A New Application for Analyzing Driving Behaviour and Environment Characterization in Transportation Systems based on a Fuzzy Logic Approach

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ABSTRACT

In the last years the physical security in transportation systems is becoming a critical issue due to the high number of accidents and emergency situations. With the increasing availability of technological applications in vehicular environments researchers aimed at minimizing the probability of road accidents. In this paper, we propose a new platform able to discover dangerous driving behaviors. We based our application on the on-board diagnosis standard, able to provide all the needed information directly from the electronic vehicle control unit . We integrated the received data with a fuzzy logic approach, obtaining a description of the driver behavior. The overall system can take several initiatives (alarms, rpm corrections, etc.), in order to notify the driver bad behavior. The performance of the proposed scheme has been validated through a deep campaign of driving simulations.

Keywords: Road safety, OBD-II, Fuzzy logic, driving behavior, transportation systems

1. INTRODUCTION

During the last decade the interest for vehicular opportunities and potentialities has heavily grown, due to the many advantages given by the technological progress. In particular, road safety has been one of the major objectives to be reached. Road accidents represents the main cause of deaths each year: in most cases they are caused by drivers' reckless driving style (pedal pressures, steering speed, etc.). The real-time identification of potentially dangerous driving styles is an important element for road safety, as it gives the opportunity to take precautions in terms of safety distance, speed, etc. The main goal of this work is the characterization of the different driving styles in various environments, with the possibility of highlighting potentially dangerous behaviors. Our approach is based on the deployment of a Smart-Device (SD, a phone, a tablet, etc.) to acquire, process data and perform the characterization (nowadays, at least one SD is present in a vehicle). The SD gives the possibility to acquire information from the Internet (e.g. weather data), from its own sensors (such as the gyroscope), from the built-in GPS and from the Electronic Control Unit (ECU) via On Board Diagnostics II (OBD-II) standard [1], [2], [3]. The SD allows to interface with the vehicle OBD-II via Bluetooth. There are many dedicated devices, like the KiWi Bluetooth (KW-BT) [4], able to read data from the ECU of the most part of vehicles. Generally, inside the KW-BT device, there is an ELM327 microcontroller, able to gather data from the OBD-II port and encapsulate it for the Bluetooth transmission. In this paper the use of the fuzzy logic paradigm [5] [6] allows us to analyze different continuous variables, dynamically evaluating their degree of membership (also called truth degree) to different fuzzy sets. Unlike the binary logic, the fuzzy one have no "static" boundaries for its sets, but include a variation of a threshold value that is as an approximation of a subjective judgment. The degree of membership of an object to a fuzzy set can take any value between [0,1], unlike the traditional concept, which is restricted only to the values 0 and 1. For our purposes it is used to identify a particular driving style, we first need to pick out the environment in which the driver is located (such as urban, suburban or highway). The identification can be made by performing a statistical analysis on the speed data, acquired experimentally from the SD and the OBD-II. After acquiring a large number of samples for different environments, a Gaussian statistical analysis has been introduced, in order to acquire information about average speeds and variance, recorded in different intervals. After a specific environment is identified, a proper rules set is built to analyze the driving styles. In our work, we started from some existing studies [7] [8] about driving styles recognition and, then, we refined them by taking into account the characteristics of different road environments (urban, suburban or highway). It is important to observe that, in different environments with equal speed and acceleration, the same behavior can be considered in different ways. For example, a driver who travels at 35 km/h in urban environment is classified with normal behavior, but if the speed of 35 km/h is maintained on the highway, the behavior is no longer normal, but it can indicate the presence of traffic jams or abnormal situations. For this reason, it is not possible to use the same fuzzy speed sets in all environments (an analysis will be made for each case). After the the Android application implementation, all the analyses have been carried out through the Fuzzy Logic and Statistical Toolboxes of MATLAB. This paper is organized as follows: Section II presents an in-depth overview on state-of-the-art of similar approaches in Vehicular Ad-hoc Networks (VANET); Section III introduces the considered scenario, while Section IV offers a deep description of the proposed scheme. Section V validates the proposed scheme and, then, conclusions are summarized in the last section.

2. STATE OF THE ART

There are many works in literature based on some criteria or schemes for recognizing the driver behavior during a trip on a road. In [9] and [10] the authors underline the importance of controlling a vehicle and how it reflects on fuel economy and emission reduction, since they are heavily influenced by road conditions and driving styles. Their main idea consists in predicting future road and environmental conditions in order to a-priori know how a driver should act to optimize consumptions. The authors state also that each individual driving style is different and it is not so easy to meet the optimal driving conditions. So, another important effort could be given by investigating the driving style factors that have a major impact on fuel economy. In [11] the importance of identifying driving styles is considered in relation to the Intelligent Transportation Systems (ITS). A driving style identification is proposed, based on the concept of normalizing driving behavior using a personalized driver modeling. The authors use a neural network to learn driver features, then the obtained model is tested and used for defining an aggressiveness index to identify abnormal driving behaviors. Another important contribution is given by the work in [12], in which the effectiveness of an accurate driving style recognition is underlined. Advanced driving assistant systems (adaptive cruise control systems, intelligent forward collision warning systems, platooning warnings, etc.) represent the future in ITS, so the analysis of driving behaviors is very crucial. In their work, the authors exploit the potentialities of a clustering method for the elaboration and analysis of the commonness and individuality of driving behavior characteristics, extracting data from the ECU of the vehicle. In addition, since the gathered data is very large, a data mining approach has been also employed for the extraction of deeper information. The work proposed by Vaitkus et al. in [13] is based on the inertial measurement signals of the vehicle with the help of GPS. The proposed monitoring system is capable to classify aggressive and normal driving styles, by applying a pattern recognition approach with a relatively high success rate. In the work presented in [14], driver behaviors are rated in common traffic conditions and, then, through a statistical analysis of the collected data, the driver is characterized as aggressive, anxious, keen, or other. In this way, assistance services can be tailored to the particular driver. The authors of [15] proposed a scheme based on a smart-phone application for detecting and classifying driving maneuvers, using the smart-phone accelerometer and vehicle gyroscopes. The work proposed in [16] used different classifying techniques to detect driving events from smart-phones using inertial sensors as well as directly from the ECU of the vehicle. They also made a deep comparison of the data obtained from both sources. Also in [17], the authors propose a scheme for identifying a driver style by inertial sensors. Their study is based on the possibility of separate data into classes, considering the basic events of accelerating, braking, and turning. All the possible maneuvers can be considered to be a composition of the basic events.

Differently from the cited works, in our proposal we considered the fuzzy approach and the modern OBD-II connection, from which an application on a generic SD can gather the appropriate data. In particular, the main contributions are:

- study and development of a fuzzy approach to be applied to vehicular environments in order to obtain a scheme able to recognize the driver behavior during a trip in a given environment;

- statistical analysis of users' average speed in different topologies and environments;

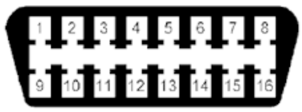
- definition of fuzzy subsets on the basis of the probabilistic distribution function (pdf) statistics of the particular type of road.

3. THE ON-BOARD DIAGNOSTICS, THE CONTROLLER AREA NETWORK (CAN) PROTOCOL AND THE FUZZY LOGIC PARADIGM

In this paragraph we will give some details about the considered components of our idea

3.1 The On-Board Diagnosis II

The term On-Board Diagnostics [1], [2] is referred to the ability of the vehicle of self-diagnosing and error reporting. OBD systems give access to the information on the "health state" of the various "emission-relevant" subsystems of the vehicle, such as catalyst, oxygen sensors, while other systems (e.g. air bags, air conditioning, etc.) does not have a self-standard, so any car manufacturer can adopt its own decisions. On-Board Diagnostics born in the late 60s and early 70s in America, when the problem of air pollution due to vehicle emissions arose. In those years, car manufacturers were beginning to install the on-board electronic equipment to check the status of the vehicle. In 1970 a congress approved the Clean Air Act and to create the Environmental Protection Agency (EPA), which established some standard levels of maximum permitted emissions and the related maintenance to be done to vehicles to reduce emissions. The OBD is able to acquire by a wired interface the read-only diagnostic signals and data in real-time from all the control units of the vehicle.



PIN	DESCRIPTION	PIN	DESCRIPTION
1	Vendor Option	9	Vendor Option
2	J1850 Bus +	10	J1850 Bus −
3	Vendor Option	11	Vendor Option
4	Chassis Ground	12	Vendor Option
5	Signal Ground	13	Vendor Option
6	CAN (J-2234) High	14	CAN (J-2234) Low
7	ISO 9141-2 K-Line	15	ISO 9141-2 L-Line
8	Vendor Option	16	Battery Power

Fig. 1. OBD-II connector and pin-out.

In Europe this standard was introduced for gasoline engines in 2001 along with the emission level Euro 3 with Directive 98/69/EC and it is usually called E-OBD (European OBD) [RIF. EOBD]. The standard OBD-II [RIF. OBD-II] specifies the type of diagnostic connector and its pins, the available electrical signaling protocols, the message format, and a list of monitoring parameters. The standard also provides an extensible list of DTCs (Data Trouble Codes), i.e. the error codes in the standard format, which can be interpreted by any user. Fig. 1 shows the structure of the OBD-II port with the related pins. As shown, the connector is composed by 16 pins arranged in two rows, and five different communication protocols have been defined, although the majority of vehicles are using only one: Variable Pulse Width (VPW, J1850, proposed by General Motors), Pulse-Width Modulation (PWM, J1850, proposed by Ford), ISO 9141 (proposed by Chrysler in Asia and Europe), KeyWord Protocol 2000 (KWP2000, ISO 14230) and ISO15765 (via CAN). The OBD-II is no longer used only to diagnose vehicle problems: the provided information could be used by telecommunication systems or SD applications installed on the vehicles to communicate to third parties. All the gathered data can be useful for any kind of application aimed at enhancing the safety and comfort level of the driver.

3.2 The CAN Protocol

The Controller Area Network (CAN or CANbus) is a standard for serial bus, introduced in the eighties with the main aim to connect in real-time various Electronic Control Units (ECU). At the moment it is the most widespread mean of communication in vehicles. CAN was specifically designed to operate also in the environments disturbed by the presence of electromagnetic waves and it uses a dedicated line differentially balanced in potential, such as RS-485. Thanks to its simplicity and robustness to noise, the CAN is now widely used also in the industry. The ISO 15765-2 [18] is an international standard for sending data packets on the CANbus. The most common application of this protocol is the transfer of diagnostic messages to devices that use the OBD-II. The wide diffusion of the CAN protocol has determined wide availability of chip transceivers, microcontrollers that integrate CAN ports, development tools, as well as a considerable decrease in the cost of these systems. The CAN protocol has an amazing ability to recognize errors and the probability that a message is corrupted and/or not recognized is practically null. All the protocols defined for the CAN bus stack are illustrated in fig 2. The communication, in the CAN bus, takes place via different devices, such as sensors or actuators, capable of producing data independently. In addition, this type of equipment, is able to request and use the data produced by any another device. The CAN bus provides the "multi-master" feature, i.e. all nodes of the network can transmit and request the transmission channel simultaneously. For more details about the CAN protocol, please refer to [18].

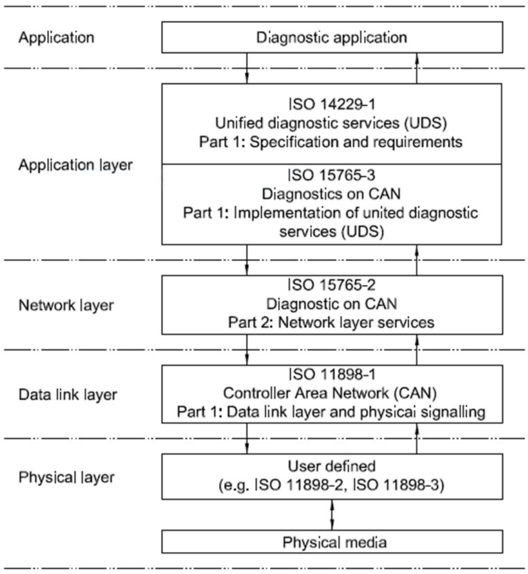


Fig. 2. ISO-OSI reference model for CAN bus.

3.3 The Fuzzy Logic (FL) paradigm

The FL challenges and changes the concept of binary logic (only two states): in the real world everything is a matter of measure, not only white or black, but also shades [19]. Unlike the binary logic, to allow a greater relationship with the natural language, the fuzzy sets do not provide "hard" boundaries but include a landmark change in the considered values. In this way a good approximation to the subjective judgment can be reached. This is why in FL some linguistic variables are used (such as "very", "somewhat", "a little", etc.) to facilitate the expression of rules and facts. The linguistic variables are coded with appropriate functions. This concept is summarized in fig. 3.

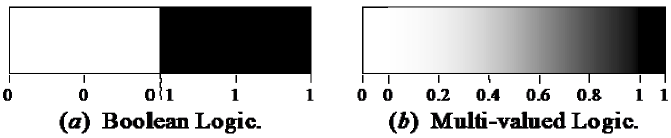


Fig. 3. Main difference between Boolean logic and FL.

The Membership Degree (MD) of an object referred to a fuzzy set can assume any value in the range [0,1], unlike a traditional set, which is restricted to the values 0 and 1 (false and true): in FL, the MD is to be intended as indicating "how much" a property is true. FL systems are based on the IF-THEN (antecedent-consequent) rules, without the ELSE part. Through some input-output relationships it is possible to approximate any function or system to describe or control. One of the most usual inference method is the Mamdani approach [20], divided into four main steps: input fuzzyfication, inference rule evaluation, aggregation and defuzzyfication. The other one is the Sugeno method [21]: the author suggested the use of a single value (singleton) as a membership function. A singleton is a fuzzy set with a membership function that is unitary at a particular point and zero otherwise. The Mamdani method is generally used to describe the knowledge and the experience in an intuitive way, while the Sugeno approach is efficient and it is used in optimization problems or adaptive control. Let X be the universe of the considered event, and let x be its elements. At the base of FL there is the Linguistic Variables (LVs) theory: a LV can assume its values as linguistic terms. For example, if we consider the "speed" variable, its universe X could be the set [0, 300] km/h, while the FL linguistic sub-sets could be 'very slow', 'slow', 'medium', 'fast', 'very fast'. Following the classical theory, the set A is defined on X by the Characteristic Function (CF) $f_A(x)$ of the A set:

$$f_A(x) = X \to \{0,1\}, \quad where \quad f_A(x) = \begin{cases} 1 & if \quad x \in A \\ 0 & if \quad x \notin A \end{cases} \tag{1}$$

and, clearly, it represents a map of the universe X to the set {0,1}. In the FL paradigm a Membership Function (MF) μA(x) is used instead:

$$\mu_A(x) = X \to [0,1], \quad where \quad \mu_A(x) = \begin{cases} 1 & if \quad x \quad completely \quad in \quad A \\ 0 & if \quad x \quad not \quad in \quad A \end{cases} \qquad 0 < \mu_A(x) < 1 \quad if \quad x \quad is \quad partially \quad in \quad A \tag{2}$$

and, clearly, it indicates the "membership amount" of x to A.

4. ENVIRONMENT IDENTIFICATION AND DRIVING BEHAVIORS

In order to characterize the different driving styles it is necessary to identify in-advance the environment in which the driver is located. A human driver instantaneously recognizes the context that surrounds him but, in order to automate the detection of a possible aggressive driving behavior, it is necessary to identify the characteristics of the current environment. In this work, we decided that characteristic parameter for each environment is the average speed, after many empirical observations, which have been made on the obtained experimental data. It is well known that the average speed maintained in urban environment is very different from the one maintained in the extra-urban one and/or motorway, due to the intrinsic topological nature of the considered roads, as well as the objective constraints that should be respected (speed limits, and traffic lights or pedestrians if present, etc.). By the deployment of different Android APP components that have been developed by us, it is possible to acquire vehicle dynamics, directly via the KW-BT interface (fuel consumption, acceleration/deceleration, torque, etc.). Fig. 4 illustrates some demo screens of the considered apps.

Fig. 4. Some screenshots of the developed APP for car life monitoring.

The APP is able to send the collected information to a remote server (via 3G/4G or WLAN if available), in order to perform an off-line elaboration. All data were collected using the "01- show current date" mode, as defined in SAE J1979 standard [22], and using the PIDs shown in table 1. More details can be found in [22].

We focused our attention on the 'vehicle speed' field, in order to discern the various types of results that could be achieved. In particular deeply analyzed the obtained samples for different environments and, excluding the zero values (when then vehicle stops), all the AVerage Speed (AVS) values have been observed to follow a Gaussian distribution.

TABLE I. An extract of all the PIDs described in SAE J1979.

PID (hex)	Data bytesreturned	Description	Minvalue	Maxvalue	Units
0C	2	Engine RPM	0	16,383.75	rpm
0D	1	Vehicle speed	0	255	km/h
0F	1	Intake air temperature	-40	215	°C
10	2	MAF air flow rate	0	655.35	grams/sec
11	1	Throttle position	0	100	%
1F	2	Run time sinceengine	0	65,535	seconds
2F	1	Fuel Level Input	0	100	%

So the general expression of the AVS pdf can be considered to be:

$$f_{AVS}(t) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \tag{3}$$

where μ and σ are, respectively, the average and standard deviation. It is possible to evaluate the error of the considered average AVS, based on confidence intervals/levels, considering the worst case error probability ξ. It is possible to select a TAVS for a mobile host so that:

Prob(CPT< TAVS) <1-ξ. (4)

The TAVS is called a (1-ξ)*100% upper confidence bound for average AVS. The assumption of a Gaussian pdf has been verified through the Kolmogorov-Smirnov (KS) normality test [23]. MATLAB gives the opportunity to simply analyze the considered data, using the kstest function. The cumulative distribution function (cdf) of the average AVS from eq. 1 is:

$$F(t) = P(X_{AVS} \le t) = \int_{-\infty}^{t} \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \tag{5}$$

and the probability that AVS is lower than a value t with a fixed error threshold ξ is:

$$P(AVS \le t) = P\left(Z \le \frac{t-\mu_{AVS}}{\sigma_{AVS}}\right) = \Phi\left(\frac{t-\mu_{AVS}}{\sigma_{AVS}}\right) = 1-\xi \tag{6}$$

where Z is a random variable equal to (AVS-μAVS)/σAVS. The $\Phi(\cdot)$ function represents the standard Gaussian distribution function. At this point, through the tabular values of the standard normal distribution, it is possible to obtain the AVS estimation for a given threshold, such as referred in [24], [25]. Clearly, the values of μ and σ are strictly dependent on the topology and mobility conditions. Road accidents are the cause of numerous deaths each year and, in most cases, the blame is attributed to dangerous driving attitudes taken by drivers. Preventively identifying a driver who is adopting a potentially dangerous driving is an important element in road safety, as it gives the opportunity to take precautions. The risk of accidents increases with the speed of the vehicle, but additional risk factors are represented by risky maneuvers, such as frequent and/or sudden lane changes, or driving while in altered states. With the term "driving style" we refer to the way a person prefers (or is used) to drive [26]. In the literature there are several studies that will identify the different driver attitudes by analyzing different data drivers. Some of them use the recognition of facial features to detect driver tiredness, others analyze the movements of the steering wheel [27], others identify a drunk driver according to data provided by the accelerometer of a smartphone which are compared with experimental data [28]. In [29] the authors used smartphone sensors to recognize the different driving styles. Our analysis is based on some studies ([30], [31], [32]) in which four riding modes (Below Normal, Normal, Aggressive, and Very Aggressive) are derived, using as input data the Euclidean norm, the transverse acceleration and vehicles speed. The use of the Euclidean norm of the acceleration in two dimensions allows to obtain more accurate information regarding the driving behavior taken along the way. The norm is calculated by eq. 7 for each point, then the signal is averaged by using a window of N

samples, as in eq. 8:

$$Norm(n)= \sqrt{Accel_{Long}^{2}\,(n) + Accel_{Trasv}^{2}\,(n)} \tag{7}$$

$$Norm(i)=\frac{1}{N}\sum_{n=1}^{N} Norm(n) \tag{8}$$

The acceleration rule has been divided into three fuzzy sets (Low, Medium and High), while the speed rule in five sets (Very Low, Low, Medium, High and Very High). Unlike the effort in [30], in our work we used trapezoidal functions. We made a characterization of driving styles in different road environments, according to the current law permissions in Italy. As regards the data relating to the standard acceleration, as illustrated in fig. 5, the membership functions described in [30] have been maintained, as well as the 15 fuzzy rules to identify the driving style.

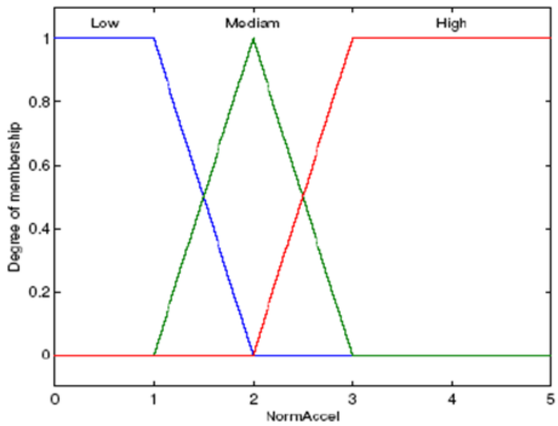


Fig. 5. The membership functions considered for the acceleration.

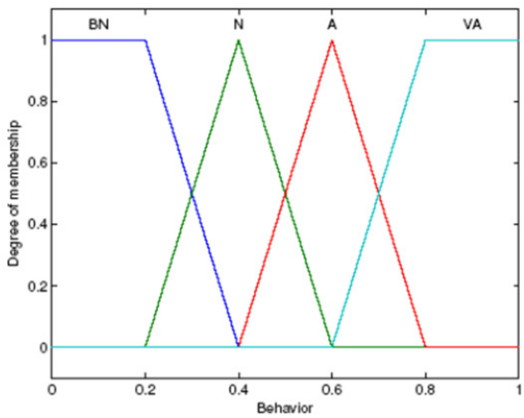


Fig. 6. The membership functions considered for the driving style recognition.

From fig. 6 we can observe that the x axis indicates the target behavior, with a value between 0 and 1: the scale indicates the level of aggressiveness of the driver. A value between 0 and 0.2 indicates a Below Normal (BN) behavior (generally too low speed for a given environment), a value of 0.4 indicates a Normal behavior, a value of 0.6 indicates an Aggressive behavior, and values equal or higher 0.8 indicate a very aggressive behavior. The intermediate values indicate the transition behaviors (for example, a value of 0.55 indicates a behavior that is a bit more than normal but a little less than aggressive and so on). Given that the considered system is a function of two variables, its output is represented with a three-dimensional graph, as shown in fig. 7, in which the different chromatic gradations highlight the transaction, in terms of membership value, from a fuzzy set to another.

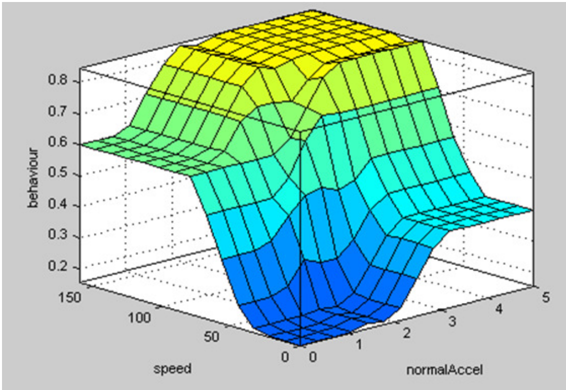


Fig. 7. Driving behavior trend in function of the considered inputs (speed and normal acceleration).

5. PERFORMANCE EVALUATION

In this subsection, the main measurements and results are shown. First of all, different speed samples have been collected through the analysis of the OBD-II data, obtained by different trips in different considered maps. Then, the data has been analyzed through the previously proposed environment recognition scheme. In particular fig. 8 shows the considered paths (urban on the left, extra-urban on the right).

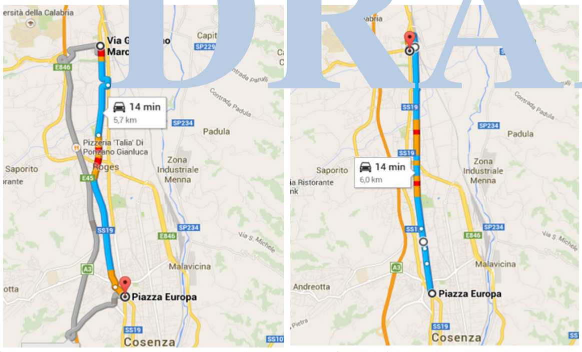


Fig. 8. Two different scenario for measuring the speed trend of vehicles.

The following tables illustrate the trend of the Gaussian parameters for the average speed in a urban scenario.

Table II. Speed for Urban Scenario (early morning)

SAMPLE	MEAN [km/h]	VARIANCE [$(km/h)^2$]	STANDARD DEVIATION [km/h]
M1	27.9351	443.086	21.04960807
M2	27.34	344.179	18.55206188
M3	27.9141	516.256	22.72126757
M4	24.6083	207.978	14.42144237
M5	27.1502	277.699	16.66430317
M6	25.4977	292.616	17.10602233
M7	29.6707	587.55	24.23943069
M8	27.5908	231.299	15.20851735
M9	24.2135	232.393	15.24444161
M10	27.9529	158.837	12.60305519

Table III. Speed for Urban Scenario (lunch time)

SAMPLE	MEAN [km/h]	VARIANCE [(km/h)2]	STANDARD DEVIATION [km/h]
PR1	34.216	474.393	21.78056473
PR2	30.2456	220.068	14.83468908
PR3	33.1402	478.109	21.86570374
PR4	33.5199	319.969	17.88767732
PR5	30.5065	155.852	12.48406985
PR6	31.7677	638.157	25.26176953
PR7	32.2651	337.468	18.37030212
PR8	31.0514	193.484	13.90985262

Table IV. Speed for Urban Scenario (late afternoon)

SAMPLE	MEAN [km/h]	VARIANCE [(km/h)2]	STANDARD DEVIATION [km/h]
PM1	32.7217	419.048	20.47066193
PM2	23.3464	389.436	19.73413287
PM3	[illegible]	[illegible]	19.87767592
PM4	[illegible]	[illegible]	[illegible]
PM5	[illegible]	[illegible]	[illegible]
PM6	[illegible]	[illegible]	[illegible]
PM7	[illegible]	[illegible]	[illegible]
PM8	[illegible]	[illegible]	[illegible]
PM9	29.6787	149.951	12.24544813
PM10	28.9043	383.131	19.5737324
PM11	37.0024	321.583	17.93273543
PM12	30.9663	208.509	14.43984072

Table V. Speed for Urban Scenario (evening)

SAMPLE	MEAN [km/h]	VARIANCE [(km/h)2]	STANDARD DEVIATION [km/h]
S1	32.165	73.4429	8.569883313
S2	37.0315	231.765	15.22383
S3	34.4443	186.414	13.65335124
S4	32.8217	124.87	11.1745246
S5	32.2918	72.9507	8.541118194
S6	31.8611	109.42	10.46040152
S7	28.7028	255.974	15.99918748
S8	34.6001	154.901	12.44592303
S9	28.7734	203.79	14.27550349

The mean values and pdf trends are summarized in fig. 9. The following figure (fig. 10) illustrates the main window of the MATLAB application used for evaluating the correctness of our scheme.

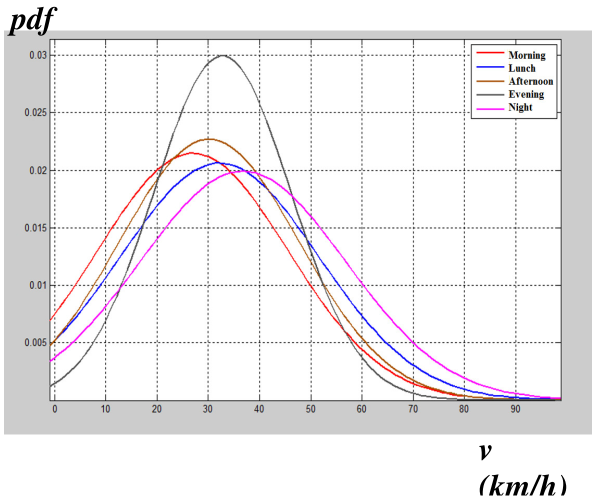


Fig. 9. Gaussian approximations for the average driving speed in different periods of a day.

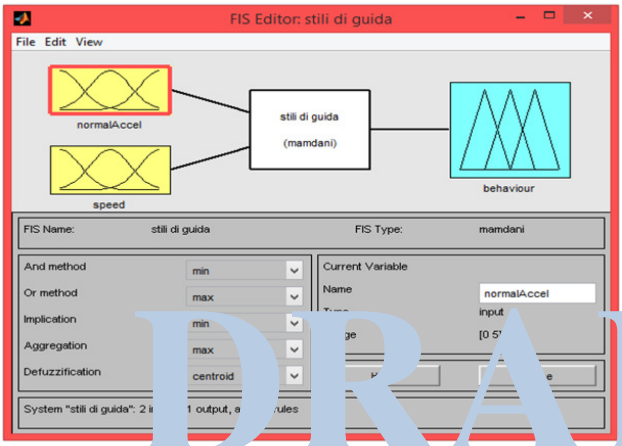


Fig. 10. Main MATLAB tool window used for evaluating the correctness of the proposed idea.

The last table illustrates the main obtained results. It is observed that for the same speed, the recognized behavior is considered differently depending on the environment (remember that the values from 0 to 0.2 indicate a “below-normal” behavior, a value of 0.4 indicates a “normal behavior”, a value of 0.6 is an “aggressive behavior” and values equal or higher than 0.8 indicate a “very aggressive” behavior). All the results are obtained by deploying the membership function illustrated in fig. 11. The terms of table VI are Urban (U), Extra-Urban Secondary (EXS), Extra-Urban Primary (EUP) and Highway (A).

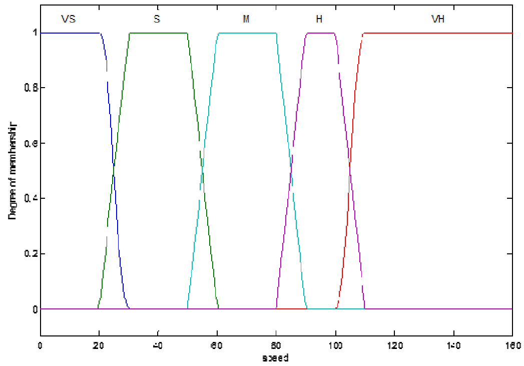


Fig. 11. Speed membership function used for an extra-urban environment.

Table VI. The Main Obtained Results.

Acceleration norm [m/s^2]	Speed [km/h]	Recognized behavior			
		U	EXS	EXP	A
0.5	38	0.4	0.153	0.153	0.153
0.5	70	0.6	0.4	0.4	0.153
0.6	90	0.6	0.6	0.4	0.4
0.6	110	0.6	0.6	0.6	0.4
2	75	0.847	0.6	0.6	0.153
4	55	0.847	0.5	0.4	0.4
3	75	0.847	0.6	0.6	0.4
3	60	0.847	0.6	0.4	0.4

6. CONCLUSIONS

In this paper a new algorithm for characterizing driving behaviors is proposed. It is based on the CAN protocol and OBD-II standard, while the decision is taken by the use of a FL approach. The choice of FL (in place of the traditional binary logic) has been dictated by the needing to manage continuous ingress/egress variables, evaluating the effects on the output for a given input. We identified four riding modes assigning to each of them an aggressiveness level. The intermediate values represent transient conditions from one style to another one. The classification of driving styles was made for each different environment, identified by a set of Gaussian curves, related to the average speed of the vehicle. The data were collected using an application developed for Android OS, which is able to acquire the data of the vehicle speed and acceleration. In the most of the cases, the application is able to correctly identify the driving behavior of the user.

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