belief $\mathrm{Bel}(A)$ is defined by

$$\mathrm{Bel}(A) = \sum_{B \subseteq A} m(B).$$

It can be seen that during the time, the mass of evidence passes through more and more accurate focal elements. When the current state is s_1 the focal element is $(s_1 \cap \Omega_2 \cap \cdots \cap \Omega_n)$. When the system reaches the state s_2 the focal element becomes $(s_1 \cap s_2 \cap \cdots \cap \Omega_n)$. And finally, if the maneuver is complete the focal element is $(s_1 \cap s_2 \cap \cdots \cap s_n)$.

Table 10
Example of belief sequence recognition rules

	Rule Begin_of_sequence
If	$\mathrm{Bel}(s_1) = 1$
	This state s_1 is the first of M
	M has not still be recognized
Then	M is in progress and $m_M^k = m'_{s_1}$
	Rule Same_sequence_same_state
If	$\mathrm{Bel}(s_i) = 1$
	This state s_i is included in M
	M is in progress
Then	M is in progress and $m_M^k = m_M^{k-1} \oplus m'_{s_i}$
	Rule Same_sequence_next_state
If	$\mathrm{Bel}(s_{i+1}) = 1$
	M is in progress
	The s_i precedes s_{i+1} in M
Then	M is in progress and $m_M^k = m_M^{k-1} \oplus m'_{s_{i+1}}$

In this Belief IDRES system, the first state reached must be the first state of M, but it is possible to quantify the quality of realization of M.

6. Results

Intensive experimentation has been realized based on the use of DSRC and IDRES systems. The experience consists in verifying that the global system recognizes the overtaking maneuver using the belief model of resolution. We propose to decompose the results analysis in two parts, one concerning the transition recognition using DSRC, the other one concerning the maneuvers recognition using IDRES.

6.1. Transition recognition using DSRC

In order to illustrate the method, the rule *Transition End of passing* has been chosen

Rule *Transition End of passing*

EV on the left lane and TV on the right lane (H_1)
TV behind EV (H_2)

Then

Transition End of passing ($C_{5,6}$)

This rule contains two conditions (H_1, H_2) and concludes with the validation of the *Transition End of passing* ($C_{5,6}$).

The left part of the table presented in Fig. 3 corresponds to the measurements of X and Y got at different times.

From these numerical values and using the symbolic models proposed in Fig. 4, the basic belief assignment

	Time	X	Y	H_1	$\overline{H_1}$	$H_1 \cup \overline{H_1}$	H_2	$\overline{H_2}$	$H_2 \cup \overline{H_2}$	$C_{5,6}$	$\overline{C_{5,6}}$	$C_{5,6} \cup \overline{C_{5,6}}$
p1	221	0.80	-2.6	1	0	0	0	0	0	0	0	1
p2	222	0.95	-2.6	1	0	0	0.3	0	0.7	0.3	0	0.7
p3	223	1.10	-2.6	1	0	0	0.6	0	0.4	0.6	0	0.4
p4	224	1.25	-2.6	1	0	0	0.9	0	0.1	0.9	0	0.1
p5	225	1.40	-2.6	1	0	0	1	0	0	1	0	0

Fig. 3. Table of mass calculations.

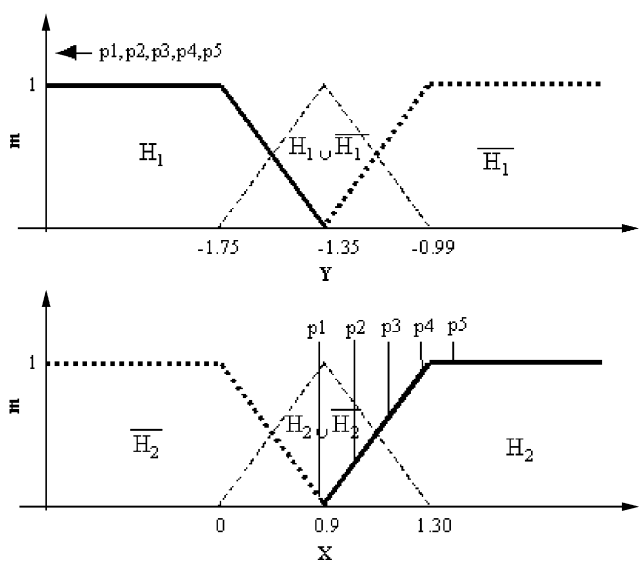

Fig. 4. Symbolic model to define the truth of H_1 and H_2.

concerning the hypothesis H_1 and H_2 are computed. For instance, at time $t = 222$ ms, the basic belief assignments are

$m_{H_1}(\overline{H_1}) = 1$	$m_{H_2}(\overline{H_2}) = 0.3$
$m_{H_1}(\overline{H_1}) = 0$	$m_{H_2}(\overline{H_2}) = 0$
$m_{H_1}(H_1 \cup \overline{H_1}) = 0$	$m_{H_2}(H_2 \cup \overline{H_2}) = 0.7$

These basic belief assignments mean:

at this time, it is certain that EV and TV are on the same lane ($m_{H_1} = 1$), but it is not certain that TV is behind EV ($m_{H_2} = 0.3$ and $m_{H_2 \cup \overline{H_2}} = 0.7$).

At any times, from m_{H_1} and $m_{\overline{H_2}}$, the basic belief assignment $m_{C_{5,6}}$ is computed by combination,

$m_{H_1} \oplus m_{H_2}$,

using Eq. (1). For instance at time 222:

$$m_{C_{5,6}}(C_{5,6}) = m_{H_1}(H_1) \cdot m_{H_2}(H_2) = 0.3$$
$$m_{C_{5,6}}(\overline{C_{5,6}}) = 0$$
$$m_{C_{5,6}}(C_{5,6} \cup \overline{C_{5,6}}) = 0.7$$

means EV state may be at the state *End of passing* (s_6), but it is not sure.

6.2. Maneuvers recognition using IDRES

The second decision level finds the car maneuver with an incremental calculation of its mass of evidence for the successive focal elements. Fig. 5 shows the evolution of the overtaking maneuver M_1, one of the possible current maneuvers, described by the sequence

$M_1 = (s_1, s_2, \ldots, s_9)$.

At time 190 ms, the sequence (s_1, s_2, s_3, s_4) has been recognized and

$m_{M_1}(s_1 \cap \cdots \cap s_4 \cap \Omega_5 \cap \cdots \cap \Omega_9) = 1$.

At time t_1, the state recognition level gives the basic belief assignment concerning s_5:

$$m_{s_5}(s_5) = 0.9$$
$$m_{s_5}(\overline{s_5}) = 0$$
$$m_{s_5}(s_5 \cup \overline{s_5}) = 0.1$$

Before, $m_{s_5}(s_5)$ was ever equal to zero meaning that $\mathrm{Bel}(s_5) = 0$. Such as the method presented in Section 5.2, m_{M_1} is combined with m_{s_5} given values at m_{M_1}:

$$m_{M_1}(s_1 \cap \cdots \cap s_5 \cap \Omega_6 \cap \cdots \cap \Omega_9) = 0.9$$
$$m_{M_1}(s_1 \cap \cdots \cap s_4 \cap \Omega_5 \cap \cdots \cap \Omega_9) = 0.1$$

From t_1 to t_2, $\mathrm{Bel}(s_6) = 0$ and becomes not equal to zero at time t_2, for instance:

$$m_{s_6}(s_6) = 1$$
$$m_{s_6}(\overline{s_6}) = 0$$
$$m_{s_6}(s_6 \cup \overline{s_6}) = 0$$

At this time, m_{M_1} is combined with m_{s_6} given values at m_{M_1}:

$$m_{M_1}(s_1 \cap \cdots \cap s_6 \cap \Omega_7 \cap \cdots \cap \Omega_9) = 0.9$$
$$m_{M_1}(s_1 \cap \cdots \cap s_4 \cap \Omega_5 \cap \cdots \cap \Omega_9) = 0.1$$

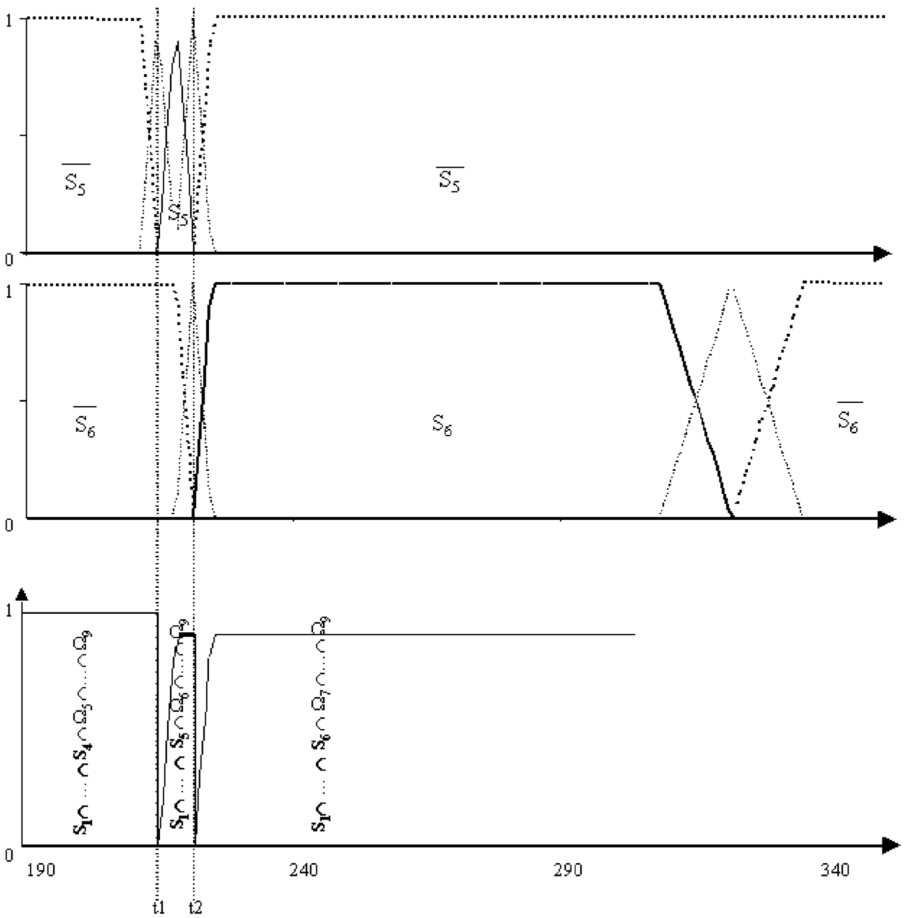

Fig. 5. An example of IDRES behavior with maneuvers recognition.

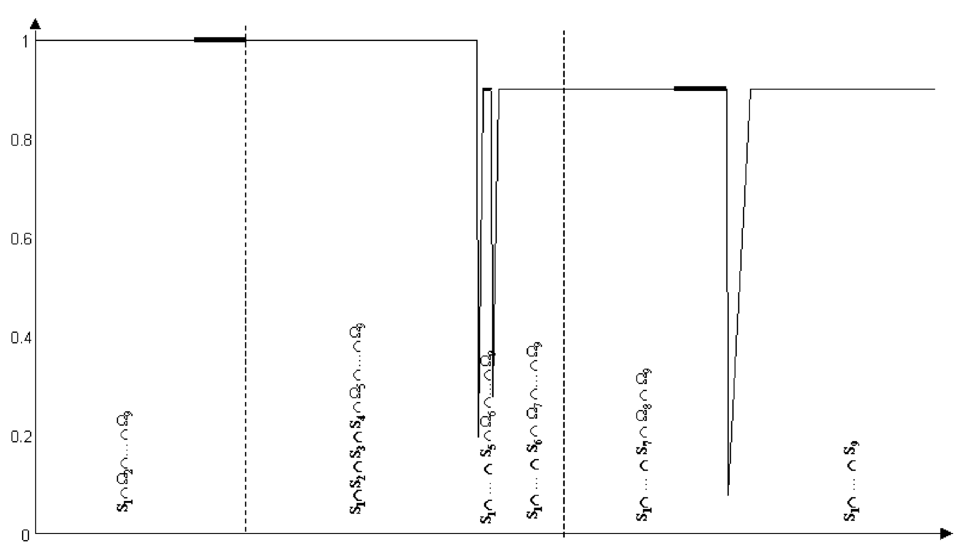

Fig. 6. Evolution of the maneuver recognition.

The maneuver recognition is totally recognized when the belief of the complete sequence is not equal to zero:

$m_{M_1}(s_1 \cap \cdots \cap s_9) \neq 0.$

Fig. 6 shows the recognition of an overtaking maneuver. It can be seen that the evolution of the focal elements mass of evidence is progressive.

7. Conclusion

This paper focuses on the recognition of a sequence of states from the numerical raw data got from the real dynamic system. The addressed applications concern the recognition of a driving maneuver. Two types of rule-based systems are presented based on two levels of rules. But if the two systems are well adapted to reach this goal, they cannot be used in real-time conditions, and they do not take into account the inaccuracy of the raw data. In the first case, the problem can easily be solved by using the knowledge of the possible current state. For the second point, it is proposed to model the uncertainty on the data by a basic belief assignment proposed in the Dempster Shafer's theory. This leads to the modeling of a confidence on the conditions, transitions, states and on the possible maneuvers that may be recognized. The algorithms of the DSRC and IDRES systems have been modified in order to take into account this confidence. Because the final results will be used by a human expert, the quality of the recognition given by this method is a fundamental obtained parameter.

The future work consists in using data coming from the real vehicle, and to complete the list of all possible maneuvers that can occur during a journey on an urban motorway.

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