# Methods handling accident and traffic jam information with belief functions in VANETs

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**Abstract.** In this paper, different methods using belief functions are proposed to share and manage information about local and spatial events on the road in V2V communications. In order to take into account messages ageing, a reinforcement mechanism considering that events disappear over the time is compared to the discounting mechanism. Two strategies for messages management are also emphasized: a first one where each message is stored and sent when possible and a second one where only fused messages are considered. Presented work shows how results can be upgraded when considering the world update, especially for dynamic events. Finally, an influence mechanism is introduced for traffic jam events to smooth and improve results when vehicles receive information about only some parts of the road.

## 1 Introduction

The car is currently by far the most used transportation mean. Many studies have been conducted in order to improve car safety and increase comfort standard using Vehicular Ad-Hoc Networks VANET [1, 2], which are wireless networks formed of highly dynamic nodes capable of being organized without infrastructure. Present work concerns Vehicle to Vehicle (V2V) communication where vehicles do not use any centralized access point to build their own information assembly. Environment is very proactive. Vehicles receive a large amount of information which is most of the time uncertain.

Different methods [3, 5, 4, 6] have been introduced in previous works to share and manage local events such as accidents in V2V communication using the theory of belief functions [7, 8] which constitutes a rich and flexible framework for representing and manipulating imprecise and uncertain information. This paper completes the work on local events presented in [6], by introducing new methods based on the notion of *update* [9], fixing the ageing coefficient and finalizing experiments. Concerning spatial events such as traffic jam, different methods have been proposed in [10, 3, 11]. We clarify in this paper first ideas given in [11], and develop and experiment a method for handling traffic jams.

In Section 2 of this paper, methods for handling accidents are proposed and compared. The proposed approach to tackle traffic jams is then exposed and tested in Section 3. Finally, Section 4 concludes and discusses future work.

## 2 Credal methods for handling accident events

### 2.1 Methods descriptions

Vehicles exchange information about events on the road. Each created message $M$ gives information about one event, it is represented as a 5-tuple $(S,t,d,\ell,m)$ :

- $S$ is the source which has perceived the event;
- $t$ is the type of the event;
- $d$ indicates the date when the source $S$ has created the message to inform about the event presence;
- $\ell$ is the location of the event;
- $m$ is a mass function held by the source $S$ and expressed on the frame $\Omega = \{\exists, \nexists\}$ where:
  - $\exists$ stands for *the event which is of type $M.t$, is present at time $M.d$ at location $M.\ell$*;
  - $\nexists$ stands for *the event which is of type $M.t$, is not present at time $M.d$ at location $M.\ell$*.

An example of a message sent and then transferred is illustrated in Figure 1.


**Fig. 1.** Example of a message sent and transferred.

In order to represent and manage information about events, traffic lanes are divided into small rectangular areas named ***cells***. Their length depends on the event type; it allows saving internal memory and bandwidth.

An event $e$ is a couple $(t,c)$ where $t$ represents the event type and $c$ is the cell where the event is located.

Obsolete messages in databases are deleted using a threshold, denoted $Del_t$ depending on the type $t$ of the event: each message $M$ such that $\Delta(now, M.d) > Del_t$ with $\Delta$ a distance measure, is suppressed. In order to fix $Del_t$ for the event type "accident", the proposed solution assumes that we have learned from a historical knowledge of accidents in a city that the duration of accidents $D$ follows a normal distribution $D \sim \mathcal{N}(\mu,\sigma^2)$ where $\mu$ is its mean and $\sigma$ is its standard deviation. Threshold $Del_t$ is chosen such that $P(D \leq Del_t) = 99\%$, i.e. $Del_t = \mu + u_{.99} * \sigma$.

Descriptions of the six proposed methods using belief functions and a simple one are then given below. Methods are summarized in Table 1. Note that method n°1 to method n°4 have been introduced in [6].

**Table 1.** Methods summary dealing with local events.

| Method | Kept messages | Update? | Ageing | Combination |
|---|---|---|---|---|
| 1 | original | no | discounting | conjunctive |
| 2 | original | no | reinforcement | conjunctive |
| 3 | fusion only | no | discounting | conjunctive / cautious |
| 4 | fusion only | no | reinforcement | conjunctive / cautious |
| 5 | original | yes | discounting | conjunctive |
| 6 | original | yes | reinforcement | conjunctive |
| 7 | last message only (yes/no) | yes | no | no |

**Method n°1 – keep original messages, discount** Each vehicle has an internal database regrouping created and received messages, where all messages $M_{e,i}$ concerning the same event $e$ are grouped into the same table $M_e$. All messages are kept in vehicle database and considered in fusion process.

In order to consider the messages ageing, the discounting operation [7, page 252] is used. It is defined by:

$$^{\alpha}m = (1-\alpha)\, m + \alpha\, m_{\Omega} \ , \tag{1}$$

where $\alpha \in [0,1]$ is called the discount rate; coefficient $\beta = (1-\alpha)$ represents the degree of reliability regarding the information provided.

Each message $M_{e,i}$ is discounted with a rate $\alpha_{e,i} = \frac{\Delta(now, M_{e,i}.d)}{Del_t}$, with this operation, over time $^{\alpha_{e,i}}M_{e,i}.m$ tends to the total ignorance $m_{\Omega}$.

For each event in vehicle database, discounted mass functions are then combined using the conjunctive rule of combination [8].

Finally, the pignistic probability [8] regarding the event presence is computed for each event.

In this method, the fusion result is not communicated to neighboring vehicles.

**Method n°2 – keep original messages, reinforce** This method differs from the first method only by the ageing mechanism. The reinforcement mechanism [12] is used, it is defined by:

$$^{\nu}m = (1-\nu)\, m + \nu\, m_A \ , \tag{2}$$

where $\nu \in [0,1]$ is the reinforcement rate, $m_A$ is a categorical mass function, and $A$ is the element expected by the agent when the mass function $m$ is totally reinforced.

In this method, each message $M_{e,i}$ is reinforced with a rate $\nu_{e,i} = \frac{\Delta(now, M_{e,i}.d)}{Del_t}$, over time $^{\nu_{e,i}}M_{e,i}.m$ tends to $m_{\nexists}$ meaning that event $e$ has disappeared.

**Method n°3 – keep only fusion result, discount** Only the fusion results are kept in databases and exchanged between vehicles in this method.

A received message $Mr$ concerning an event $e$ already identified is fused with message $M_e$ such that the new mass function of $M_e$ is obtained as follows:

– First the mass function of the message having the oldest date among $M_e$ and $Mr$ is discounted to take into consideration its aging (rate equal to $\frac{|\Delta(Mr.d,M_e.d)|}{Del_t}$).
– Then if $Mr.S \cap M_e.S = \emptyset$, the new mass function $M_e.m$ is obtained from the conjunctive combination of the corrected mass function (among $M_e.m$ and $Mr.m$) and the non-corrected mass function, otherwise the cautious rule [13] is used.
– The new set of sources $M_e.S$ is equal to $M_e.S \cup Mr.S$.
– The date of $M_e$ becomes the most recent date among $M_e.d$ and $Mr.d$.
– To give an overview of the situation to the driver, for each event $e$, the mass function $M_e.m$ is discounted with a rate $\alpha_e = \frac{\Delta(now,M_e.d)}{Del_t}$, and the pignistic probability is computed.

If the event $e$ is not already identified in the vehicle database, message $M_e$ is created with the attributes of $Mr$: $M_e.S = \{Mr.S\}$, $M_e.t = Mr.t$, $M_e.d = Mr.d$, $M_e.\ell = Mr.\ell$ and $M_e.m = Mr.m$.

The Algorithm 1 is used for the management of a received message.

**Algorithm 1** Methods n°3 and n°4: management of a received message not already considered in vehicle database.

**Require:** A received message $Mr$.
**Require:** $Cell_t(\ell)$ returns the cell number for the type $t$ on which $\ell$ is located.
**Ensure:** Message $Mr$ processing, when $Mr$ is not already considered in vehicle database.

```
begin
if ∃M_e ∈ M t.q. Mr.t = M_e.t and Cell_{M_e.t}(M_e.ℓ) = Cell_{Mr.t}(Mr.ℓ) then
    {Mr corresponds to an event e already identified in M.}
    if Mr.d > M_e.d then
        M_e.m ←^{|Δ(M_e.d,Mr.d)| / Del_{M_e.t}} M_e.m
        M_e.d ← Mr.d
    end if
    if M_e.d > Mr.d then
        Mr.m ←^{|Δ(M_e.d,Mr.d)| / Del_{Mr.t}} Mr.m
    end if
    if M_e.S ∩ Mr.S = ∅ then
        {The sources are independant.}
        M_e.m ← M_e.m ∩○ Mr.m
    else
        {The sources are not independent.}
        M_e.m ← M_e.m ∧○ Mr.m
    end if
    M_e.S ← M_e.S ∪ Mr.S
    M_e.ℓ ← M_e.ℓ ∪ Mr.ℓ
else
    {A new event is detected.}
    Create a new event e, and add Mr in the table Me.
end if
end
```

Note that the main difference between this method and the method proposed by Cherfaoui et al. in [3] is that in the latter, only one source is kept for each event, which does not allow to decide finely of the dependence between messages before fusing them.

**Method n$^o$4 – keep only fusion result, reinforce** This method is a variant of the third method, where the difference is the using of the reinforcement mechanism instead of the discounting mechanism, over time mass function tends to $m_{\nexists}$.

**Method n$^o$5 – keep original messages, consider world update, discount** This method differs from the first method by considering the world update [9]. When a received message contradicts (in term of pignistic probabilities) the acquired knowledge in the vehicle database, the latter is updated instead of being rectified if the date of the received message is greater than the last update considered in the vehicle database. Messages before an update are considered as no more relevant and are suppressed. This suppression is processed before the fusion of messages, it is defined by Algorithm 2.

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**Algorithm 2** Methods n$^o$5 and n$^o$6: suppression of messages which dates are earlier than the last world update.

**Require:** Event $(t,c)$ with $t$ the type of the event and $c$ the cell where the event is located.
**Ensure:** Suppression of messages to consider world update for the event $(t,c)$.
**begin**
{Get the date of the earlier message informing that the event $(t,c)$ is present.}
$d_{\exists} \leftarrow maximum(M_{(t,c),i}.d)$ where $M_{(t,c),i}.m(\{\exists\}) > 0$.
{Get the date of the earlier message informing that the event $(t,c)$ is not present.}
$d_{\nexists} \leftarrow maximum(M_{(t,c),i}.d)$ where $M_{(t,c),i}.m(\{\nexists\}) > 0$.
Suppress all messages $M_{(t,c),i}$ having a date $M_{(t,c),i}.d \leq minimum(d_{\exists}, d_{\nexists})$.
**end**

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**Method n$^o$6 – keep original messages, consider world update, reinforce** This method differs from the previous method only by the use of the reinforcement mechanism instead of the discounting mechanism.

**Method n$^o$7 – keep only the last message yes/no** Messages inform if "yes" or "no" an event is present (confidence degree is equal to 100%), and only the last message is considered, it is given as a result to the driver. The aim is to compare the proposed methods using belief functions to this simple method in Section 2.2.

### 2.2 Experiments

Performance rates of models are measured for each type $t$ of event and for each vehicle $v$ by the adequacy to the reality of the information given to the driver. Formally, at each time step $\tau$, the set equal to the union of the events present in the vehicle database and the existing events in the reality is considered and denoted by $E_t^{v,\tau}$, and performance rates are computed for each type $t$ of event and for each vehicle $v$ by:

$$Perf_t^{v,\tau} = 1 - \frac{\sum_{e \in E_t^{v,\tau}} \left(BetP_e^{v,\tau}(\{\exists\}) - R_e^\tau\right)^2}{\mid E_t^{\tau,v} \mid} \ , \tag{3}$$

where: $R_e^\tau = 1$ if event $e$ is present at time $\tau$, 0 otherwise; $\mid E_t^{v,\tau} \mid$ is the cardinality of $E_t^{v,\tau}$; $BetP_e^{v,\tau}(\{\exists\})$ is the pignistic probability in vehicle $v$ at time $\tau$ concerning the presence of the event $e$ (if no message concerns event $e$ in vehicle $v$ database, $Betp_e^{v,\tau}(\{\exists\}) = 0$).

The experiments are realized using a developed Matlab™ simulator [6]. The sampling period $\Delta\tau = 4$ seconds, this means that vehicles exchange their databases and messages are processed every 4 seconds. The range of wireless communication is 200 meters.

Created messages have all the same confidence degree: $m(\{\exists\}) = 0.6$ or $m(\{\nexists\}) = 0.6$.

Accident duration follows a normal distribution $D \sim \mathcal{N}(1800, 300^2)$, the deletion threshold is then obtained $Del_t = 2498$ seconds. Scenario is tested with different values of accident duration obtained from this normal distribution.

In this scenario, an accident occurs at the beginning of each simulation, and 20 different durations are tested.

Only 5 vehicles are present. One vehicle denoted by $v$ receives from distinct sources four messages just after their creation, the first and second messages confirm the accident at 30% and 70% of its duration after its beginning, and the other messages deny the accident at 30% and 50% of its duration after its disappearance. The adequacy to the reality (the average over all the simulation) of vehicle $v$ is illustrated in Figure 2 for each launch (20 durations) and each method. These tests are repeated 9 new times. The mean of the average and the mean of the standard deviation of the adequacy to the reality are presented for each method in Table 2.

**Table 2.** Accident scenario: means of the average and the standard deviation of the adequacy to the reality

| | All the simulation | Before accident disappearance | After accident disappearance |
|---|---|---|---|
| Method n°1 | 0.771984(0.00997779) | 0.666177(0.00224502) | 0.82572(0.01586986) |
| Method n°2 | **0.855809**(0.00522433) | 0.61829(0.0184514) | **0.975492**(0.01473972) |
| Method n°3 | 0.757644(0.01202747) | 0.665513(0.00221531) | 0.804534(0.01895642) |
| Method n°4 | 0.850178(0.00439378) | 0.618887(0.0165816) | 0.96674(0.01362776) |
| Method n°5 | 0.783468(0.00600582) | 0.666177(0.00224502) | 0.842962(0.00966614) |
| Method n°6 | 0.853815(0.00439366) | 0.61829(0.0184514) | 0.9725(0.01366174) |
| Method n°7 | 0.796106(0.000916845) | **0.696715**(0.001044568) | 0.846654(0.001000312) |

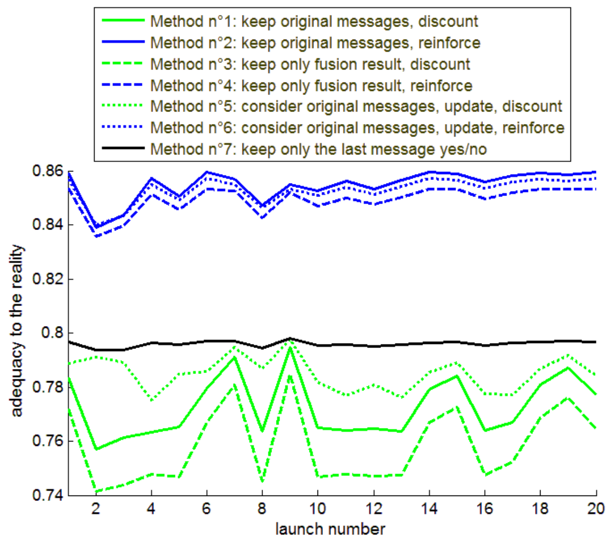



**Fig. 2.** Accident scenario: the average of the adequacy to the reality for each simulation.

These tests show that the used reinforcement mechanism is more in line with the accident disappearance than the discounting operation. In addition, the discounting mechanism does not manage correctly messages denying the event, indeed after the disappearance of an event, discount result tends to the ignorance, which means that the probability of the event presence increases over time while it should remain as low as possible.

Before receiving the first message denying the accident, methods n$^{o}$5 and n$^{o}$6 give respectively the same result as methods n$^{o}$1 and n$^{o}$2. When the vehicle receives messages denying the accident, methods n$^{o}$5 and n$^{o}$6 stop considering old messages confirming the presence of the event. This allows to increase the performance when using the discounting mechanism; but it is not the case when using the reinforcement mechanism, because at this moment, the result of the old messages reinforced is closer to $m_{\nexists}$ than the result of the new message denying the accident.

Simple method n$^{o}$7 gives good results in this scenario for two reasons: created messages have a confidence equal to 100% and tell the reality; and messages denying the accident are received. Note that this method has bad results after the disappearance of the accident until receiving a first message denying the accident.

Methods where only the fusion result is kept in vehicle database do not allow managing finely the obsolescence of messages before their combination. For this reason, they give a worse result than the other methods using belief functions.

## 3 A credal method for handling traffic jam events

### 3.1 Method description

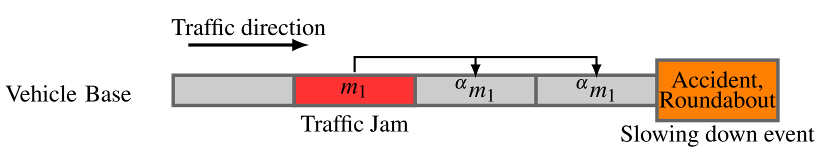
Traffic jam is a very dynamic event, for this reason it is important to update information in vehicle database when receiving more recent information contradicting the acquired knowledge in vehicle database. The first step of the proposed method for handling traffic jam events is the same as the methods n$^o$5 and n$^o$6 proposed for accident events, but in this method no ageing mechanism is employed. The threshold $Del_t$ is used only to delete obsolete messages, it can be fixed according to a maximal value known from a historic knowledge (4 hours for example).

In order to predict the overall road situation when the vehicle database contains information about only some parts of the road, a secondary mechanism called *influence mechanism* is proposed to smooth and improve the overview of the situation given to driver. The result of this mechanism is not communicated to other vehicles.

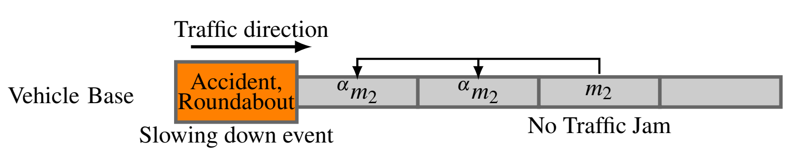
Traffic jam is an extensive event evolving in the reverse direction of roads, and disappearing in the same direction of the traffic.

The influence mechanism can be explained in the following manner:

- Let $\beta_t$ be the influence rate.
- For each event $(traffic\_jam, c)$ result obtained from the first step of the method:
  - if it informs that the cell $c$ is occupied by a traffic jam, generate influences on following cells (Figure 3(a)) by discounting with a rate equal to $1-\beta_t$, and stop this operation when arriving to a slowing down event like an accident (known in vehicle database) or a roundabout.
  - if it informs that the cell $c$ is not occupied by a traffic jam ($BetP(\{\nexists\}) > 0.5$), generate influences on previous cells (Figure 3(b)).




(a) Case of a mass function $m_1$ in favour of traffic jam ($BetP_1(\{\exists\}) > .5$).




(b) Case of a mass function $m_2$ in favour of no traffic jam ($BetP_2(\{\nexists\}) > .5$).

**Fig. 3.** Illustrations of influences computations in the method dealing with traffic jams.

For each cell, results of the first step and obtained influences are combined using the conjunctive rule of combination, and the pignistic probability is then computed.

In previous work [10, 3], the spatiality of events are managed by considering the distance between the observed point and the points where information telling about the event presence is available. These methods do not take into consideration how traffic jam evolve and disappear according to the roads and their traffic direction.

### 3.2 Experiments

The scenario described in Figure 4 has been developed. A traffic jam appears progressively on a road, and disappears a few minutes later. A message is created to confirm the traffic jam, and another one is created to deny it after its disappearance.

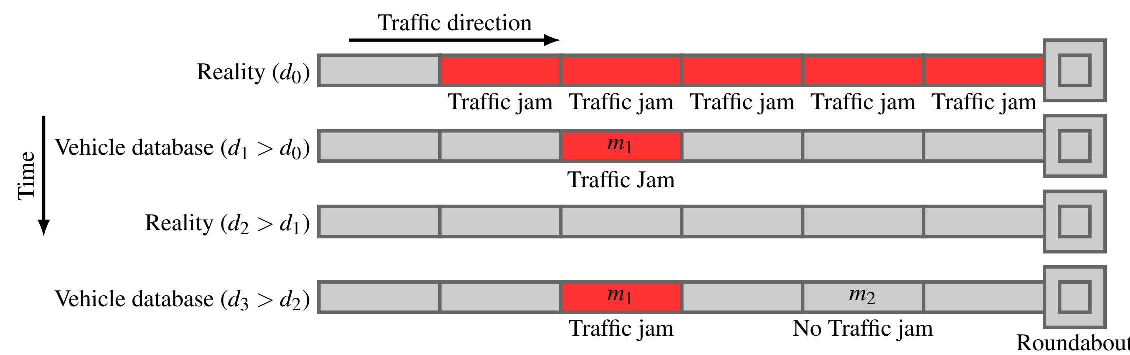



**Fig. 4.** Tested scenario: a traffic jam appears on the road and disappears a few minutes later.

The proposed method is tested with and without applying the influence mechanism: $\beta = 0.8$ (which means that "the method know that a traffic jam is present, but it is not absolutely sure) and $\beta = 0$ respectively. The obtained mean of the adequacy to the reality for all vehicles present in the map (the map is 1.2km x 1.2km, so the traffic jam interests all vehicles) is equal to 0.6389 when applying the influence mechanism, and 0.2442 without the influence mechanism. This experiment shows the interest of the influence mechanism.

This scenario is also tested where vehicles create and receive messages concerning the traffic jam on all cells (confirm or deny). The proposed method for handling traffic jam event is compared to the second method for handling accident event. The obtained mean of the adequacy to the reality is respectively 0.9285 and 0.7452. This experiment shows the interest of considering world update, cells are considered not occupied once a first method denying the event is received (or created).

## 4 Conclusion and future work

In this paper, methods are proposed to exchange and manage information about accident and traffic jam events on the road in V2V communications using belief functions. Different strategies are compared concerning messages ageing; influences mechanisms and information considered and kept in internal databases.

Future work must consider irregular areas, other types of spatial events such as flog blanket, and links between different types of event. The used simulator is a research tool; a more realistic one has to be used in future work.

## References


1. Car 2 car communication consortium C2C-CC: http://www.car-to-car.org/
2. S. Olariu, M.C. Weigle: Vehicular networks: from theory to practice. Chapman & Hall/CRC, ed. 1, (2009)
3. V. Cherfaoui, T. Denoeux, Z.L. Cherfi: Distributed data fusion: application to confidence management in vehicular networks. International Conference on Information Fusion (FUSION'2008), 846–853, Germany (2008)
4. B. Ducourthial, V. Cherfaoui, T. Denœux: Self-stabilizing Distributed Data Fusion. Lecture Notes in Computer Science, 7596, 148–162, (2012)
5. M. Bou Farah, D. Mercier, É. Lefèvre, F. Delmotte: Towards a robust exchange of imperfect information in inter-vehicle ad-hoc networks using belief functions. IEEE Intelligent Vehicles Symposium, IV'2011, 436–441, Baden-Baden, Germany, June 5-9 (2011)
6. M. Bou Farah, D. Mercier, É. Lefèvre and F. Delmotte: A high-level application using belief functions for exchanging and managing uncertain events on the road in vehicular ad-hoc networks. Annals of telecommunications: special issue on belief functions and uncertainty management in networks and telecommunication, 69, 185–199, (2014)
7. G. Shafer: A Mathematical Theory of Evidence. Princeton University Press, N.J. (1976)
8. P. Smets and R. Kennes: The Transferable Belief Model. Artificial Intelligence, vol. 66, pp. 191–243 (1994)
9. H. Katsuno, A. Mendelzon: On the difference between updating a knowledge base and revising it. 2nd International Conference on Principles of Knowledge Representation and Reasoning (KR'91), 387–394 (1991)
10. J. Lang, P. Muller: Plausible reasoning from spatial observations. 17th Conference in Uncertainty in Artificial Intelligence, Seattle, Washington, USA, 285–292 (2001)
11. M. Bou Farah, D. Mercier, É. Lefèvre, F. Delmotte: Exchanging dynamic and imprecise information in V2V networks with belief functions. 16th International IEEE Conference on Intelligent Transport Systems (ITSC'2013), The Hague, The Netherland, 967–972 (2013)
12. D. Mercier, T. Denœux, M.-H. Masson: Belief function correction mechanisms. Studies in Fuzziness and Soft Computing, B. Bouchon-Meunier et al. (Eds.), 249, 203–222, January (2010)
13. T. Denœux: The cautious rule of combination for belief fonctions and some extensions. 9th International Conference on Information Fusion (FUSION'2006), Florence, Italy, 1–8 (2006)