Different Intelligent Approaches for Modeling the Style of Car Driving

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Abstract: In this paper, we propose a hierarchical pattern of the style of driving, which is composed of three levels, one to recognize the emotional state, other to recognize the state of the driver, and finally, the last one corresponds to the style of driving. Each level is defined by different types of descriptors, which are perceived in different multi-modal ways (sound, vision, etc.). Additionally, we analyze three techniques to recognize the style of driving, using our hierarchical pattern, one based on fuzzy logic, another based on chronicles (a temporal logic paradigm), and another based on an algorithm that models the functioning of the human neocortex, exploiting the idea of recursivity and learning in the recognition process. We compare the techniques considering the dynamic context where a car driver operates.

1 INTRODUCTION

With the popularity of advanced systems driver assistance (ADAS) in vehicles, and setting the context of a man-machine system, the problem of interaction between drivers and ADAS becomes important, but more important is how adapts it to the characteristics of each driver.

In order to make the ADAS can suit to individual drivers, it is necessary that the ADAS can count adaptive systems that can consider internal characteristics of each human being, as fatigue, inattention, and in this case, its type of driving (Lin et al. 2014). There are a lot of work about the emotions in a car, e.g., in (Aguilar et al. 2016), (Cordero & Aguilar 2016) is proposed a recognition model of the emotional state, using chronicles and static patterns. On the other hand, in (Eyben et al. 2010) show how the emotions are a key issue not only in a general oncoming human-computer interaction, but also in the in-car communication. (Katsis et al. 2015) present a revision of the works in emotion recognition, focusing on those influencing the driver's performance. The work of (Aypar et al. 2014) is focused on an alerting mechanism based on the driver state recognition. (Guoying & Danpan 2016) propose a pattern recognition approach to identify the driver steering behavior. There are much more works about the emotions of the car driver, but in general, they propose simple models, or they study only the emotions (Kolli et al. 2011), (Tawari & Trivedi 2010), (Paschero et al. 2012), (Wang, J. et al., 2013).

The main contribution of this paper is to propose a hierarchical pattern of the style of driving, which consider three levels of recognition, one to recognize the emotional state, other to recognize the state of the driver, and finally, the last one corresponds to the style of driving. Each level is composed of different descriptors, which require a multi-modal approach in order to be perceived, and they are related between them because they are descriptors between them. In addition, the paper analyses three techniques to recognize the style of driving, one based on fuzzy logic, another based on chronicles, and another based on an algorithm that models the functioning of the human neocortex, called Ar2P. We compare the techniques, evaluating their capabilities to define countersteering strategies, to adapt it to the driver, or to Internet of things (IoT).

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2 FORMAL DEFINITION OF THE PATTERN OF THE STYLE OF DRIVING OF A CAR DRIVER

In general, a pattern can be considered as the abstraction of a set of objects, and normally is defined by a set of descriptors. In this paper, we propose to model the style of driving of the car driver using a hierarchical pattern, which is composed of 3 levels:

First level: *Pattern of the style of driving*. Its aim is to model how the driver drives. In the literature, classically the style of driving can be aggressive, ecological, urban, and normal. This level must detect the style, based on the descriptors of the Table 1.

Table 1: Descriptors of the Pattern of the style of driving.

Descriptor	Description
Type of roads	It describes the type of the road.
Driver state	It describes the state of the car driver, and it is defined by the second level of our pattern.
Emotion of the driver	It defines the emotional state of the driver, and it is defined by the third level of our pattern.
Environmental condition	It characterizes the current environmental conditions.
States of the road	It characterizes the current conditions of the road.
Traffic characteristic	It defines aspects linked to the transit laws.

Second level: *Driver state*. Its aim is to describe the state of the car driver. In the literature, normally, the state of a car driver can be wakeful, stressed, lethargic, pleasant, fatigued, calm, boring, falling asleep, among others. This level must detect the state of the driver, based on the descriptors of the Table 2.

Table 2: Descriptors of the Pattern of the driver state.

Descriptor	Description
Class of the vehicle	It describes the type of vehicle.
Action control over the vehicle	It describes the current action of the driver of the car.
Emotion of the driver	See description in Table 1.
Vehicle condition	It defines the current conditions of the vehicle.
Characteristics of the driver	It defines the profile of age, or physical condition, of the driver.
Driving experience	It characterizes the experience of the driver as a car driver.
Driving hour	It defines the current hour of the day.

Third level: *Emotions of the Driver*. Its aim is to describe the emotions of the driver. This level must detect the current emotion of the car driver. Particularly, we are going to use the six basic emotions defined in the literature: happiness, sadness, fear, anger, disgust, and surprise. The descriptors that define this pattern are described in Table 3.

Table 3: Descriptors of the Pattern of the Emotions of the Driver.

Descriptor	Description
Driver behavior	It defines the current behavior of the driver in the vehicle.
Action control over the vehicle	See description in Table 2.
Physiological behavior of the driver	It defines the current physiological conditions of the driver.
Vehicle condition	See description in Table 2
Voice expressions of the driver	It characterizes the current tone of voice of the car driver.
Facial expressions of the driver	It characterizes the current facial expressions of the car driver.
Body expressions of the driver	It describes the current body expression of the driver.

The main goal of the hierarchical pattern is to recognize the style of driving. To recognize the style of driving, we need different descriptors (see Table 3), which describe it. Particularly, one of the descriptors is the state of the driver, which again is described by a set of descriptors (see Table 2). Other descriptor is the emotional state of the driver, which also is described by a set of descriptors (see Table 1). Thus, each level has a different set of descriptors, which are perceived in different ways (sound, vision, etc.) that implies to use a multi-modal approach for the perception.

The descriptors describe various aspects: facial, acoustic, body language, among others. The current status of the descriptors are determined by the events that are captured in the environment of the vehicle in a given moment. For that, we use information from the different sensors in the car, to characterize these events. For example, for the speed of the car, we can define the set of events of the Table 4. And so for the rest of descriptors of our hierarchical multimodal model.

Now, according to the current values of the descriptors, are determined the current emotion of the driver, the current state of the driver, and finally, his/her style of driving, using the hierarchical multimodal model. Table 5 shows an example of the possible emotions recognized by the pattern of the third level of our hierarchical multimodal model, according to the value of the descriptors of this pattern. Table 6 shows an example of the possible style of driving recognized by the pattern of the first level of our hierarchical multimodal model, according to the value of the descriptors of this pattern. It is important to remark that Table 5 and 6 show some of the emotions and styles that can be recognized, Also, they show some of the possible combinations of the values of the descriptors for the recognition of these emotions and styles (e.g., Table 5 shows two examples of events (ED2 and ED3) to recognize the "happiness" emotion, but there may be more combinations of values of the descriptors to recognize it). For the possible states of the driver (second level of our hierarchical multimodal model), it is similar.

Table 4: Events about the speed of the car.

Id Event	Description	Speed
S1	High speed	> 100 Km/h
S2	Normal speed	≥ 40 and ≤ 100 Km/h
S3	Low speed	< 40 Km/h

3 APPROACHES FOR THE MODELING OF THE STATES OF A CAR DRIVER

3.1 Based on Chronicles

A chronicle can be defined as a set of events, linked by a set of temporal constraints (Aguilar 2011). Each chronicle is an event pattern with temporal relationships between them, and a set of chronicles characterizes the possible evolution of a system studied. To define a chronicle, normally two predicates are used: event and hold. An event expresses a change in an attribute, for example: Event(state(light): (on, off), t2). A hold specifies that an attribute holds a value during a time interval, for example: Hold(position(robot, home), (t2, t4)).

In general, a chronicle model C is defined by a pair (S, T), where S is the set of events and T the temporal constraints between the events. A chronicle instance c of a chronicle model C is a set of event occurrences, which is consistent with the time constraints of C.

The hierarchical pattern recognition system based on chronicles paradigm consists of 3 types of chronicles: i) First type, represents the emotional patterns of the driver. Its aim is to describe the emotions of the driver; ii) Second type, represents the patterns of the driver state. Its aim is to describe the driver's condition; iii) Third type, represents the patterns of the driving styles. Its aim is to establish how the person drives.

Every emotion, state, or driving style of the driver will be modelled by a different chronicle, which contains the events and the temporal relationships to recognize them. A specific emotion, state or driving style can be recognized by several chronicles, an each chronicle is defined by the set of descriptors defined in the previous section. An example of a chronicle of the first type, to recognize the anger, is:

```
Chronicle Anger {
event(F3, T4),
event(P1, T3),
event(B5, T5),
event(H1, T6 ),
event(V1, T1),
event(S1, T2)
T1   T3,
hold(F3, (4, 10)),
hold(S1,(6, 20)),
When recognized {emit event(ED1)}}
```

According to this chronicle, the pattern of anger can be recognized when the voice event "Tone treble and volume high and speaking rate fast" (V1) arrives at time T1, and holds between 4 and 10 units of time; the speed event "High speed" (S1) occurs at the time T2, and holds between 6 and 20 units of time, the pressure event "Strong pressure of the steering wheel" (P1) appears at time T3 and it is less than or equal to T1, the facial event " Eyes and Eyebrows open, with curves and tight lips, and face wrinkles in the center" (F3) ocurrs at time T4, the body event "Posture Flattened" (B5) ocurrs at time T5, and the heart event "Fast Heast rate" (H1) arrives at time T6.

An example of a chronicle of the third type, to recognize an aggressive driver, is the following:

```
Chronicle Aggressive {
event(ED1, TED1),
event(ST3, TST3),
event(R1, T4),
event(E2, T3)
TED1   TST3,
T3   3 T4,
hold(ST3, (5, 15)),

When recognized {Report the style of driving to the driver assistance system}}
```

Table 5: Emotions of a driver.

Id Event	Emotion	Driver behavior	Action control over the vehicle	Physiological behavior of the driver	Vehicle condition	Voice expressions of the driver	Facial expressions of the driver	Body expressions of the driver
ED1	anger	the car driver pulls the door	pressing the steering-wheel	heart rate high, the pupil dilatation of the driver high	mechanical failure or electrical failure	the driver is shouting	the driver is serious	the driver moves violently
ED2	happiness	the driver uses the seat belt	normal	heart rate normal	normal	the driver is singing	the driver is smiling	the driver reacts slowly
ED3	happiness	the driver uses the seat belt the driver is calm	normal	heart rate normal	normal	the driver is whistling	the driver has a calm face	the body of the driver is calm
ED4	fear	the driver uses the seat belt	braking	the color of the face white	any	normal	the driver is serious	

Table 6: Style of driving.

Id Event	State of the driver	Type of roads	Driver state	Emotion of the driver	Environmental condition	States of the road	Traffic characteristic
SD1	aggressive	any	stressed	anger	is raining	the road has potholes	does not follows traffic signs
SD2	ecological	rural	relaxed	happiness	any	any	follows speed limits
SD3	normal	urban	relaxed	happiness	any	any	any

The structure of the chronicles of the second is similar. This is just a sample of the proposed chronicles used by the ADAS, where: i) The emotions (anger, happiness, fear, among others) make up the chronicles of type 1 (EDi), representing the emotional patterns of the driver; ii) The driver states (stress, pleasant, wakefulness, sleepy, among others) are the chronicles of type 2 (STi), representing the patterns of driver states; iii) The styles of driving (aggressive, ecological, normal) are the chronicles of type 3 (SDi), representing the patterns of the driving styles.

The chronicles of type 1 and 2 are composed of the primary events captured through different types of sensors (pressure sensor on the steering wheel, driver's heart rate sensor, speed sensor, among others). The chronicles type 3 are a mixture of the primary events and the events recognized in the hierarchical system. This level communicates with the driving system to generate the relevant actions according to the identified driving style.

3.2 Based on Ar2P

Ar2P (Algoritmo Recursivo de Reconocimiento de Patrones, for its acronym in Spanish) is a model for pattern recognition, inspired in the pattern recognition theory of mind (Puerto & Aguilar, 2016), (Puerto & Aguilar, 2017). Each layer in the hierarchy is an interpretation space identified as Xi, from i=1 to m. X1 is the level of recognition of atomic patterns, and Xm is the level of recognition of complex patterns (a complex pattern is characterized by being composed of patterns of lower levels). Each level is composed of Γji recognition modules, (for j = 1, 2, 3... # of modules at level i). ρji is the recognized pattern by the module j at level i. The function of each recognition module is to recognize its corresponding pattern. s() represents the presence of a pattern to be recognized. This input is specific to each recognition module. For the top-down case, the output signal of the higher-levels is the input signal at the lower-levels.

There is a ν relationship of structural composition among the Γji of different Xi, such that Γrt → Γlk, where t < k, and the relationship "→" indicates that Γrt of Xt is contained or forms part of Γlk, which belongs to layer Xk of higher level. There may be different versions of the same pattern (redundancy/robustness) represented by different Γrt, from r = 1,2,3...until possible variations of the object in the real world. Each level i produce an output signal (recognition or learning) based on the responses of its modules. The output of each Γji consists of a specific signal of recognition of its pattern ρji, which is transmitted through the dendrites to its higher levels. This signal contains information about the characteristics of the pattern that represents. Such recognition is diffused through all the dendrites of which the recognition module is connected. When it is not recognized, it sends a signal that maybe involves learning.

According to the hierarchical architecture of Ar2P, the hierarchy of patterns to recognize the style of driving, would be as follows: at the first level X1 are the pattern recognition modules of emotions of the driver, at the second level X2 are the pattern recognition modules of drive state, and finally, at the level X3 the pattern recognition modules of style of driving. Table 7 shows the mathematical formulation of the recognition model. Ar2P uses dynamic pattern recognition modules, what contains the information needed to recognize a pattern (descriptors, weight, etc.). Table 8 represents the structure of a pattern recognition module (Puerto & Aguilar 2017).

Table 7: Mathematical Formulation of the Recognition Problem.

#	Equation
1	$\rho_d = < D_n, f_\Delta, \Delta\tau>$ A dynamic pattern is formally defined as a 3-tuple
2	$D_n = [d_1, d_2, d_3 \ldots d_i, d^1, d^2, d^3 \ldots d^j]$ D_n is a vector that collects all the n descriptors of d: d_i denotes a characteristics descriptor, and d^j denotes a perception descriptor.
3	$\widehat{d_x} \equiv [v_{1x}, v_{2x}, v_{3x}, \ldots, v_{kx}]$ It is the domain vector of each characteristics descriptor
4	$\widehat{d^y} \equiv [v^{1y}, v^{2y}, v^{3y}, \ldots, v^{ky}]$ It is the domain vector of each perception descriptor
5	$f_\Delta = [fcd_1, fcd_2 \ldots fcd_i, fcd^1, fcd^2 \ldots fcd^j]$ They are the change functions, specific to each descriptor.
6	$\Delta\tau d_1 = [(t_1, v_{11}), (t_2, v_{21}), (t_3, v_{31}) \ldots (t_\tau, v_{\tau 1})]$ It is a vector of "change event" of each descriptor.

Table 8: Structure of a dynamic pattern recognition module (Γρ).

E			
S		C	
Signal	State	Pointer (P)	Weight (W)
1	F	$Pointer_1$	[0,1]
...	…	…	…
N	F	$Pointer_i$	[0,1]
1	F	$Pointer^1$	[0,1]
…	…	…	…
M	F	$Pointer^j$	[0,1]
U: <ΔU1, ΔU2>			

S: S=<Signal, State> is an array that represents the set of signals (descriptors) that conform to the pattern recognized by Γρd and their respective states. The state variable is "true" when the signal is present and "false" otherwise. C= <P, W>, P are pointers to the time series $\Delta\tau d_i$ (characteristics descriptor) and $\Delta\tau d^j$ (perception descriptor). The weight column (W) contains the value of the descriptor importance in the recognition. U: is the thresholds vector used by the module (Γρd) to recognize its respective pattern. There are two types of thresholds: ΔU1 is the threshold for the recognition by key signals of characteristics or perception, and ΔU2 is the threshold for the recognition by partial or total mapping of signals of characteristics or perception. Each module produces a recognition signal (So), or petition signal towards lower levels. So as petition becomes the input signal s() for the pattern recognition modules of the lower levels. When there's a recognition signal, it is distributed to its higher levels attainable.

Suppose we would like to recognize an "aggressive" pattern. Table 9 shows the instantiation of the first level of the pattern recognition module in this case. Table 10 shows the instantiation of the last level of the pattern recognition module, for the case where the driver emotion is "anger". For the rest of the emotions of the driver, this last level is similarly instantiated. The instantiation of the second level, for the states of the driver, is similar.

Table 9: Structure of a dynamic pattern recognition module for the aggressive pattern: Γρd=aggressive.

E			
S		C	
Signal	State	Domain values	Weight
Road rural	F	$<$ Road rural$>^j$	0.5
Road urban	F	$<$ Road urban$>^j$	0.6
Stressed	F	$<$ Stressed$>_i$	0.8
Anger	F	$<$ Anger$>_i$	0.8
Rain	F	$<$Rain$>^j$	0.5
Damage road	F	$<$ Damage road$>^j$	0.6
Does not follows traffic signs	F	$<$ numerous traffic tickets, reckless driving, DWI (driving while intoxicated), DUI (driving under the influence), etc.$>^j$	0.8

Table 10: Structure of a dynamic pattern recognition module for the driver emotion pattern: Γρd= Anger.

E			
S		C	
Signal	State	Domain	Weight
The car driver pulls the door	F	< sound of strong door $>^j$	0.6
High speed	F	< 150 Km/s ≥ speed ≤ 200$>_i$	0.8
Strong pressing the steering-wheel	F	< grade of pressing the steering-wheel$>_i$	0.6
Pupil dilation high	F	< pupil diameter from 6 to 9 mm $>_i$	0.6
Heart rate high	F	< from 200-100 beats/min $>_i$	0.8
Mechanical failure	F	< mechanical failure considered $>^j$	0.5
Electrical failure	F	< electrical failure considered $>^j$	0.5
The driver is shouting	F	< The driver is shouting $>_i$	0.8
The driver is serious	F	< The driver is serious $>_i$	0.8
Driver moves violently	F	< violent movements management considered $>^j$	0.6
U: <ΔU1, ΔU2>			

3.3 Based on Fuzzy Logic

A fuzzy controller is a rule-based fuzzy system, composed of a set of inference rules of the type IF <Condition> THEN <Action>, that defines the control actions according to several ranges of the controlled variables in the problem. Before these rules can be used, all input signals must be converted into linguistic/fuzzy variables. In general, the basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains the fuzzy rules; a set of fuzzy variables, each one defined by a set of membership functions; and a reasoning mechanism that performs the inference procedure.

We propose to instance the hierarchical multimodal model of style of driving, using a Multilayer Fuzzy Classifier System (MFCS). In (Camargo & Aguilar 2014) is presented a MFCS that consists of a number of fuzzy systems hierarchically distributed, which have the advantage that the total number of rules of the knowledge base is smaller, and simpler than a conventional fuzzy system. The output of a Fuzzy Classifier System (FCS) is the input to the next FCS.

In Figure 1, we show our MFCS model for the recognition of the style of driving, which is composed by three FCS, a) a FCS to recognize the emotional state, b) a FCS to recognize the state of the driver, and finally, c) a FCS to recognize the style of driving.

The inputs are the same descriptors defined in the section 2 for each level, but in this case are defined as fuzzy variables. With these fuzzy variables, we can describe the set of fuzzy rules of each FCSi.

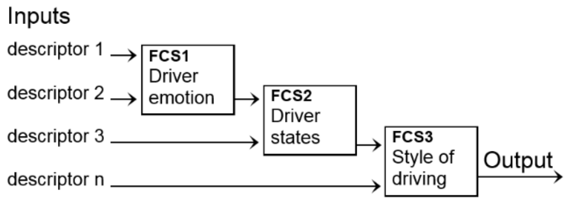

Figure 1: MFCS Model to recognize styles of driving.

For example, for the case of the FCS1, some of the possible fuzzy rules are:

- If (use-horn is excessive) and (heart rate is high) and (facial expression is very serious), then (driver-emotion is anger).
- If (driver hits steering wheel) and (voice is high) and (facial expression is serious), then (driver-emotion is very anger).

For the case of the FCS3, some of the possible fuzzy rules are:

- If (driver state is very stressed) and (emotion is anger) then (style-of-driving is aggressive).
- If (driver state is stressed) and (weather is raining) and (road has potholes) then (style-of-driving is aggressive).

In the case of the FCS2, the fuzzy rules are similar.

4 COMPARISON OF APPROACHES

In this section, we perform a qualitative comparison considering the capabilities of each technique in three safety-related states (Huang et al. 2010).

4.1 Counter Steering Strategies (Reasoning Capabilities)

It consists in detecting the negative styles of driving (aggressive, etc.), in order to guide the driver into a positive style of driving, for safe driving:

Chronicles: We can observe the process of reasoning based on temporal logic in a natural way with the chronicles. For example, a pattern of an emotion like the sadness is defined by a set of events at different times, as facial expressions of type "eyes and eyebrows with tears that arrive at time T1, and the voice event " low volume" that occurs at time T2. That is, the reasoning mechanism is based on the events of the descriptors and their temporal relationships, and it manages the incertitude according to when the events occur.

Ar2P: has the ability to deal with uncertain knowledge. This is achieved within the structures of representation of the pattern (i.e., the pattern recognition modules) using, among other things, the notion of weight of the descriptors. Particularly, these modules use meta-variables, such as weights and value domains, which support different forms or changes in the descriptors of a pattern. At the level of the reasoning mechanism, it allows inferring a situation, and navigating among the modules.

Fuzzy Logic: allows an approximate reasoning, which implicitly can manage the incertitude, using the idea of imprecision and information granularity in the definition of the fuzzy descriptors of our multimodal pattern model. The fuzzy theory provides a mechanism for representing linguistic constructs, such as “many,” “low,” “medium,” “often,” “few”. Fuzzy logic provides an inference structure that enables the utilization of these constructs in our fuzzy descriptors, through our MFCS. Additionally, our MFCS is an excellent strategy to describe the different levels of our pattern model. Finally, it can convert linguistic strategy into control actions, based on the diagnostic process inferred.

4.2 Adaptation Strategies (Learning Capability)

It consists in the capability of a quick adaptation to the personality of the driver:

Chronicles: A same situation (an emotion, a style of driving, etc.) can be described by different chronicles, to express the diversities of contexts where a same situation can occur (for example, an aggressive behavior). However, the main problem is to learn the set of chronicles required. In the literature, there are two types of learning process in the chronicles paradigm (Aguilar 2011): to learn the structure of a chronicle, or to parameterize a general chronicle. This is an open problem. In a real system like our proposition, we can define general chronicles for each descriptor of our model, and then parameterize these chronicles to each driver. This approach requires a robust chronicle database, which would be constantly learned to adapt them to the driver and new situations.

Ar2P: uses two strategies of adaptation (Puerto & Aguilar 2016) the first one, called new learning, occurs when the input pattern was not recognized (there is not a module that recognizes it). The second one, called reinforcement learning, occurs when the input pattern was recognized. These two learning mechanisms allow a quick adaptation to the style of driving of the driver. On the other hand, AR2P paradigm has the ability to adapt their pattern recognition modules in accordance with the recognized patterns, readjusting the importance of the weights, in order to improve the management of the incertitude.

Fuzzy Logic: A FCS can learn the rules and the structures of the fuzzy variables. That means, the membership functions of the fuzzy variables can be adapted to the context, and the rules of the database can be modified (their antecedent and consequent components) (Camargo & Aguilar 2014). For example, when the fuzzy definition of the happy emotions is not adequate, the membership functions can be modified. Similarly, for the case of the fuzzy rules, the rules must adapt to reflect the specific patterns of each individual (maybe, the reasons of an aggressive behavior of an individual can be very different with respect to other individuals). To achieve this, the FCS allows the modification of the rules when it is presented new information.

4.3 Communication of the Driver’s Emotional State (Communication Capabilities)

In this case, we like to evaluate the scenario of the IoT, where the exchange of information is natural between heterogeneous devices, such as two vehicles.

Chronicles: The communication within different chronicles are events. That is valid for the case where the chronicles are in the same car, or in different cars. These events can include specific information required by the chronicles, but it is the only information required. The hierarchical model of driving patterns communicates the required messages with the events generated by the different descriptors, or chronicles recognized, which contains relevant information about how drives a driver, in order to generate the actions concerning with the recognized driving style. In the previous scenario, the vehicle 1 (v1) sends an event to inform that the driver is “falling asleep”, to the rest of the vehicles.

Ar2P: only need to send the signals about the recognition of a given descriptor (for example, the emotional state of the driver). This signal is the input of one of the modules of recognition in the other vehicle, such as the complex pattern is not important to know. In the previous scenario, the vehicle 1 (v1) sends a signal to inform that has recognized the driver is "falling asleep" to the rest of the vehicles.

Fuzzy Logic: In this case, we have two possibilities: to send a discrete value, which must be defuzzifiered in the other vehicle (that is, the output fuzzy descriptor must be defuzzifiered and sent to the other vehicles), to send the values of the fuzzy variables (but on the other side the fuzzy system must be similar). The main problem is that we can have multiple outputs (multiple active rules, which can represent several styles of driving active), and they must be sent to the other vehicles in order to have a real idea of the context.

5 CONCLUSIONS

In this paper, we have proposed a hierarchical pattern of the style of driving, which consider 3 levels of recognition, one to recognize the emotional state, other to recognize the state of the driver, and finally, the last one corresponds to the style of driving. Our model is flexible because it allows incorporate new descriptors in the model, for example, about the traffic flow, among other things.

In addition, the paper analyses three techniques to recognize the style of driving, one based on fuzzy logic, another based on chronicles, and other based on Ar2P. We have compared these techniques in 3 cases: for defining countersteering strategies, or its adaptive capability to the driver, or to communicate the style of driving of the driver recognized. Each technique has its advantage and disadvantage, and depend on the real context (IoT) to choose to one of them.

As future work, we will carry out the implementation of these techniques in a simulated context, to measure the three previous criteria using specific metrics for each one. In this way, we will carry out a quantitative comparison, which is complementary to the qualitative comparison analysed in this work.

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