Are you a Good Driver? A Data-driven Approach to Estimate Driving Style

Iván Silva Feraud
Escuela Técnica Superior de Ingeniería de Sistemas Informáticos, Universidad Politécnica de Madrid, Madrid, Spain
Facultad de Sistemas, Telecomunicaciones y Electrónica, Universidad de Especilidades Espíritu Santo, Guayaquil, Ecuador
i.silva@alumnos.upm.es

José Eugenio Naranjo
Escuela Técnica Superior de Ingeniería de Sistemas Informáticos, Universidad Politécnica de Madrid, Madrid, Spain
joseeugenio.naranjo@upm.es

ABSTRACT
In recent years, the study of aggressive driving behavior has reached interest due to its correlation with traffic accidents. Traffic accidents are considered the third cause of deaths in the United States. Prior research has reported the possibility to estimate aggressive driving style using in-vehicle data (e.g., acceleration, speeding, lane changes, among others). However, traffic violations have not yet been considered in the analysis of aggressive driving style. This paper proposes a model to estimate driver's aggressive driving style by considering aggressive events from in-vehicle data, and traffic violations data using a fuzzy logic model. In-vehicle data and GPS data from twenty-five drivers in different routes were collected, to generate a fuzzy logic model that captures aggressive events and traffic violations. We validate these results by comparing the results between the fuzzy logic model and human experts scores, showing an accuracy of 0.84 and a recall of 0.8974. Future work should consider to revise the rules and membership values to improve misclassification errors.

CCS Concepts
• Computing methodologies → Artificial intelligence • Applied computing → Transportation

Keywords
fuzzy logic; driver behaviors; aggressive driving style; traffic violations

1. INTRODUCTION
Reports from World Heal Organization (WHO) estimate that approximately 1.2 million people die every year because of road traffic crashes in the world. Traffic crashes not only cost people's lives but are also expensive; they cost roughly 3% of the gross domestic product (GDP) of countries [18]. Research suggests that 90% of traffic crashes are caused by risky driving behaviors [21]. For instance, a report presented in [4] stated that in the United States, aggressive behavior is the principal cause of crash vehicles. An aggressive driver, which is motivated by his impatience, annoyance, hostility and an attempt to save time [23], is likely to increase the risk of collision. Therefore, it may be beneficial for governmental institutions to explore low-cost and easy-to-deploy solutions by looking at driver's aggressive driving behavior, aiming at improving his awareness when driving too aggressively.

Many studies have established some behavioral factors that point to "safe" or "unsafe" driving styles, using diverse approaches to better understand driver's behavior [10, 12]. The two most common approaches to determine the aggressive driving behavior of drivers is through self-report and data-driven. In a self-report approach, it is common to analyze the aggressive driving behavior through data collected from questionnaires regarding the driver's emotional states (e.g., anger, irritation, frustration) or motivational states (e.g., boredom, competition, punishment) [6, 12, 15]. Whereas, the second approach tries to automatically model driver's behavior through Artificial Intelligence (AI), Statistics or Machine Learning (ML) techniques. These techniques use driver events as inputs (e.g., speed, acceleration, the distance between cars, lane changes, etc.) [3, 16] to classify driver's aggressive behavior. Whilst the first approach could be considered cheaper and easy to deploy, responses are subjective, which may not provide realistic data [2, 7]. On the other hand, models from statistical and artificial intelligence techniques may be more reliable, due to the use of driver's in-vehicle data, which may yield in a better representation of driver's styles. Thus, in this paper, we focused our analysis by following a data-driven approach, as we are aware that vehicles now are equipped with modern sensors, and these are becoming cheaper as technology improves.

Several studies have reported diverse models to identify aggressive driving styles, using data from Global Positioning Systems (GPS), accelerometer, video recordings, and On-Board Diagnostics (OBD2) sensors [16]. From these input data, most of the studies have mainly identified unsafe driver events such as speeding, quick lane changes, and sudden accelerations, with the intention to automatically classify the driver's aggressiveness [25]. However, few studies have considered traffic violations data as an unsafe driver event to determine aggressive driving behaviors.

Traffic violations are considered an unsafe driving behavior that causes high percentages of traffic accidents. During 2016, in the United States there were 10.111 traffic fatalities caused by speeding, and represent the 27% of deaths due to traffic accidents [1]. Thus, incorporating traffic violations to the analysis may give us a better understanding of aggressive driving behaviors, by relying not on only in the analysis of in-vehicle data but also adding contextual information of the road and safety driver's behavior.

This work aims to develop an offline fuzzy logic system to estimate the aggressive driver's style considering traffic violations

ICCMS 2019, January 16–19, 2019, Melbourne, VIC, Australia

ACM ISBN 978-1-4503-6619-9/19/01…$15.00
DOI:https://doi.org/10.1145/3307363.3307375

and aggressive events. To this end, we propose a model that takes the following input variables: i) average accelerations and decelerations events, number of sudden accelerations and decelerations; and, ii) traffic violations values from a previous model, reported in [8]. We validate our model by comparing the results of the fuzzy model with the evaluations of external experts.

This work is explained as follows: Section 2 describes previous work on aggressive driving style and background on fuzzy logic models. Section 3 presents the methodology, data collection, the design and implementation of the proposed fuzzy model. Section 4 reports the results obtained from the model, and finally, in Section 5, we present the conclusions and future work to generalize our results.

2. PREVIOUS WORK

In this section, we describe previous work on aggressive driving style, making emphasis on the variables that have been used to estimate driving styles. Also, we provide a brief explanation of fuzzy logic models and how they have been applied in automobile research topics.

2.1 Aggressive Driving Style

A report presented in [4] stated that driver's aggressive style is the principal cause of car crashes in the United States. The aggressive driving style is a behavior that increases the risk of collision. This behavior can be due to driver's impatience, annoyance, hostility or attempts to minimize traveling time [11]. The aggressive driving style is the driver's categorization through unsafe events such as speeding, quick lane changes and suddenly accelerations and decelerations [3].

In [19], the authors presented a system to classify the aggressive driver behavior into two categories, either safe or risky. Authors calculated sudden accelerations, sudden braking, and sharp turns as input variables. They built a Support Vector Machine (SVM) model, yielding an accuracy of 0.709 and recall of 0.833.

In another work proposed by [14], authors developed a system to classify aggressive behaviors for elderly and young people. Lateral accelerations information was extracted from driver's vehicle. Thus, to detect the driver's aggressiveness profile, a Gaussian Mixture Model (GMM) and a Periodogram method were used to identify significant periodicities in the data.

Another study presented in [11], implemented a model to evaluate drivers who show an driving style. Information from the vehicle was obtained such as longitudinal/lateral acceleration values, speed, engine RPM values, and turn events. Then, authors derived a set of events such as start, stop, speed, turns and maximum engine RPM. Authors reported a Bayesian classifier to predict the driver's aggressive style with an average accuracy of 90.5%.

In summary, the most used variables are derived from the vehicle's acceleration such as average acceleration and deceleration, lateral accelerations and sudden acceleration and braking. There-fore, in this study, we report the use of similar input variables that will feed our fuzzy logic model.

2.2 Fuzzy Logic

Fuzzy Logic is a branch of Artificial Intelligence (AI), which is characterized for considering uncertainty in the data by adding truth and false concepts from common logic to a machine-generated model [17]. To design a fuzzy logic model, we need to follow three steps: 1) Fuzzification: this stage defines the membership functions and linguistic variables of the inputs. 2) Rules Evaluation: in this stage, we will apply the fuzzy logic rules to calculate the output; and, 3) Defuzzification: and finally, in this step, a fuzzy inference system (FIS) converts the output to a crisp result [22]. The two most used types of FIS are Takagi-Sugeno Fuzzy Model (Sugeno) and Mamdani Fuzzy Inference System. While Mamdani may capture human input better, Sugeno is more computationally efficient than Mamdani [9, 13].

Fuzzy logic models using in-vehicle data have been investigated in prior works. Some seminal works have studied the how the driving style affects the fuel consumption, by evaluating the performance drivers [24]. Dörr et al. [5] proposed an online model using fuzzy logic to characterize driver styles, reporting an accuracy of 0.68. Also, in work presented by Aljaafreh et al.[3], the authors proposed a fuzzy system to classify aggressive driving using driver style. They categorized the driver style using the following categories: below normal, normal, aggressive, and very aggressive. Authors analyzed the driver's aggressive patterns using the Euclidean norm of the longitudinal and lateral accelerations and deceleration values; and speed, as input variables of the system. The system was built using fifteen fuzzy rules by analyzing events of an aggressive driver that match with the category of a driver. This work can be considered the most related one to our approach. However, we want to go further, by considering not only acceleration features, but also by adding traffic violations, which are also considered critical for modeling driving styles behavior.

In summary, this work proposes to model a fuzzy logic system to capture driving styles using in-vehicle data. Besides, we incorporate traffic violations data (speeding), with the aim of adding road information from traffic signs. In the next section, we explain in detail how we designed and validated the fuzzy logic system.

3. METHODOLOGY

This study aims to estimate the driving style, through in-vehicle data based on acceleration and traffic violations using a data-driven approach. In this work, we propose an offline fuzzy logic model, giving the capacity to work with uncertainty data and computer's faster processing. Figure 1 depicts an overall architecture of the model. For instance, we can see that data logs from traffic signs and in-vehicle data feed a Traffic Violations Model. This model was presented in a previous work [8], in which we estimated traffic violations from in-vehicle data. The output of the model is a value between 0 and 1, in which 0 means that a driver has moderate traffic violations and 1 means a high level of traffic violations. Thus, the result of this model will serve as an input variable. Next, in-vehicle data measures are calculated, giving us a set of input variables. Then, these input variables will feed the Fuzzy Inference System. Finally, the output will be one of the three linguistic labels that capture the driving style. Below, we explain the design of the fuzzy logic model and the experimental setup to test our model.

3.1 Design of the Fuzzy Logic Model

The fuzzy logic model that will estimate the driving style is per-formed by a data-driven approach, motivated by the previous works (see section 2) and the advice of experts. Our fuzzy model was designed using a Sugeno FIS, and it was implemented using the MATLAB tool1. We decided to use Sugeno FIS because it gives faster results than other FIS [9, 13]. Thus, we defined: 1) a set of variables to serve as inputs of the model and its membership functions; 2) a set of linguistic labels to define the output of the model and, 3) a set of rules to represent the fuzzy model based on the input variables and the linguistic labels.

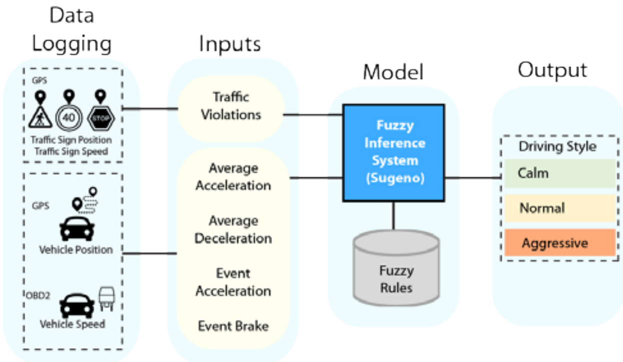

Figure 1. Architecture of the driving style model

Inputs and Membership Functions: From previous works, we identified that the most used feature to determine aggressive events was the acceleration (see Section 2). Figure 2 (first column) depicts a total of five input variables that will feed our model. The first two input variables correspond to the average acceleration (AvgAcc) and deceleration (AvgDec), which will be calculated from the driver's acceleration from the whole route.

The third and fourth input variables correspond to driving events such as harsh acceleration (EventAcc) and braking (EventBrake). We measure this inputs when the value of instant acceleration exceeds a threshold assigned. The thresholds needed to detect these two event types have been taken from [20]. Furthermore, we add three different threshold levels depending on the traffic flow, as shown in Table 1. Our motivation for this was that it is not the same to drive in an overcrowded route rather than in a clear route. For example, if the route is overcrowded, the vehicle cannot accelerate faster; and therefore, we would assign a threshold of 1 (m/s^2) for this route. Thus, we end up with an input variable EventAcc, which counts the number of occurrences when the instant acceleration takes one of the threshold values (harsh acceleration) depending on the assigned level; and another variable EventBrake, which counts on the negative values of the instant acceleration (braking).

Table 1. Thresholds defined for harsh accelerations and brakes

Event types	Threshold of traffic flow		
	Low	**Medium**	**High**
EventAcc	a >= 2 m/s^2	a >= 1.5 m/s^2	a >= 1 m/s^2
EventBrake	a >= -2 m/s^2	a >= -1.5 m/s^2	a >= -1m/s^2

The fifth input variable relates to the output of Traffic Violations Model, which estimates the traffic violations, based on the driver's over speed and the severity of infraction (see [8] for details).

Figure 2 shows the linguistic labels assigned to each input variable (column 2) and its membership function (column 3). We applied triangular and trapezoidal membership functions due to its easiness to assign interval values to a linguistic label for each input. For example, the first input variable 'AvgAcc' has associated 'Low', 'Normal' and 'High' linguistic labels. Moreover, from the member-ship function we can see that the 'Low' linguistic label is linked with values from 0 to 0.65; 'Normal' is associated with values from 0.4 to 0.9; and 'High' is associated with values from 0.65 to 1.2.

Rules: When designing fuzzy logic systems, we should be aware that the number of rules determines the time response of the model. As our ultimate aim is to develop an online system to detect driver's style, we decided to have the minimum number of rules. Thus, we ended up with eight rules, as depicted in table 2. For example, in rule number 1, we can see that the antecedent relates with EventAcc and AvgAcc input variables. If both variables yield a value of 'high' after being evaluated from its membership function, then the consequent will be 'aggressive'.

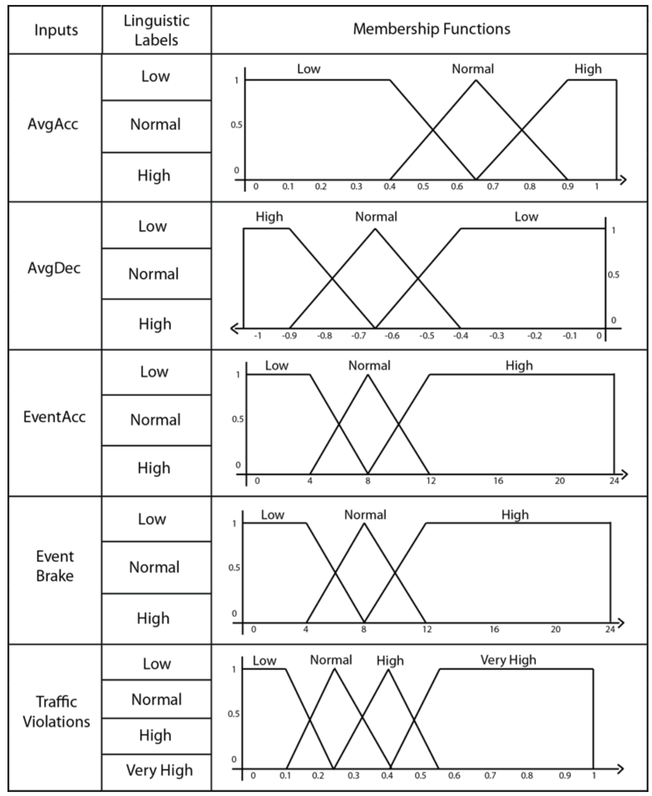

Figure 2. Input variables description with their linguistic labels and membership functions

Table 2. Rules defined from inputs variables

Rules	Antecedents		Consequent
1	EventAcc AvgAcc	High High	Aggressive
2	EventBrake AvgDec	High High	Aggressive
3	AvgAcc	Low	Calm
4	EventAcc EventBrake	High High	Aggressive
5	AvgDec EventBrake	Low Low	Calm
6	AvgAcc AvgDec	Normal Normal	Normal
7	Traffic Violations	Very High	Aggressive
8	Traffic Violations	Low	Calm

Output: We determined three linguistic labels to estimate the driving style, namely calm, normal and aggressive; and each label has a constant membership function from 0 to 1. Table 4 summarizes the thresholds used to link the corresponding linguistic label with the constant membership function. For instance, if the model estimates a value between 0 to 0.35, the driving style will be assigned as ’calm’. Instead, if the model estimates a value between 0.35 to 0.70, the driving style will be ’normal’. Finally, if the value is between 0.70 to 1, the driving style will be ’aggressive’.

3.2 Simulations

To test the design of the fuzzy model, we carried out a sensitive analysis by generating a dataset (n=60) from expert’s knowledge and equally distributing of the data with three possible outputs of the model (i.e., calm, normal and aggressive). The model has an accuracy of 78% based in the simulated data. Table 3 shows the confusion matrix, and the most errors occur in the case of normal driving style.

Table 3. Results of the test with simulated data

	Calm	Normal	Aggressive
Calm	16	4	0
Normal	3	14	3
Aggressive	0	3	17

3.3 Equipment and Data Collection

Data from traffic signs were logged previously to the experimentation. One of the researchers drove the selected route and logged in the GPS position of the traffic sign with a smartphone and the traffic sign value (e.g., 50 Km/h). As this step was manually done, we foresee that in the future, automatic data capture can be applied using additional sensors (e.g., extract traffic signs from real-time video cameras).

Two devices were used to collect the in-vehicle data: an OBD2 device, plugged in into the car; and a smartphone with Torque application installed2. The OBD2 captures and send the speed of the vehicle to Torque, via Bluetooth. Besides, Torque saves the position (latitude and longitude) and the timestamps from the smartphone, so we assume that the position of the smartphone is the position of the vehicle. Thus, for each driver, we capture the speed data and vehicle GPS.

3.4 Experiment Setup

The proposed model is determined by a data-driven approach. Hence, we first collected the data from two experiments, in two different contexts. Next, we defined our linguistic labels and the membership functions values that will feed the fuzzy logic model. Finally, to validate the data-driven model design, experts were asked to evaluate drivers to then compare the results given by them and the model.

3.4.1 Experiment 1

Fifteen drivers (9 males, 6 females), from 24 to 56 years old, with non-professional driving license, participated in this experiment. This experiment was carried out in Guayaquil city. We selected a route with a duration of 25 minutes approximately, an average distance of 19 kilometers and 23 speed limit signs (e.g., 40 Km, 70 Km, 90 Km) including different types of routes (e.g., highways, suburban roads and urban roads). Traffic flow plays an important role in the estimation of driving styles due to the limitation or freedom of the driver to accelerate. Since the data collection with drivers were done in a ’Low’ traffic flow context, we selected a threshold of 2 m/s^2 (see table 1) for EventAcc and EventBrake variables.

3.4.2 Experiment 2

Ten drivers (all males), from 25 to 55 years old, with a non-professional driving license, participated in this experiment. This experiment was carried out in Madrid city. We selected a similar route as to experiment 1. This route had a duration of 23 minutes approximately, an average distance of 17 kilometers and 23 speed limit signs (e.g., 40 Km, 70 Km, 100 Km) including different types of route (e.g., highways, suburban roads and urban roads). For this experiment, we selected a threshold of 1.5 m/s^2 for EventAcc and EventBrake variables, since the route had a ’Medium’ traffic flow.

3.4.3 Human Evaluation

Human experts were asked to evaluate each driver’s style using a score from 0 to 100, being 0 the lower and 100 the higher score for the driving style. All experts have been working in automobile research related areas. Six and nineteen experts evaluated the driver’s style from the input variables (see the input column from Figure 1) collected in the experiments 1 and 2, respectively. Next, the inter-rater reliability coefficient was calculated from the human evaluations. The ICC from the six experts was 0.921, and the ICC from the nineteen experts was 0.934. These coefficients denote good reliability for the evaluation made by humans. The average score of the human evaluation per driver was considered as the ground truth.

To have the same criterion as the fuzzy logic model, we discretized the scores of the experts, first by scaling down the score into a [0,1] interval and then by applying the fuzzy logic output thresholds. Table 4 describes the thresholds and the final distribution of drivers per driving style label.

Table 4. Thresholds and distribution of drivers per driving style

Labels	Thresholds	Distribution
Calm	[0 , 0.35]	2
Normal	[0.35 , 0.70]	13
Aggressive	[0.70 , 1]	10

4. RESULTS AND DISCUSSION

Our fuzzy model was able to estimate the driving style with 84% of accuracy and recall of 89.74%. All drivers that were evaluated as calm and aggressive were correctly classified by the model. By contrast, from the normal driver’s category, 16% were misclassified. Moreover, the Kappa coefficient was 0.828, which indicates a similarity agreement between the experts and the model. Analyzing the scores (0 to 1 interval) given by the fuzzy model and experts, we observed that experts (avg.=0.624, stdev.=0.189) and fuzzy model (avg.=0.614, stdev.=0.232) gave similar scores. These results suggest that our model is capable of mimicking the expert’s knowledge. Eventually, to avoid misclassification errors, the rules and the values from the membership functions with ’Normal’ label should be further revised.

Also, it is worth to note that, even that a driving style approach may be considered suitable for classification purposes, it lacks to deter-mine why a driver is considered aggressive or not. To overcome this problem, self-report measures may be considered in the analysis of aggressive styles, aiming for a holistic approach. For instance, to measure emotional states, we could compare the perceived state from drivers and our model.

A limitation of this study is the small sample of drivers to test our model. More data is needed, specifically for ’calm’ drivers, to generalize our results and improve the fuzzy model. Moreover, from the distribution of drivers per driving style, we can see that experts tend to evaluate drivers either as 'normal' or aggressive'. That is, possibly the results of the evaluation of the experts may be biased.

5. CONCLUSION

This work proposed a fuzzy logic model to estimate driving styles using a data-driven approach. The fuzzy model was designed using a Sugeno FIS, with eight rules and, five input variables from in-vehicle data, including traffic violations. In contrast with prior studies from the literature that use self-report measures, we validated our fuzzy model from experts' evaluation, which was considered the ground truth. Our model was capable of classifying the driver's with an accuracy of 84%, suggesting that a driving style approach may be beneficial for this context. However, more data need to be collected to generalize our findings.

As future work, we can improve the system by introducing more unsafe events such as tailgating or lateral accelerations, which are also good descriptors of driving styles. We can also improve and automate the design of the fuzzy logic model by creating the inference rules through artificial intelligence techniques, such as neural networks or genetic algorithms.

6. REFERENCES

[1] National Highway Traffic Safety Administration. 2017. 2016 Fatal Motor Vehicle Crashes: Overview. Technical Report. National Highway Traffic Safety Administration, 1200 New Jersey Avenue SE., Washington, USA.

[2] Anders af Wåhlberg. 2009. Driver Behaviour and Accident Research Methodology: Unresolved Problems.

[3] Ahmad Aljaafreh, Nabeel Alshabatat, and Munaf S Najim Al-Din. 2012. Driving style recognition using fuzzy logic. In Vehicular Electronics and Safety (ICVES), 2012 IEEE International Conference on. IEEE, 460–463.

[4] American Automobile Association et al. 2009. Aggressive driving: Research update. American Automobile Association Foundation for Traffic Safety (2009).

[5] Dominik Dörr, David Grabengiesser, and Frank Gauterin. 2014. Online driving style recognition using fuzzy logic. In Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on. IEEE, 1021–1026.

[6] Chris S Dula and Mary E Ballard. 2003. Development and evaluation of a measure of dangerous, aggressive, negative emotional, and risky driving. Journal of Applied Social Psychology 33, 2 (2003), 263–282.

[7] Leonard Evans. 2004. Traffic safety.

[8] Iván Silva Feraud, María Mercedes Lara, and José Eugenio Naranjo. 2017. A fuzzy logic model to estimate safe driving behavior based on traffic violation. In Ecuador Technical Chapters Meeting (ETCM), 2017 IEEE. IEEE, 1–6.

[9] Kerim Guney and Nurcan Sarikaya. 2009. Comparison of Mamdani and Sugeno fuzzy inference system models for resonant frequency calculation of rectangular microstrip antennas. Progress In Electromagnetics Research 12 (2009), 81–104.

[10] Paul B Harris, John M Houston, Jose A Vazquez, Janan A Smither, Amanda Harms, Jeffrey A Dahlke, and Daniel A Sachau. 2014. The Prosocial and Aggressive Driving Inventory (PADI): A self-report measure of safe and unsafe driving behaviors. Accident Analysis & Prevention 72 (2014), 1–8.

[11] Jin-Hyuk Hong, Ben Margines, and Anind K Dey. 2014. A smartphone-based sensing platform to model aggressive driving behaviors. In Proceedings of the 32nd annual ACM conference on Human factors in computing systems. ACM, 4047–4056.

[12] John M Houston, Paul B Harris, and Marcia Norman. 2003. The Aggressive Driving Behavior Scale: Developing a self-report measure of unsafe driving practices. North American Journal of Psychology 5, 2 (2003), 269–278.

[13] JJ Jassbi, Paulo JA Serra, Rita A Ribeiro, and Alessandro Donati. 2006. A comparison of mandani and sugeno inference systems for a space fault detection application. In Automation Congress, 2006. WAC'06. World. IEEE, 1–8.

[14] Dong-Woo Koh and Hang-Bong Kang. 2015. Smartphone-based modeling and detection of aggressiveness reactions in senior drivers. In Intelligent Vehicles Symposium (IV), 2015 IEEE. IEEE, 12–17.

[15] Barbara Krahé and Ilka Fenske. 2002. Predicting aggressive driving behavior: The role of macho personality, age, and power of car. Aggressive Behavior 28, 1 (2002), 21–29.

[16] Gys Albertus Marthinus Meiring and Hermanus Carel Myburgh. 2015. A review of intelligent driving style analysis systems and related artificial intelligence algorithms. Sensors 15, 12 (2015), 30653–30682.

[17] Luis Álvarez Munárriz. 1994. Fundamentos de inteligencia artificial. Vol. 1. Editum.

[18] World Health Organization. 2015. Global status report on road safety 2015. World Health Organization.

[19] Tatsuaki Osafune, Toshimitsu Takahashi, Noboru Kiyama, Tsuneo Sobue, Hi-rozumi Yamaguchi, and Teruo Higashino. 2017. Analysis of accident risks from driving behaviors. International Journal of Intelligent Transportation Systems Research 15, 3 (2017), 192–202.

[20] Johannes Paefgen, Flavius Kehr, Yudan Zhai, and Florian Michahelles. 2012. Driving behavior analysis with smartphones: insights from a controlled field study. In Proceedings of the 11th International Conference on mobile and ubiquitous multimedia. ACM, 36.

[21] Eleni Petridou and Maria Moustaki. 2000. Human factors in the causation of road traffic crashes. European journal of epidemiology 16, 9 (2000), 819–826.

[22] Timothy J Ross. 2009. Fuzzy logic with engineering applications. John Wiley & Sons.

[23] Leo Tasca. 2000. A review of the literature on aggressive driving research. Ontario Advisory Group on Safe Driving Secretariat, Road User Safety Branch, Ontario Ministry of Transportation Ontario, Canada.

[24] D Vangi and A Virga. 2003. Evaluation of energy-saving driving styles for bus drivers. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 217, 4 (2003), 299–305.

[25] Afonso Vilaca, Pedro Cunha, and André L Ferreira. 2017. Systematic literature review on driving behavior. In Intelligent Transportation Systems (ITSC), 2017 IEEE 20th International Conference on. IEEE, 1–8.