Hindawi
Journal of Advanced Transportation
Volume 2020, Article ID 4607858, 14 pages
https://doi.org/10.1155/2020/4607858

Research Article

Improving Driver Assistance in Intelligent Transportation Systems: An Agent-Based Evidential Reasoning Approach

M. Benalla, B. Achchab, and H. Hrimech

Laboratoire Analyse et Modélisation des Systèmes et Aide à la Décision ENSA de Berrechid, Université Hassan 1er de Settat, Settat, Morocco

Correspondence should be addressed to B. Achchab; boujemaa.achchab@uhp.ac.ma

Received 10 July 2019; Revised 10 November 2019; Accepted 22 November 2019; Published 4 January 2020

Academic Editor: Maria Vittoria Corazza

Providing accurate real-time traffic information is an inherent problem for intelligent transportation systems (ITS). In order to improve the knowledge base of advanced driver assistance systems (ADAS), ITS are strongly concerned with data fusion techniques of all kinds of sensors deployed over the traffic network. Driver assistance is devoid of a comprehensive evidential reasoning system on contextual information, more specifically when a combination involves inside and outside sensory information of the driving environment. In this paper, we propose a novel agent-based evidential reasoning system using contextual information. Based on a series of information handling techniques, specifically, the belief functions theory and heuristic inference operations to achieve a consensus about daily driving activity in automatically inferring. That is quite different from other existing proposals, as it deals jointly with the driving behavior and the driving environment conditions. A case study including various scenarios of experiments is introduced to estimate behavioral information based on synthetic data for prediction, prescription, and policy analysis. Our experiments show promising, thought-provoking results encouraging further research.

1. Introduction

Intelligent transportation systems are settled with the objective to overcome some classical problems related to traffic management and also to improve the user experience often on a complex network. ITS range back to 90s with the first program of intelligent vehicle highway society (IVHS) [1, 2]. The goal of such systems is to strengthen the links between all components of the traffic network, for instance, vehicles, infrastructure, and traffic signals, based on next-generation technologies. ITS aim to be equipped with as many sensors as possible. Therefore, huge masses of heterogeneous data are generated providing sufficient multidimensional valuable real-time traffic information.

Current research is addressing data fusion techniques for traffic management [3]. As a result, a deep interest arises to study their use in ITS. The information required to comprehend the traffic state with all its constituents comes from multiple sources [4]. The fusion of such sources is perceived, rightly, as a well-adapted answer to the operational needs of traffic management centres and traffic information operators, allowing them to achieve their goal more efficiently [3]. However, various challenges arise when one is interested in large-scale traffic networks, mainly in mathematical and computational models. A lot of overlapping information is involved in the inference process making context measuring not willingly depicted either by logical formalism or by classical probabilistic estimates [5].

Research work in the field of data fusion in ITS revolves principally around 8 fields [3, 6]: advanced traveller information systems (ATIS), automatic incident detection, advanced driver assistance (ADA), network control, crash analysis and prevention, traffic demand estimation, traffic forecasting, and traffic monitoring and accurate position estimation.

In this paper, we address the problem of evidential reasoning on contextual information for driver assistance. Evidential reasoning basically means reasoning with evidence. Its potential usefulness is in handling a wide variety of uncertainty analysis problems using belief functions theory. In [7], decision-making in belief functions framework is reviewed. The author discloses useful approaches that can be used in reasoning-based evidence. Moreover, evidential reasoning has been applied in many systems for activity recognition [8, 9]. The basic premise of using evidential reasoning for situation identification is as follows. Firstly, sensor readings are used as evidence and translated into context within an activity model or network. Secondly, fusion operations of the former are performed to determine more complex patterns in the activity of interest [9].

Over the last decade, there has been active research on how to represent and exploit context or contextual information in evidential reasoning. Contextual information is a novel topic in multisensor data fusion that allows, by the use of specific and expert information in the world of interest, to enhance the classical detection algorithms and improve performance of reasoning process. In other words, contextual information is a translation of the information source throughout nodes of reasoning network or process using heuristic inference operations (HIO). Devlin [10] takes this view, defining context as follows: a feature $\mathscr{F}$ is contextual for an action $\mathscr{A}$ if $\mathscr{F}$ constraints $\mathscr{A}$ and may affect the outcome of $\mathscr{A}$, but not a constituent of $\mathscr{A}$. The reader is referred to [11] for more details with regard to contextual information. Thus, context is a powerful information source and can be used both to transform source data into information and knowledge and also to acquire knowledge.

In this context, we present a novel distributed intelligent evidential reasoning system for ADA applications. The solution takes advantage of contextual information, thereby various sensory information are combined using Dempster–Shafer theory (D-S) or belief functions theory including HIO. It is a multilevel fusion-based approach where at each level, many agents constantly cooperate. They collect and process data from the driving environment and communicate them to a higher level in charge of the inference process using evidential reasoning. Accordingly, rule-based knowledge is provided both for driver assistance and traffic management center.

The remainder of this paper is organized as follows. Section 2 reviews several publications related to our proposal. In Section 3, we give the evidential reasoning approach on the basis of D–S theory, including HIO. Section 4 presents the case study and scenarios of experiments. In Section 5, we summarize the findings and outline future research. In Appendix, an illustrative example of case study using the proposed evidential reasoning based on contextual information is provided.

2. Related Work

The application of data fusion techniques in transportation systems was started in the earlier 90s. R. Sumner is the first scholar to discuss the importance of use of such techniques for effectiveness in some ITS projects, more precisely in *Pathfinder* and *TravTek* projects [12]. Right after, many research studies have been undertaken with a goal to expand a substantial corpus of theoretical and practical results in the area. Subsequently, useful guidelines are available to researchers and practitioners in further applications of data fusion techniques in ITS fields. The authors in [3, 13] have proposed a comprehensive survey about progress and challenges made in different ITS fields that use data fusion methods. In the sequel, we highlight research works related to our proposal.

ATISs have been created with the prodigious need for accurate, timely information to help road traffic users to decide on their destinations and reach them quickly and safely [14]. The Advance project has been one of the first ITS projects using data fusion techniques [14]. Research works with the same extent are proposed in the literature and are intended together to address travel time estimations and predictions using different data sources such as loop detectors, probe vehicle, GPS, Laser scanner, optical sensor, and QoS indicators [6, 15, 16]. They incorporate different data fusion engines such as D-S theory [17–20]. ADA is also another active research field influenced by data fusion techniques. The purpose of ADA is to improve the passengers' safety as well as to reduce drivers' interaction in dynamic environments often caused by imprecise decision-making or errors associated with the human nature. Most of the works focus on localization and tracking of driving behavior to maintain the driver guidance throughout routing [21–25]. The Kalman filtering, Support Vector Machine, Naive Bayesian, Gaussian Mixture models, and Neural Networks are of common practice in this class of problems.

However, the use of contextual information in conjunction with evidential reasoning remains poor within ADA applications. The authors in [26] propose a multilevel information fusion approach by setting some properties of D–S theory. Their aim is to detect road congestion applied to vehicular ad hoc networks (VANETs). The work of [27] suggests an approach to extract the lane marking information for the technology of vehicle to infrastructure (V2I) by combining two types of sensors. The works in [28, 29] deal with uncertainties aspects encountered in road safety assessment. On another side, the authors in [30] investigate the problem of transportation of dangerous goods by addressing the accident probability under conflicting situations with the help of Dempster's rule of combination.

The application of evidential reasoning for driver assistance using contextual information, to the best of our knowledge is a new research area and this study serves as the first step in this direction. In this context, we provide a formal framework for reasoning with perceptual data using a body of techniques specifically designed for manipulating and reasoning from evidential information. To achieve this goal, we have used a layered and modularized system design, in which sensory information from the automotive environment is combined with careful thought to driving behavior. The intention behind this work is to propose an effective up-to-date solution able to improve the driver assistance using a comprehensive evidential reasoning framework.

3. Evidential Reasoning Approach

3.1. Main Approach. The present work provides enhanced driver assistance by means of a comprehensive evidential reasoning framework with contextual information. An association is therefore established between inside and outside sensory information of driving environment. Both sensors used here belong to the anonymous and binary class [31]. Inside sensory information (in-vehicle sensors) defines reaction with physical properties of vehicles, such as acceleration and braking. Outside sensory information (out-vehicle sensors) defines indicators with straight influence on driving operation, such as traffic intensity and weather conditions. Moreover, out-vehicle sensors pertain to indicators of smart cities services used to research and develop smart mobility inside cities. In general, smart cities are set-up on 74 indicators, 31 factors, and 6 characteristics [32].

In order to combine the aforementioned sensory information, only Dempter–Shafer theory is not sufficient since such a combination produces imprecise and disaggregated information. Consequently, decision-making becomes less accurate and leads to wrong actions and hence the obvious need to include heuristic inference operations to improve the clarity of inference.

The evidential reasoning approach proposed in this research extends the state-of-the-art data fusion models [33, 34] by the use of contextual information for recognition enhancement. It is a multilevel reasoning solution for ADA applications. In Figure 1 is shown the solution including two main parts. The left-hand side part models the activity of interest based on inside sensory information. The right-hand side takes action of exogenous factors that affect the activity of interest based on outside sensory information. There are several links for evidential reasoning. We distinguish between connection, association, and transition among evidential reasoning network components as given in legend in Figure 1. Each of them carries meticulous function to the inference stages. Thus, each component constitutes a reasoning node and contributes to the overall evidential reasoning process.

As it is highlighted previously, evidential reasoning implementation is agent-driven. Following that out-vehicle sensors are modelled with a fully connected graph $\mathscr{K}_n$, $n \in 1;6$, $\mathscr{G} = (\mathscr{S}, \mathscr{E})$ as illustrated in Figure 2. $\mathscr{S}$ is the set of vertexes and of $\mathscr{E}$ is the set of edges. Each $S_v \in \mathscr{S}$ embodies one service of smart cities which can be mobility, environment, living, and so on. Each service can provide at least one indicator based on outside sensory information. Sensory information is collected using convenient agents, an example of indicator the traffic density pertaining to Mobility service. An edge, $e \in \mathscr{E}$: $e = (S_v, S_w)$ joining S_v to S_w, corresponds on one hand to multisensor data to be combined between vertexes S_v and S_w and on the other hand to the *agent* that connects those vertexes. In a formal term, $A_{(S_v,S_w)}$ denotes the agent with a task of data amalgamation between the pair (S_v, S_w). Multisensor data fusion is supported by Dempster's rule of combination, whereas transition among components of evidential reasoning network is performed with the help of HIO. In the sequel, we present all mathematical operations required to apply evidential reasoning for data association as shown in legend of Figure 1.

3.2. Basics of Dempster–Shafer Theory. Dempster–Shafer theory is a mathematical theory of evidence [35]. It is used to handle incomplete information in doubt situations. This theory captures and combines whatever certainty or knowledge exists in the event classification capability of the information sources [15].

The frame of discernment is the main part of this theory. It is named so because all bodies of evidence are expressed relative to this surrounding framework [5]. Let Θ be the frame of discernment and 2^Θ the power set that comprises all subsets of Θ including the empty set $\varnothing$. If $\Theta = E$, then we have

$$\mathscr{P}(E) = 2^E = \left\{E_i \mid 1 \le i \le 2^{|E|}, E \ne \varnothing\right\}. \quad (1)$$

E_i is a subset of E, called a focal element. The frame of discernment allows for distributing supports for propositions over the frame using a mass function. E is a frame of discernment, then a function m: $2^E \mapsto [0,1]$ is called a basic probability assignment (bpa) whenever

$$\begin{gathered} m(\varnothing) = 0, \\ \sum_{E_i \subseteq E} m(E_i) = 1. \end{gathered} \quad (2)$$

$m(E_i)$ is called a basic probability number of E_i. It is the measure of evidence or belief that is committed exactly to E_i.

In D-S theory, two independent mass functions m_1 and m_2 can be combined using Dempster's combination rule. It is used to find the conjunction of the events and the associated bpa. Suppose E and F are two distinct bodies of evidence over a same frame of evidence H, with m_1 and m_2 the associated bpa of E and F, respectively. A new function m is formed by combining m_1 and m_2: $m = m_1 \oplus m_2$ as follows:

$$m(H_k) = (1 - C)^{-1} \sum_{E_i \cap F_j = H_k \ne \varnothing} m_1(E_i) m_2(F_j), \quad (3)$$

where

$$C = \sum_{E_i \cap F_j = \varnothing} m_1(E_i) m_2(F_j), \quad (4)$$

H_k is a subset of H and C is called the conflict coefficient and measures evidence that have empty set intersection (i.e., no data relation). The operator $\oplus$ is both commutative and associative.

3.3. Belief and Plausibility Functions. The belief and the plausibility functions are the distribution of lower and upper degrees of belief, respectively, of a proposition of interest. Thus, they induce rules based on the mass allocations for various propositions. The belief function, denoted as bel, shows the degree of belief to which the evidence supports E_i. E is a frame of discernment; then a function bel: $2^E \longmapsto [0,1]$ is a belief function if and only if

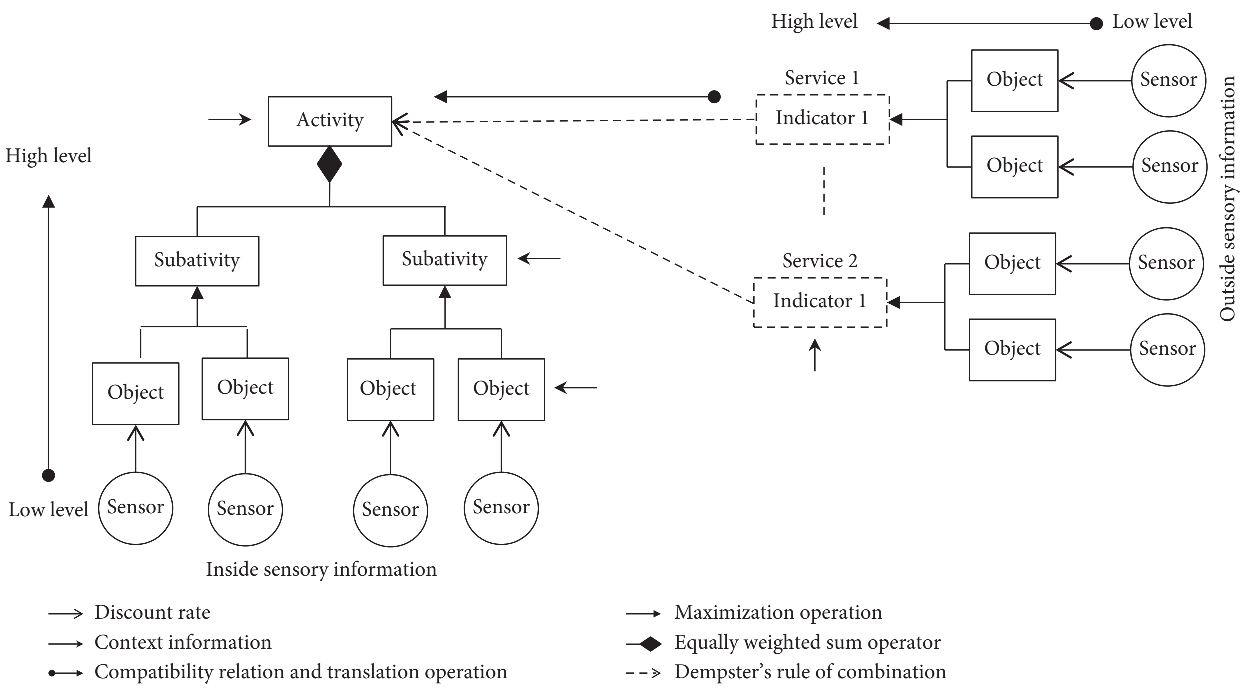

Figure 1: Evidential reasoning network for data association.

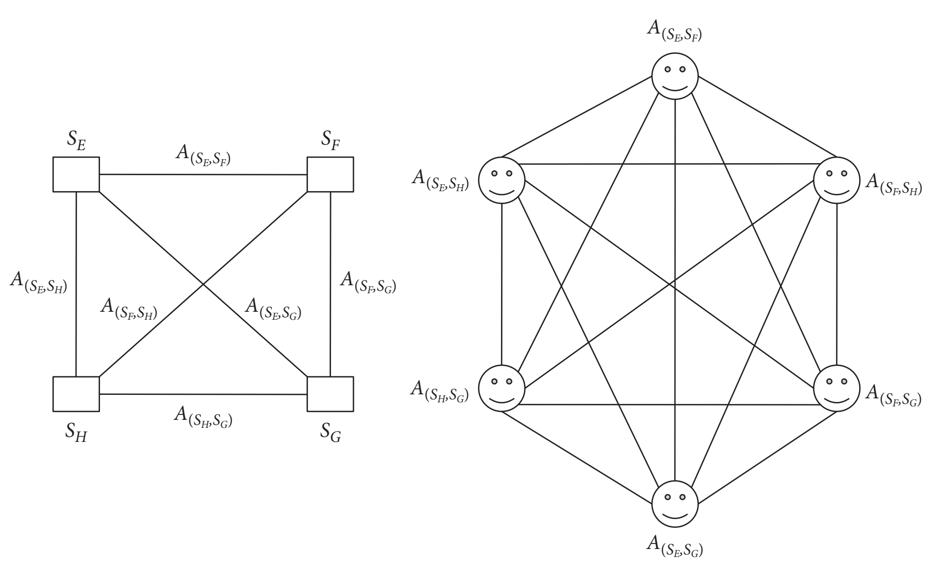

Figure 2: A graph construction for 4 smart cities services where services are associated with edges (left) or with vertexes (right).

$$\mathrm{bel}(E_i) = \sum_{E_j \subseteq E_i} m(E_j). \tag{5}$$

The plausibility function, denoted as pl, shows the degree of belief to which E_i remains plausible. E is a frame of discernment; then a function pl: $2^E \longmapsto [0,1]$ is a plausibility function if and only if

$$\mathrm{pl}(E_i) = \sum_{E_j \cap E_i \neq \varnothing} m(E_j). \tag{6}$$

3.4. Heuristic Inference Operations

3.4.1. Compatibility Relation. In evidential reasoning, the relation between two frames of evidence is defined by a compatibility relation. A compatibility relation simply describes the possibilistic relationship between two frames [35, 36]. The compatibility relation $\Theta_{E,F}$ between two frames E and F is a set of pairs of the Cartesian product of the two frames:

$$\Theta_{E,F} \subseteq E \times F. \tag{7}$$

A pair (E_i, F_j) is included in $\Theta_{E,F}$ if and only if they can be true simultaneously. There is at least one pair (E_i, F_j) included for each E_i in E (the analogue is true for each F_j in F).

3.4.2. Translation Operation. The translation operation [5] is used to transfer repeatedly the distribution mass from a frame to another, via a compatibility mapping, until it reaches the frame of question. Using the compatibility relation $\Theta_{E,F}$ we can define a compatibility mapping $C_{E\longmapsto F}$ for translating propositions relative to E to propositions of interest relative to F. Thus, if a proposition E_k is true, then the proposition $C_{E\longmapsto F}(E_k)$ is also true:

$$C_{E\longmapsto F}\colon 2^E \longmapsto 2^F, \tag{8}$$

where

$$C_{E\longmapsto F}(E_k) = \left\{F_j \,\middle|\, \left(E_i, F_j\right) \in \Theta_{E,F}, E_i \in E_k\right\}. \tag{9}$$

In translating a mass m_1 of E from a frame E to a frame F via compatibility mapping, the following computation is applied to derive the translated mass distribution m_2 of F:

$$m_2\left(F_j\right) = \sum_{C_{E\longmapsto F}(E_i)=F_j} m_1(E_i). \tag{10}$$

3.4.3. Equally Weighted Sum Operator. In some cases, beliefs distribution cannot be combined due to their nature of dependence. For instance, the composite of the following subactivities, namley, braking, acceleration, contact with gearbox, and steering wheel rotating, as we are going to see in the case study, conducts to the same activity that is Driving Activity. For such a setting, we use the equally weighted sum operator for aggregating different beliefs distribution into one composite node [37]. Assume m_i mass functions $i \in 1; n$; hence, the equally weighted sum operator is given by

$$m(E_i) = \alpha_1 m_1 \widehat{\oplus} \alpha_2 m_2 \widehat{\oplus} \cdots \widehat{\oplus} \alpha_n m_n(E_i) = \frac{1}{n}\sum_{j=1}^{n} \alpha_j m_j(E_i), \tag{11}$$

where E_i is a subset of E and $\alpha_j > 0$. α_j weights represent sources reliability.

3.4.4. Maximization Operation. The maximization operation [38] is used to calculate the aggregated belief values on a node formed from its alternatives, as for traffic density which can be measured from its delegated sensors. The maximization operation for belief functions $\mathrm{bel}(E_i)$, $\mathrm{bel}(F_j)$, and plausibility functions $\mathrm{pl}(E_i)$, $\mathrm{pl}(F_j)$, is given as

$$\begin{aligned} \mathrm{bel}(H_k) &= \mathrm{Max}\left(\mathrm{bel}(E_i), \mathrm{bel}\left(F_j\right)\right), \\ \mathrm{pl}(H_k) &= \mathrm{Max}\left(\mathrm{pl}(E_i), \mathrm{pl}\left(F_j\right)\right), \end{aligned} \tag{12}$$

where H_k is the composite of alternatives E_i and F_j. Its complement is defined acceleration as follows:

$$1 - \mathrm{Max}\left(\mathrm{bel}(E_i), \mathrm{bel}\left(F_j\right)\right) = \mathrm{Min}\left(1 - \mathrm{bel}(E_i), 1 - \mathrm{bel}\left(F_j\right)\right), \tag{13}$$

$$1 - \mathrm{Max}\left(\mathrm{pl}(E_i), \mathrm{pl}\left(F_j\right)\right) = \mathrm{Min}\left(1 - \mathrm{pl}(E_i), 1 - \mathrm{pl}\left(F_j\right)\right). \tag{14}$$

4. Experimental Data Analysis

4.1. Case Study. In appendix, we use an example to illustrate mathematically the evidential reasoning approach and we also investigate the driving activity (DA) at a small scale, including only one indicator in addition to the driving activity itself using two activated sensors. On the other hand, within this section, we focus on the same activity but at large scale including several indicators and many activated sensors. We have used synthetic data based on the discount rate, which is a metaknowledge [39–42]. The discount rate r of a source E, with $r \in [0, 1]$ is defined as follows [5]:

$$m_E^{\%} = \begin{cases} (1-r)m_E(E_i), & \text{if } E_i \neq E, \\ r + (1-r)m_E(E), & \text{if } E_i = E. \end{cases} \tag{15}$$

where

$$\begin{cases} r = 0, & \text{the source is completely reliable,} \\ r = 1, & \text{the source is completely unreliable,} \\ 0 < r < 1, & \text{the source is reliable with a rate } r. \end{cases} \tag{16}$$

Modern-day vehicles and ITS infrastructure are seen as a perfect integration of numerous sensors, each of which varies in intelligence, which all interact and look after some critical aspects of automotive environment. Driving activity consists of many subactivities, specifically braking, acceleration, contact with gearbox, and steering wheel rotation. Each subactivity is monitored by one or many sensors providing sufficient information about driver's interaction with environment. Outside sensory information are exogenous factors with straight influence on driving maneuvers such as weather conditions, conveyed by indicators pertaining to smart cities services. In the study, we have considered three smart cities services, each of which includes one indicator. The services are mobility, environment, and living; the associated indicators are given, namely, traffic density, weather conditions, and age.

Aiming at enhanced driver assistance, all sensory information undergoes an evidential reasoning process to help further explain the requirement of the monitoring environment. Indeed, driving subactivities (DSA) are used to find out what activity is most likely to have been performed in within-day driving operation by considering effects of exogenous factors.

Sensors are highly distributed; sensor configuration is very dynamic; sensors come and go; sensors' performance varies over time. Our first attempt to implement the idea of the evidential reasoning approach is through using software agents to simulate as realistic as possible the case study (see Figure 3). The simulation is performed using

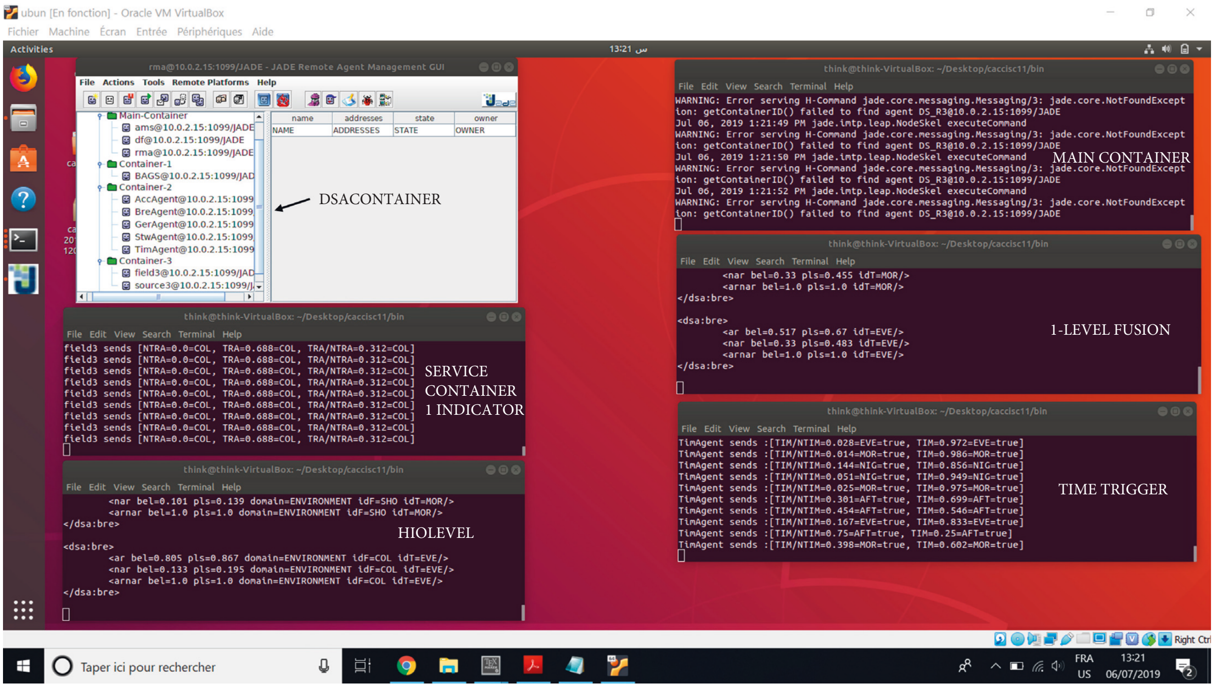

FIGURE 3: Small-scale simulation of case study as expanded in Appendix.

Jade framework; it is a container-driven platform with sophisticated speech acts and coordination.

Evidential reasoning starts over frames of evidence. A specification of the set of propositional spaces, which delimits a set of possible world situations for sensory information, is required. Sensors typically provide evidence in support of certain conclusions. Thus, a total of 7 low-level frames of evidence are involved in the case study. In Tables 1 and 2, inside and outside sensory information are given. In order to measure within-day activity, a time frame is included. This frame encompasses the four phases of day, most notably morning, afternoon, evening, and night.

For representation purposes, all sensory information elements and time frame were shrunk. For example, the sensory information *medium* and time slot *evening* have the representative form MED and EVE within the numerical results subsection. More details are given in Tables 3–7 and Appendix.

4.2. Numerical Results. At the beginning of reasoning, basic probability assignments are attributed to the most precise propositions of evidence bodies involved in the case study. For demonstration purposes, we have only listed a part of numerical results because of huge amount of outcomes. In Appendix, we give evidential reasoning steps to obtain one bel and pl value as marked by an asterisk (*) in Table 3 in the case of using HIO solely. The same applies for the case of fusion with one indicator of smart cities services as shown in Table 4. Indeed, Table 3 (case 1) gives the belief values of DA in terms of DSAs in case of no fusion (i.e., only HIO without Dempster's rule of combination), with one activated sensor (i.e., only one DSA sensor is activated) and with the time dimension, including all periods of day. Therefore, we can see that the bel values are less than 0.5 and the most frequent DSAs in DA likely performed are (a) steering wheel with an evidence of 0.314 in the morning period, (b) braking with evidences of 0.378 and 0.380 in the afternoon and evening periods, respectively, and (c) acceleration with an evidence of 0.377 in the night period. These results do not provide much useful context-aware information and are weak to be considered since the pl values of the opposite performing activity ¬DA in terms of DSAs are all more than 0.5.

This time, we consider the data fusion operation using Dempster's rule of combination including one service indicator of smart cities and with one activated sensor. Table 4 (scenario 1) gives the belief values of DA combined with the Mobility service, for the MEDIUM traffic density indicator in the night period. In comparison with Table 3 (case 1), we can clearly see that the bel values of DA are increased for all DSAs and the pl values of ¬DA are decreased for all DSAs. In addition, the most frequent DSA in DA likely performing in such conditions is acceleration with an evidence of 0.697. Similarly, we observe that in the situation of integrating other indicators of smart cities services, the bel values of DA increase and the values of the upper probability function of ¬DA (i.e., plausibility) decrease. In detail, Table 4 (scenario 2) gives the belief values of DA combined with the Environment service in the case of Cold weather in the Afternoon period, while Table 4 (scenario 3) gives the belief values of DA combined with the Living service in the case of Senior age in the Evening period. Here, the combination results provide valuable information on the driving activity. They propose novel perception ways of driving subactivities by highlighting the interaction intensity with the driving environment.

Table 1: Frames of evidence (FoE) of outside sensory information (SI).

Service	Indicator	SI				FoE	Elements of FoE	
		S_1	S_2	S_3	S_4		E_1	E_2
Mobility	Traffic density	Low	Medium	Heavy	—	TRA	TRA	¬TRA
Environment	Weather	Cold	Normal	Hot	Rain	WEA	WEA	¬WEA
Living	Age	Junior	Adult	Senior	—	AGE	AGE	¬AGE

Table 2: FoE of inside SI.

DSA	FoE	Elements of FoE	
		E_1	E_2
Braking	BRA	BRA	¬BRA
Acceleration	ACC	ACC	¬ACC
Contact with gearbox	GER	GER	¬GER
Steering wheel rotation	STW	STW	¬STW

Table 3: Belief values of DA with a number of activated sensors in all periods of day.

Case 1: one activated sensor								
(ACC)		(BRA)		(GER)		(STW)		Period of day
bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})	
*0.298	*0.702	0.307	0.693	0.259	0.741	0.314	0.686	Mor
0.342	0.658	0.378	0.622	0.294	0.706	0.322	0.678	Aft
0.353	0.647	0.380	0.620	0.353	0.647	0.296	0.704	Eve
0.377	0.623	0.340	0.660	0.355	0.645	0.303	0.697	Nig
Case 2: two activated sensors								
(ACC, BRA)		(ACC, GER)		(ACC, STW)		Period of day		
bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})			
0.531	0.469	0.533	0.467	0.512	0.488	Mor		
0.549	0.451	0.514	0.486	0.502	0.498	Aft		
0.562	0.438	0.530	0.470	0.521	0.479	Eve		
0.544	0.456	0.462	0.538	0.445	0.555	Nig		

Table 4: Belief values of DA with one activated sensor combined with one service in different scenarios.

Scenario 1: with mobility service for medium traffic in the night period				
DA/DSA	$ACC_{(nig,med)}$	$BRA_{(nig,med)}$	$GER_{(nig,med)}$	$STW_{(nig,med)}$
$bel(\{DA\})_{(tra)}$	*0.697	0.647	0.478	0.623
$pl(\{\neg DA\})_{(tra)}$	*0.303	0.353	0.522	0.376
Scenario 2: with environment service for cold weather in the afternoon period				
DA/DSA	$ACC_{(aft,col)}$	$BRA_{(aft,col)}$	$GER_{(aft,col)}$	$STW_{(aft,col)}$
$bel(\{DA\})_{(wea)}$	0.647	0.572	0.659	0.735
$pl(\{\neg DA\})_{(wea)}$	0.353	0.428	0.341	0.266
Scenario 3: with living service for senior age in the evening period				
DA/DSA	$ACC_{(eve,sen)}$	$BRA_{(eve,sen)}$	$GER_{(eve,sen)}$	$STW_{(eve,sen)}$
$bel(\{DA\})_{(age)}$	0.715	0.680	0.528	0.580
$pl(\{\neg DA\})_{(age)}$	0.285	0.320	0.471	0.420

Table 5: Belief values of DA with one activated sensor combined with different services in different scenarios.

Scenario 1: with mobility and environment services situation of medium traffic and normal weather in the evening period				
DA/DSA	$ACC_{(eve,med,nor)}$	$BRA_{(eve,med,nor)}$	$GER_{(eve,med,nor)}$	$STW_{(eve,med,nor)}$
$bel(\{DA\})_{(tra,wea)}$	0.922	0.896	0.834	0.731
$pl(\{\neg DA\})_{(tra,wea)}$	0.079	0.104	0.166	0.269
Scenario 2: *with mobility, environment, and living services situation of medium traffic, rain weather, and senior age in the night period*				
DA/DSA	$ACC_{(nig,med,rai,sen)}$	$BRA_{(nig,med,rai,sen)}$	$GER_{(nig,med,rai,sen)}$	$STW_{(nig,med,rai,sen)}$
$bel(\{DA\})_{(tra,wea,age)}$	0.918	0.946	0.908	0.955
$pl(\{\neg DA\})_{(tra,wea,age)}$	0.081	0.055	0.091	0.045

Table 6: Belief values of acceleration subactivity combined with living and environment services, in the case of junior age and hot weather in all periods of day.

DA/DSA	$\mathrm{ACC}_{(\mathrm{mor,jun,hot})}$	$\mathrm{ACC}_{(\mathrm{aft,jun,hot})}$	$\mathrm{ACC}_{(\mathrm{eve,jun,hot})}$	$\mathrm{ACC}_{(\mathrm{nig,jun,hot})}$
$\mathrm{bel}(\{\mathrm{DA}\})_{(\mathrm{age,wea})}$	0.756	0.775	0.855	0.780
$\mathrm{pl}(\{\neg\mathrm{DA}\})_{(\mathrm{age,wea})}$	0.244	0.227	0.146	0.219

Table 7: Belief values of DA with more activated sensors combined with several services in different scenarios.

Case 1: two activated sensors								
(ACC, BRA)		(ACC, GER)		(ACC, STW)		Period of day	Service	SI
bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})	bel ({DA})	pl ({¬DA})			
0.801	0.199	0.740	0.260	0.667	0.333		Mobility	Low
0.864	0.136	0.823	0.167	0.777	0.223	Aft	Environment	Hot
0.747	0.254	0.846	0.154	0.764	0.236		Living	Jun
Case 2: three activated sensors								
(ACC, BRA, STW)		(ACC, GER, STW)		(BRA, GER, STW)		Period of day	Service	SI
Bel ({DA})	pl ({¬DA})	bel ({DA})	Pl ({¬DA})	bel ({DA})	pl ({¬DA})			
0.905	0.095	0.877	0.123	0.730	0.271	Mor	Mobility	Hea
0.915	0.085	0.853	0.147	0.898	0.102	Eve	Environment	Hot

In the same fashion, the evidential reasoning process is applied using one activated sensor and more services. Table 5 (scenario 1) gives the belief values of DA where data are combined with two services, namely, Mobility and Environment, in the cases of Medium traffic and Normal weather, respectively, in the Evening period. We observe that the bel values tend toward 1 representing as a result new high beliefs that determine precisely the most likely DSA performing in DA and which is in this situation acceleration with an evidence of 0.922. Equally important, when we investigate three services such as in Table 5 (scenario 2), the bel values keep increasing and come very closer to 1. Thus, there is an average increase of evidence values of 0.588 in comparison with Table 3. In this scenario of the experiment, the awareness about the driving activity is quite high and can be taken into account. This awareness constitutes a rule-based knowledge for both decision-makers and expert systems which can have a positive influence on the overall decision-making process at the traffic management center. On the same scale, our approach further suggests the possibility to obtain results centred-sub-activity along the day. Accordingly, having a comprehensive chronological information on the oscillations is likely to hold each DSA as shown in Table 6.

As a direct result, the bel values keep increasing at each newly joined indicator of smart cities services, reducing then the imprecision and the ambiguity about the driving activity in dynamic driving environments. By the same extent, when we evaluate more than two DSAs by virtue of switching on more than one sensor as in Table 3 (case 2) and Table 7 (case 1), the bel values increase. It is very obvious here that the numbers of sensors have a significant impact on the overall result. In these scenarios, the subactivities of acceleration and braking are the most striking what it alludes to the type of interaction with the driving environment. In addition, the same observation is made when three sensors are activated, making the focus on the instant interactivity of three DSAs as shown in Table 7 (case 2). The pieces of evidence are almost certain; that is, they converge towards 1. These results provide useful learning rules about the driving behavior and reinforce decision-making in driver assistance systems. Moreover, Figure 4 gives a full insight of the amount of ambiguity narrowed on each DSA by comparing the bel and pl functions in the case of application of HIO solely and in the case of application of HIO with Dempster's rule of combination on several indicators of smart cities services.

In the final analysis, all results set out a new dimension of convenient perception of the driving activity and directly contribute to broadening the knowledge base of ITS, more precisely the driver assistance field. In addition, the results clearly show that the inclusion of other indicators of smart cities services helps to provide a better understanding of the activity of interest. The worked example reveals learning rules derived from the driving behavior which can be exploited using fuzzy logic or decision trees in favour of the domain expert. An example of use of this system is for the traffic management center to adjust the traffic flow, reduce the driver's interaction with the driving environment such as in the situation of heavy traffic, and keep efficiency in terms of performance by enhancing the safety rules of road traffic as well as the drivers' safety. Our approach may also be the subject of integration in smart mobility solutions by addressing the routing phenomenon with uncertain information for ATIS. The WAZE project by Google, the Red Swarm by the Networking, and Emerging Optimization research group at the University of Malaga [43] and the work of [44] are among smart mobility solutions based on a category of technological infrastructure that makes our solution perfectly fit in them. Thus, plans are currently in place to test the approach within those kinds of systems with a real dataset and as validation of results.

5. Agents-Driven Evidential Reasoning

To support the construction, modification, and interrogation of evidential analysis, an implementation of the evidential

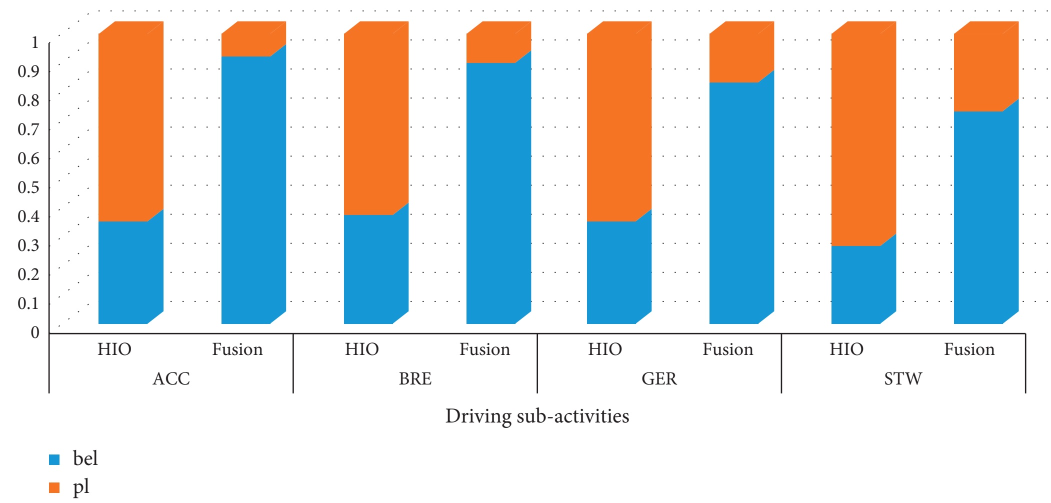

Figure 4: Stacked bel and pl functions for each DSA in the evening period.

reasoning approach is achieved using software agents. It offers a low-level setting to modify the sensors parameters (e.g.,. discount rate, enabling), to add an evidential operation by performing evidential reasoning with or without fusion, to include many services as well as indicators, and to interrogate XML files of the output data at each stage of evidential reasoning (e.g., only HIO, 1-fusion, 2-fusion).

The formal framework is divided into four parts: (a) specifying agents and their containers, each agent container delimits possible area of working; (b) defining the type of communication among agents; (c) representing mapping relation between frames of evidence; and (d) establishing evidential reasoning process from bodies of evidence. The source code is available on Google Drive link, Beta version, including a user guide for Win, Linux, and Mac OSx users. Endeavors are being undertaken to provide more features by including a graphical interface and improving the evidential reasoning process.

6. Outlook and Conclusion

Evidential reasoning provides true baselines for intelligent transportation systems. Driver assistance is now more concerned with data fusion techniques specifically using contextual information. Admitting that accurate real-time traffic information consolidates the decision-making in traffic management, needs for an evidential reasoning system on contextual information seem to be more relevant and beneficial, mainly when an association is made between inside and outside sensory information of driving environment. In this work, we have proposed a novel approach of evidential reasoning to strengthen the driver assistance. A combination method of evidence pieces is calculated using D-S theory and heuristic inference operations. Computation mechanism is developed with a multiagent system. The results seem very promising and carry elements of answers to overlapping difficult questions that are not readily deduced using classical probabilistic estimates. We could identify learning rules derived from the driving activity, subsequently improving the driver assistance.

As a concluding remark, theoretical properties of D-S theory and the compatibility relation are still to be managed more together. This is particularly useful when explaining lines of reasoning. Also, there are a number of evidential operators in the literature besides the one proposed in this research. It is interesting to apply other evidential operators and compare their performances. Finally, it may be interesting to postulate alternative to the belief functions theory, using other frameworks such as the transferable belief model and Dezert–Smarandache theory. Synthetic data are used to validate our approach; this is appreciated to be a limitation, in terms of not validating with real data.

Appendix

In this appendix we show a worked example using the proposed evidential reasoning approach based on contextual information. The example investigates improving driver assistance by the way of driving activity analysis. Outcomes are developed for one bel and pl value as marked by an asterisk (*) in Table 3 in the case of application HIO solely and the same applies for the case of fusion with one indicator of smart cities services (1-fusion level) as shown in Table 4.

For the sake of simplicity, we confine ourselves to one sensor per each subactivity and several ones per each indicator of smart cities services. Moreover, a discount rate is assigned to each sensor in the case study. Accordingly, the evidential reasoning network for data association is as follows (Figure 5).

The evidential reasoning process starts from a low level based on sensors. Data are preprocessed independently for each sensor and expanded throughout network nodes until reaching the activity of question. Hence, a sensor can have two states: *activated* or *inactivated*. Sensors surrounded in bold are those with activated state.

Θ denotes the evidence frame associated to sensor $S_i \in \mathcal{S}$, where $i \in [\![1; p]\!]$. Let s be the possibility that the sensor is activated and $\neg s$ the possibility that it is inactivated. Then,

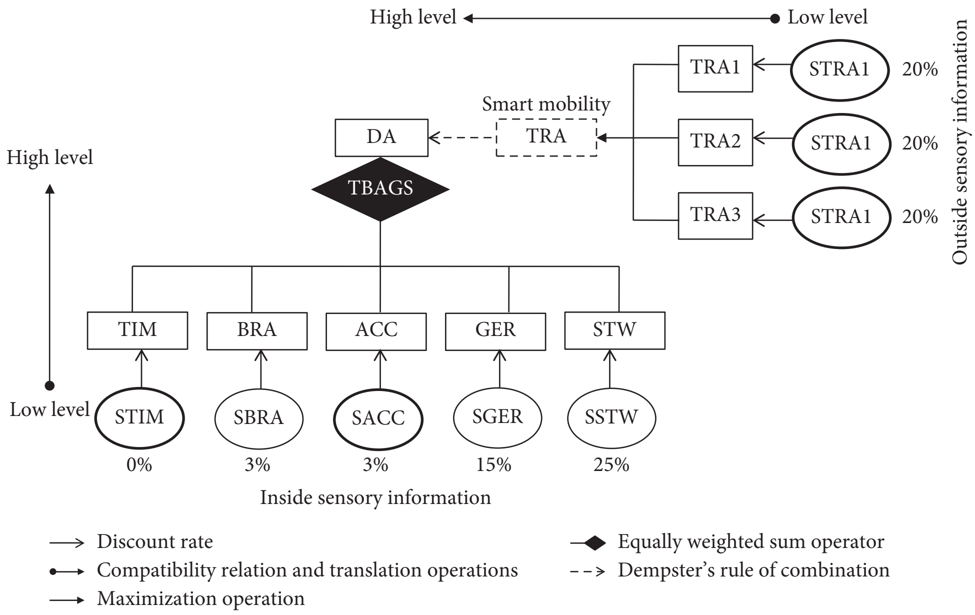

Figure 5: An example of evidential reasoning network for driving activity.

$$\Theta = \{s, \neg s\}, \tag{A.1}$$

Θ is the set of possibilities, and

$$2^{\Theta} = \{\varnothing, \{s\}, \{\neg s\}, \Theta\} \tag{A.2}$$

the set of its subsets.

Within this example, the traffic density indicator pertaining to Mobility service is chosen. Driving activity is analysed in terms of acceleration subactivity using a time slot. Also, Table 8 lists all evidence frames of sensors used in study with their associated discount rate. In the sequel, we provide the steps to follow to apply the evidential reasoning process based on network in Figure 5.

A. Step 1. Basic Probability Assignments (bpa)

At the beginning of reasoning, basic probability assignments are attributed to the most precise propositions of evidence bodies involved in the case study. Therefore, a mass function is assigned to each frame of evidence. Note that the activated sensors are surrounded in bold; hence, the bpa distribution is as follows:

$$\begin{aligned} m_{\mathrm{BRA}}(\{\neg s\mathrm{BRA}\}) &= 1; \\ m_{\mathrm{ACC}}(\{s\mathrm{ACC}\}) &= 1; \\ m_{\mathrm{GER}}(\{\neg s\mathrm{GER}\}) &= 1; \\ m_{\mathrm{STW}}(\{\neg s\mathrm{STW}\}) &= 1; \\ m_{\mathrm{TIM}}(\{\neg sTIM\}) &= 1; \\ m_{\mathrm{TRA1}}(\{\neg sTRA1\}) &= 1; \\ m_{\mathrm{TRA2}}(\{\neg sTRA2\}) &= 1; \\ m_{\mathrm{TRA3}}(\{\neg sTRA3\}) &= 1. \end{aligned} \tag{A.3}$$

B. Step 2. bpa Altered by the Discount Rate

As there is no standard method to generate the bpa, it was decided to generate them based on the discount rate. Manufacturers' statistics about anonymous and binary sensors reveals that such sensors perform with a degree of fault tolerance that differs from one type to another. Thus, by applying the discount rate formula, we have

$$\begin{aligned} m^{\%}_{\mathrm{BRA}}(\{\neg s\mathrm{BRA}\}) &= 0.97, \\ m^{\%}_{\mathrm{BRA}}(\Theta_{\mathrm{BRA}}) &= 0.03; \\ m^{\%}_{\mathrm{ACC}}(\{s\mathrm{ACC}\}) &= 0.97, \\ m^{\%}_{\mathrm{ACC}}(\Theta_{\mathrm{ACC}}) &= 0.03; \\ m^{\%}_{\mathrm{GER}}(\{\neg s\mathrm{GER}\}) &= 0.85, \\ m^{\%}_{\mathrm{GER}}(\Theta_{\mathrm{GER}}) &= 0.15; \\ m^{\%}_{\mathrm{STW}}(\{\neg s\mathrm{STW}\}) &= 0.75, \\ m^{\%}_{\mathrm{STW}}(\Theta_{\mathrm{STW}}) &= 0.25; \\ m^{\%}_{\mathrm{TIM}}(\{s\mathrm{TIM}\}) &= 1, \\ m^{\%}_{\mathrm{TIM}}(\Theta_{\mathrm{TIM}}) &= 0; \\ m^{\%}_{\mathrm{TRA1}}(\{s\mathrm{TRA1}\}) &= 0.80, \\ m^{\%}_{\mathrm{TRA1}}(\Theta_{\mathrm{TRA1}}) &= 0.20; \\ m^{\%}_{\mathrm{TRA2}}(\{s\mathrm{TRA2}\}) &= 0.80, \\ m^{\%}_{\mathrm{TRA2}}(\Theta_{\mathrm{TRA2}}) &= 0.20; \\ m^{\%}_{\mathrm{TRA3}}(\{s\mathrm{TRA3}\}) &= 0.80, \\ m^{\%}_{\mathrm{TRA3}}(\Theta_{\mathrm{TRA3}}) &= 0.20. \end{aligned} \tag{B.1}$$

Table 8: FoE and their discount rate.

FoE	Discount rate (%)
$\Theta_{BRA} = \{s\text{BRA}, \neg s\text{BRA}\}$	3
$\Theta_{ACC} = \{s\text{ACC}, \neg s\text{ACC}\}$	3
$\Theta_{GER} = \{s\text{GER}, \neg s\text{GER}\}$	15
$\Theta_{STW} = \{s\text{BRA}, \neg s\text{BRA}\}$	25
$\Theta_{TIM} = \{s\text{TIM}, \neg s\text{TIM}\}$	0
$\Theta_{TRA1} = \{s\text{TRA1}, \neg s\text{TRA1}\}$	20
$\Theta_{TRA2} = \{s\text{TRA2}, \neg s\text{TRA2}\}$	20
$\Theta_{TRA3} = \{s\text{TRA3}, \neg s\text{TRA3}\}$	20

C. Step 3. Translation Operation among Frames of Evidence

The translation operation (Section 3.4.2) is needed to transfer repeatedly the distribution mass from low levels until reaching high levels frames of evidence. To this end, using the compatibility relation as shown in Table 9, we can define a compatibility mapping to translate propositions between frames of question in the following way.

$$\begin{aligned}
m_{BRE}(\{\neg \text{BRE}\}) &= m^{\%}_{BRE}(\{\neg s\text{BRE}\}) = 0.97,\\
m_{BRE}(\Theta'_{BRE}) &= m^{\%}_{BRE}(\Theta_{BRE}) = 0.03;\\
m_{ACC}(\{\text{ACC}\}) &= m^{\%}_{ACC}(\{s\text{ACC}\}) = 0.97,\\
m_{ACC}(\Theta'_{ACC}) &= m^{\%}_{ACC}(\Theta_{ACC}) = 0.03;\\
m_{GER}(\{\neg \text{GER}\}) &= m^{\%}_{GER}(\{\neg s\text{GER}\}) = 0.85,\\
m_{GER}(\Theta'_{GER}) &= m^{\%}_{GER}(\Theta_{GER}) = 0.15;\\
m_{STW}(\{\neg \text{STW}\}) &= m^{\%}_{STW}(\{\neg s\text{STW}\}) = 0.75,\\
m_{STW}(\Theta'_{STW}) &= m^{\%}_{BRE}(\Theta_{STW}) = 0.25;\\
m_{TIM}(\{\text{TIM}\}) &= m_{TIM}(\{s\text{TIM}\}) = 1.
\end{aligned} \tag{C.1}$$

Here, outside sensory information and traffic sensory information are considered as sensors with rate identification (RI) technology. Their positions on routes make them transmitting information on the traffic state with variational identification rates. In our case, these pieces of information determine the density of traffic flow per time slot. Accordingly, a sensor of traffic provides a contextual information in the range of *low*, *medium*, and *heavy*. Sensors STRA1, STRA2, and STRA3 are supposed identified a *medium* traffic state with rates identification of 40%, 50%, and 55% respectively; then we have

$$\begin{aligned}
m_{TRA1}(\{\text{TRA1}\}) &= m^{\%}_{TRA1}(\{s\text{TRA1}\}) * \text{RI}_{STRA1}\\
&= 0.80 \times 0.40 = 0.320,\\
m_{TRA1}(\Theta'_{TRA1}) &= 1 - m_{TRA1}(\{\text{TRA1}\}) = 1 - 0.320 = 0.680,\\
m_{TRA2}(\{\text{TRA2}\}) &= m^{\%}_{TRA2}(\{\text{sTRA2}\}) * \text{RI}_{STRA2} = 0.80 \times 0.50\\
&= 0.400,\\
m_{TRA2}(\Theta'_{TRA2}) &= 1 - m_{TRA2}(\{\text{TRA2}\}) = 1 - 0.400 = 0.600,\\
m_{TRA3}(\{\text{TRA3}\}) &= m^{\%}_{TRA3}(\{s\text{TRA3}\}) * \text{RI}_{STRA3} = 0.80 \times 0.55\\
&= 0.440,\\
m_{TRA3}(\Theta'_{TRA3}) &= 1 - m_{TRA3}(\{\text{TRA3}\}) = 1 - 0.440 = 0.560.
\end{aligned} \tag{C.2}$$

Table 9: An example of compatibility relation.

Sensor frame	Object frame		
	$\{\text{BRA}\}$	$\{\neg\text{BRA}\}$	Θ'_{BRA}
$\{s\text{BRA}\}$	True	False	False
$\{\neg s\text{BRA}\}$	False	True	False
Θ_{BRA}	False	False	True

D. Step 4. Maximization Operation

The consensus about the traffic indicator is formed from the aggregated belief values coming from its delegated sources. In such a condition, we use the maximization operation as proposed by Zadeh; hence,

$$\begin{aligned}
m_{TRA}(\{\text{TRA}\}) &= \text{Max}(m_{TRA1}(\{\text{TRA1}\}), m_{TRA2}\\
&\quad (\{\text{TRA2}\}), m_{TRA3}(\{\text{TRA3}\}))\\
&= \text{Max}(0.320, 0.400, 0.440) = 0.440,\\
m_{TRA}(\{\Theta_{TRA}\}) &= \text{Min}(1 - m_{TRA1}(\{\text{TRA1}\}), 1 - m_{TRA2}\\
&\quad \cdot (\{\text{TRA2}\}), 1 - m_{TRA3}(\{\text{TRA3}\}))\\
&= 1 - \text{Max}(1 - m_{TRA1}(\{\text{TRA1}\}), 1 - m_{TRA2}\\
&\quad \cdot (\{\text{TRA2}\}), 1 - m_{TRA3}(\{\text{TRA3}\}))\\
&= 1 - 0.440 = 0.560.
\end{aligned} \tag{D.1}$$

E. Step 5. Equally Weighted Sum Operator on a Composite Node

Due to the nature of dependence of subactivities of driving activity, the beliefs distribution must be summed up into one aggregated belief. In the first place, we continue the translation operation among frames:

$$\begin{aligned}
m1_{TBAGS}(\{\text{TBAGS}\}) &= m_{TIM}(\{\text{TIM}\}) = 1,\\
m2_{TBAGS}(\{\text{TBAGS}\}) &= m_{ACC}(\{\text{ACC}\}) = 0.97,\\
m2_{TBAGS}(\{\Theta_{TBAGS}\}) &= m_{ACC}(\Theta'_{ACC}) = 0.03,\\
m3_{TBAGS}(\{\neg\text{TBAGS}\}) &= m_{BRA}(\{\neg\text{BRA}\}) = 0.97,\\
m3_{TBAGS}(\{\Theta_{TBAGS}\}) &= m_{BRA}(\Theta'_{BRA}) = 0.03,\\
m4_{TBAGS}(\{\neg\text{TBAGS}\}) &= m_{GER}(\{\neg\text{GER}\}) = 0.85,\\
m4_{TBAGS}(\{\Theta_{TBAGS}\}) &= m_{GER}(\Theta'_{GER}) = 0.15,\\
m5_{TBAGS}(\{\neg\text{TBAGS}\}) &= m_{STW}(\{\neg\text{STW}\}) = 0.75,\\
m5_{TBAGS}(\{\Theta_{TBAGS}\}) &= m_{STW}(\Theta'_{STW}) = 0.25.
\end{aligned} \tag{E.1}$$

Using the equally weighted sum operator, the following calculations are applied, where $\alpha_j = 1,\ j \in 1; m$:

$$\begin{aligned}
m_{\text{TBAGS}}(\{\text{TBAGS}\}) &= \frac{1}{n}\sum_{j=1}^{n} m_j(\{\text{TBAGS}\}) \\
&= \frac{1}{5}\left(m1_{\text{TBAGS}} \hat{\oplus} m2_{\text{TBAGS}} \hat{\oplus} m3_{\text{TBAGS}}\right. \\
&\quad \left.\hat{\oplus} m4_{\text{TBAGS}} \hat{\oplus} m5_{\text{TBAGS}}\right)(\{\text{TBAGS}\}) \\
&= \frac{1}{5}(1 + 0 + 0.97 + 0 + 0) = 0.394, \\
m_{\text{TBAGS}}(\{\neg\text{TBAGS}\}) &= \frac{1}{n}\sum_{j=1}^{n} m_j(\{\neg\text{TBAGS}\}) \\
&= \frac{1}{5}\left(m1_{\text{TBAGS}} \hat{\oplus} m2_{\text{TBAGS}} \hat{\oplus} m3_{\text{TBAGS}}\right. \\
&\quad \left.\hat{\oplus} m4_{\text{TBAGS}} \hat{\oplus} m5_{\text{TBAGS}}\right)(\{\neg\text{TBAGS}\}) \\
&= \frac{1}{5}(0 + 0.97 + 0 + 0.85 + 0.75) = 0.514, \\
m_{\text{TBAGS}}(\{\Theta_{\text{TBAGS}}\}) &= \frac{1}{n}\sum_{j=1}^{n} m_j(\{\Theta_{\text{TBAGS}}\}) \\
&= \frac{1}{5}\left(m1_{\text{TBAGS}} \hat{\oplus} m2_{\text{TBAGS}} \hat{\oplus} m3_{\text{TBAGS}}\right. \\
&\quad \left.\hat{\oplus} m4_{\text{TBAGS}} \hat{\oplus} m5_{\text{TBAGS}}\right)(\{\Theta_{\text{TBAGS}}\}) \\
&= \frac{1}{5}(0 + 0.03 + 0.03 + 0.15 + 0.25) = 0.092.
\end{aligned} \tag{E.2}$$

At this stage, the process of evidential reasoning provides information about the driving activity using only HIO. To calculate upper and lower probabilities or plausibility and belief functions, the following calculation is applied. But as always, we need to call again the translation operation on the driving activity node.

$$\begin{aligned}
m1_{\text{DA}}(\{\text{DA}\}) &= m_{\text{TBAGS}}(\{\text{TBAGS}\}) = 0.394, \\
m1_{\text{DA}}(\{\neg\text{DA}\}) &= m_{\text{TBAGS}}(\{\neg\text{TBAGS}\}) = 0.514, \\
m1_{\text{DA}}(\{\Theta_{\text{DA}}\}) &= m_{\text{TBAGS}}(\{\Theta_{\text{TBAGS}}\}) = 0.092, \\
m2_{\text{DA}}(\{\text{DA}\}) &= m_{\text{TRA}}(\{\text{TRA}\}) = 0.440, \\
m2_{\text{DA}}(\{\Theta_{\text{DA}}\}) &= m_{\text{TRA}}(\{\Theta_{\text{TRA}}\}) = 0.560.
\end{aligned} \tag{E.3}$$

Below, we give the bel and the pl values in the case of application of HIO solely. Recall that we are evaluating the driving activity in terms of acceleration subactivity. We suppose that the time sensor triggers the morning period; hence,

$$\begin{aligned}
\text{bel}(\{\text{DA}\}) &= m1_{\text{DA}}(\{\text{DA}\}) = 0.394, \\
\text{pl}(\{\text{DA}\}) &= m1_{\text{DA}}(\{\text{DA}\}) + m1_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.394 + 0.092 = 0.486, \\
\text{bel}(\{\neg\text{DA}\}) &= m_{\text{DA}}(\{\neg\text{DA}\}) = 0.514, \\
\text{pl}(\{\neg\text{DA}\}) &= m_{\text{DA}}(\{\neg\text{DA}\}) + m_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.514 + 0.092 = 0.606.
\end{aligned} \tag{E.4}$$

F. Step 6. Fusion Operation Using Dempster's Rule of Combination

The association between inside and outside sensory information—the mass function $m1$ and $m2$—respectively, is done using Dempster's rule of combination. Based on Table 10, the combination of mass functions can be calculated.

$$\begin{aligned}
m_{\text{DA}}(\{\text{DA}\}) &= m1_{\text{DA}} \oplus m2_{\text{DA}}(\{\text{DA}\}) \\
&= \frac{m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\text{DA}\}) + m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\Theta_{\text{DA}}\})}{1 - m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\neg\text{DA}\})} \\
&= + \frac{m1_{\text{DA}}(\{\Theta_{\text{DA}}\}) \cdot m2_{\text{DA}}(\{\text{DA}\})}{1 - m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\neg\text{DA}\})} \\
&= \frac{0.173 + 0.221 + 0.040}{1 - 0.226} = 0.561, \\
m_{\text{DA}}(\{\neg\text{DA}\}) &= m1_{\text{DA}} \oplus m2_{\text{DA}}(\{\neg\text{DA}\}) \\
&= \frac{m1_{\text{DA}}(\{\neg\text{DA}\}) \cdot m2_{\text{DA}}(\{\Theta_{\text{DA}}\})}{1 - m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\neg\text{DA}\})} \\
&= \frac{0.288}{1 - 0.226} = 0.372, \\
m_{\text{DA}}(\Theta_{\text{DA}}) &= m1_{\text{DA}} \oplus m2_{\text{DA}}(\Theta_{\text{DA}}) \\
&= \frac{m1_{\text{DA}}(\Theta_{\text{DA}}) \cdot m2_{\text{DA}}(\Theta_{\text{DA}})}{1 - m1_{\text{DA}}(\{\text{DA}\}) \cdot m2_{\text{DA}}(\{\neg\text{DA}\})} \\
&= \frac{0.052}{1 - 0.226} = 0.067.
\end{aligned} \tag{F.1}$$

Table 10: Product of bpa of mass functions $m1$ and $m2$.

$m2 \cdot m1$		$m1$ {DA}	$m1$ {¬DA}	$m1$ Θ_{DA}
$m2$	{DA}	0.173	0.226	0.040
	Θ_{DA}	0.221	0.288	0.053

Table 11: Belief values of DA with one activated sensor combined with mobility service.

DSA	$\text{ACC}_{(\text{mor,med})}$ Belief function		Plausibility function	
DA	$\text{bel}(\{\text{DA}\})_{\text{tra}}$	0.561	$\text{pl}(\{\text{DA}\})_{\text{tra}}$	0.628
	$\text{bel}(\{\neg\text{DA}\})_{\text{tra}}$	0.372	$\text{pl}(\{\neg\text{DA}\})_{\text{tra}}$	0.439

In addition, the bel and the pl values in this case (i.e., HIO with Dempster's rule of combination) are

$$\begin{aligned}
\text{bel}(\{\text{DA}\}) &= m_{\text{DA}}(\{\text{DA}\}) = 0.561, \\
\text{pl}(\{\text{DA}\}) &= m_{\text{DA}}(\{\text{DA}\}) + m_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.561 + 0.067 = 0.628, \\
\text{bel}(\{\neg\text{DA}\}) &= m_{\text{DA}}(\{\neg\text{DA}\}) = 0.372, \\
\text{pl}(\{\neg\text{DA}\}) &= m_{\text{DA}}(\{\neg\text{DA}\}) + m_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.372 + 0.067 = 0.439.
\end{aligned} \tag{F.2}$$

In order to check the results, it is possible to calculate the belief and plausibility functions over Θ; bel and pl of Θ is seen as the *checksum* of final results.

$$\begin{aligned}
\text{bel}(\Theta_{\text{DA}}) &= m_{\text{DA}}(\{\text{DA}\}) + m_{\text{DA}}(\{\neg\text{DA}\}) + m_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.561 + 0.372 + 0.067 = 1, \\
\text{pl}(\Theta_{\text{DA}}) &= m_{\text{DA}}(\{\text{DA}\}) + m_{\text{DA}}(\{\neg\text{DA}\}) + m_{\text{DA}}(\Theta_{\text{DA}}) \\
&= 0.561 + 0.372 + 0.067 = 1.
\end{aligned} \tag{F.3}$$

Recall that we are evaluating the driving activity in terms of acceleration subactivity, the indicator of traffic density is medium, and the time sensor has triggered the morning period. Thus, in Table 11, we summarize the result of applying of evidential reasoning approach on this example of case study.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The first author is grateful for the support provided by the "Centre National pour la Recherche Scientifique et Technique (CNRST)" of Morocco, under contract no. K005/006.

References

[1] K. J. Button and D. A. Hensher, *Handbook of Transport Systems and Traffic Control*, Emerald Insight, Bingley, UK, 2001.

[2] D. J. Dailey and P.-J. L. Patricia Harn, *ITS Data Fusion: ATIS/ATMS Regional IVHS Demonstration T9903, ITS Research Program*, 1996.

[3] N.-E. E. Faouzi, H. Leung, and A. Kurian, "Data fusion in intelligent transportation systems: progress and challenges—a survey," *Information Fusion*, vol. 12, no. 1, pp. 4–10, 2011.

[4] L. A. Klein, *Sensor Technologies and Data Requirements for ITS Applications*, Artech House, Norwood, MA, USA, 2001.

[5] J. D. Lowrance, T. D. Garvey, and T. M. Strat, *A Framework for Evidential-Reasoning Systems*, Springer, Berlin, Germany, 2008.

[6] A. Garcaa-Ortiz, S. Amin, and J. Wootton, "Intelligent transportation systems, enabling technologies," *Mathematical and Computer Modelling*, vol. 22, no. 4, pp. 11–81, 1995.

[7] T. Denæux, "Decision-making with belief functions: a review," *International Journal of Approximate Reasoning*, vol. 109, pp. 87–110, 2019.

[8] X. Hong, C. Nugent, M. Mulvenna, S. McClean, B. Scotney, and S. Devlin, "Evidential fusion of sensor data for activity recognition in smart homes," *Pervasive and Mobile Computing*, vol. 5, no. 3, pp. 236–252, 2009.

[9] S. McKeever, J. Ye, L. Coyle, and S. Dobson, "Using dempster-shafer theory of evidence for situation inference," in *Smart Sensing and Context*, P. Barnaghi, K. Moessner, M. Presser, and S. Meissner, Eds., Springer, Berlin, Germany, pp. 149–162, 2009.

[10] K. Devlin, *Confronting Context Effects in Intelligence Analysis: How Can Mathematics Help?*, Center for the Study of Language and Information, Stanford University, Stanford, CA, USA, 2005.

[11] L. Snidaro, J. Garcia, J. Llinas, and E. Blasch, *Context-Enhanced Information Fusion, Boosting Real-World Performance with Domain Knowledge*, Springer, Cham, Switzerland, 2016.

[12] R. Sumner, "Data fusion in pathfinder and travtek," in *Proceedings of the Vehicle Navigation and Information Systems Conference, 1991*, vol. 2, pp. 71–75, Florence, Italy, May 1991.

[13] N.-E. E. Faouzi and L. A. Klein, "Data fusion for ITS: techniques and research needs," *Transportation Research Procedia*, vol. 15, pp. 495–512, 2016.

[14] O. S. Jennifier Noonan, *Intelligent Transportation Systems Field Operational Test Cross-Cutting Study Advance Traveler Information Systems*, Technical Report FHWA-JPO-99-38, U.S Department of Transportation, Federal Highway Administration, Washington, DC, USA, 1998.

[15] N.-E. El Faouzi, L. A. Klein, and O. De Mouzon, "Improving travel time estimates from inductive loop and toll collection data with dempster-shafer data fusion," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2129, no. 1, pp. 73–80, 2009.

[16] K. De Mouzon and Y. Chung, "A data fusion algorithm for estimating link travel time," *Journal of Intelligent Transportation Systems*, vol. 7, no. 3-4, pp. 235–260, 2002.

[17] L. A. Klein, P. Yi, and H. Teng, "Decision support system for advanced traffic management through data fusion," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1804, no. 1, pp. 173–178, 2002.

[18] P. Teng, H. Lu, and Y. Zhang, "Rough sets and probability masses for dempster-shafer data fusion at a traffic management center," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1836, no. 1, pp. 151–156, 2003.

[19] L. A. Zhang, "Dempster-shafer data fusion at the traffic management center," in *Proceedings of the 79th Annual Meeting Transportation Research Board*, Washington, DC, USA, January 2000.

[20] S. C. Byun, D. B. Choi, B. H. Ahn, and H. Ko, "Traffic incident detection using evidential reasoning based data fusion," in *Proceedings of the 6th World Congress on Intelligent Transportation Systems (ITS)*, Toronto, Canada, November 1999.

[21] L. Yan, C. Wu, D. Zhu et al., "Driving mode decision making for intelligent vehicles in stressful traffic events," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2625, no. 1, pp. 9–19, 2017.

[22] V. Leonhardt and G. Wanielik, "Neural network for lane change prediction assessing driving situation, driver behavior and vehicle movement," in *Proceedings of the 2017 IEEE 20th International Conference on Intelligent Transportation Systems*, pp. 1–6, Yokohama, Japan, October 2017.

[23] M. Bertozzi, L. Bombini, P. Cerri, P. Medici, P. C. Antonello, and M. Miglietta, "Obstacle detection and classification fusing radar and vision," in *Proceedings of the 2008 IEEE Intelligent Vehicles Symposium*, pp. 608–613, Eindhoven, Netherlands, June 2008.

[24] F. Garcia, P. Cerri, A. Broggi, A. de la Escalera, and J. M. Armingol, "Data fusion for overtaking vehicle detection based on radar and optical flow," in *Proceedings of the 2012 IEEE Intelligent Vehicles Symposium*, pp. 494–499, Dearborn, MI, USA, June 2012.

[25] E. Martí, D. Martín, J. García, A. de la Escalera, J. Molina, and J. Armingol, "Context-aided sensor fusion for enhanced urban navigation," *Sensors*, vol. 12, no. 12, pp. 16802–16837, 2012.

[26] L. Zhang, D. Gao, W. Zhao, and H.-C. Chao, "A multilevel information fusion approach for road congestion detection in vanets," *Mathematical and Computer Modelling*, vol. 58, no. 5-6, pp. 1206–1221, 2013.

[27] X. Zhao, K. Mu, F. Hui, and C. Prehofer, "A cooperative vehicle-infrastructure based urban driving environment perception method using a d-s theory-based credibility map," *Optik—International Journal for Light and Electron Optics*, vol. 138, pp. 407–415, 2017.

[28] A. A. Rassafi, S. S. Ganji, and H. Pourkhani, "Road safety assessment under uncertainty using a multi attribute decision analysis based on Dempster-Shafer theory," *KSCE Journal of Civil Engineering*, vol. 22, no. 8, pp. 3137–3152, 2018.

[29] S. Y. Sohn and S. H. Lee, "Data fusion, ensemble and clustering to improve the classification accuracy for the severity of road traffic accidents in korea," *Safety Science*, vol. 41, no. 1, pp. 1–14, 2003.

[30] Y. Leung, R. Li, and N. Ji, "Application of extended Dempster-Shafer theory of evidence in accident probability estimation for dangerous goods transportation," *Journal of Geographical Systems*, vol. 19, no. 3, pp. 249–271, 2017.

[31] D. H. Wilson and C. Atkeson, *Simultaneous Tracking and Activity Recognition (STAR) Using Many Anonymous, Binary Sensors*, Springer, Berlin, Germany, 2005.

[32] R. Giffinger and H. Gudrun, "Smart cities ranking: an effective instrument for the positionning of cities?," *ACE: Architecture, City and Environment*, vol. 4, no. 12, pp. 7–25, 2010.

[33] J. Ye, S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: a review," *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 36–66, 2012.

[34] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: a review of the state-of-the-art," *Information Fusion*, vol. 14, no. 1, pp. 28–44, 2013.

[35] G. Shafer, *A Mathematical Theory of Evidence*, Princeton University Press, Princeton, NJ, USA, 1976.

[36] R. R. Yager, "Non-monotonic compatibility relations in the theory of evidence," *International Journal of Man-Machine Studies*, vol. 29, no. 5, pp. 517–537, 1988.

[37] S. McClean and B. Scotney, "Using evidence theory for the integration of distributed databases," *International Journal of Intelligent Systems*, vol. 12, no. 10, pp. 763–776, 1997.

[38] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.

[39] A. N. Steinberg, C. L. Bowman, and F. E. White, "Revisions to the JDL data fusion model," *Proceedings of SPIE*, vol. 3719, pp. 430–441, 1999.

[40] J. Zhu, X. Wang, and Y. Song, "A new distance between bpas based on the power-set-distribution pignistic probability function," *Applied Intelligence*, vol. 48, no. 6, pp. 1506–1518, 2018.

[41] Y. Song, X. Wang, J. Zhu, and L. Lei, "Sensor dynamic reliability evaluation based on evidence theory and intuitionistic fuzzy sets," *Applied Intelligence*, vol. 48, no. 11, pp. 3950–3962, 2018.

[42] J. Zhang and Y. Deng, "A method to determine basic probability assignment in the open world and its application in data fusion and classification," *Applied Intelligence*, vol. 46, no. 4, pp. 934–951, 2017.

[43] D. H. Stolfi and E. Alba, "Red swarm: reducing travel times in smart cities by using bio-inspired algorithms," *Applied Soft Computing*, vol. 24, pp. 181–195, 2014.

[44] J. Dallmeyer, R. Schumann, A. D. Lattner, and I. J. Timm, "Don't go with the ant flow: ant-inspired traffic routing in urban environments," *Journal of Intelligent Transportation Systems*, vol. 19, no. 1, pp. 78–88, 2015.