Methods using belief functions to manage imperfect information concerning events on the road in VANETs

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Abstract

Different models using belief functions are proposed and compared in this article to share and manage imperfect information about events on the road in vehicular networks. In an environment without infrastructure, the goal is to provide to driver the synthesis of the situation on the road from all acquired information. Different strategies are considered: discount or reinforce towards the absence of the event to take into account messages agings, keep the original messages or only the fusion results in vehicles databases, consider the world update, manage the spatiality of traffic jams by taking into account neighborhood. Methods are tested and compared using a Matlab$^{\mathrm{TM}}$ simulator. Two strategies are introduced to tackle fog blankets spatiality; they are compared through an example.

Keywords: Vehicular Ad-hoc Networks (VANET); Theory of belief functions; Transferable Belief Model (TBM); Events on the road; Decentralized data fusion; Imperfect information exchange.

1. Introduction

Nowadays, vehicles are by far the most used means of transport. Their popularization has created safety and environmental problems. In the world, more than one million people die every year as a result of a road traffic crash; and between 20 to 50 million more people suffer non-fatal injuries [43].

The improvement of road safety has become a government priority in most developed countries. Projects using Vehicular Ad-Hoc Networks (VANETs) have been launched worldwide to improve road safety, reduce traffic congestion and pollution, and bring more comfort to drivers [12, 6, 41, 42, 39, 2].

Ad-hoc networks are formed of wireless nodes, communicating to share information. They are capable of being organized without infrastructure. In mobility, they are called Mobile Ad-Hoc Networks (MANETs). Vehicular networks [12, 31, 4] are branch of MANETs where nodes are vehicles. Compared to MANETs, they are characterized by:

- the technological advancement of vehicles: high energy and computing capacity;
- the vehicles behavior: high mobility, speeds heterogeneity, organized trajectories;
- the roads environment which impacts vehicles speed and connectivity.

Three modes of communication are possible in VANETs: Vehicle-to-Infrastructure (V2I) mode where vehicles communicate only with infrastructures, Vehicle-to-Vehicle (V2V) mode where vehicles communicate only together, and hybrid mode which combines V2I and V2V communication modes.

This present work concerns V2V communication mode where vehicles do not use any centralized access point to build their own information assembly. The vehicle network environment is dynamic and complex,

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sources are often heterogeneous, and therefore the exchanged information may be imperfect. In this article, we focus on the management of imperfect information exchanged between vehicles concerning events on the road.

Previous works have proved that vehicular communication can improve traffic safety through the exchange of information [23]. Some projects have proposed to manage data in vehicular networks. We can cite VESPA project [16] which allows drivers sharing information about events on the road such as accidents and parking places.

Belief function theory [32, 33] offers flexibility in uncertainty modeling and provides rich tools for managing different types of imperfection. It is used to represent uncertainty, manage and fuse the various acquired information. This theory is increasingly used for information fusion in VANETs, we can cite [7] where authors propose a system allowing pedestrian crossing detection.

In an environment without infrastructure where each vehicle is a fusion center and creates its own vision, the goal is to provide to each driver the synthesis of the situation on the road as close as possible to the reality. Different models using the theory of belief functions are proposed. The carried work distinguishes local events (such as accident) and spatial events (such as traffic jam), which do not have the same characteristics. Proposed models are tested and compared using a developed Matlab$^{\text{TM}}$ simulator [40].

In previous research projects, different methods [13, 8, 21, 9, 10, 11] have been introduced to share and manage road events in inter-vehicle communication using belief functions.

In [13], a first method has been presented where roads are divided into segments and one event is considered per segment. Exchanged messages inform of the presence or the absence of events. Fusion of messages for each event is kept in vehicles databases and exchanged with neighborhood. In order to choose the combination rule to fuse information, messages are considered dependent if at least one message is a fusion result, or messages have the same source and the same event perception date. Authors consider messages agings by ignoring the presence or the absence of events over time [32].

In [10], authors exposed four methods using belief functions to tackle local events. Two agings mechanisms have been proposed: the first ignores the presence or the absence of events over time; the second suppose that events disappear over time. These mechanisms are tested with two scenarios; each one has been launched once; scenarios have been tested with one duration since the event duration has not been fixed. Two strategies for messages management have been proposed: in the first strategy original messages are kept in vehicle database; in the second one only fusion result is kept for each event. These strategies have been tested with two scenarios; each one has been launched once (only one event duration has been tested).

This paper extends this work by developing new methods based on the notion of *update* [24] and by proposing a way to automatically compute the messages agings (by discounting or reinforcing) using historical data. In total, six methods are proposed to manage messages informing about local events. They are tested and compared within 3 scenarios using a Matlab$^{\text{TM}}$ simulator [40].

Concerning spatial events such as traffic jams, different methods using belief functions have been proposed [25, 13, 9, 11].

In [25], belief regarding the presence of an event on a geographical point o is obtained by: discounting [32] neighboring information according to their distance from the point o; then combining the obtained information [17]. In [13], authors propose to use the cautious combination rule [19] to fuse information located on a same road segment.

In this paper, the management of traffic jams events is also tackled using two methods based on an influence mechanism [9, 11]. We consider in particular the cases where only fusion results are kept in vehicles databases and where original messages are conserved. Methods are also tested and compared using the same simulator as for local events.

Two different strategies are proposed to manage fog blankets influences. The first one is inspired from Lang and Muller work [25]; the second one a new strategy to ensure a better adequacy of influences to the reality.

This article is organized as follows. Needed basic concepts on data fusion and the theory of belief functions are recalled in Section 2. Methods for handling local events such as accidents are proposed and compared using our simulator [40] in Section 3. The proposed approach to tackle traffic jams is then exposed and tested in Section 4. Two different strategies are proposed in Section 5 to manage fog blankets influences. Finally, Section 6 concludes the article and discusses future work.

2. Data fusion: necessary notions

Data fusion is used to improve: the reliability of a judgment by the contribution of redundant information; or the interpretation ability by the provision of complementary information.

2.1. Belief revision versus belief world update

The consideration of new information is modeled by a revision or a world update.

Belief revision [22, 3] consists in strengthen or correcting the knowledge with new information.

World update [24, 26, 20] indicates a context switch and a possible change in the world. All beliefs are modified by giving priority to the most recent information.

2.2. Belief functions

Belief functions [32, 33] are used in this article to represent and manage imperfect information. This theory is a generalization of the probability theory.

2.2.1. Representing Information

Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_K\}$ denotes a finite set containing all the possible answers to a given question Q of interest; Ω being called the *frame of discernment*.

Information given by different sources regarding the answer to question Q can be represented by a *basic belief assignment (BBA)*, also called a *mass function*, denoted by m. It is defined from 2^Ω (the set of all possible subsets of Ω) to $[0, 1]$ such that the sum of all the masses is equal to 1:

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

A mass $m(A)$ represents the belief supporting A, where A is a subset of Ω. It is the mass allocated to the hypothesis: *the answer to question Q belongs to the subset A of* Ω.

The theory of belief functions allows the allocation of belief to subsets of Ω with no influence on the singletons, contrary to the probability theory [32, 33]. Note that due to a lack of information, the part of belief cannot always be given to a singleton.

Each subset A of Ω such that $m(A) > 0$ is called a *focal element* of m.

The mass $m(\Omega)$ represents the degree of ignorance of the source which has provided the information m. A mass function is said to be *dogmatic* if $m(\Omega) = 0$ and *non-dogmatic* if $m(\Omega) > 0$.

The mass on the empty set $m(\emptyset)$ represents the conflict. Discussions on this point can be found in [36] and [28, Section 5]. A mass function is said to be *normal* if $m(\emptyset) = 0$ and *subnormal* if $m(\emptyset) > 0$.

In particular, a mass function m can have only one focal element A: $m(A) = 1$. In this case this BBA is denoted m_A and said to be *categorical.* The total ignorance is represented by the categorical mass function m_Ω, it is also called the *vacuous belief function.*

Another particular case is a mass function m having no more than two focal elements including Ω; it is called a *simple mass function* and verifies:

$$\begin{cases} m(A) &= 1 - \omega \ , \\ m(\Omega) &= \omega \ , \end{cases} \tag{2}$$

with $A \subset \Omega$ and $\omega \in [0, 1]$. Such a BBA can be simply noted A^ω.

A BBA m can be represented by its commonality function defined by:

$$q(A) = \sum_{A \subseteq B} m(B) \ , \forall A \subseteq \Omega \ . \tag{3}$$

2.2.2. Manipulating Information

Discounting operation. An agent may have some doubts regarding the reliability of the source which has provided a received mass function m. The discounting operation [32, page 252] allows taking into account such a metaknowledge. Let $\alpha \in [0,1]$ be the discounting rate, a discounted mass function m is denoted ${}^{\alpha}m$ and defined by:

$$\begin{cases} {}^{\alpha}m(A) &= (1-\alpha)\, m(A), \quad \forall A \subset \Omega, \\ {}^{\alpha}m(\Omega) &= (1-\alpha)\, m(\Omega) + \alpha \ , \end{cases} \tag{4}$$

where the coefficient $\beta = 1 - \alpha$ represents the degree of reliability regarding the information which have been provided [32, 28]. When the source is fully reliable, α is equal to 0. On the contrary, when the source is not reliable and consequently the mass function cannot be considered, α is equal to 1.

The discounting operator can be defined more simply as:

$${}^{\alpha}m = (1-\alpha)\, m + \alpha\, m_{\Omega} \ . \tag{5}$$

Operation of reinforcement towards an element of the frame. An agent may want to reinforce a mass function m which seems to be too cautious in the sense that it is not specific enough. This operation can be realized using the reinforcement correction mechanism [27]. Let $\nu \in [0,1]$ be the reinforcement rate, a reinforced mass function m towards an element A is defined by:

$${}^{\nu}m = (1-\nu)\, m + \nu\, m_A \ , \tag{6}$$

where the categorical mass function m_A is the mass function m totally reinforced (when $\nu = 1$).

Conjunctive rule of combination. Two BBA m_1 and m_2 obtained from distinct and reliable sources, can be combined using the conjunctive rule of combination, which is the unnormalized version of Dempster's rule [17], denoted by $\bigcirc\!\!\!\!\cap$ and defined by:

$$(m_1 \bigcirc\!\!\!\!\cap\, m_2)(A) = m_{1 \bigcirc\!\!\!\!\cap 2}(A) = \sum_{B \cap C = A} m_1(B) \cdot m_2(C) \ , \forall A \subseteq \Omega \ . \tag{7}$$

With this combination, masses are transferred to focal elements intersections. This operator is commutative, associative and non-idempotent (which means that: $m \bigcirc\!\!\!\!\cap\, m \neq m$).

Cautious rule of combination. If sources of BBA m_1 and m_2 are considered non-distinct and reliable, they can be combined using the cautious rule of combination [19], denoted by $\bigcirc\!\!\!\!\wedge$ and defined as:

$$(m_1 \bigcirc\!\!\!\!\wedge\, m_2)(A) = m_{1 \bigcirc\!\!\!\!\wedge 2}(A) = \bigcirc\!\!\!\!\cap_{A \subset \Omega}\, A^{w_1(A) \wedge w_2(A)} \ , \forall A \subseteq \Omega \ , \tag{8}$$

where $\wedge$ denotes the minimum operator, and w is the conjunctive weight function [34] defined by:

$$w(A) = \prod_{A \subset B} q(B)^{(-1)^{|B|-|A|+1}} \ , \quad \forall A \subset \Omega \ . \tag{9}$$

The cautious rule of combination is commutative, associative and idempotent (which means that: $m \bigcirc\!\!\!\!\wedge\, m = m$).

2.2.3. Making a decision

In order to make a decision, a BBA m defined on Ω and representing the available information regarding the answer to question Q, can be transformed into a probability measure with the *pignistic transformation* [35] defined by:

$$BetP\{m\}(\{\omega\}) = \sum_{\{A \subseteq \Omega, \omega \in A\}} \frac{m(A)}{|A|\,(1 - m(\emptyset))}, \quad \forall \omega \in \Omega. \tag{10}$$

3. Credal methods for handling local events

In this section, six methods using belief functions are presented to manage messages informing about local events such as accidents for example. These methods are tested and compared using a Matlab$^{\text{TM}}$ simulator.

3.1. Methods descriptions

3.1.1. Environment

The environment is without infrastructure, each vehicle has its own messages database (Figure 1).

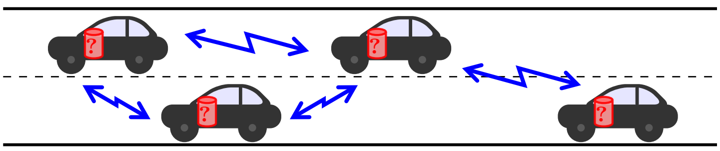


Figure 1: Illustration of the environment.

Every time two vehicles can communicate, they exchange all the messages stored in their databases. Each vehicle has its own fusion module in order to manage messages and give an overview of the road situation to driver.

3.1.2. Messages creations

Vehicles exchange information about events on the road. A vehicle can create a message informing about the presence of an event. Each created message M gives information about one event; it is represented as a 5-tuple (S, t, d, ℓ, m), where:

- S is the vehicle (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, it is not necessarily the date at which message M has been received;
- ℓ is the location of the event;
- m is a mass function held by the source S, representing the confidence of S regarding the fact that the event is present, and expressed on the frame of discernment $\Omega = \{\exists, \nexists\}$ where: $\exists$ stands for *the event which is of type t, is present at time d at location ℓ*; and $\nexists$ stands for *the event which is of type t, is not present at time d at location ℓ.*

Each attribute $x \in (S, t, d, \ell, m)$ of a message M will be denoted by $M.x$.

Note that the source $M.S$ is not necessarily the source which have transferred the message M. An example of a message sent and then transferred is illustrated in Figure 2.

Figure 2: Example of a message sent then transferred.

3.1.3. Map discretization

Several created or received messages can inform about the same event.

In order to represent and manage information about events, traffic lanes are divided into small rectangular areas named ***cells*** (Figure 3). Their length depends on the event type; it allows saving internal memory and bandwidth.

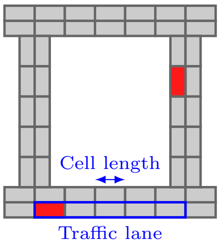


Figure 3: Discretization of map into cells.

An event e is a couple (t, c) where t represents the event type and c is the cell where the event is located. In other words, two messages M_1 and M_2 inform about the same event e if $M_1.t = M_2.t$, and $M_1.\ell$ and $M_2.\ell$ are located on the same cell c.

3.1.4. Deleting obsolete messages

In this paragraph, a procedure is presented in order to suppress obsolete messages which are considered as too old and no more up to date.

Let Del_t be a threshold depending on the type t of the event. The suppression procedure consists in deleting a message M if $\Delta(now, M.d) > Del_t$ with Δ a distance measure.

We assume that we have learned from a historical knowledge that the duration D of accidents in a city follows a normal distribution $D \sim \mathcal{N}(\mu, \sigma^2)$ where μ is its mean and σ is its standard deviation. It allows fixing Del_t for accident event type by choosing Del_t such that $P(D \leq Del_t) = 99\%$, i.e. $Del_t = \mu + u_{.99} * \sigma$ with $u_{.99}$ the 99^{th} quantile of the standard normal distribution.

3.1.5. Consider messages agings

In order to consider the agings of the messages, two aging mechanisms are proposed and compared.

Discounting. The discounting mechanism (Equation 4) ignores the presence or the absence of events over time. This operation tends to the total ignorance as illustrated in Figure 4. In other words, an information totally discounted ignores if the event is present or absent.

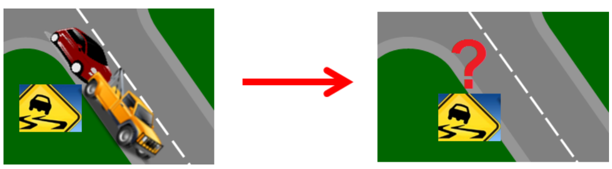


Figure 4: Discounting mechanism: ignorance of the presence and the absence of events over time.

Reinforcement to the event disappearance. The proposed reinforcement mechanism (Equation 6) considers that events disappear over time. With this operation, the mass function totally reinforced is the categorical mass function $m_{\overline{\exists}}$. This mechanism is illustrated in Figure 5.

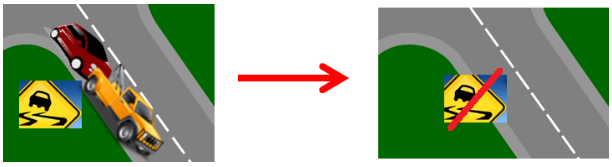


Figure 5: Reinforcement mechanism: suppose that events disappear over time.

3.1.6. Messages management

Two strategies are proposed to manage messages in vehicles databases.

Keep original messages. The first strategy consists in keeping original messages in vehicle database. It is illustrated in Figure 6.

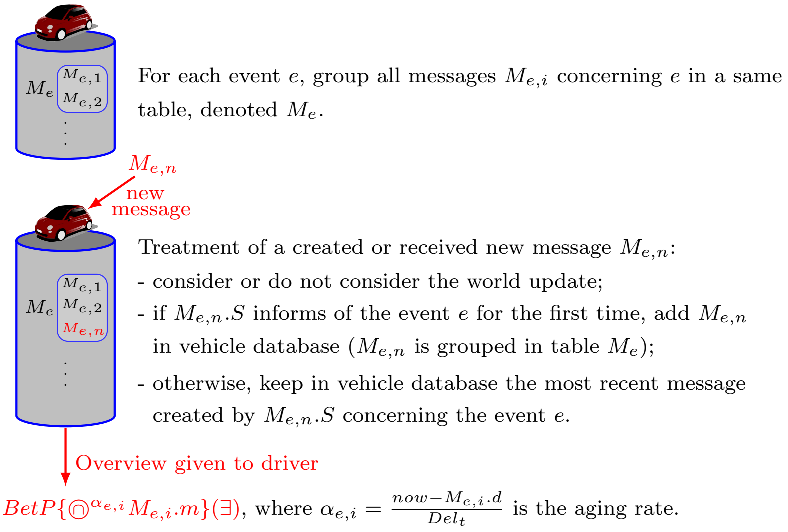


Figure 6: Messages management: keep original messages in vehicle database.

For each vehicle, created and received messages $M_{e,i}$ informing about a same event e are grouped together into a same table M_e in the internal database. When a new message $M_{e,n}$ is created or received, the following treatments are realized:

- The world update mechanism is exposed in next section; it is not considered for all methods. If the world update is considered, the first treatment of the message $M_{e,n}$ is processed with the world update mechanism.
- If $M_{e,n}$ is already present in vehicle database ($\exists i, M_{e,n}.x = M_{e,i}.x \ \forall x \in (S, t, d, \ell, m)$), it is ignored. Otherwise, the message $M_{e,n}$ goes to the next test.
- If the source $M_{e,n}.S$ has already sent a message $M_{e,i}$ concerning the event e, and $M_{e,n}$ concerns an update of the message $M_{e,i}$ previously stored, the new message $M_{e,n}$ replaces the message $M_{e,i}$ if $M_{e,n}.d > M_{e,i}.d$. This occurs when a source creates a new message to correct the information previously sent.
- If the source $M_{e,n}.S$ informs for the first time of an event e, add the message $M_{e,n}$ in vehicle database. It is grouped in an existing table M_e if e is already known in vehicle database, otherwise a new table M_e is created in vehicle database where $M_{e,n}$ is added.

Each time an overview of the road situation has to be given to driver, for each event e, messages stored in table M_e are fused as follows:

- In order to consider messages agings, each mass function $M_{e,i}.m$ is corrected using the discounting or the reinforcement mechanism described in the previous section. The resulting mass function becomes ${}^{\alpha_{e,i}}M_{e,i}.m$ where $\alpha_{e,i} = \frac{now - M_{e,i}.d}{Del_{M_{e,i}}.t}$ is the aging rate.
- Corrected mass functions are combined conjunctively using equation (Equation 7). The resulting mass function is $\textcircled{\cap}_i^{\alpha_{e,i}} M_{e,i}.m$.
- Pignistic probability regarding the presence of the event e is obtained using equation (Equation 10).

Keep only fusion result. In the second strategy, only the fusion result is kept in vehicle database for each event. This strategy is illustrated in Figure 7. Note that the world update mechanism is not tested for handling local events when only fusion results are kept in vehicle database. Authors believe that it is sufficient to test this mechanism with only the first strategy.

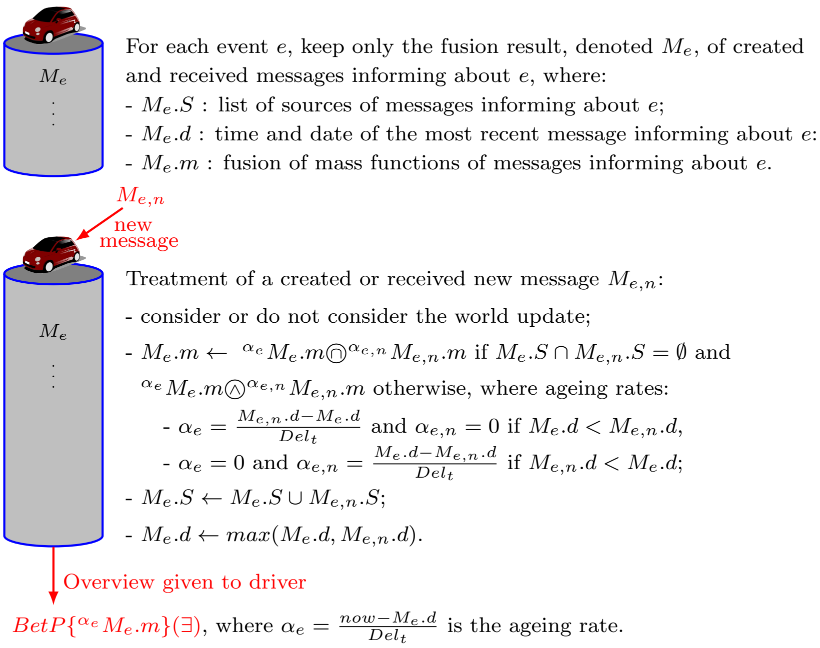


Figure 7: Messages management: keep only fusion result for each event in vehicle database.

For each event $e = (t, c)$, the fusion result of created and received messages informing about e is denoted M_e. The attributes of M_e are the following:

- $M_e.S$: list of all sources of created and received messages informing about e.
- $M_e.d$: time and date of the most recent message (created or received) informing about e.
- $M_e.m$: mass function resulting of the fusion of mass functions of all created and received messages informing about e.

When a new message $M_{e,n}$ is created or received, the following treatments are realized:

- If the event e is not known in the vehicle database, a fusion result M_e is created with the following attributes: $M_e.S = \{M_{e,n}.S\}$, $M_e.d = M_{e,n}.d$ and $M_e.m = M_{e,n}.m$. Otherwise, the message $M_{e,n}$ goes to the next test.

- The message $M_{e,n}$ is fused with M_e as follows:
  - The mass function of the oldest message among $M_{e,n}$ and M_e is corrected using the discounting or the proposed reinforcement mechanism to take into account the aging difference. The aging rate is equal to $\frac{|M_{e,n}.d - M_e.d|}{Del_t}$.
  - Resulting mass functions are combined conjunctively using equation (Equation 7) if $M_{e,n}$ and M_e are provided from distinct sources ($M_e.S \cap M_{e,n}.S = \emptyset$), otherwise they are combined cautiously using equation (Equation 8).
  - The list of sources $M_e.S$ becomes the union of $M_e.S$ and $M_{e,n}.S$.
  - The time and date of the fusion result become the most recent time and date among $M_e.d$ and $M_{e,n}.d$.

When an overview of the road situation has to be given to the driver, for each event e:

- In order to consider fusion result aging, the mass function $M_e.m$ is corrected using the discounting or the proposed reinforcement mechanism. The resulting mass function becomes $^{\alpha_e}M_e.m$ where $\alpha_e = \frac{now - M_e.d}{Del_{M_e.t}}$ is the aging rate.
- Pignistic probability regarding the presence of the event e is obtained using equation (Equation 10).

3.1.7. World update mechanism

When recent information contradicts previous knowledge present in vehicle database, the world update [24] can be considered. Instead of being rectified, previous information is forgotten and suppressed from vehicle database.

Figure 8 illustrates an example where a first message is received informing that a parking place is available. Few minutes later, a second message is received having a date (attribute d) greater than the first message date, informing that this parking place is not available. Instead of fusing these messages, the world update mechanism considers that the priority is the most recent message (which is the second one), and only the latter is considered.

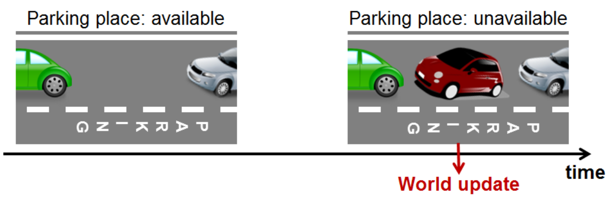


Figure 8: World update example.

In order to consider world update, the procedure defined by Algorithm 1 is processed when receiving a new message $M_{e,n}$. It is processed before the procedure of messages management described in previous section as shown in Figure 6 and Figure 7. The world update mechanism is proposed in this section only when original messages are kept in vehicle database. Note that, when world update is considered, no contradiction is present in vehicle database. For each event, all messages stored in vehicle database inform that either the event is present or the event is absent.

3.1.8. Summary of proposed methods

Six methods using belief functions are proposed to manage local events. They are summarized in Table 1. The difference between proposed methods stands on the following:

- Aging mechanism: methods n°1, n°3 and n°5 use the discounting mechanism; methods n°2, n°4 and n°6 use the reinforcement mechanism;

Algorithm 1 Procedure of world update when original messages are kept in vehicle database.

Require: Event $e = (t, c)$ with t the type of the event and c the cell where the event is located; a new message $M_{e,n}$.

begin

if $\forall i$, $(BetP\{M_{e,i}.m\}(\{\exists\}) > 0.5$ and $BetP\{M_{e,n}.m\}(\{\nexists\}) > 0.5)$ or $(BetP\{M_{e,i}.m\}(\{\nexists\}) > 0.5$ and $BetP\{M_{e,n}.m\}(\{\exists\}) > 0.5)$ **then**

  if $M_{e,n}.d > maximum(M_{e,i}.d)$ **then**

    {World update.}

    Suppress all messages $M_{e,i}$ from vehicle database.

    Add $M_{e,n}$ to vehicle database.

  else

    Do not consider $M_{e,n}$ (treatment of $M_{e,n}$ is canceled before the process of messages management).

  end if

end if

end

Table 1: Methods summary dealing with local events.

Methods	Combination
Method n°1: keep original messages, discount	conjunctive
Method n°2: keep original messages, reinforce	conjunctive
Method n°3: keep only fusion result, discount	conjunctive, cautious
Method n°4: keep only fusion result, reinforce	conjunctive, cautious
Method n°5: keep original messages, update, discount	conjunctive
Method n°6: keep original messages, update, reinforce	conjunctive

- Messages management: with methods n°1, n°2, n°5 and n°6, original messages are kept in vehicle database; with methods n°3 and n°4, only the fusion result is kept in vehicle database for each event.
- Considering world update: only methods n°5 and n°6 consider world update.

The third method, where only fusion results are kept in vehicle database and the discounting operator is used, is the closest method to previous work [13]. In [13], fused messages are always combined using the cautious rule. In the proposed method n°3, the list of sources is kept in vehicle database in order to consider finely the dependence between messages, and use the most suitable combination operator (either the conjunctive rule or the cautious rule) to combine information.

3.1.9. Differences when using Bayesian inference

In order to expose the advantages of belief functions compared to Bayesian inference, differences are discussed below when using probabilities instead of belief functions in proposed methods.

Created messages. A created message is a 5-tuple (S, t, d, ℓ, P), where $P(\exists) = BetP\{m\}(\exists)$ and $P(\nexists) = BetP\{m\}(\nexists)$. For example, instead of a simple mass function $\exists^{0.6}$, the probability function is $P(\exists) = 0.8$ and $P(\nexists) = 0.2$. Partial or total ignorance cannot be represented with probabilities, they are replaced by precise probability degrees on hypothesis (or singletons), which is equivalent to a precise statistical knowledge.

Discounting operation. Discounting consists in distributing the part of ignorance equitably to $\exists$ and $\nexists$. Let's consider the mass function $\exists^{0.6}$ and the discounting rate 0.2. The resulting discounted mass function is the mass function $\exists^{0.48}$. The equivalent discounted probability function is $P(\exists) = 0.74$ and $P(\nexists) = 0.26$: discounting rate being 0.2, first 20% of probabilities is removed (the result is $P(\exists) = 0.64$ and $P(\nexists) = 0.16$), then distributed equitably.

Reinforcement operation. Concerning reinforcement, let us consider the mass function $\exists^{0.6}$ and the reinforcement rate 0.2. The resulting reinforced mass function is the mass function where $m(\exists) = 0.48$, $m(\nexists) = 0.2$ and $m(\Omega) = 0.32$. The equivalent reinforced probability function is $P(\exists) = 0.64$ and $P(\nexists) = 0.36$: reinforcement rate being 0.2, 20% of $P(\exists)$ is transferred to $P(\nexists)$.

Information fusion. The fusion of two probability functions using Bayes' theorem is equivalent to the fusion of mass functions having only singletons as focal sets using the conjunctive rule of combination (7) followed by a normalization. In other words, probabilities on each singleton are multiplied then normalized. The resulting pignistic probability (10) when using belief functions gives the same result.

Let e_1 and e_2 be two pieces of evidence. Using Bayesian approach, the a posteriori probability resulting of these information combination is the following [5, 1]:

$$P(\exists|e_1, e_2) = \frac{P(e_1, e_2|\exists)P(\exists)}{P(e_1, e_2|\exists)P(\exists) + P(e_1, e_2|\nexists)P(\nexists)}\ , \tag{11}$$

where $P(e_1, e_2|\exists) = P(e_1|\exists)P(e_2|\exists)$ and $P(e_1, e_2|\nexists) = P(e_1|\nexists)P(e_2|\nexists)$.

Compared to the conjunctive rule of combination, Bayesian approach requires additional knowledge which is difficult to determine:

- The a priori probabilities $P(\exists)$ and $P(\nexists)$ are respectively the probability that the event exists and the probability that it does not exist, in the absence of evidence.
- The a posteriori probability $P(e_i|\exists)$ is the probability that e_i confirms the presence of the event, given that it is present; and the a posteriori probability $P(e_i|\nexists)$ is the probability that e_i confirms the absence of the event, given that it is absent.

In addition, there is no equivalent rule to the cautious rule of combination in probabilities.

Conclusion. Compared to probabilities, the theory of belief functions is more rich and flexible; it allows representing and manipulating uncertain information more easily. Ignorance can be represented and discounting operation is more simply used with belief functions. With the Bayesian inference, information fusion requires additional knowledge which can be difficult to obtain in vehicular networks.

3.2. Experiments

3.2.1. Performance measure

For each type t of event and for each vehicle v, the performance of methods are measured by the adequacy to the reality of the information given to the driver.

Formally, at each time step τ, 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 $E_t^{v,\tau}$. Performance rates are computed for each type t of event and for each vehicle v by:

$$Perf_t^{v,\tau} = 1 - \frac{\sum_{e \in E_t^{v,\tau}} (BetP_e^{v,\tau}(\{\exists\}) - R_e^\tau)^2}{\mid E_t^{\tau,v} \mid}\ , \tag{12}$$

where:

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

3.2.2. Simulator and method parameters

The experiments are realized using a developed Matlab$^{\text{TM}}$ simulator [40]. 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.

We consider that the length of an accident cell is 50 meters and a traffic lane is composed of 12 accident cells. The used map in scenarios n°1 and n°2 is composed of 3 lines and 3 columns of traffic lane couples (two directions). In scenario n°3, it is composed of 4 lines and 4 columns of traffic lane couples as illustrated in Figure 11.

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. Scenarios are tested with different values of accident duration obtained from this normal distribution.

Note that the maximum speed of all vehicles is fixed at 45 km/h. All vehicles circulate at this speed when no slowing down event is present. Vehicles speed decreases of: 90% on the cells where an accident is present; 70% before a roundabout (67 meters before the roundabout).

3.2.3. Tested methods

The six proposed methods using belief functions are tested and compared through 3 different scenarios described in next sections.

They are also compared to a simple method, denoted "Method n°7: keep only the last message yes/no", where:

- messages inform if "yes" or "no" an event is present with a confidence degree equal to 100%;
- only the last message (the most recent one) is considered and kept in vehicle database and it is given as a result to the driver.

3.2.4. Scenario n°1

Scenario n°1 description. In this scenario, an accident occurs at the beginning of each simulation.

A vehicle v receives from distinct sources four messages just after their creation:

- The first message informs that the accident is present; it is created at 30% of the accident duration after its beginning.
- The second message confirms that the accident is present; it is created at 70% of the accident duration after its beginning.
- The third message is created at 30% of the accident duration after its disappearance, it denies the accident presence.
- The last message informs that the accident is absent; it is created at 50% of the accident duration after its disappearance.

10 series of 20 simulations are tested. In each series, 20 accident durations (an accident duration per simulation) are obtained randomly from the normal distribution $D \sim \mathcal{N}(1800, 300^2)$.

Scenario n°1 results. For the vehicle v and the accident event type, for each method, the average over all the simulation of the adequacy to the reality is illustrated in Figure 9 for each launch of the first series of 20 accident durations.

These tests are repeated 10 times (200 simulations in total). The mean of the average and the mean of the standard deviation of the adequacy to the reality are presented in Table 2 for each method.

These tests show that when the threshold Del_t can be fixed, the used reinforcement mechanism outperforms the discounting operation, which is less in line with the accident disappearance. In addition, the discounting mechanism supposes that over time, the probability of the event presence is equal to the

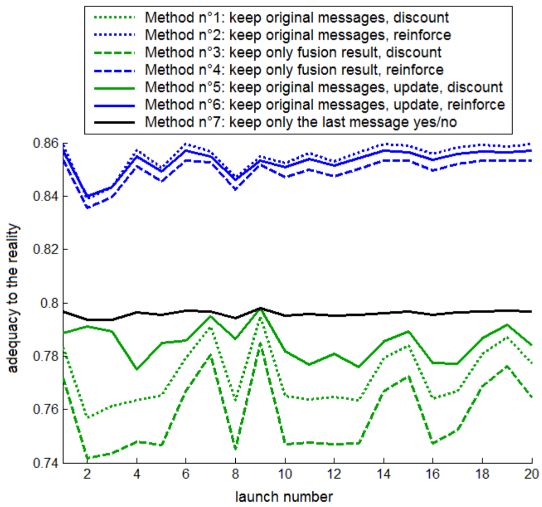


Figure 9: Local events scenario n°1: the average of the adequacy to the reality for each simulation of the first series.

Table 2: Local events scenario n°1: 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	0.772(0.00998)	0.666(0.00225)	0.826(0.0159)
Method n°2	**0.856**(0.00522)	0.618(0.0185)	**0.976**(0.0147)
Method n°3	0.758(0.012)	0.666(0.00222)	0.805(0.019)
Method n°4	0.85(0.00439)	0.619(0.0166)	0.967(0.0136)
Method n°5	0.783(0.00601)	0.666(0.00225)	0.843(0.00967)
Method n°6	0.854(0.00439)	0.618(0.0185)	0.975(0.0137)
Method n°7	0.796(0.000917)	**0.697**(0.00104)	0.847(0.001)

probability of the event absence, even if the discounted message denies the presence of the accident. This mechanism does not manage correctly messages denying an event, the probability of the event presence should remain as low as possible instead of increasing over time.

When original messages are kept in vehicle database, before receiving the first message denying the accident, methods considering the world update give the same result as methods not considering the world update. After receiving messages denying the accident, methods n°5 and n°6 stop considering old messages confirming the presence of the event. When using the discounting operator, the world update mechanism improves the performance result. But it is not the case when using the reinforcement operator, because when the world update is received, the result of the old messages reinforced is closer to $m_{\nexists}$ than the result of the new message denying the accident.

With the simple method n°7, created messages have a confidence equal to 100%, and in this scenario messages denying the presence of the accident are received. For these reasons, this method gives good results, but it has bad results after the disappearance of the accident until receiving a first message denying the accident.

When only the fusion result is kept in vehicle database, messages are not finely managed in order to consider their obsolescence. For this reason, methods using this strategy give a worse result than the other methods: with the discounting operator before the disappearance of the accident, and with the reinforcement operator after its disappearance.

3.2.5. Scenario n^{o}2

Scenario n^{o}2 description. The aim of this scenario is to compare the proposed strategies for managing messages (keep original messages or only fusion results) in a scenario where dependent and independent messages are received. Methods n^{o}1 to n^{o}4 are tested.

In this scenario, an accident occurs at the beginning of each simulation.

It proceeds as follows:

- A vehicle v_1 perceives the accident and creates a message at 10% of the accident duration after its beginning; this message is communicated to vehicles v_2 and v_3 just after its creation.
- The vehicle v_2 perceives the accident and creates a message at 20% of the accident duration after its beginning; v_2 communicates with vehicle v just after this message creation.
- The vehicle v_3 perceives the accident and creates a message at 30% of the accident duration after its beginning; v_3 communicates its database with vehicle v just after this message creation.

When original messages are kept in vehicle database, vehicle v stores in its database original messages created by v_1, v_2 and v_3. When only fusion result is kept, v receives the fusion of messages created by v_1 and v_2 (combined conjunctively) then the fusion of messages created by v_1 and v_3 (combined conjunctively); v combines these fusion results with the cautious operator because the source v_1 is common.

Like in the previous scenario, 10 series of 20 simulations are tested. In each series, 20 accident durations are obtained from the normal distribution $D \sim \mathcal{N}(1800, 300^2)$.

Scenario n^{o}2 results. For one series of 20 tests, the average over all the simulation of the adequacy to the reality is illustrated in Figure 10 for each launch and each method.

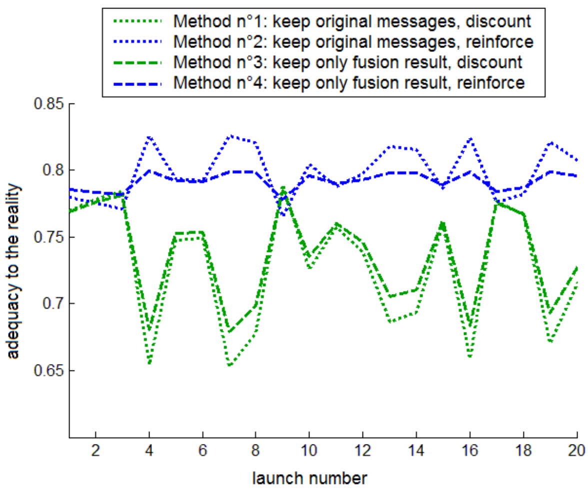


Figure 10: Local events scenario n^{o}2: the average of the adequacy to the reality for each simulation of the first series.

These tests are repeated 10 times (200 simulations in total). The mean of the average and the mean of the standard deviation of the adequacy to the reality are presented in Table 3 for each tested method.

The results of this scenario confirm the conclusions of the previous scenario.

Cautious operator was used in this scenario when only fusion result is kept in vehicle database.

When the discounting operator is used, the belief of the accident presence is lower with method n^{o}3 compared to method n^{o}1. For this reason the result before accident disappearance is better with method n^{o}1, and method n^{o}3 is more performant after accident disappearance.

Table 3: Local events scenario n°2: 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	0.719(0.0606)	**0.758**(0.00223)	0.686(0.0399)
Method n°2	**0.799**(0.0239)	0.604(0.0544)	**0.995**(0.00913)
Method n°3	0.731(0.0451)	0.739(0.00158)	0.725(0.0906)
Method n°4	0.79(0.00851)	0.61(0.494)	0.972(0.0227)

When the reinforcement operator is used, the belief of accident presence decreases rapidly, and the disappearance of the accident is better predicted when original messages are kept in vehicle database. The second method gives the best result.

In some simulations, results of methods using discounting operator are close to results of methods using reinforcement operator. This is due to the accident duration which is very long compared to the fixed mean duration.

3.2.6. Scenario n°3

Scenario n°3 description. In this scenario, 3 accidents are present on the map with a large number of vehicles.

Because of the simulation duration using the developed Matlab^{TM} simulator, all methods are tested once and the accident duration follows a normal distribution $D \sim \mathcal{N}(600, 100^2)$ (reduced accident duration). The obsolescence threshold is therefore revised : $Del_t = 832.63$ seconds.

This scenario is exposed in Figure 11. Two subscenarios are tested, they differ in the density of vehicles.

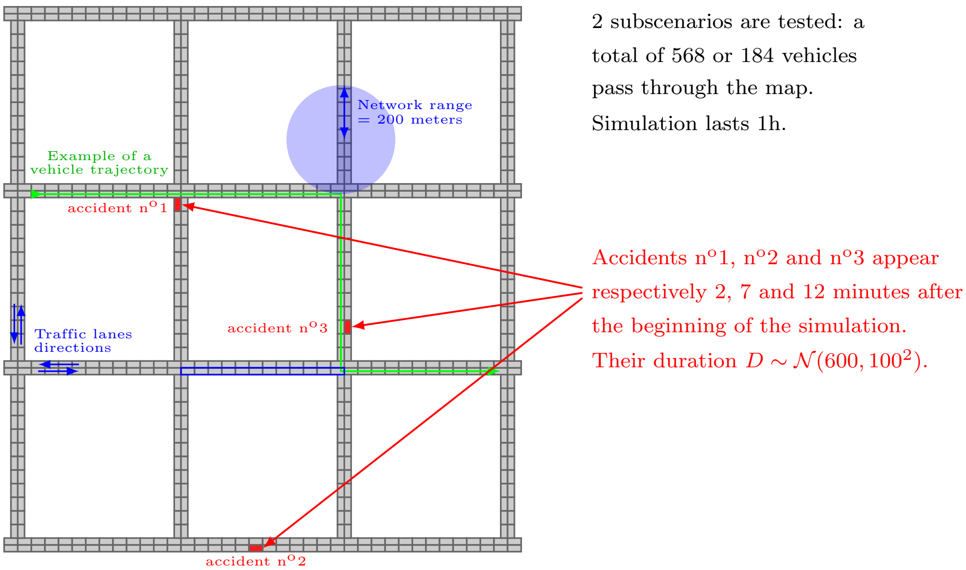


Figure 11: Local events scenario n°3: description of the reality.

Scenario n°3 results. For all vehicles, the average over all the simulation of the adequacy to the reality is illustrated in Table 4 for each method.

Results confirm the following:

- Strategy where original messages are kept in vehicle database allows managing finely messages.

Table 4: Local events scenario n°3: average over all the simulation of the adequacy to the reality.

	568 vehicles	184 vehicles
Method n°1	0.785	0.705
Method n°2	0.882	**0.791**
Method n°3	0.805	0.698
Method n°4	0.845	0.772
Method n°5	0.848	0.728
Method n°6	**0.883**	0.79
Method n°7	0.875	0.755

- When the obsolete threshold can be fixed, the proposed reinforcement mechanism predicts better the disappearance of local events, compared to the discounting operator which is usually used in the theory of belief functions. With the latter, even messages denying events tend to the total ignorance over time.
- The world update improve results according to the aged mass function acquired before the reception of a first message informing of the accident disappearance. In a dense environment, where messages informing of the world update rapidly, this strategy allows to improve results.

4. Credal methods for handling traffic jams

4.1. Methods description

Two methods are proposed for handling traffic jams. They are based on proposed methods in previous section for handling local events; only differences are exposed in this section. These methods are adapted to the specifications of traffic jams which are their dynamics and spatiality.

In the first method, original messages are kept in vehicle database. In the second one, only fusion result is kept for each event. Other aspects of these methods are common for both methods.

4.1.1. Manage the dynamics of traffic jams

The duration of a traffic jam is very random. Some last only few minutes and others can last few days, as the longest traffic jam of history which lasted 11 days in Beijing in 2010 [14].

The duration of traffic jams is difficult to predict. For this reason, it is important to update information in vehicle database when more recent information contradicting the acquired knowledge in vehicle database is received. In addition, no aging mechanism is employed, the threshold Del_t is used only to delete obsolete messages. It can be fixed according to a maximum value known from a historic knowledge (4 hours for example).

The world update mechanism is exposed in previous section by Algorithm 1 when original messages are kept in vehicle database. This mechanism is the same when only fusion result is kept in vehicle database, but its algorithm differs by checking only one message (the fusion result) instead of all messages concerning an event e in vehicle database. Algorithm 2 presents the procedure of the world update mechanism when only fusion result is kept in vehicle database for each event e.

This mechanism is used to handle traffic jams in both proposed methods. It is the first treatment processed when a new message is created or received as shown in Figure 6 and Figure 7.

4.1.2. Manage the spatiality of traffic jams

Traffic jam event is a spatial event. It evolves in the reverse direction of traffic lanes and disappears in the same direction of roads.

When vehicle database contains information about some parts of the road, it is possible to predict overall road situation. An *influence mechanism* is proposed in order to improve the overview of the road situation given to driver. Its result is not exchanged with other vehicles.

Algorithm 2 Procedure of world update when only fusion result is kept in vehicle database.

Require: Event $e = (t, c)$ with t the type of the event and c the cell where the event is located; a new message $M_{e,n}$.

begin

if $(BetP\{M_e.m\}(\{\exists\}) > 0.5$ and $BetP\{M_{e,n}.m\}(\{\nexists\}) > 0.5)$ or $(BetP\{M_e.m\}(\{\nexists\}) > 0.5$ and $BetP\{M_{e,n}.m\}(\{\exists\}) > 0.5)$ **then**

  if $M_{e,n}.d > M_e.d$ **then**

    {World update.}

    $M_e \leftarrow M_{e,n}$.

  else

    Do not consider $M_{e,n}$ (treatment of $M_{e,n}$ is canceled before the process of messages management).

  end if

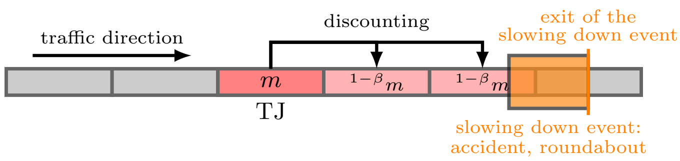
end if

end

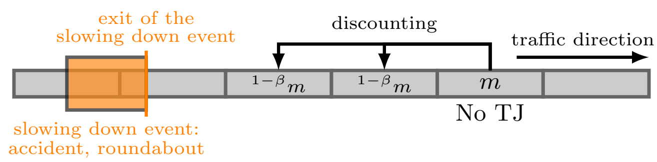
The generation of influences can be explained in the following manner: Let β_t be the influence rate. For each cell c on which vehicle has information about the presence or the absence of a traffic jam event, let m be the result of the fusion of mass functions of all stored messages concerning this event ($\circledcirc^{\alpha_{e,i}} M_{e,i}.m$ when original messages are kept in vehicle database and ${}^{\alpha_e}M_e.m$ when only fusion results are kept: Figure 6 and Figure 7). The influence of m is the discounted mass function ${}^{1-\beta}m$ where $1 - \beta$ is the discounting rate.

- If m informs that a traffic jam is present on the cell c, generate influences on following cells and stop this operation when arriving to a slowing down event exit (Figure 12(a)).
- If m informs that a traffic jam is not present on the cell c, generate influences on previous cells and stop this operation when arriving to a slowing down event exit (Figure 12(b)).

Note that a slowing down event can be: related to map infrastructures and always present on the map (the map is known by all vehicles) as a roundabout; or an event on the road known in vehicle database like an accident.



(a) Case of a mass function m in favor of the presence of a traffic jam (TJ): $BetP\{m\}(\{\exists\}) > 0.5$.



(b) Case of a mass function m in favor of the absence of a traffic jam (No TJ): $BetP\{m\}(\{\nexists\}) > 0.5$.

Figure 12: Illustrations of influence mechanism to manage traffic jams spatiality.

The influence mechanism consists for each cell c in combining conjunctively: obtained influences on cell c and the result of the combination of mass functions of all created or received messages ($\circledcirc^{\alpha_{e,i}} M_{e,i}.m$ when original messages are kept in vehicle database and ${}^{\alpha_e}M_e.m$ when only fusion results are kept: Figure 6 and 7). Note that the world update is considered before combining this information.

The pignistic probability regarding the presence of the event is then computed to give an overview of the road situation to driver.

4.1.3. Summary of proposed methods

Two methods using belief functions are proposed to manage traffic jams. They are summarized in Table 5.

Table 5: Methods summary dealing with traffic jams.

Methods	Combination
Method n°1: keep original messages, update, influence	conjunctive
Method n°2: keep only fusion result, update, influence	conjunctive, cautious

The difference between proposed methods stands on the messages management: with method n°1, original messages are kept in vehicle database; with method n°2, only the fusion result is kept in vehicle database for each event.

In both methods, the world update is considered and the influence mechanism is processed.

In previous work [25, 13], 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 evolves and disappears according to the roads and their traffic direction.

4.2. Experiments

Two scenarios are tested using the developed Matlab™ simulator. Parameters of traffic jam experiments are the same of those fixed for accident experiments, except the traffic lane length which is set to 804 meters in the first scenario and 402 meters in the second one. In addition, we consider that the length of a traffic jam cell is 67 meters; and the used map is composed of 3 lines and 3 columns of traffic lane couples.

4.2.1. Scenario n°1: test the influence mechanism

Scenario description. The aim of the first scenario is to test the influence mechanism. The reality concerning events on the road is described in Figure 13.

Axis τ is the time axis, knowing that the time stamp $\Delta\tau$ is equal to 4 seconds: $\tau = 1$ corresponds to 4 seconds after the beginning of the simulation, $\tau = 2$ corresponds to 8 seconds after the beginning of the simulation, $\tau = t$ corresponds to $4 \times t$ seconds after the beginning of the simulation.

In this scenario, 151 vehicles pass through the illustrated traffic lane, where an accident appears at the beginning of the simulation and disappears 99×4 seconds after its beginning. Only 16 vehicles create messages and communicate.

This accident generates a traffic jam progressively on cells n°7, n°8, n°6, n°5, n°4 and n°3. At $\tau = 73$, all these cells are congested. Accident disappears at $\tau = 99$, and the traffic is transferred on cells preceding the roundabout at $\tau = 103$ on cells n°7 to n°12. The traffic jam is then resorbed progressively; it disappears completely from the traffic lane at $\tau = 147$. Corresponding instants of events appearance and disappearance are exposed in τ time axis in Figure 13.

A vehicle v receives the following messages:

- At $\tau = 39$: a first message informing that the accident is present.
- At $\tau = 58$: a message informing that a traffic jam is present on cell n°5.
- At $\tau = 103$: a message informing that the accident in absent.

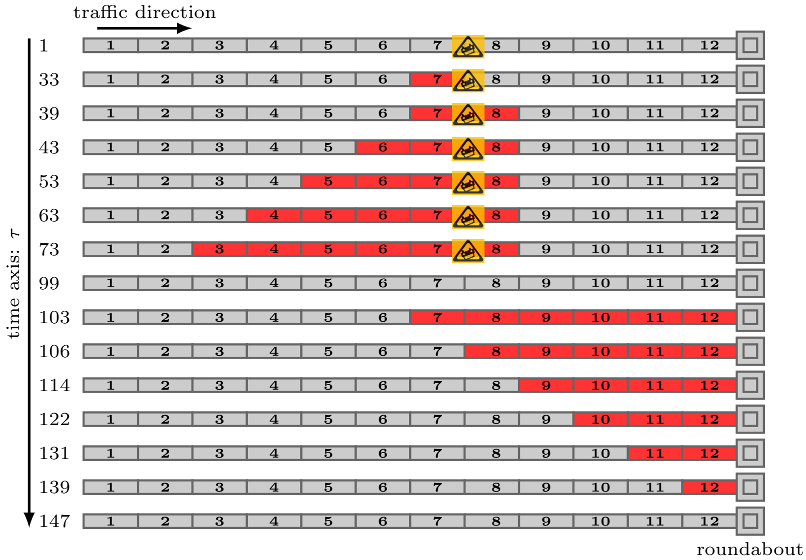


Figure 13: Traffic jams scenario n°1: description of the reality concerning events.

- At $\tau = 115$: a message informing that a traffic jam is present on cell n°9.
- At $\tau = 139$: a message informing that the traffic jam is absent from the cell n°11. A message denying an event is created by a vehicle when the database of this vehicle tells the contrary. This message is created only when the influence mechanism is used. When the influence mechanism is not used, vehicle does not have information about the cell n°11, for this reason no message is created to deny this information.

Scenario results. The overview given to driver is illustrated in Figure 14 with and without the use of the influence mechanism. Note that the colors of cells are associated to the values of pignistic probabilities. More the color of a cell is closed to red, more the pignistic probability regarding the presence of the event is important.

Influences of the received information concerning cell n°5 are generated on cells n°6 and n°7; the generation is stopped when arriving to a slowing down event. After receiving at $\tau = 103$ the message denying the presence of the accident, the influences of the message concerning cell n°5 are generated until the roundabout; it predicts the transfer of the traffic. Then, when a message denying the presence of the traffic jam is received, it allows predicting the disappearance of the traffic jam on all previous cells.

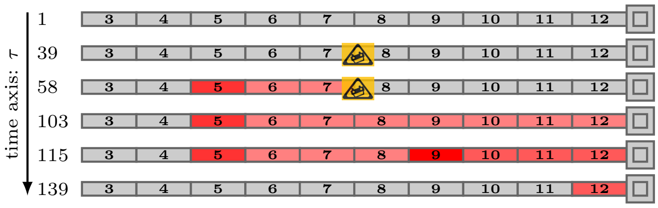
The average of the adequacy to the reality for all communicating vehicles (16 in total) is exposed in Table 6 with and without applying the influence mechanism.

Table 6: Traffic jams scenario n°1: average of the adequacy to the reality for all communicating vehicles.

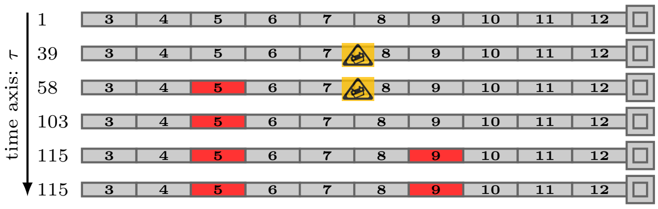
Methods n°1 and n°2: keep original messages or fusion results, update, influence	0.548
Keep original messages or fusion results, update	0.343

This scenario illustrates how the proposed influence mechanism improves results. It allows better predicting the overall road situation when information is acquired concerning only some parts of the road.

Note that in this scenario, where at more one message is created for each traffic jam cell, results do not depend on the messages management strategy (keep original messages or only the fusion result for each event).



(a) Keep original messages or fusion results, update, influence.



(b) Keep original messages or fusion results, update.

Figure 14: Traffic jams scenario n°1 : overview given to driver of vehicle v.

4.2.2. Scenario n°2: compare the proposed methods

Scenario description. The aim of the second scenario is to compare the proposed methods: strategy where original messages are kept in vehicle database and strategy where only fusion result is kept for each event.

The reality concerning events on the road is described in Figure 15.

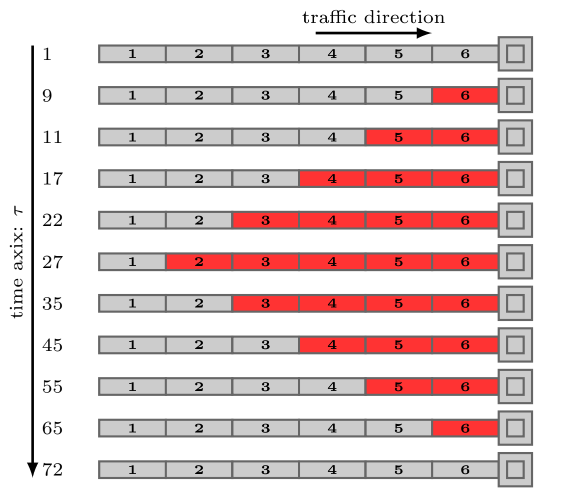


Figure 15: Traffic jams scenario n°2: description of the reality concerning events.

In total, 131 vehicles pass through a traffic lane. The flow rate is equal to 1 vehicle per second during 2 minutes, then 0.1 vehicle per second. Vehicles are slowed down before the roundabout. A traffic jam appears progressively on the road on cells n°2 to n°6, and disappears a few minutes later. Only 15 of these vehicles create and exchange messages: they create as soon as possible messages to inform of the road situation.

Scenario results. The average of the adequacy to the reality for all communicating vehicles (15 in total) is exposed in Table 7 for each method.

Table 7: Traffic jam scenario n°2: average of the adequacy to the reality for all communicating vehicles.

Method n°1: keep original messages, update, influence	0.88191
Method n°2: keep only fusion result, update, influence	0.88185

The first method manages finely messages, but the performance difference is not important enough. In a dense environment, where a big amount of information is exchanged, the strategy where only fusion result is kept for each event allows saving bandwidth and internal memory. This strategy is more adapted in this environment, where usually traffic jams can be present.

5. Manage fog blankets influences

Unlike traffic jams, the spatiality of fog blankets does not depend on maps. To manage this spatial event, roads are divided into cells, without taking into account traffic directions. In other words, if a fog blankets event is present on a traffic lane, it is also certainly present on its opposite. The influences of a fog blankets event concern surrounding cells, without any certainty of its presence or its absence.

In order to best manage influences of fog blankets events, two strategies are proposed in this section. An example is then provided to illustrate these strategies as well as their differences.

The first strategy is inspired from Lang and Muller work [25]. The second ont is a new strategy proposed to ensure a better adequacy of influences to the reality.

5.1. First strategy: inspired from Lang and Muller work [25]

On each cell on which information is acquired in the vehicle database, this strategy consists in influencing previous and following cells gradually.

On a cell c, let m be the mass function obtained before applying the influence mechanism. The cells preceding and following c are denoted c_{-1} and c_{+1} respectively.

This strategy consists in influencing these cells by discounting m. The obtained result is ${}^{1-\beta}m$ where β is the influence degree.

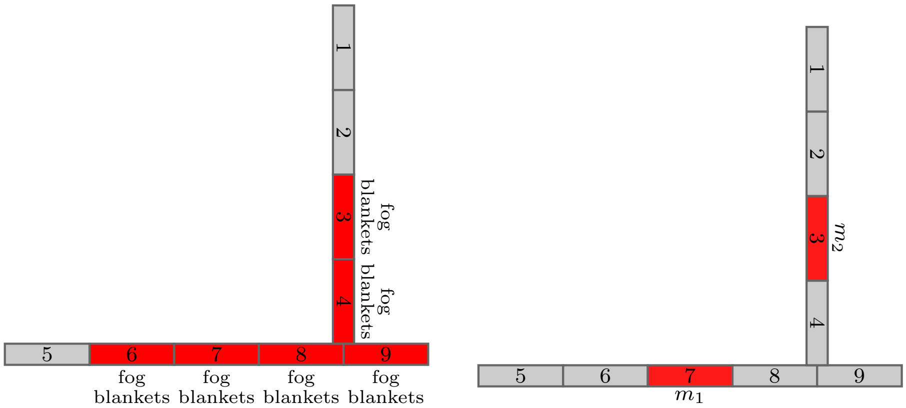
This operation is performed several times. It stops on cells located at a distance greater than the mean of fog blankets expansion (according to historical knowledge). For example, the result of influence attributed to the cell preceding c_{-1} and to the cell following c_{+1} is the mass function ${}^{1-\beta}{}^{1-\beta}m$.

5.2. Second strategy: a new strategy to ensure a better adequacy of influences to the reality

The second strategy consists in generating influences of fog blankets events for each couple of cells on which non contradicting messages have been received.

Let m_a and m_b be the mass functions informing of fog blankets events on cells c_a and c_b respectively. If m_a and m_b inform both of the presence or both of the absence of a fog blankets event, and the distance between the centers of cells c_a and c_b is less than the mean of the fog blankets expansion, influences of the couple (c_a, c_b) are generated as follows:

- Let $C_{a,b}$ be the circle which have as a diameter the segment formed of the centers of c_a and c_b cells.
- All the cells having a center located in the circle $C_{a,b}$ are influenced.
- The influence is obtained by discounting mass functions m_a and m_b, then combining them conjunctively. The result is the mass function ${}^{1-\beta}m_a \textcircled{\cap} {}^{1-\beta}m_b$, where β is the influence rate.



(a) Reality concerning events.

(b) Vehicle database before applying an influence mechanism.

Figure 16: Fog blankets scenario: description.

5.3. Example illustrating the differences between proposed strategies

Figure 16 illustrates the description of the scenario. Fog blankets events are present on six cells (illustrated with red color) on the map in the reality. A vehicle receives messages informing about the presence of fog blankets on two cells: m_1 and m_2 are the mass functions of the received messages informing about the cells n°3 and n°7 respectively.

The result of the first strategy is exposed in Figure 17. This mechanism allows predicting fog blankets on preceding and following cells. But the generated influences can contradict the reality. In this scenario, the influences generated on cells n°1, n°2 and n°5 do not match with the reality.

The result of the second strategy is illustrated in Figure 18. Contrary to the first strategy, the second one does not generate false influences in this scenario.

However, the second strategy does not allow predicting fog blankets on all preceding and following cells: it does not predict this event type on cells n°6 and n°9.

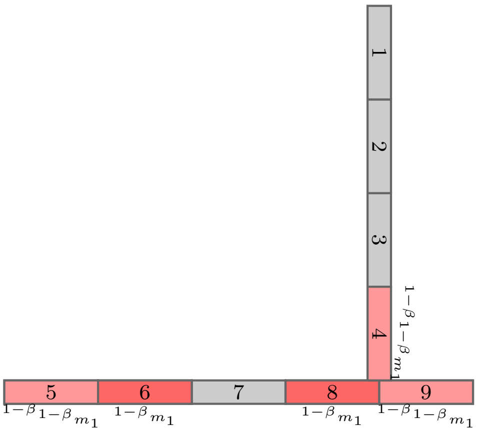
In order to best predict the reality, the objective of the second strategy is to generate influences when the vehicle database holds enough information. This strategy avoid the generation of false influences. It is more suitable than the first one to tackle fog blankets events which spatiality is difficult to master. Of course, to validate them, it remains to test these two strategies on more complex scenarios in future work.

6. Conclusion and future work

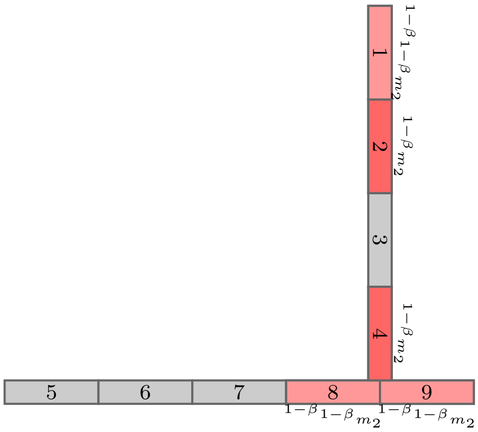
In this paper, different methods have been proposed to exchange and manage information about local events and traffic jams on the road in V2V communications using belief functions. Different strategies are compared to manage as best as possible fusion of acquired information, messages agings of local events and dynamics and spatiality of traffic jams.

Different scenarios have been tested in order to compare proposed strategies, using a developed Matlab$^{\mathrm{TM}}$ simulator.

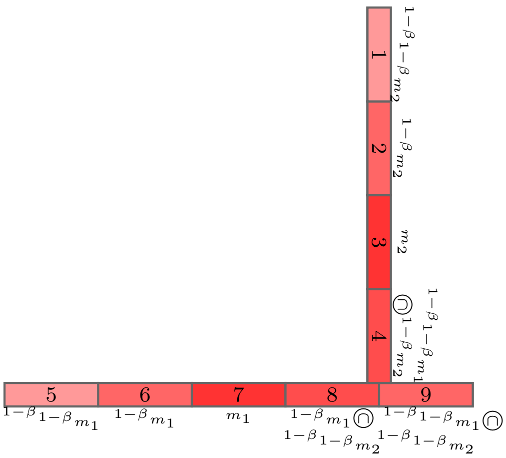
Results show that the proposed reinforcement operator predicts better the messages agings, compared to the discounting operator usually used with belief functions. When original messages are kept in vehicle database, they can be managed more finely; but the strategy where only fusion results are kept, is more adapted to traffic jams events which often occur in dense environment where it is essential to save bandwidth and internal memory. The world update mechanism does not always improve results, but it allows managing the dynamics of traffic jams which have a highly variable duration. Finally, the proposed influence mechanism



(a) Influences of the mass function m_1.

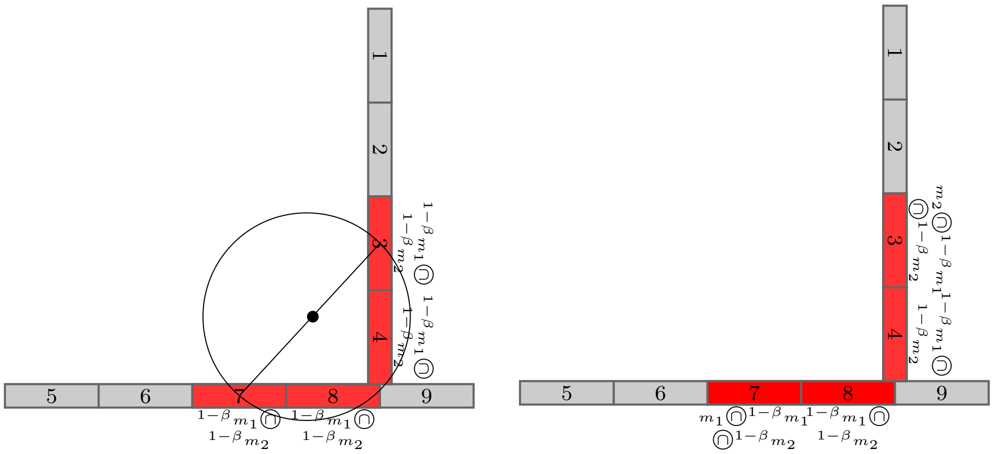


(b) Influences of the mass function m_2.



(c) Overview given to driver when applying the first strategy to generate influences.

Figure 17: Fog blankets scenario: results when applying the first strategy to generate influences.



(a) Influences of the couple (m_1,m_2).

(b) Overview given to driver when applying the second strategy to generate influences.

Figure 18: Fog blankets scenario: results when applying the second strategy to generate influences.

allows improving the overview of the overall road situation given to driver. It takes into account roads and traffic directions to generate influences.

Two different strategies have been proposed to manage fog blankets influences without considering traffic directions. They are compared through an example. Spatiality of fog blankets events are difficult to master. In order to avoid the generation of false influences, the best suitable strategy consists in generating influences only when vehicle database holds a confirmation of the event in the neighborhood.

The theory of belief functions is more rich and flexible than its Bayesian counterpart, however it is more computationally demanding. In [15] and references herein there is a theoretical study showing that belief functions outperform the Bayesian approach in case of high uncertainty, the two models leading to the same results in case of precise knowledge.

In future work, irregular areas must be considered and proposed influence mechanisms to tackle fog blankets must be tested.

The used simulator is a research tool; a more realistic one has to be used in future work. The authors can utilize TraNS [38] or NCTUns [29] simulators: the first one combines SUMO [37] (mobility simulator) and NS-2 [30] (network simulator) simulators; the second one includes in a single module mobility and network simulations.

Finally, methods should also be tested, and surely adapted, when malicious nodes are present.

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