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Fuzzy-based Driver Monitoring System (FDMS): Implementation of two intelligent FDMSs and a testbed for safe driving in VANETs

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ABSTRACT

Vehicular Ad hoc Networks (VANETs) have gained a great attention due to the rapid development of mobile Internet and Internet of Things (IoT) applications. On the other hand, the competition in the automotive industry has turned into an unprecedented race to who will be the first to provide the fully autonomous cars. However, the fully autonomous driving is still a bit far from deployment, and for now, they are providing automation only at a certain level and, at the same time, are offering connected services through their mobility service platforms. With Fog and Edge computing integrated in VANETs, these mobility platforms will be standardized to provide services for every car on the road, which will help VANETs to accomplish one of its main goals, the road safety. In this paper, we propose an intelligent Fuzzy-based Driver Monitoring System (FDMS) for safe driving. We present and compare two fuzzy-based systems: FDMS1 and FDMS2. To make a decision, FDMS1 considers Vehicle's Environment Temperature (VET), Noise Level (NL) and Heart Rate (HR). While, for FDMS2, we consider Respiratory Rate (RR) as a new parameter to decide Driver's Situational Awareness (DSA). We evaluate the ability of the driver to safely operate the vehicle by monitoring his condition and subsequently, based on the system output, a smart box informs the driver and provides assistance. We show through simulations and experiments the effect of the considered parameters on the determination of the driver's situation and demonstrate the actions that can be performed accordingly.

1. Introduction

Every year the lives of approximately 1.35 million people are cut short as a result of a road traffic accident. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury [1]. For years, in order to improve the road safety, many governments have undertaken initiatives by launching Intelligent Transport Systems (ITSs). ITS is a new road and traffic system which combines state-of-the-art information, communication, and control technologies to properly create an information network based on people, vehicles and roads.

As a key part of ITS, the Vehicular Ad hoc Networks (VANETs) not only aim to help reducing the traffic accidents but also to enhance the traffic efficiency and the travel comfort of passengers and drivers. In VANETs, vehicles have networking capabilities and they send/receive valuable information such as safety warnings and traffic information to/from adjacent vehicles and roadside units (RSUs) via vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication. Although VANETs are already deployed in reality providing several services, the current architectures struggle to offer delay-sensitive and location awareness services.

To solve these encountered challenges, the integration of Fog computing in current VANETs was proposed, as Fog has a number of attributes that make it the ideal platform to deliver numerous services in infotainment, traffic support, safety, and analytics: geo-distribution (across cities, and along roads and highways), low latency and mobility and location awareness [2]. Different from Cloud computing data centers, this architecture analyzes data close to devices for minimizing latency and decision making in real time, thus fulfilling requirements of many VANET applications.

With Edge computing in VANETs, which means vehicles having resources and services of computing, networking, storage and control capabilities, a significant amount of data can be processed at/through the vehicles, consequently offloading massive traffic flow from the core networks. In addition, the vehicles are now manufactured to be equipped also with various forms of Internet of Things (IoT) sensors, smart cameras and different wireless communication technologies which are used to gather important information regarding the environment and road conditions. However, the difficulty lies on how to understand the sensed

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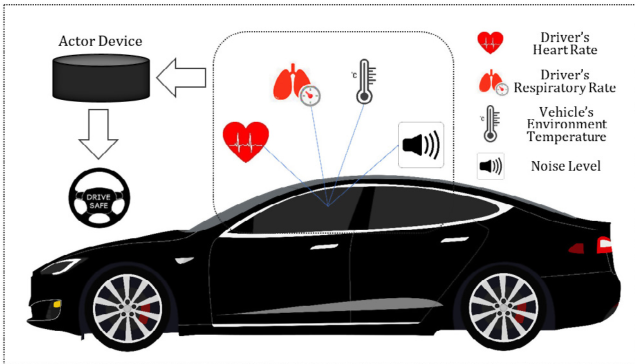


Fig. 1. Proposed system architecture.

data and how to make intelligent decisions based on the provided information.

As a result, various intelligent computational technologies and systems such as fuzzy logic, machine learning, neural networks, adaptive computing and others, are being or already deployed by many car manufacturers [3]. They are focusing on these auxiliary technologies to launch and fully support the driverless vehicles.

Fully autonomous vehicles still have a long way to go but driving support technologies are becoming widespread, even in everyday cars. The goal is to improve both driving safety and performance relying on the measurement and recognition of the outside environment and their reflection on driving operation.

On the other hand, we are focused on the in-car information and driver's vital information to detect a potential accident or a risky situation, and alert the driver about the danger, or take over the steering if it is necessary. We aim to realize a new Driver Monitoring System (DMS) by using Fuzzy Logic (FL) as it can make real-time decisions based on the uncertainty and vagueness of the provided information. A model of our proposed system is given in Fig. 1. In this work we evaluate two fuzzy based systems and compare them by simulation and experimental results. For the experiments we use some IoT devices equipped with various sensors to obtain in-car environment data and driver's vital signs.

The remainder of this paper is as follows. Section 2, presents an overview of IoT, Fog/Edge computing, VANETs and a literature review. The proposed fuzzy-based systems and their implementation are described in Section 3. In Section 4, we discuss the simulation and experimental results. Finally, conclusions and future work are given in Section 5.

2. Background overview and related work

In this section we briefly introduce IoT, Fog computing and Edge computing as enabling technologies for full deployment and management of VANET applications and services. Moreover, we provide a short description of VANETs in terms of the coordination of the computing resources as well as several research papers relevant to this work.

2.1. Internet of things

The IoT has become one of the most popular networking concepts that has the potential to bring out many benefits by creating a smart environment, which will permit the collection of information from the environment and make the daily life more convenient by helping people to making tough decisions. For that to happen, a high interaction between people, objects, processes and services must be guaranteed [4]. While there will be a significant increase of the number of deployed devices within the environment, there should be a scalable infrastructure in enabling sufficient and full utilization of available resources as to take advantage of the IoT. Smart transportation and smart cities are the most important applications of IoT based in VANETs. They include intelligent traffic management in which data from the smart traffic light nodes and traffic information center infrastructures, could be reachable by any vehicle, at any point and at any time. Such applications are delay-sensitive and require mobility support, and to satisfy these demands, the use of Fog computing was proposed.

2.2. Fog computing

Fog computing is a highly virtualized platform that provides compute, storage, and networking services between end devices and traditional Cloud computing data centers offering low latency and location awareness, geographical distribution, mobility support, interoperability and real-time interactions [2]. These attributes make Fog computing the appropriate platform that meets all the requirements of VANET scenarios [5,6]. However, as the number of vehicles increases, so does the amount of data generated by these vehicles. Therefore, Cloud computing still has an important role when it comes to big data management and analytics.

2.3. Edge computing

As more and more sensors are installed on modern vehicles, massive amounts of data are generated from monitoring the on-road and on-board status [7]. If that data is sent back across a long network link to be analyzed, logged and tracked, that takes much more time than if the data is processed at the edge, close to the source of the data [8]. Vehicles, which are equipped with networking capabilities, powerful computing units and large storage devices will try to process the data and if not capable, it will seek to use the resources of adjacent vehicles. This becomes crucial, in particular when a connection vehicle-fog server cannot be established as well as when the fog servers where vehicles are trying to get services are overloaded. Thus, by using Edge computing, a massive traffic flow can be offloaded from the core networks and a better content distribution efficiency can be achieved.

2.4. Vehicular Ad hoc networks

By integrating Cloud, Fog and Edge computing in VANETs, a hybrid system between centralized and distributed computing is created [9]. The basic components of this Cloud-Fog-Edge VANET architecture with the content distribution is given in Fig. 2. The safety applications data generated through on-board and on-road sensors are processed first in the vehicles as they require real-time processing. If more storing and computing resources are needed, the vehicle can request to use those of the other adjacent vehicles, assuming a connection can be established and maintained between them for a while. With the vehicles having created multiple virtual machines on other vehicles, the virtual machine migration must be achievable in order to provide continuity as one/some vehicle may move out of the communication range. However, to set-up virtual machines on the nearby vehicles, multiple requirements must be met and when these demands are not satisfied, the fog servers are used. Cloud servers are used as a repository for software updates, control policies and for the data that need long-term analytics and are not delay-sensitive. The implementation of this architecture promises not only to be the enabling environment for future autonomous and connected cars, but also to provide numerous services for their drivers and passengers.

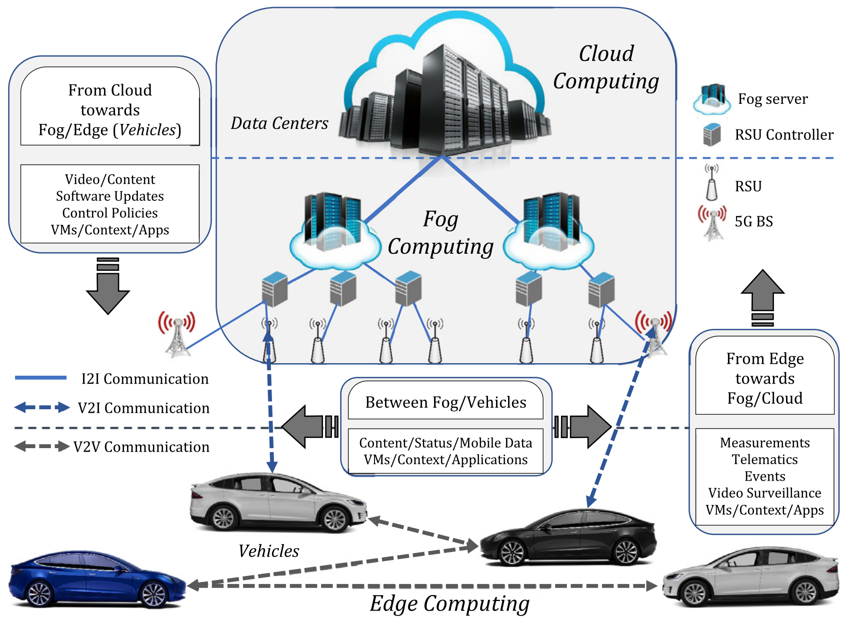


Fig. 2. The Cloud-Fog-Edge VANET architecture.

2.5. Related works

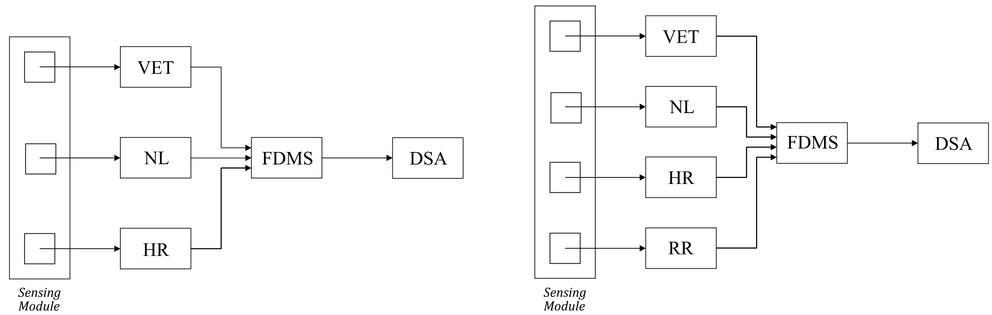
Although the developments in autonomous vehicle design indicate that this type of technology is not that far away from deployment, the current advances fall only into the Level 2 of the Society of Automotive Engineers (SAE) levels [10]. However, the automotive industry is very competitive and there might be many other new advances in the autonomous vehicle design that are not launched yet. Thus, it is only a matter of time before driverless cars are on the road.

On the other side, there will be many people who will still be driving even on the era of autonomous cars. The high cost of driverless cars, lack of trust and not wanting to give up driving might be among the reasons why those people will continue to drive their cars. Hence, many researchers and automotive engineers keep working on Driver Assistance Systems (DASs) and DMSs as a primary safety feature, required in order to achieve full marks in safety.

DASs and DMSs are intelligent systems that reside inside the vehicle and help the driver in a variety of ways. These systems rely on a comprehensive sensing network and artificial intelligence techniques, and have made it possible to commence the era of connected cars. They can invoke action to maintain driver attention in both manual and autonomous driving. While the sensors are used to gather data regarding the inside/outside environment, vehicle's technical status, driving performance and driver's condition, the intelligent systems task is to make decisions based on these data. If the vehicle measurements are combined with those of the surrounding vehicles and infrastructure, a better environment perception can be achieved. In addition, with different intelligent systems located at these vehicles as well as at fog servers more efficient decisions can be attained.

Substantial research has been done over the years to build and improve DASs and DMSs. Many big automotive companies such as Toyota, Nissan, Mercedes-Benz, BMW, Volvo, and Saab as well as third parties including Seeing Machines, Veoneer and SmartEye are conducting continuous research to develop such intelligent systems. Dong et al. [11] report in their review article several projects that have been performed by such companies. Most of these projects are based on smart cameras used to track eye gaze, head pose, pupil size, and mouth activity and use computer vision algorithms to process the obtained data in order to observe the driver's attention. Many academia researchers are engaged in the research and development of these systems as well. Yao et al. [12] proposed a vision system to determine the driver's vigilance by integrating a number of facial features, including those of the mouth, eyes and gaze. Ji et al. [13] developed a probabilistic model that employ visual cues which characterize eyelid movement, gaze movement, head movement, and facial expression to model and predict driver fatigue. There are also many other studies based on such behavioral measures. These include pupils' motion [14], eye blinking [15–17], percentage of eyelid closure (PERCLOS) [15,18], yawning [19], as well as other facial actions e.g., lip stretch, jaw drop, inner brow raise, outer brow raise [20, 21]. Authors report good result and well performance of their systems. However, such systems still have limitations as they use facial feature extraction and vision-based approaches. These methodologies require a long moving-averaged window to track slow changes in a driver's vigilance. Moreover, they encounter several illumination challenges. Since normal cameras do not perform good at night, many researchers have adopted infrared illumination techniques [15,22,23]. However, such systems suffer light reflection as sunlight and reflections from glasses (when wearing glasses) could cause the performance to considerably drop to 30% [15].

Farid et al. [24] used Hidden Markov Models with Gaussian mixtures to distinguish between attentive and inattentive driving in car-following situations by analyzing the vehicle following distance and steering angle. Zhong et al. [25] performed a localized energy analysis of the steering-wheel angle dynamics and vehicle tracking to detect driver fatigue and found a trend of localized energy increase with driving time. In [26], the chaos theory was employed to explain the dynamics of steering-wheel motion and estimate driver fatigue. Different research works study driver performance by adopting the steering-wheel position, accelerator pedal position, forces on the pedals, lane boundaries, upcoming road curvature, and vehicle velocity [27–30]. The aforementioned studies predict the driver attention based on driver–vehicle interaction instead of monitoring driver's actual condition in real-time. Moreover, to monitor driver performance based on the vehicle operation requires modifications of the vehicle structure, which is impractical and unwise in a real assessment [31].



(a) Proposed system model for FCMS1

(b) Proposed system model for FCMS2

Fig. 3. Proposed systems.

On the other hand, the driver biological signals which include *electroencephalogram* (EEG), *electrocardiogram* (ECG), *electro-oculogram* (EOG), and *electromyogram* (EMG), have been found to be highly accurate when used to detect a driver's drowsiness [11, 32]. The heart rate also varies significantly between the different stages of drowsiness, such as alertness and fatigue [33,34]. In addition to heart rate, the respiratory rate can be used to measure mental stress [35].

Environmental factors, such as temperature, noise, humidity, etc. are considered capable of affecting the driver as well. Landstrom et al. [36] evaluated the efficiency of temperature variations as an indication against drivers' drowsiness. The results showed that chances of drowsy driving can be greatly reduced by maintaining a cooler temperature in the vehicle. Such good results of the effect of temperature motivated us to consider this parameter in our system.

On the other side, there are several research papers that are in line with our research work regarding the method used to determine the driver's situation. Bergasa et al. [15] used blink frequency, eye closure duration, PERCLOS, nodding frequency, fixed gaze, and frontal face pose as inputs to fuzzy inference system for fatigue detection. They reported that their system achieves a fatigue detection accuracy of 98%. However, the light reflection causes a drop of 30% on the detection accuracy. A simpler fuzzy system considering following four parameters, PERCLOS, head-nodding frequency, slouching frequency, and posture adjustment frequency is implemented in [37]. Similar to [15], authors use vision-based methods for extracting features which are translated to input data for the system. Despite the fact that this system uses less parameters, authors report that it runs slowly. In order to enable it to run much faster, they list as a future work, implementation of their system in C language instead of Matlab. A more complete work regarding the type of considered parameters is proposed in [31]. Authors consider heart rate, blood pressure, temperature, vehicle speed and PERCLOS as input parameters for their proposed Fuzzy Bayesian Network to determine the output value, driver's fatigue. They conducted experiments for ten subjects for awake and drowsy predictions with a total of 3220 test samples. Their system revealed a high rate of true awake and drowsy samples with an accuracy of 96% and 97%, respectively. However, authors state that the FBN is complex, and the calculation complexity of the FBN output probability depends on the number of fuzzy members in each membership function, as well as the number of elements (nodes) in the Bayesian network.

3. Proposed systems

Our research work on DMSs is presented in the following. The focus and objective of this work was to develop a non-complex and non-intrusive DMS which determines the driver's situation in real-time by considering different types of parameters. The considered parameters include environmental factors and driver's vital signs that are able to contribute to determine his actual condition. We propose and implement two systems. One considering three input parameters and another considering four. Having three or more parameters which are not correlated with each other result in a non-deterministic polynomial-time hard (NP-hard) problem.

Table 1
System parameters and their term sets.

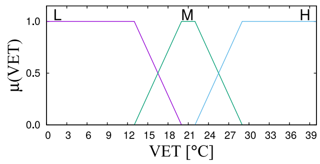
Fuzzy system		Parameter	Term sets
FDMS2	FDMS1	VET	Low (L), Medium (M), High (H)
		NL	Quiet (Q), Noisy (N), Very Noisy (VN)
		HR	Slow (S), Normal (No), Fast (F)
		RR	Slow (Sl), Normal (Nm), Fast (Fa)
FDMS1		DSA	Very Bad (VB), Bad (B), Normal (Nor), Good (G), Very Good (VG)
FDMS2		DSA	Extremely Bad (EB), VB, B, Nor, G, VG, Extremely Good (EG)

In our previous works we have considered different approaches and intelligent systems such as Neural Networks (NNs), Genetic Algorithms (GAs), Hill Climbing (HC), Simulated Annealing (SA), Particle Swarm Optimization (PSO) and Tabu Search to deal with the NP-hard problems. The results have showed that different intelligent algorithms have different efficiency for different problems. From our experience, NNs give good results for rule learning and recognition problems. GAs show good results for optimization and allocation problems. On the other hand, FL can be used for decision making and control problems. For this reason, we consider FL to implement the proposed driver monitoring systems. In addition, by using the fuzzy rule expression which is close to an expert natural language, it allows the modeling of such inherently ambiguous notions as driver situations in an efficient and effective way [38–43].

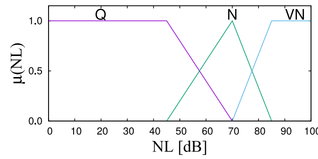
3.1. Description of proposed Fuzzy-based systems

The proposed Fuzzy-based Driver Monitoring Systems (FDMSs) are shown in Fig. 3, with Figs. 3(a) and 3(b) showing FDMS1 and FDMS2, respectively. For the implementation of FDMS1, we consider three input parameters: Vehicle's Environment Temperature (VET), Noise Level (NL) and Heart Rate (HR) to determine the Driver's Situational Awareness (DSA). For FDMS2 the Respiratory Rate (RR) is taken into consideration as an extra parameter to determine the same output, with some modifications on the term sets and membership functions used for its defuzzification. The term sets of input parameters are defined respectively as:

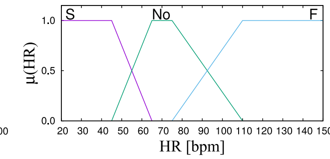
$T(VET) = \{Low\ (L),\ Medium\ (M),\ High\ (H)\};$



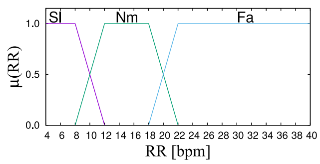
(a) VET



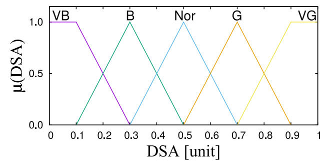
(b) Noise Level



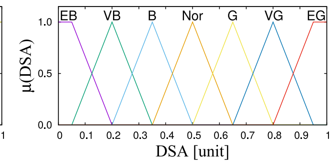
(c) Heart Rate



(d) Respiratory Rate

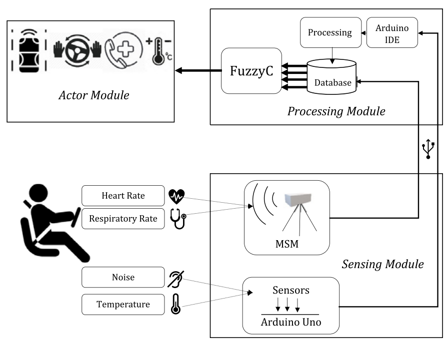


(e) DSA - FDMS1

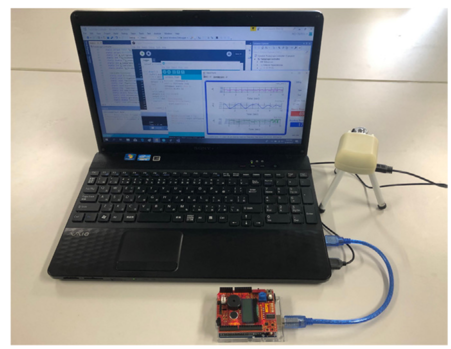


(f) DSA - FDMS2

Fig. 4. Membership functions.



(a) The testbed scheme.



(b) Snapshot of testbed.

Fig. 5. FDMS testbed.

$T(NL) = \{Quiet\ (Q),\ Noisy\ (N),\ Very\ Noisy\ (VN)\};$

$T(HR) = \{Slow\ (S),\ Normal\ (No),\ Fast\ (F)\};$

$T(RR) = \{Slow\ (Sl),\ Normal\ (Nm),\ Fast\ (Fa)\}.$

All the term sets for each linguistic parameters used for FDMS1 and FDMS2 are shown in Table 1. Based on the linguistic description of input and output parameters we make the Fuzzy Rule Base (FRB). The FRB forms a fuzzy set of dimensions $|\ T(x_1)\ | \times |\ T(x_2)\ | \times \cdots \times |\ T(x_n)\ |$, where $|\ T(x_i)\ |$ is the number of terms on $T(x_i)$ and n is the number of input parameters. FDMS1 (FDMS2) has three (four) input parameters with three linguistic terms each, therefore, there are 27 (81) rules in the FRB. The FRB of FDMS1 and FDMS2 is shown in Table 2 and in Table 3, respectively. The control rules of FRB have the form: IF "conditions" THEN "control action". The membership functions used for fuzzification are given in Figs. 4(a)–4(d). In Figs. 4(e) and 4(f) are shown the membership functions used for the output parameter. We use triangular and trapezoidal membership functions because they are suitable for real-time operation.

3.2. Testbed description

In order to evaluate the proposed systems, we implemented a testbed and carried out experiments in a real scenario [44,45]. A scheme and a snapshot of the testbed is given in Fig. 5. As shown in Fig. 5(a), the testbed is composed of sensing and processing modules, with the actor module showing examples of actions that can be performed based on the provided output. The sensing module is made of non-contact sensors and consists of two parts. The first part is implemented in Arduino Uno while the second one consists of a Microwave Sensor Module (MSM) called DC6M4JN3000. We set-up sensors on Arduino Uno to measure the vehicle's environment temperature and noise and used the MSM to measure the driver's heart and respiratory rate. The processing module is composed of three software, i.e., Processing, Arduino IDE and Visual Studio, running on Windows OS, which are used to obtain the sensed data and to run our Fuzzy program called FuzzyC. The sensing components are connected to the processing device via USB cable. We used the Arduino IDE and Processing to get the sensed data from the first sensing part, whereas the MSM generates its data in the appropriate format we use in our FuzzyC. Depending on the input data, the FDMS1 and FDMS2 which are implemented in FuzzyC, determine the DSA. Based on the DSA, the actor module decides if an action is needed, and if so, which is the appropriate task to be performed.

4. Proposed system evaluation

In this section we present and compare the simulation and experimental results for our proposed systems. We show the effect of the considered parameters on the determination of the driver's situation by both FDMS1 and FDMS2. In addition, we explain how the output values are translated into actions that can support the driver to drive safely.

4.1. Simulation results

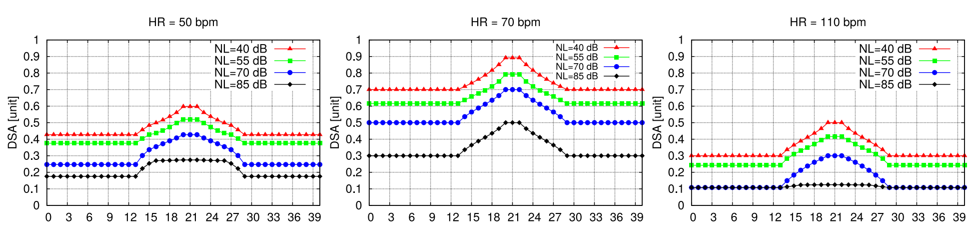
The simulation results for FDMS1 are presented in Fig. 6. We show the relation between DSA and VET for different NL values. The NL values considered for the simulations are 40, 55, 70 and 85 dB which simulate a quiet, typical, noisy and very noisy environment, respectively. The HR is considered as a constant parameter. We vary the VET parameter from 0 to 40 °C.

Table 2
FRB of FDMS1.

Rule	VET	NL	HR	DSA	Rule	VET	NL	HR	DSA	Rule	VET	NL	HR	DSA
1	L	Q	S	B	10	M	Q	S	Nor	19	H	Q	S	B
2	L	Q	No	G	11	M	Q	No	VG	20	H	Q	No	G
3	L	Q	F	B	12	M	Q	F	Nor	21	H	Q	F	B
4	L	N	S	VB	13	M	N	S	B	22	H	N	S	VB
5	L	N	No	Nor	14	M	N	No	G	23	H	N	No	Nor
6	L	N	F	VB	15	M	N	F	B	24	H	N	F	VB
7	L	VN	S	VB	16	M	VN	S	VB	25	H	VN	S	VB
8	L	VN	No	B	17	M	VN	No	Nor	26	H	VN	No	B
9	L	VN	F	VB	18	M	VN	F	VB	27	H	VN	F	VB

Table 3
FRB of FDMS2.

Rule	VET	NL	HR	RR	DSA	Rule	VET	NL	HR	RR	DSA	Rule	VET	NL	HR	RR	DSA
1	L	Q	S	Sl	VB	28	M	Q	S	Sl	B	55	H	Q	S	Sl	VB
2	L	Q	S	Nm	Nor	29	M	Q	S	Nm	G	56	H	Q	S	Nm	Nor
3	L	Q	S	Fa	VB	30	M	Q	S	Fa	B	57	H	Q	S	Fa	VB
4	L	Q	No	Sl	Nor	31	M	Q	No	Sl	VG	58	H	Q	No	Sl	Nor
5	L	Q	No	Nm	VG	32	M	Q	No	Nm	EG	59	H	Q	No	Nm	VG
6	L	Q	No	Fa	Nor	33	M	Q	No	Fa	VG	60	H	Q	No	Fa	Nor
7	L	Q	F	Sl	EB	34	M	Q	F	Sl	B	61	H	Q	F	Sl	EB
8	L	Q	F	Nm	B	35	M	Q	F	Nm	G	62	H	Q	F	Nm	B
9	L	Q	F	Fa	EB	36	M	Q	F	Fa	B	63	H	Q	F	Fa	EB
10	L	N	S	Sl	EB	37	M	N	S	Sl	VB	64	H	N	S	Sl	EB
11	L	N	S	Nm	B	38	M	N	S	Nm	G	65	H	N	S	Nm	B
12	L	N	S	Fa	EB	39	M	N	S	Fa	VB	66	H	N	S	Fa	EB
13	L	N	No	Sl	B	40	M	N	No	Sl	G	67	H	N	No	Sl	B
14	L	N	No	Nm	G	41	M	N	No	Nm	EG	68	H	N	No	Nm	G
15	L	N	No	Fa	B	42	M	N	No	Fa	G	69	H	N	No	Fa	B
16	L	N	F	Sl	EB	43	M	N	F	Sl	VB	70	H	N	F	Sl	EB
17	L	N	F	Nm	VB	44	M	N	F	Nm	Nor	71	H	N	F	Nm	VB
18	L	N	F	Fa	EB	45	M	N	F	Fa	VB	72	H	N	F	Fa	EB
19	L	VN	S	Sl	EB	46	M	VN	S	Sl	EB	73	H	VN	S	Sl	EB
20	L	VN	S	Nm	VB	47	M	VN	S	Nm	B	74	H	VN	S	Nm	VB
21	L	VN	S	Fa	EB	48	M	VN	S	Fa	EB	75	H	VN	S	Fa	EB
22	L	VN	No	Sl	VB	49	M	VN	No	Sl	Nor	76	H	VN	No	Sl	VB
23	L	VN	No	Nm	Nor	50	M	VN	No	Nm	VG	77	H	VN	No	Nm	Nor
24	L	VN	No	Fa	VB	51	M	VN	No	Fa	Nor	78	H	VN	No	Fa	VB
25	L	VN	F	Sl	EB	52	M	VN	F	Sl	EB	79	H	VN	F	Sl	EB
26	L	VN	F	Nm	VB	53	M	VN	F	Nm	B	80	H	VN	F	Nm	VB
27	L	VN	F	Fa	EB	54	M	VN	F	Fa	EB	81	H	VN	F	Fa	EB



(a) HR = 50 bpm (b) HR = 70 bpm (c) HR = 110 bpm

Fig. 6. Simulation results for FDMS1.

In Fig. 6(a), we consider the HR value 50 bpm. A "normal" situation for the driver with his heart beating 50 times per minute is when there is not any annoying noise and also the ambient temperature is between 17 and 25 °C.

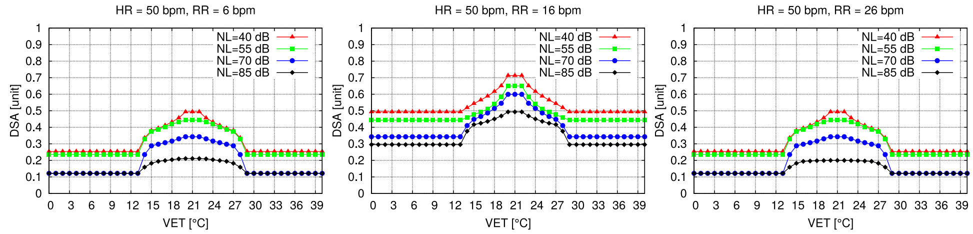
A scenario where the driver's heart is beating at 70 times per minute is shown in Fig. 6(b). Here, we can see many situations that are decided as "normal" or "good" even in the cases where a noise is in background or the vehicle's environment temperature is not a comfortable one.

In Fig. 6(c), we increase the value of HR to 110 bpm. We can see that there is not any situation that can be decided to be either "good" or "very good" by FDMS1.

The simulation results for FDMS2 are shown in Figs. 7–9. We see the effect of driver's respiratory rate on the decision of DSA.

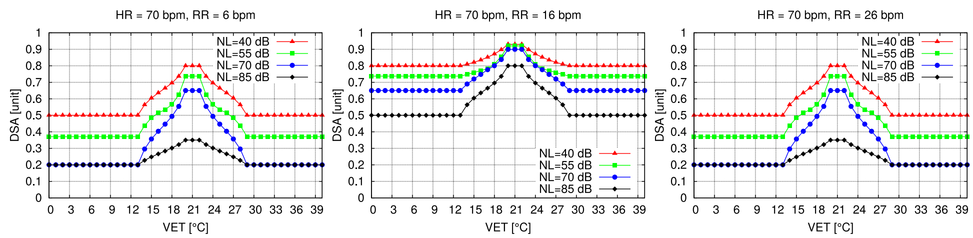
In Fig. 7, we consider the HR value 50 bpm and change the RR from 6 to 26 bpm. From Figs. 7(a) and 7(c) it can be seen that when the driver breathes abnormally, a "normal" situation by FDMS2 is considered only when NL is 40 dB and VET is around 20 to 22 °C. Comparing with FDMS1, for same heart rate, the range of temperature and noise for which FDMS2 decides a situation as "normal", is narrowed. On the other hand, when the driver respires normally, these ranges widen (see Figs. 7(b) and 6(a)).

In Fig. 8, we present the simulation results for HR 70 bpm. When the driver's respiratory rate is "normal" (see Fig. 8(b)), the DSA values decided by the system are higher than all the other considered scenarios. This is due to the driver's vital signs, that indicate a very good status of the driver's body, therefore, he could manage to drive safely in uncomfortable situations regarding the environment temperature and noise level. From Figs. 8(a) and 8(c) it can be seen that the DSA values are decreased as the respiratory rate decreases or increases and the effect of temperature and noise is more intense.



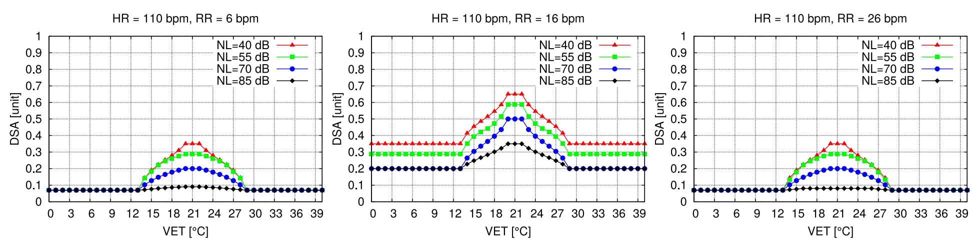
(a) RR = 6 bpm (b) RR = 16 bpm (c) RR = 26 bpm

Fig. 7. Simulation results for FDMS2 [HR = 50 bpm].



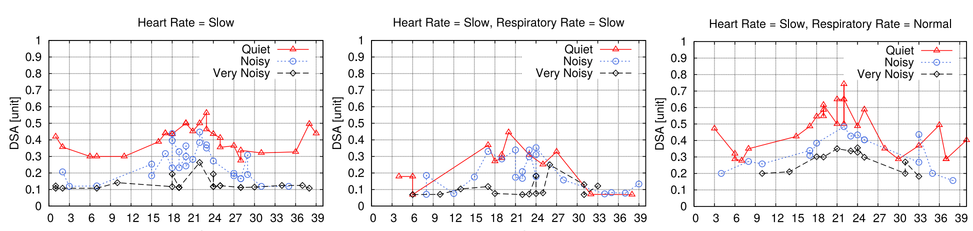
(a) RR = 6 bpm (b) RR = 16 bpm (c) RR = 26 bpm

Fig. 8. Simulation results for FDMS2 [HR = 70 bpm].



(a) RR = 6 bpm (b) RR = 16 bpm (c) RR = 26 bpm

Fig. 9. Simulation results for FDMS2 [HR = 110 bpm].



(a) FDMS1 (b) FDMS2 (RR = Slow) (c) FDMS2 (RR = Normal)

Fig. 10. Experimental results for slow heart rate.

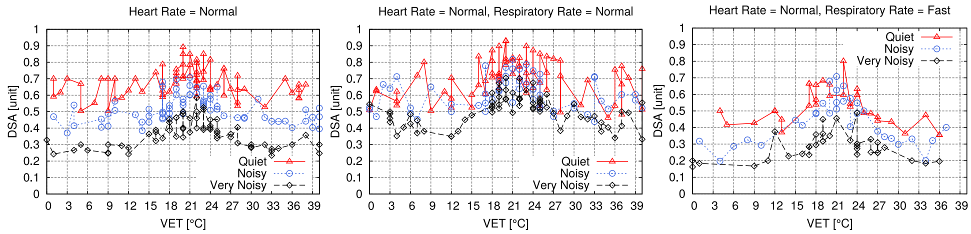
In Fig. 9, we increase the value of HR to 110 bpm. If the driver breathes normally, we can see some "good"/"normal" DSA values, especially when the ambient is quiet and/or the temperature is around 17 to 25 °C. However, as his respiratory rate increases/decreases significantly, there is not any situation that can be considered even as a "normal" situation. Comparing with Fig. 6(c), if the driver is breathing normally, for the same noise levels and temperatures, we get higher DSA values, otherwise, it is the FDMS1 which provides higher DSA values.

In the cases where the driver's situation is decided as bad or very bad continuously for relatively long time, the system can perform a certain action. For example, the system may limit the vehicle's maximal speed, suggest him to have a rest, or to call the doctor if he breathes abnormally and/or his heart beats at very low/high rates.

4.2. Experimental results

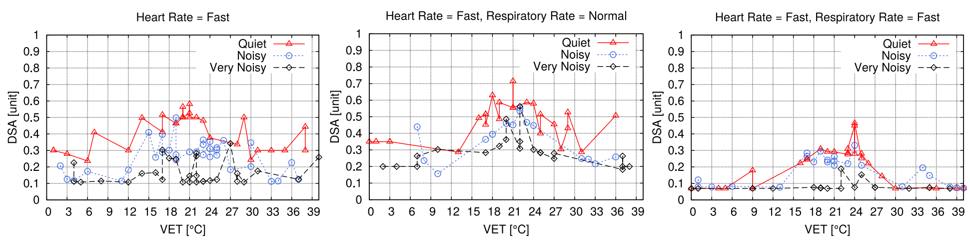
The experimental results for our proposed systems are presented in Figs. 10–12. In Fig. 10 are shown the results of DSA for slow heart rate. As we can see there were just a few DSA values decided as "normal". These values were achieved when the ambient was quiet and the temperature was around 18 to 24 °C. If the driver's respiratory rate is taken into consideration, the number of "normal" DSA values is increased slightly when he breathed normally, and decreased when he experienced difficulty in breathing.

The results of DSA when HR was "normal" are presented in Fig. 11. Here, when the driver breathed normally, many values were decided as "good" or "very good". Several values were decided as "extremely good" as well. As we explained in the



(a) FDMS1 (b) FDMS2 (RR = Normal) (c) FDMS2 (RR = Fast)

Fig. 11. Experimental results for normal heart rate.



(a) FDMS1 (b) FDMS2 (RR = Normal) (c) FDMS2 (RR = Fast)

Fig. 12. Experimental results for fast heart rate.

simulation results, (Fig. 8), we got higher DSA values due to the driver's vital signs which indicated a very good status of the driver's body.

In Fig. 12 are shown the results of DSA for fast heart rate. The results are almost the same with that of Fig. 9 where the "good" and "normal" values happen to be only when the driver breathes normally and the ambient is quiet or the temperature is between 17 and 25 °C. When he breathed rapidly any situation was decided as "bad", "very bad" or "extremely bad". In these situations, the driver might have been experiencing forms of anxiety which increases the risk of a potential accident.

5. Conclusions

In this work, we gave an overview of the deployment of Fog and Edge computing in VANETs and showed how these technologies can be very helpful for future VANET applications. Moreover, we proposed and implemented an intelligent fuzzy-based system for safe driving in VANETs. We presented two fuzzy-based systems: FDMS1 and FDMS2 to decide the driver's situational awareness. For FDMS1 we considered vehicle's environment temperature, noise level and driver's heart rate as input parameters. These parameters, together with driver's respiratory rate were considered as input parameters for FDMS2. We showed through simulations and experiments the effect of the considered parameters on the determination of the driver's situation. We paid more attention to the effect of driver's respiratory rate, for which we presented a comparison between the two systems. Some deductions from the evaluation results are as follows.

The changes in respiratory rate, in most cases, cause a variation of 0.2 to 0.3 (20%–30%) in the DSA value. On the other hand, this variation is around 15%–20% in contrast with the DSA values decided by FDMS1 where this parameter is not taken into consideration. Such changes show a great importance of respiratory rate because this difference is translated into 1–2 levels on the determination of the driver's condition. Although adding another parameter increases the complexity of the system, it does not cause any problems as the system still runs in real time.

In addition, we demonstrated a few actions that can be performed based on the output of our system. However, it may occur that the system provides an output which determines that an action should be taken, even though the driver feels comfortable and is able to drive safely. Therefore, we intend to estimate the system performance by looking into correct detection and false positives to determine its accuracy.

On the other side, there are many other factors which have a great impact in the driving safety. The vehicle technical conditions must be taken into consideration as many car accidents happen due to mechanical failures. In addition, external factors such as the driving environment (traffic density, weather conditions, the quality and type of the road, etc.) are capable of affecting the driver capability and vehicle performance, and must be included as well.

In the future, we would like to enhance our intelligent system by considering other parameters that have a high accuracy on the determination of the driver's ability to drive, e.g., EEG and PERCLOS, as well as the aforementioned parameters to achieve what is ultimately the goal of the DMSs, to reduce driving risk.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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