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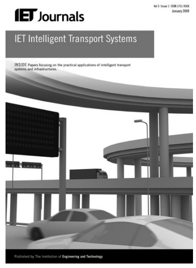

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Proactive, knowledge-based intelligent transportation system based on vehicular sensor networks

George Dimitrakopoulos, George Bravos, Mara Nikolaidou, Dimosthenis Anagnostopoulos

Department of Informatics and Telematics, Harokopion University of Athens, 89, Harokopou Street, PC: 17671, Athens, Greece
E-mail: gdimitra@hua.gr

Abstract: Information and Communication Technologies (ICT) rapidly migrate towards the Future Internet era, which is characterised, among others, by powerful and complex network infrastructures and innovative applications, services and content. An application area that attracts immense research interest is transportation. In particular, traffic congestions, emergencies and accidents reveal inefficiencies in transportation infrastructures, which can be overcome through the exploitation of ICT findings, in designing systems that are targeted at traffic/emergency management, namely Intelligent Transportation Systems. This study presents such a system that operates on the basis of collecting information from various sources (vehicles and infrastructure objects) through vehicular sensor networks, intelligently processing it, integrating knowledge and experience coming from the past and, finally, issuing directives to the driver for facilitating transportation. The overall approach is presented in detail, whereas a novel heuristic is proposed for the algorithmic process towards reaching decisions. Indicative simulation results showcase its efficiency, mostly with regards to proactively identifying a potential forthcoming danger and accordingly notifying the driver.

1 Introduction

Information and Communication Technologies (ICT) have been long standing at the forefront of international research interest. This is reflected on efforts in international projects and standardisation activities, as well as on discussions in international fora, which aim, in principle, at the provision of innovative services and applications, tailored to individualised user needs [1, 2]. The common denominator of the latest trends in networking technologies is the Future Internet (FI) [3], which will be connecting people, content and things, based on novel high throughput and low-latency network infrastructures and related technologies. The FI era envisages mechanisms that promise easier overcoming of the structural limitations of telecommunication infrastructures and their management systems, so as to further facilitate the design, development and integration of novel services and applications [4–7].

An area of applications where ICT find prosperous ground in the FI era, is transportation. The motivation for this is that many cities face a growing volume of traffic, which is associated with several unpleasant phenomena, such as time delays, high pollution, degradation of life quality, as well as accidents and emergencies. The above reveal important inefficiencies related to transportation, as identified by research community of both, public agencies and private industry [8, 9]. Those inefficiencies have established transportation management as a key service that should be offered by ICT [10–12]. In this respect, several innovative and cost-effective mobile services and applications for traffic networks are under investigation, emerging as the cornerstone of the so called Intelligent Transportation Systems (ITS) [13–16]. By enabling vehicles to communicate with each other via vehicle-to-vehicle (V2V) communication, as well as with roadside base stations via vehicle-to-infrastructure (V2I) communication, ITS can contribute to safer and more efficient roads.

In the light of the above, this paper proposes a novel transportation management approach, namely ‘i-Drive’, targeted at proactively managing vehicles and the surrounding transportation infrastructure quickly and efficiently, in a way that guarantees significant improvements in traffic/safety/emergency management.

The proposed approach combines (i) wireless sensors placed on the vehicles and on specific parts of the transportation infrastructure (traffic lights, road signs), (ii) wireless sensor networks [17, 18] formed by neighbouring vehicles and parts of the infrastructure, thus referred to as ‘vehicular sensor networks’ (VSNs) and (iii) a computationally efficient heuristic for evaluating the available information and proactively issuing directives to the drivers and the overall transportation infrastructure, which may be valuable in context handling.

The particular contribution of the paper mainly lies in the utilisation of a knowledge-based decision making algorithm, which can increase the overall levels of safety through recognising potential emergencies a priori, improving thus the total transportation quality. Moreover, it laterally also addresses the integration of the advantages of VSNs in ITS through the description of a whole framework that can incorporate various services/applications that can improve the quality of transportation.

The structure of this paper is as follows. The next section presents the motivation for this work, through an overview on the research in ITS and some open issues. Section 3 presents the 'i-Drive' components in detail. Section 4 describes the i-Drive decision making algorithm, which reflects its core. Moreover, Section 5 contains extensive simulation results that showcase i-Drive's effectiveness, whereas concluding remarks are drawn in Section 6.

2 Motivation: related work in ITS and challenges

This section presents the motivation for this work, through an overview of the ongoing related work on ITS, along with some key open issues that the i-Drive approach aims at covering.

The automotive world has been lately experiencing a trend related to the extensive use of ICT inside vehicles and in transportation infrastructures. The results of this trend are reflected on the term 'ITS' (as mentioned above), which envisages systems that are either related to road infrastructures, making the infrastructure 'intelligent', or used inside vehicles traveling on road, attributing vehicles with intelligence [19]. For example, a vehicle equipped with an ITS might be aided to avoid an emergency situation caused by another vehicle that has suddenly gone out of order, through V2V and V2I communication technologies. In this case, after gathering the necessary information, the vehicle's intelligent management system that is part of its ITS, informs the driver that he should slow down and potentially make a turn, so as to avoid hazardous implications. Intelligence lies in the ITS's proactive decision upon alternatives, which would be otherwise feasible only after the driver could see/identify the emergency.

In general, research in ITS focuses on the following areas:

(a) Traffic assessment and management, where some research efforts deal with traffic information systems based on ad-hoc networks, whereas others present centralised solutions for the traffic management and hazard recognition [20].
(b) In-vehicle and on-road safety management, which tries to assess the driving style via non-intrusive sensors – monitoring of the driver. The most popular concepts are measuring the deviation from the middle of the driving lanes or detecting conspicuous signal characteristics of the steering wheel angle [21].
(c) Driver modelling techniques, which try to provide accurate analyses of cognitive processes of drivers in semi-automated vehicles, to predict the impact of future driver assistant systems on driver workload, behaviour and safety [22].
(d) Emergency management, which can be divided in (i) management of increased traffic caused by emergency situations, and (ii) management of emergencies that directly affect the safety of the route of individual vehicles [23, 24].
(e) Additionally ITS can affect environmental effects of transportation by reducing emissions of vehicles although enhanced traffic and transportation management [25].
(f) Other areas that the research community focuses on are potential application of technologies like sensor networks or network entities' control techniques in the potential development and deployment of evolutionary ITS [21, 25].

However, despite the establishment of ITS, there is still way to go for maximising transportation efficiency and safety. The approach proposed herein aims to contribute towards this direction. This is justified as follows:

- Currently, the collection of context information, the solution of optimisation problems and the application of reconfiguration decisions is an off-line process, applied in medium (or long) time scales. However, the traffic conditions that should be handled by vehicles may frequently change, in a sudden or recurring manner. So, on the one hand, traffic needs to be assessed in real-time. On the other hand, traffic patterns resulting from a learning process could add accuracy to the messages communicated to the drivers; in this context, our approach tries to assess and exploit real-time traffic information through the (networks of) sensors and the associated decision making algorithm.
- Legacy traffic assessment and management systems are mainly centralised. Moreover, the communication among the central management entities and the vehicles is being done through internet, satellite or cellular systems. Specifically, vehicles dispose positioning systems and obtain information on the traffic situation. The driver is thus capable of deciding on the proper direction to follow. This means that, in principle, such systems are complex, as well as unsuitable for adapting, in short time scales, to context changes. The i-Drive approach, in turn, operates in a completely autonomous manner, exchanging information amongst neighbouring vehicles without any central control and policy making entity.
- Intelligence embedded in vehicles is still at a very low level and there is no assessment in the vehicle of the overall safety status that would relies on a correlation of the global traffic condition and the vehicle and driver behaviour. i-Drive contributes to a significant increase in the vehicle's intelligence, through its valuable help and support that provides to the driver a priori.

3 i-Drive description

3.1 High level description

The whole framework, in which i-Drive operates, is shown in Fig. 1. It comprises wireless sensors placed on the vehicles and on specific objects of the transportation infrastructure (traffic lights, road signs), as well as VSNs formed by neighbouring vehicles and parts of the infrastructure. Last, i-Drive utilises the potential of VSNs in ITS and validates this through an efficient heuristic.

In general, the sensors are required to decide on how to process in-vehicle data, which aggregated data are to be sent, how often etc. Sensor measurements are processed in a hierarchical manner with specialised reasoning techniques, which yield information about the vehicle–driver interactions at various abstraction levels. Moreover, the information exchanged is classified in Section 3. The communication is enabled in a V2V–VSN (among neighbouring vehicles), as well as in a V2I–VSN (between vehicles and infrastructure objects) manner and it results in information exchange transformed into collective intelligence. This intelligence is adopted by the i-Drive components, with the goal to decide upon issuing directives to the drivers and the overall transportation infrastructure. Moreover, communication, in this respect is fast (VSNs

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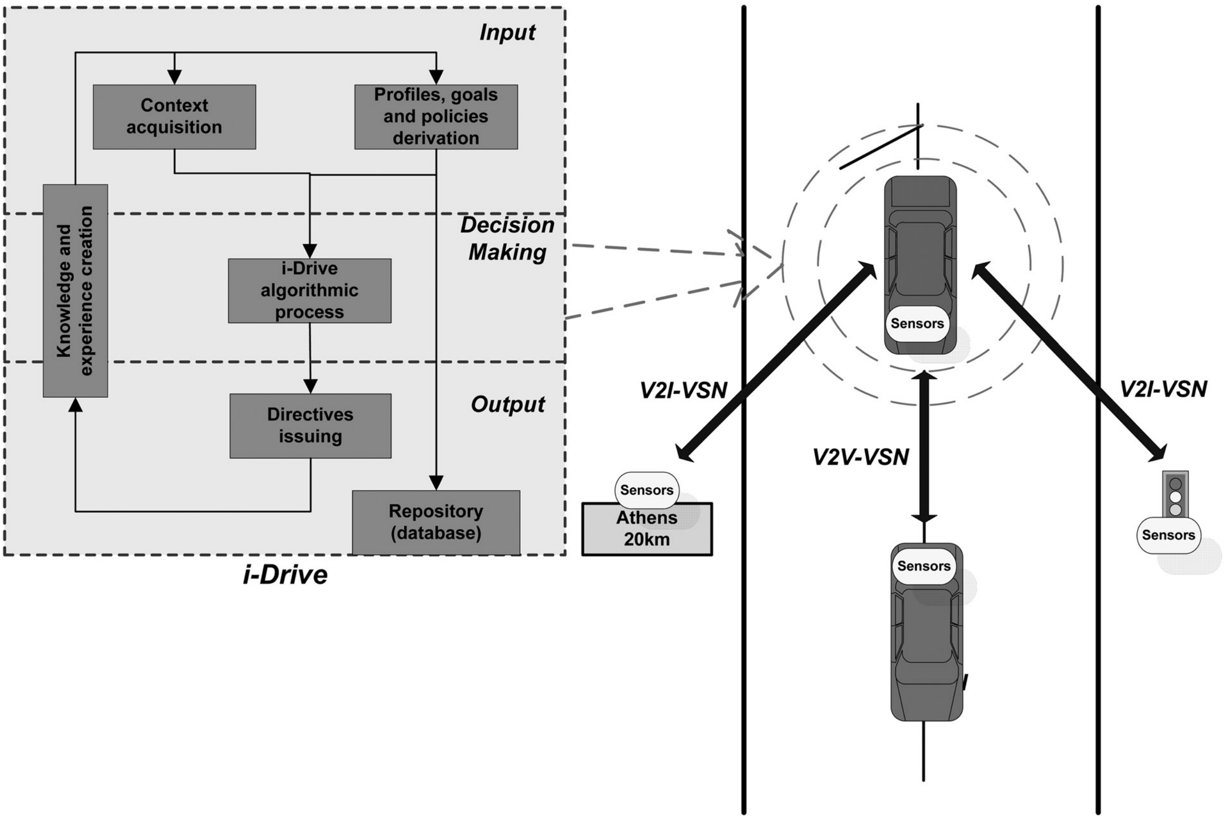

Fig. 1 *i-Drive functional architecture*

impose only a few microseconds of delay), minimising the associated time needed to reach a decision.

3.2 Detailed description of components

As shown in Fig. 1, i-Drive itself reflects an approach that disposes certain inputs and outputs, described below, whereas its description has been influenced by several related research attempts with regards to decision making [11, 13, 17, 21].

3.2.1 Input: *Context acquisition*: The input includes contextual information acquired from the vehicle's sensors and the V2V–VSNs, regarding the status of the i-Drive vehicle, its velocity, direction, neighbouring vehicles' positions, directions and velocities. Additionally, input information is acquired from the V2I–VSNs related to the condition of elements or segments of the transportation infrastructure (traffic lights, road signs, road conditions, congestion levels, overall load in telecommunications network).

Let it be noted that sensor measurements provide i-Drive with input information very often (once per microseconds, as assumed herein), so as to cater for timely delivery of crucial information to the driver. Last, information transferred to i-Drive includes time-stamps for considering also transmission delays, whereas, as mentioned also above, propagation delays are of minor importance to this paper, because of the presupposition of the reliable operation of VSNs. For the same reason, other aspects such as handling of errors are to be considered in future research attempts.

Profiles, goals and policies derivation: Last, the input includes information on the driver's profiles. To do so, a predefined set of driver states is inferred from interpreted driver monitoring data (this information is also retrieved from the vehicle sensors). In this respect, plan recognition techniques are explored to derive driver state and behaviour. This means that sequences of interactions between the driver and the vehicle, the raw signals about driver's physical condition (eye blink frequency, eyelid opening, head movement, profile, operating the foot pedals, pressing buttons on the instrument panel, steering wheel activity etc.) as well as vehicle state information, are all acquired in the form of a facial driver recognition, which allows for the detection of differences between changing driving styles. Plan recognition techniques use an algorithmic process (defined in [26]), in order to compare the diver profile parameters (mentioned below) with the set of driver states and identify the closest one.

Finally, driver's goals, priorities and policies are also included. Goals and policies aim at maximising the performance, safety, reliability and stability of the decisions taken, from an end-to-end perspective.

3.2.2 Output: *Directives issuing*: The i-Drive algorithmic process results in issuing commands (directives) towards the driver, so as to adapt the vehicle's road behaviour and tackle any emergency situations, through emergency braking or through vehicle direction correction (again based on perception and reasoning). Commands are issued in the form of alert notifications of various levels of significance, as will be shown in the sequel. Moreover, congestion can be avoided through the reconsideration of the vehicle's advisable route, as well as through notifying the driver accordingly.

i-Drive algorithmic process: Several approaches can be envisaged for the decision making process. In general, decision making should guarantee optimal safety, performance, reliability and stability, from the end-to-end perspective. Moreover, cost factors can also be addressed, this being left for future reference. As will be described below, i-Drive utilises a heuristic that can exploit the input in terms of optimising an objective function (OF) [27], which includes several aspects of the vehicle's behaviour (overall delay, mean velocity etc.).

Knowledge and experience creation: The information acquired is processed and appropriately interpreted, so as to infer knowledge and experience. To do so, all combinations of input parameters and related decisions are kept in an appropriately structured database. The knowledge model captures the following aspects:

(a) It keeps track of certain contextual situations (recurrent or emergencies) and the way they have been confronted is retained, so as to serve for future decisions.
(b) It tries to estimate what constitutes a dangerous situation, in terms of improving the specification of certain values of parameters that would be more 'subjective' than others, such as the road condition and the congestion level.
(c) It tries to estimate the importance of each parameter, judging from previous situations encountered and decisions taken, so as to gradually learn and improve the specification of parameters' weights.

Several context matching and reasoning techniques can be envisaged for this part of i-Drive, whereas the algorithm proposed in [26] is utilised herein. In particular, whenever a specific contextual situation is encountered, i-Drive performs an initial search in the appropriate part of the (classified) database, so as to check whether a similar situation has been encountered also in the past and how it has been tackled (through an optimal or suboptimal solution). In affirmative, the algorithm proposed herein does not need to run and the previous decision is applied again. Otherwise, the i-Drive algorithm needs to run and reach a decision, through the process described in the following. Since sensor measurements provide i-Drive with input information continuously, through the exploitation of knowledge and experience, the algorithm needs to run only when something changes (when the present contextual information has not been addressed before). In this respect, valuable time is saved and the overall complexity is reduced.

4 Decision making algorithm

This section describes in detail the algorithmic process utilised by i-Drive, in order to discuss the usability of the proposed approach.

The algorithm has been structured following past research attempts in the optimisation of reconfigurable and cognitive network segments, applied in transportation [2, 13]. It is thus divided into phases, for facilitating its operation.

4.1 First phase: information acquisition and classification

As mentioned also above, the number of vehicles in range is defined through the sensors that are embedded in vehicles. Let the set of vehicles in range be N. i is defined for representing a vehicle and can take values from 1 to N. Moreover, we assume that the set of vehicles in-range moving in the same direction and ahead of the i-Drive vehicle (which will be denoted as vehicle i, is N_a (thus n_a represents a vehicle of this kind and can take values from 1 to N_a), the set of vehicles in-range moving in the same direction and behind vehicle i is N_b (with n_b representing a vehicle of this kind and taking values from 1 to N_b), and the set of vehicles in-range moving in the opposite direction is N_c (with n_c representing such a vehicle and taking values from 1 to N_c). Therefore $N_a + N_b + N_c = N$.

Based on what was previously mentioned, the algorithm is based on input parameters gathered (a) from the infrastructure through the V2I–VSNs, (b) from vehicle i's own sensors and (c) through the V2V–VSNs. The set of parameters is denoted as M. Each parameter, j ($j = 1, \ldots, M$), can refer to a specific aspect. The value of parameter j of vehicle i is denoted as v_j^i (e.g. notation v_{velocity}^i denotes the current velocity of vehicle i).

The parameters are summarised in Fig. 2*a* and further categorised on Table 1. The categorisation on the table has been extracted from combining common sense with several relevant research attempts [26–28], whereas an additional normalisation process is used (see below) to cater for the further justification of this type of categorisation.

Finally, the importance of each parameter, j ($j = 1, \ldots, M$) is indicated by a weight value w_j. In principle, the sum of the w_j weights, over all $j = 1,\ldots, M$, will be one. The w_j values can constitute a vector of weights $\tilde{w}$.

4.2 Second phase: normalisation and processing

In order to proceed with the decision making process, it is necessary to quantise the aforementioned input parameters, so as to homogenise versatile parameters and collectively use the information they offer in issuing commands (decisions). This is the subject of this phase.

The information acquired from vehicle i's sensors and from the V2I–VSN is normalised to 1, so that the values closest to 1 depict a more 'dangerous' situation. In this respect, nor_{v_j} represents the normalised value of parameter j.

It holds that

$$\text{nor}_{v_j} = \frac{v_j}{5}, \quad j = 1, \ldots, M \tag{1}$$

assuming that i-Drive has been pre-set to match parameter values with five quantisation levels (see also Table 1 – an increase in the number of levels would add even more accuracy to i-Drive).

In order to normalise the values of the input parameters acquired through the V2V–VSN), we use three sets of values (arising from sets N_a, N_b and N_c) and produce three 'danger factors', denoted as F_i, $i = N_a, N_b, N_c$.

In order to calculate F_i, $i = N_a, N_b, N_c$, we need to estimate the level of danger arising from certain combinations of parameter values. For example, regarding the vehicles that move in the same direction with the i-Drive vehicle and are in front of it (set N_a), it is critical to examine if each one's velocity is less than the ith vehicle velocity and if each one's acceleration is negative (i.e. dangerously decelerating).

Based on that information, we estimate the factor F_{N_a} that is then used for the final decision.

On the other hand, concerning the vehicles behind the ith vehicle, it is critical to examine if each one's velocity is higher and each one's acceleration is positive (i.e. dangerously accelerating). So, according to that data, we estimate the factor F_{N_b}.

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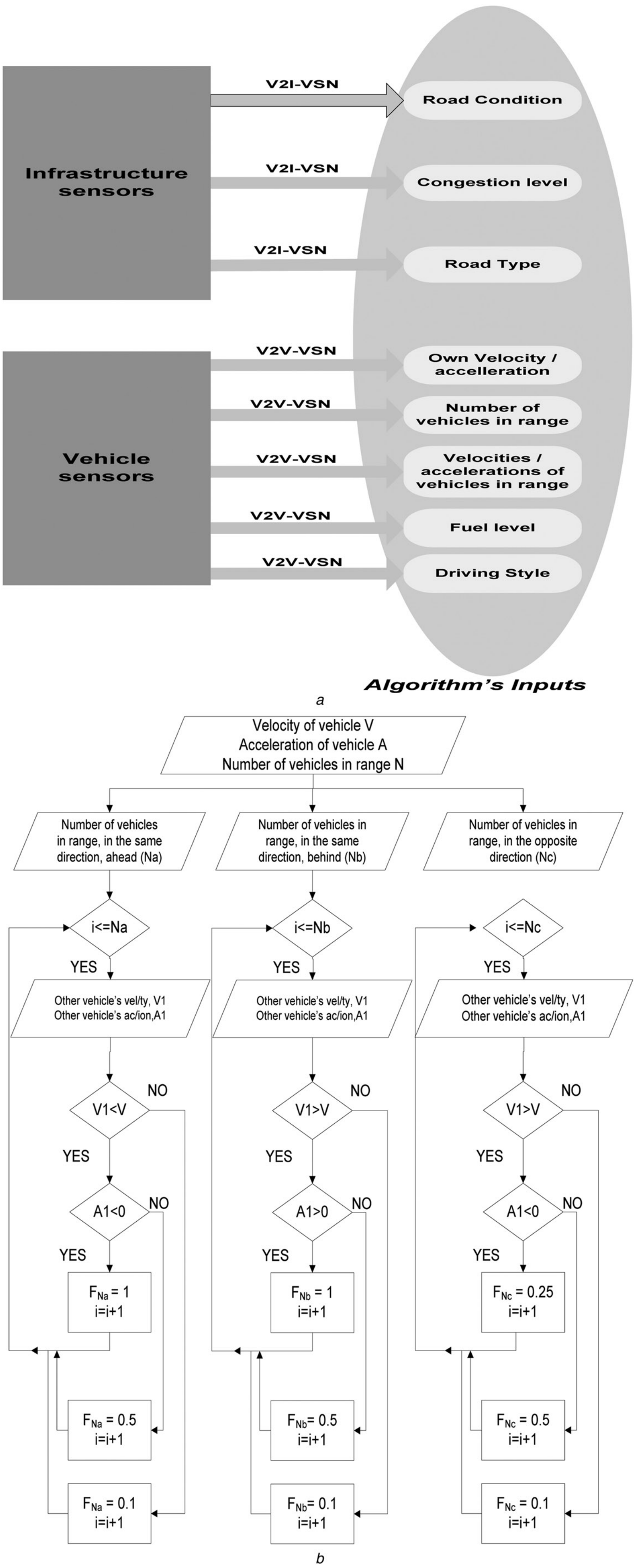

Fig. 2 *Parameters are summarised*

a i-Drive input parameters
b Process to compute Fi

Table 1 Indicative values of various input parameters

Parameter	Parameters' values				
	5	4	3	2	1
driving style	aggressive	normal-aggressive	normal	normal-passive	passive
fuel level	marginal	low	medium	high	full
road type	village road (small, maybe sand)	small city/area road, one direction	small city/area road, two directions	big road, at least two lines per direction	national road
vehicle condition	bad condition/needs service immediately	quite bad condition/ about to need service	average condition	quite good condition	very good condition/ just had service/new
road condition	snowy and windy	foggy	wet/slippery	with obstacles/ abnormalities	good
congestion level	very high	quite high	average	quite low	very low
Velocity	> 150 km/h	120–150 km/h	90–120 km/h	60–90 km/h	< 60 km/h

Finally, regarding vehicles moving in the opposite direction, the combination of high velocity and positive values of acceleration may be dangerous and is used to estimate the relative factor F_{N_c}. Let it also be noted that for estimating the level of danger of frontal collision, it would be desirable to evaluate also the directions of the vehicles, with this forming part of our future activities. However, F_{N_c} is used here only for an indicative assessment of danger.

Moreover, we assume again that values close to '1' indicate higher levels of danger (as considered also for the own vehicle and the V2I–VSN extracted parameters).

Based on the above, the values of the F_i, $i = N_a$, N_b, N_c factors used in order to make the final decision are calculated as follows

$$F_{N_a} = \sum_{\forall n_a \in N_a} k_{n_a} \frac{(v^i_{\text{velocity}} - v^{n_a}_{\text{velocity}})}{v^i_{\text{velocity}} + v^{n_a}_{\text{velocity}}} \quad (2)$$

where $k_{n_a} = 1$, if vehicle n_a is decelerating (measured through the velocities in two consecutive sensor measurements), or else $k_{n_a} = 0$, if vehicle n_a is accelerating.

In the same manner, we calculate factors F_{N_b} and F_{N_c}

$$F_{N_b} = \sum_{\forall n_b \in N_b} k_{n_b} \frac{(v^{n_b}_{\text{velocity}} - v^i_{\text{velocity}})}{v^{n_b}_{\text{velocity}} + v^i_{\text{velocity}}} \quad (3)$$

where $k_{n_b} = 1$, if vehicle n_b is accelerating (measured through the velocities in two consecutive sensor measurements), or else $k_{n_b} = 0$, if vehicle n_b is decelerating

$$F_{N_c} = \sum_{\forall n_c \in N_c} k_{n_c} \frac{(v^{n_c}_{\text{velocity}} - v^i_{\text{velocity}})}{v^{n_c}_{\text{velocity}} + v^i_{\text{velocity}}} \quad (4)$$

where $k_{n_c} = 1$, if vehicle n_c is accelerating (measured through the velocities in two consecutive sensor measurements), or else $k_{n_c} = 0$, if vehicle n_c is decelerating.

An instance of the above, for facilitating understanding the algorithm operation, is provided on Fig. 2*b*.

4.3 Third phase: calculation of OF and evaluation

After gathering the necessary data, the algorithm produces its output, which is depicted on a decision that is taken based on these parameters and has the following alternatives:

1. 'Idle'
2. 'Warning'
3. 'Low importance alert – front'
4. 'Low importance alert – rear'
5. 'High importance alert – front'
6. 'High importance alert – rear'

For reaching the output, the heuristic operates through evaluating an OF [27]. The OF is as follows

$$\text{OF}_{\text{total}} = \text{OF}_1 + \text{OF}_2 \quad (5)$$

where

$$\text{OF}_1 = \sum_j w_j \text{nor}_{v_j} \quad (6)$$

and

$$\text{OF}_2 = \frac{F_{N_a}}{N_a} + \frac{F_{N_b}}{N_b} + \frac{F_{N_c}}{N_c} \quad (7)$$

The first part of the OF (OF_1) refers to V2I–VSN parameters, as well as to the i-Drive vehicle own parameters, which can be directly normalised through the process described in the second phase of the algorithm.

The second part of the OF (OF_2) is extracted from the information acquired from the other vehicles in-range (through the V2V–VSNs) and calculated through the F_i danger factors defined also in the second phase.

In total according to our approach there are ten input parameters for the algorithm.

The decision to be made depends on the desired application's characteristics. In this paper, we assume the case where i-Drive has been configured to reach a decision based on the alternatives mentioned before. In particular:

If $0 < \text{OF}_{\text{total}} < 0.25$, then the alert level is supposed to be 'Idle'.

If $0.25 < \text{OF}_{\text{total}} < 0.5$, then the alert level is set to 'Warning' and the driver is notified.

If $0.5 < \text{OF}_{\text{total}} < 0.75$, then the 'Low-importance' alert is triggered and the driver is notified accordingly.

If $\text{OF}_{\text{total}} > 0.75$, then the 'High-importance' alert is triggered and the driver is more persistently notified.

In all cases, a separation in the alert is made depending on the origin of danger (front/rear).

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5 Results and discussion

5.1 Scenarios and simulation setup

This section presents some indicative results from the i-Drive software prototype that is currently being implemented using the Matlab software package. The implementation enables the user to easily input and modify the critical parameters, as well as to properly visualise the outcomes of the algorithm.

The scenarios have been constructed using information and being influenced by several research attempts [26, 29]. They derive from the inputs of the functionality, namely, the context, personal and service profiles and policies. Their goal is to show how fast the proposed functionality can reach decisions that could be exploited by drivers when anticipating emergency situations. Two scenarios are thus used for this process. The scenarios are differentiated by means of the danger levels as well as the conditions that cause the danger. The first scenario is a lower danger level scenario that studies the impact of the road type on the i-Drive decisions, whereas the second scenario investigates the impact of the road condition on the i-Drive outcomes.

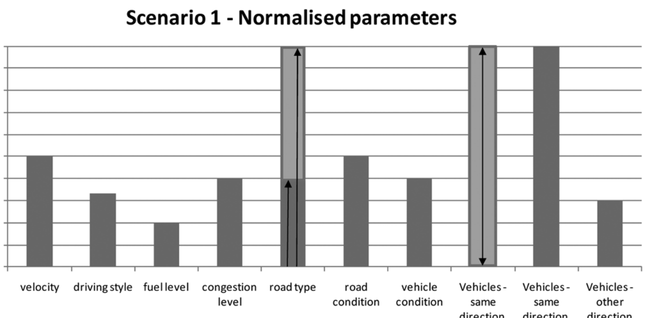
Moreover, it has to be mentioned that in this paper we assume that the parameters regarding the road condition and type are of quite high importance, while the parameters regarding the other vehicles' moving in the same direction are of very high importance. In that framework, and having in mind that there are ten input parameters in total, the weights of the first two parameters are set to 0.1, and the weights of the two latter are set to 0.2. All the other weights are set to 0.067, so the sum of all weights is equal to 1, as also mentioned above. Last, it is left as part of our future activities to invent intelligent methods to estimate the parameters' weights, such as with the use of neural networks or through Bayesian networking techniques.

Finally, the results have been obtained using the Matlab software package.

5.2 Scenario 1 – impact of road type

The goal of the first scenario is to showcase the i-Drive efficiency when a vehicle in front of the i-Drive vehicle exhibits changes in its velocity. Two road type cases are considered, that is, a highway and a village road, so as to test the response of i-Drive concerning the different levels of danger that arise there from. The input to the scenario is described by the parameter values presented in Fig. 3*a*. As shown in figure, most parameters remain constant, except for the road type and the velocity (and acceleration) of a vehicle $n_a \in N_a$. Moreover, regarding the last three paremeters of Fig. 3*a*, they are computed based on the information shown in Fig. 3*b*. In this figure the velocities as well as the accelerations of the vehicles in range are depicted. Velocities are measured in km/h, while accelerations are presented in m/s^2. As shown, the velocity of one vehicle in range – and specifically ahead of our car – is not constant, but varying from 0 to 100 km/h, and the same applies for its acceleration, varying from -4 to 5 m/s^2.

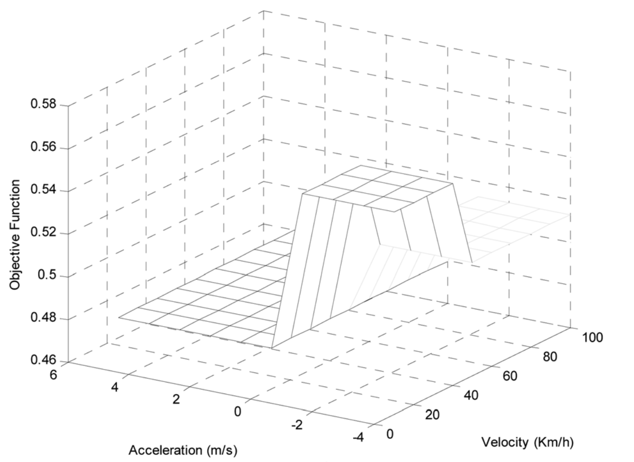
Regarding most factors, this scenario represents a relatively 'low danger' situation. Hardly any parameter is over 0.5.



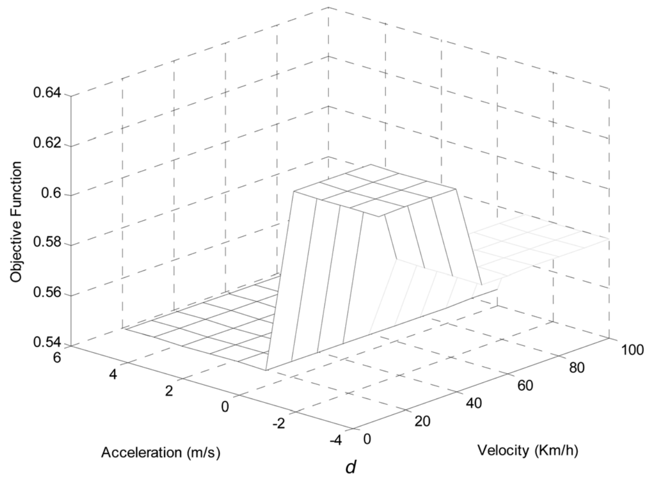
a

	Velocities		Accelerations	
Vehicles in same direction, ahead	55	0 → 100	3	-4 → 5
Vehicles in same direction, behind	60		5	
Vehicles in opposite direction	45	60	5	3

b



c



d

Fig. 3 *Input to the scenario is described by the parameter values*

a Scenario 1 – input parameters
b Velocities and accelerations of vehicles in range
c OF evolution, highway case
d OF evolution, village road case

Therefore the danger that results from the altering situation of a vehicle ahead of our car, is going to be clearly depicted.

Let us now investigate how i-Drive operates as the velocity and acceleration of a vehicle in front of the i-Drive one changes, assuming the case of a highway. The OF values are shown in Fig. 3*c*. In particular, as long as the acceleration of the vehicle in question is positive, then the OF's value is under 0.5 and therefore the output of the system is 'Warning – front'. This means that the i-Drive vehicle driver just needs to be aware of this fact. On the other hand, when the front vehicle's acceleration becomes negative, then OF = 0.52, if the velocity is over 50 km/h, and OF = 0.55, if the velocity is under 50 km/h. This implies that the vehicle decelerates. In both cases, the i-Drive output is a 'low importance – front' alert.

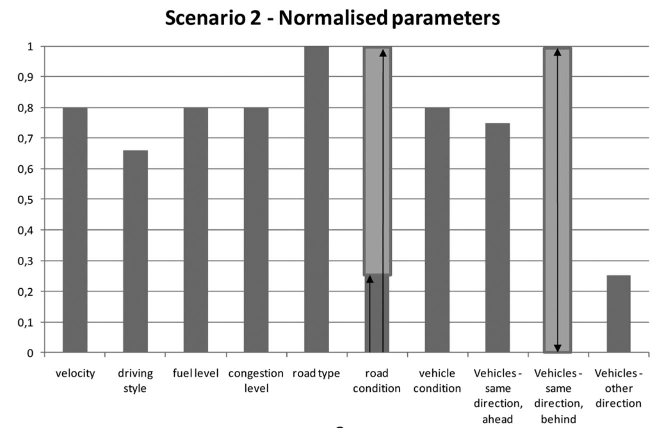
In general, the scenario showcases a rather low level of danger, due to the fact that a vehicle in front of the i-Drive vehicle decelerates slowly and all vehicles move in a highway. However, i-Drive can provide the driver with a significant information, which is even more significant when the decelerating vehicle is not directly in front of the i-Drive one, but maybe a couple of vehicles further. This means that the driver is informed a priori about a forthcoming potential danger.

We apply the i-Drive algorithm now in the same scenario but in a village road. The results are depicted in Fig. 3*d*. With respect to the previous case, we now see that the OF value is over 0.5 even if the acceleration of the second vehicle ahead is positive. When the acceleration becomes negative, then OF = 0.58, if the velocity is over 50 km/h, and OF = 0.62, if the velocity is under 50 km/h. As a result, in all cases the output of the system is a 'low importance – front' alert, implying the existence of a dangerous situation in front of our vehicle that should be taken into account by the driver. In the last case, the OF value is even closer to the 'high importance alert – front'. In this respect, i-Drive considers the same situation more dangerous, because of the nature of road (village road).

5.3 Scenario 2 – impact of road condition

The goal of the second scenario is to showcase the i-Drive efficiency when a vehicle behind the i-Drive vehicle exhibits changes in its velocity. Two road conditions are considered, that is, a good condition road and a snowy/slippery road. The input parameters to this scenario are depicted on Fig. 4*a*. As the figure indicates, it is a scenario that is characterised by quite high levels of danger. For example, all parameters apart from one have normalised values over 0.5.

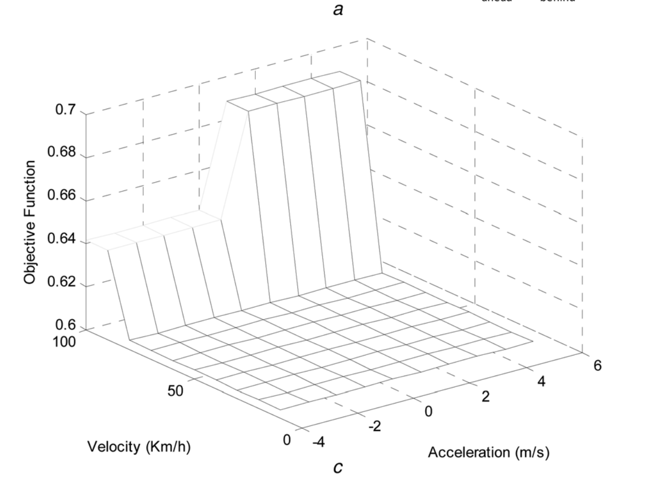
The scenario assumes that there is a constant changing in the velocity and acceleration of a vehicle behind the i-Drive vehicle. In total, the situation regarding the vehicles in range is summarised in Fig. 4*b*. In that table, the velocities as well as the accelerations of the vehicles in ragne are depicted. As previously mentioned, velocities are measured



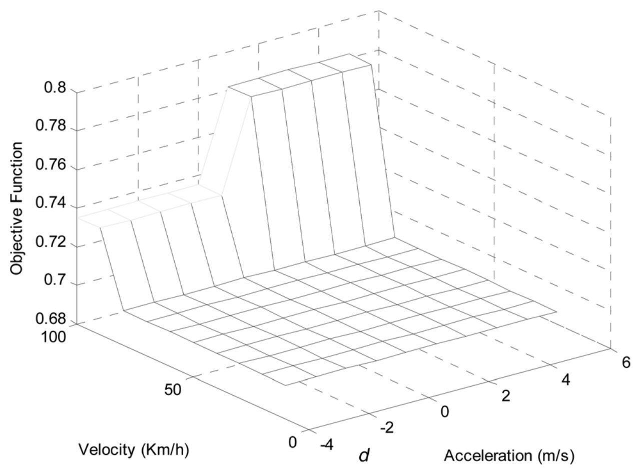
a

	Velocities				Accelerations			
Vehicles in same direction, ahead	75	20	60	50	4	-3	7	-5
Vehicles in same direction, behind	50	0 → 100			-5	-4 → 5		
Vehicles in opposite direction	25	75			5	-3		

b



c



d

Fig. 4 *Input parameters to this scenario*

a Scenario 2 – input parameters
b Velocities and accelerations of vehicles in range
c OF evolution, good road condition case
d OF evolution, slippery/snowy road condition case

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in km/h, while accelerations are presented in m/s^2. In this scenario, the velocity and acceleration of a vehicle behind our car is changing.

Fig. 4*c* shows the OF values in the case of good road condition. As the i-Drive vehicle drives at 80 km/h and the vehicle behind reaches values that are over 80 km/h, the OF value increases. The same applies when the acceleration of the other vehicle is positive. For all cases, the value of OF is between 0.5 and 0.75, which means that there is a 'low importance alert – rear' for the driver, whose attention is drawn to the fact that there is a vehicle behind that accelerates. This alert is mainly due to the sum of all the other danger factors, expressed through the increased normalised values of all the parameters.

On the other hand, Fig. 4*d* depicts the OF values in the case of a snowy/slippery road condition, where we see that when the velocity of the vehicle behind the i-Drive vehicle is over 80 km/h, then the OF value reaches 0.74, which is the limit for 'high importance alert – rear'. When the vehicle's acceleration also becomes positive, then this value goes over 0.75 and the driver obtains a 'high importance alert – rear'.

In general, this scenario reveals the capability of i-Drive to provide useful information to the driver regarding potential oncoming danger that originates in the rear of the vehicle and is therefore maybe hard to perceive otherwise.

In conclusion, both scenarios show that i-Drive constitutes an important, helpful tool in the hands of a driver regarding his a priori notification of potential forthcoming dangers. This is achieved because of fast and reliable decision making regarding the origin and the intensity of the danger.

6 Conclusions and future work

Latest trends in ICT refer to their migration towards the FI era, which promises easier overcoming of the structural limitations of telecommunication infrastructures and their management systems, facilitating the design, development and integration of novel services and applications. One important area of applications lies within the area of transportation, mainly by promoting the seamless integration of information of various types from transportation networks, to benefit drivers and provide several innovative services.

This paper in particular has presented a proactive, knowledge-based intelligent transportation system based on VSNs, namely i-Drive. i-Drive is capable of benefiting from V2X communication in order to acquire collective information, transfer it into knowledge and experience and proactively issue significant directives to drivers. Indicative simulation results have shown that i-Drive is capable of a priori identifying potential dangers and, as such, can contribute to the goal of increasing integrated safety /emergency management in the future world of transportation. In this respect, the particular value of the contribution of this paper lies in the utilisation of a knowledge-based decision making algorithm, which can increase the overall levels of safety through recognising potential emergencies a priori, improving thus the total transportation quality. Moreover, the paper has also managed to address the integration of the advantages of VSNs in ITS through the description of a whole framework that can incorporate various services/applications that can improve the quality of transportation.

Concerning potential extensions of this work, an important step will be to support enhanced frontal collision danger recognition, through the evaluation of the vehicles' relative angles and directions through their coordinates.

Another area of interest will include the utilisation of neural network techniques as well as Bayesian networking concepts, in order to estimate the values of the parameters' weights in a manner that is knowledge-based, which will add more accuracy and reliability in the i-Drive concept.

Moreover, i-Drive could be integrated in a larger ITS that would include the provisioning of services such as 'live co-driver comments' regarding forthcoming turns, traffic conditions expected ahead etc., which would convert i-Drive to an integrated 'all-in-one' solution addressing both safety (frontal collisions detection, dangerous turns) and comfort (directions to avoid traffic congestion).

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