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Driving Behavior Assessment Using Fuzzy Inference System and Low-Cost Inertial Sensors

Neda Navidi and Rene Jr. Landry

LASSENA, Department of Electrical Engineering, École de Technologie Supérieure (ETS), Montreal, QC H3C 1K3, Canada

Abstract: Continuous vehicle tracking as well as monitoring driving behaviour, is significant services that are needed by many industries including insurance and vehicle rental companies. The main goal of this paper is to provide methods to model the quality of the driving behaviour based on FIS (fuzzy inference systems). The models consider vehicle dynamics as long as the human behaviour parameters, expressed by a set of raw measurements which are obtained from various environmental sensors. In addition, assessment-driving behaviour model is simulated and tested by two different FISs: Mamdani and Sugeno-TSK. The simulation results illustrate the critical distinctions between the two FISs using the proposed driving behaviour models. These differences are based on various processing times, robust behaviour of the FISs, outputs MFs (membership functions), fuzzification-techniques, flexibility in the systems design and computational efficiency.

Key words: Driving behaviour assessment, FIS, Mamdani type, Sugeno-TSK type, MFs.

1. Introduction

In recent years, the rate of vehicle accident fatalities has been one of the main concerns in rural and urban communities. PHAC (Public Health Agency of Canada) has reported more than 2,209 fatalities and 11,451 serious injuries every year [1]. Car accidents may impose expenses to governments, namely as needed medical treatments, rehabilitation assistance and property damages. Such expenses are estimated to be more than one hundred billion dollars per year in Canada [1].

Vehicle tracking is one of the significant concerns for the insurance and the vehicle rental companies. Monitoring driver's behaviour helps develop the pricing solutions based on car usage (PAYD: pay as you drive), the driving habits (PHYD: pay how you drive) or the area of operation (PWYD: pay where you drive) [2].

In this paper, the parameters involved for the estimation of the driving behaviour include the vehicle position, the longitudinal and lateral accelerations, and so the velocity. Moreover, the environmental scenarios include the vehicle inter-distance and lane change related to lane keeping. Some of these measurements can be obtained by GNSS (Global Navigation Satellite Systems) and low cost INSs (Inertial Navigation Systems), while others can be obtained using OBD (on-board diagnostic) system of the vehicle.

However, discussion on how to obtain the required raw measurements is not the goal of this paper. The contributions of this paper are to propose a new FIS (fuzzy inference systems) model for characterizing the driving behaviour and so evaluating of this model by two FIS types. In the end, the two FIS types will be analysed and compared together to figure out which is the best one in characterizing the driving behaviour.

The paper is organized as following: Section 2 presents the preliminaries of the work. Section 3 gives the proposed methodology for the characterization of driving behaviour. Section 4 presents the proposed fuzzy inference systems including the various MFs (membership functions). Furthermore, this section gives the comparison between Mamdani and and Sugeno types implemented fuzzy systems. Sections 5

Corresponding author: Neda Navidi, Ph.D. candidate; research fields: electrical engineering, driving behaviour assessment, navigation, positioning and tracking systems. E-mail: neda.nav3@gmail.com.

and 6 present the simulation results and the conclusions of this paper, respectively.

2. Preliminaries

In this section, the initial criteria and the methods used for driver behaviour classification are reviewed. Later, the utilization of artificial intelligent techniques for this purpose are also reviewed.

2.1 Methods for Driver Behaviour Classification

Three important methods exist which contribute to the classification of the driving behaviour: measuring the driver brain activities, measuring the physical characteristics of the driver and measuring the dynamics of the vehicle.

2.1.1 Measuring the Driver Brain Activities

The brain-activity mapping methods necessitates the existence of physiological signals of the driver's brain, which are mainly based on EEG (electron encephalogram), ECG (electro-cardiogram), EOG (electro-oculography) and SEMG (surface-electromyogram) techniques [3]. From the techniques above, EEG is the most commonly accepted method for extracting the drivers' characteristics.

Determination of the driver behaviour based on EEG is divided into time domain techniques and frequency domain techniques. Some of the typical techniques in the time domain EEG are the aggregate of the amplitude-squares, the mean values and the standard deviation. Moreover, ARMV (auto regressive moving average), the power spectrum density and the average frequency are the most typically techniques in the frequency domain EEG [3]. The main drawback of this method is the use of one or more sensors on the driver's body.

2.1.2 Measuring Physical Characteristics of the Driver

In the physical- and facial-expression detection methods, the use of eyes and lip indications is commonly accepted. Such facial expression recognition methods evaluate the driver actions by means of ECD (eye closures duration), fixed gaze, blink frequency, energy of blinking, average eye closure speed, etc. [4]. Also, some researchers have proposed to consider lip and mouth movements to recognize the driver's attention.

Three main states of lip movement related to driver's attention are: normal, yawing and talking. In addition, the researchers have proposed the FACS (facial action coding system) [5]. This latter is based on the coding of the eyes and the lip movements and it utilizes the machine learning to detect the manners. However, changing the light and the shadow disturbs the physical characteristics because of using the camera and the visual signals [5].

2.1.3 Measuring Dynamics of the Vehicle

Instead of considering the driver behaviour based on the physiological or physical characteristics, this method takes into account the dynamics and the behaviour of the vehicles, as the core of the data collection. It is relied on measuring the speed, steering wheel position, brake and turn signal statuses, as long as lateral and longitudinal accelerations.

2.2 Artificial Intelligent Techniques for Driving Behaviour Monitoring

Modelling human behaviour based on linear techniques is not acceptable in the real world. Thus, the non-linear techniques based on machine learning methods are widely employed for the monitoring of driving behaviour. These techniques are summarized as follows.

2.2.1 NNs (Neural Networks)

NNs (neural networks) algorithms are commonly used to observe the statistical modelling of the driving behaviours [6, 7]. There are some significant advantages of NNs for monitoring driving behaviour as: (1) allowing the pattern extraction without the awareness and facts of the relation between the inputs and the outputs; (2) less demand for formal training; and (3) recognition of all probable interactions between the predictor variables. On the other hand, the black-box nature and the complex computation of ANNs are the two main drawbacks of these algorithms [6, 7].

2.2.2 SVMs (Support Vector Machines)

SVMs (support vector machines) are capable of computing the different emotional states of the driver by their effective nonlinear methods [8]. Additionally, the SVMs are employed for the purpose of pattern categorization, the linear or nonlinear relationships between I/O (input-output) and the objet detection [8].

2.2.3 HMMs (Hidden Markov Models)

HMMs (hidden Markov models) are used for the driving states identification as the monitoring of the automotive vehicle [9]. For achieving this goal, the usage of Baum-Welch re-estimation method is considered in many issues [10].

2.2.4 FISs

FISs are a rule-based expert method for its ability to mimic human thinking and the linguistic concepts rather than the typical logic systems. The advantage of the FISs appears when the driving behaviour estimation remains complex due to the system high complexity. Also, FISs are utilized for the knowledge induction process as they are the worldwide approximators [5].

In the other word, FISs are proper method where: (1) Process of analysis is complex and time-consuming by controventional methods; (2) Available raw measurements are interpreted approximately or inaccurately. The two major types of FISs are Mamdani and Sugeno-TSK that the recent literatures focused on the comparison of these two methods [5].

3. Proposed Methodology

The diagram of the proposed methodology is shown in Fig 1. First, the driver actions are acquired using INS, GNSS and OBD. Later, the features of the driver actions are applied to recognize the most likely driving behaviour by the fuzzy controller. Finally, the outputs of this controller are utilized to estimate the drivers' behaviour and performance.

The proposed model contains all features of driver actions that are essential to evaluate the strengths and the weaknesses of the driver performance. The goal of the model is the categorization of the driver behaviours based on two types of FISs for the estimation of the differences between methods. All the related driving states in our proposed model are summarized as follows:

- SS (standing state): the velocity of the lateral and the longitudinal axes is zero or near zero and the vehicle does not have any movement [11];
- RS (routine state): the vehicle moves constantly, so the longitudinal velocity of the vehicle and the steering position should be stable and the velocity of the lateral should be close to zero [12];
- AS (acceleration state): there is the incremental acceleration in the longitude of the vehicle. Also, the angle of the throttle paddle is increasing;

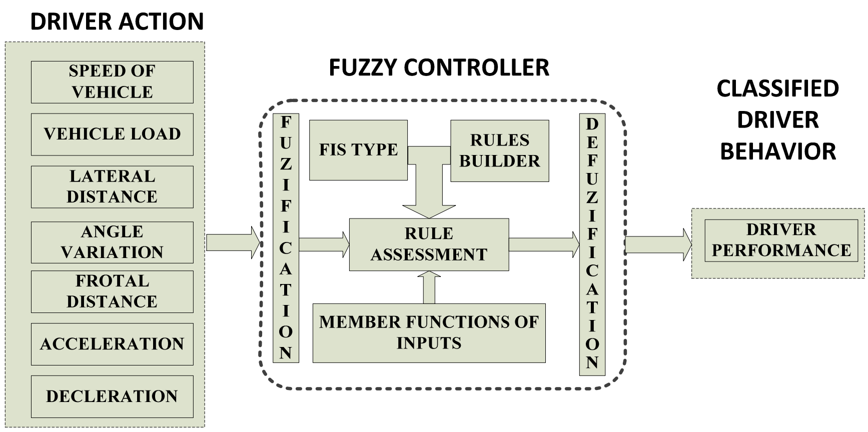


Fig. 1 Proposed methodology for the classification of driver behavior.

- DS (deceleration state): in this state, there is the decreasing acceleration in the longitude of the vehicle so the angle of the throttle paddle is decreasing;
- LCS (lane changing state): in this state, there is a steering angle kept over a predefined short period of time;
- T (L/R) S (turning left or right state): the vehicle is in the LCS and the steering angle is maintained over a longer predefined period of time;
- CFS (car following state): in this state, vehicle is detected to be within a pre-determined distance from a vehicle at its front;
- VSM (virtual state machine) presents the various connections of the above driving states as shown in Fig. 2. The transition from one to another state depends on the various driver actions of the proposed methodology that are the functions of the vehicle dynamics.

4. Fuzzy Inference System for the Proposed Driving Monitoring

The driver classification is based on these three criteria: driver action, the related driving states as well as raw measurement based on the dynamics of the vehicle. So these parameters are modelled by their fuzzy-nature for the evaluation of the system. In this paper, a proper fuzzy logic system based on the methodology diagram in Fig. 1 and proposed SVM in Fig. 2, is analysed completely. As it is shown in Fig. 3, in this system, the flexibility of the different inputs and mapping them to the fuzzy set values in each MF (membership function) are considered.

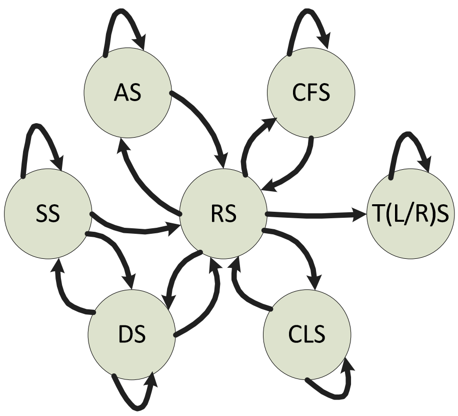


Fig. 2 VSM for the proposed assessment-driving behavior.

The proposed FIS algorithm is modelled in MATLAB and Simulink to evaluate the algorithm in two different types [11, 13]. First, Mamdani-type of the system is evaluated. Second, this model is evaluated by Sugeno-TSK type. In the end, the result of the proposed model with two FIS types will be compared accurately. The proposed FIS model consists of seven inputs and two outputs FISs. The inputs are diversified by the different parameters as shown in Fig. 4.

4.1 Proposed Model of Membership Functions (MFs) in FISs

In fuzzy set theory; in contrast to crisp sets where a component is either in a set or not in the set; components are referred to a range of values between 0 and 1. The range of the values expresses the MFs of the components in the FISs. As it is shown in Fig. 4, FISs employ linguistic representations such as "low", "medium", "ideal" and "turning".

In the proposed FIS model, each input namely vehicle speed, vehicle load, lateral distance, frontal distance, acceleration and deceleration is specified to one type of the membership function based on the nature of the parameters like the Gaussian function, the trapezoidal function, the triangular function, etc. The detailed parameters as long as the specified MF are:

4.1.1 Vehicle Speed

The vehicle speed and the vehicle load parameters can affect the driver behaviour [14]. Before using these parameters in the fuzzy controller, they should be fuzzified in the linguistic term using membership functions. The variable "vehicle speed" in Fig. 4a is represented by the linguistic terms namely very-slow, slow, medium, fast and very-fast. The linguistic terms are demonstrated by five fuzzy sets that are defined by the five membership functions in Fig. 4a.

The membership functions define the grade of membership of the variable in the five fuzzy sets. For example, if vehicle speed is 0 km/h, the grade of membership functions in the fuzzy sets very-slow approaches 1 and the degree of membership functions in the fuzzy sets very-fast approaches 0. However, when the vehicle speed is 90 km/h, there is a progressive transition from slow to medium which is performed by the overlapping period in Fig. 4a. Then, the different values of this period referred to both fuzzy sets with various grades of membership functions.

4.1.2 Vehicle Load

The vehicle load is the second input of the model which is defined by:

$$vehicleload = \frac{T_e}{T_{\max}} \quad (1)$$

where, T_e: current torque at the vehicle speed (rmp);

$T_{\max}$: maximum torque at the same vehicle speed (rmp).

The range of the vehicle load value is from 0 (which is mentioned the idle operating condition) to 1 (that is mentioned the full vehicle load operation) [15]. The vehicle load MF is presented by the triangular function in the linguistic term: zero, low, medium and high load, as shown in Fig. 4b.

4.1.3 Lateral Distance from the Boundary Lines

The vehicle distance from the boundary lines membership functions are described by the Gaussian functions in the linguistic terms of the low, ideal and high as it is shown in Fig. 4c. The range of the lateral distance value is from 0 to 1.8 m which is mentioned distance between left boundary line and right one. The linguistic terms of "low" and "high" present that vehicle is "near to left boundary line" and "near to right boundary line", respectively. So the linguistic term of "ideal" refers to the vehicle travels in the ideal distance from both boundary road lines.

4.1.4 Angle Variation

The angle variation describes the relative angle between the vehicle path and the boundary line. These relative angles characterize the turning or changing of the lane to the left/right. It is presented in the linguistic terms of the turning left, lane change to left, straight, lane change to the right and turn-right in Fig. 4d.

4.1.5 Frontal Distance

The safe distance between two vehicles on the road is one of the considerable factors to evaluate driving safety level. If the distance is low, the possibility of the accident will be high. Thus, keeping a safe frontal distance is one skill of the best driver. The frontal distance MF is described in the linguistic terms of low, medium and high in Fig. 4e.

4.1.6 Acceleration and Deceleration

The acceleration and the deceleration of the vehicle MF are described by the linguistic term of irregular and normal as shown in Fig. 4f [16].

Mamdani and Sugeno-TSK are the two practical FIS types which are used in the model as presented in Fig. 3. The proposed MFs are evaluated by both types of FIS for the determination of differences between these methods. The inputs to both engines are exactly the same.

4.2 Mamdani-Type vs. Sugeno/TSK-Type

The main difference between the two fuzzy algorithms (Mamdani and Sugeno/TSK) is based on the process and the rule consequences. The fuzzy rules for both types are described in Table 1.

The differences between Mamdani type and Sugeno-TSK type are: (1) Mamdani FIS needs more processing time than Sugeno-TSK type; (2) in the noisy environments, Sugeno-TSK type behaves more robust compared to Mamdani type; (3) Mamdani type FIS utilizes the outputs MFs and fuzzification-technique, but Sugeno-TSK type utilizes the weighted average to estimate the crisp outputs; (4) Mamdani type has less flexibility in the system design compared to Sugeno-TSK type; (5) in the Mamdani type, using both MIMO (multi input-multi output) and MISO (multi input-single output) is possible but Sugeno-TSK type is utilized in MISO systems; and (6) Sugeno TSK is more accurate and efficient in term of computation than Mandani type [17, 18].

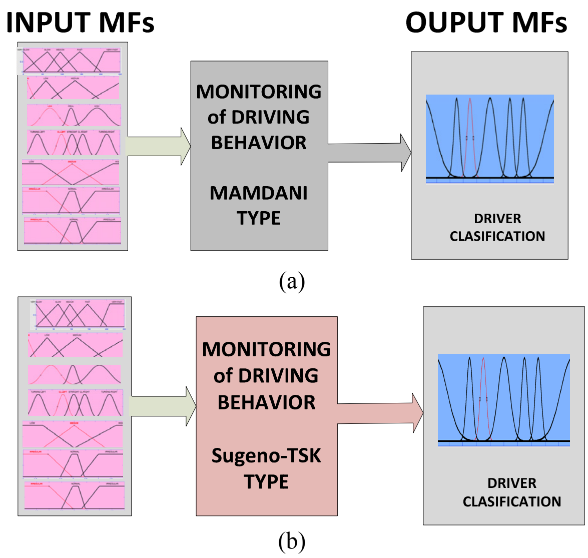
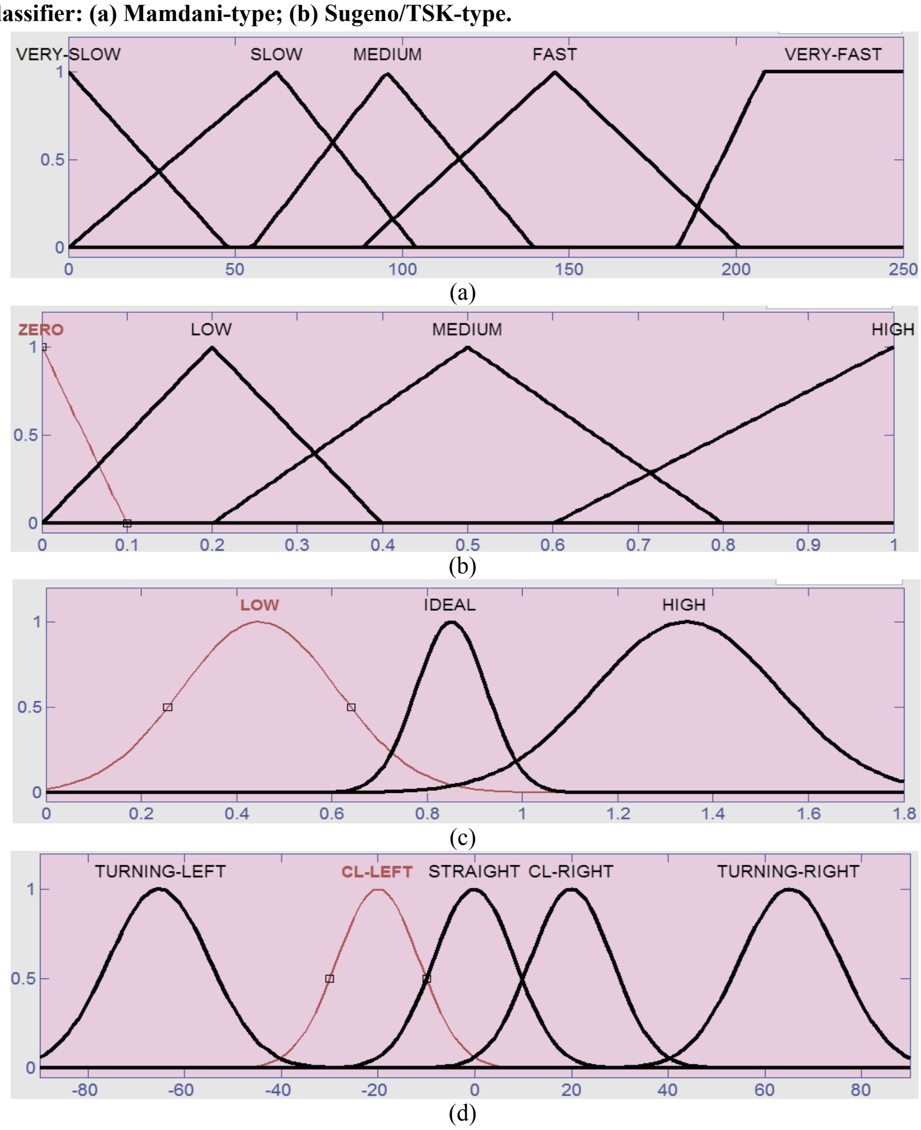
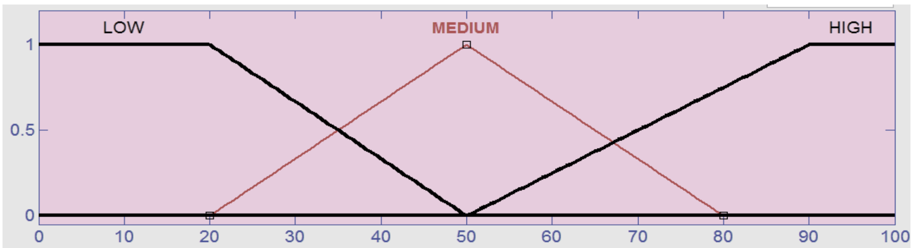
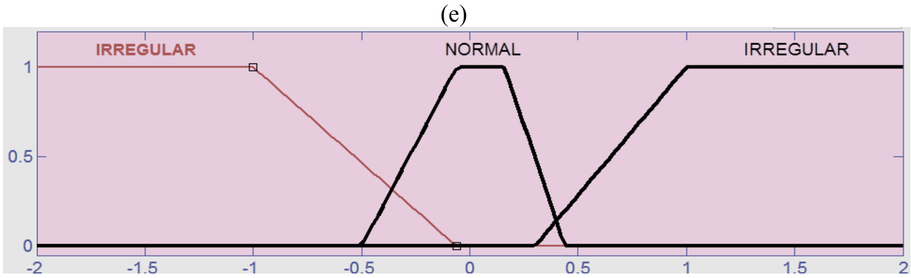


Fig. 3 Driving classifier: (a) Mamdani-type; (b) Sugeno/TSK-type.





(e)



(f)

Fig. 4 MFs of: (a) vehicle speed ($\frac{km}{h}$); (b) normalized vehicle load; (c) lateral distance (m); (d) angle variation (degree); (e) frontal distance (m); (f) acceleration/deceleration of the vehicle (m/s^2).

Table 1 Fuzzy rules in Mamdani and Sugeno-TSK types.

Fuzzy rules in Mamdani type	Fuzzy rules in Sugeno/TSK type
If X_1 is A_{i1} and X_2 is A_{i2}... and X_n is A_{in} so Y is B. where, $X_1, \ldots, X_n$: input variables; Y: output variables; $A_{i1}, \ldots, A_{in}$: linguistic values of the input; B: linguistic value of the output.	If X_1 is A_{i1} and X_2 is A_{i2}... and X_n is A_{in}, so Y is: $\sum_{i=1}^{n} a_i x_i + c$ where, $X_1, \ldots, X_n$: input variables; Y: output variables; $A_{i1}, \ldots, A_{in}$: linguistic values of the input; B: linguistic value of the output; a_i and c: constants values.

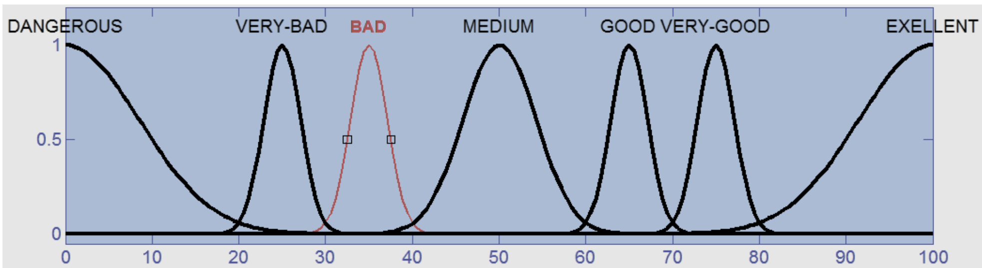


Fig. 5 Mamdani-based DBS (driving behavior score) MFs.

The Mamdani-based output of the proposed FIS model for classifying the driving behaviour is presented in the Fig. 5. The Mamdani-based output is the DBS which changes from 0 to 100 and is fuzzified in seven levels. In this paper, the driver's behaviours are divided in to dangerous, very bad, bad, medium, good, very good and excellent as MFs. These seven levels are important to differentiate between the likelihood levels. In Fig. 5, the values of 0 and 100 show the dangerous and excellent behaviour of the driver, respectively.

The Sugeno-TSK-based output of the proposed FIS model exploits weighted average instead of fuzzy set values in Mamdani-based output. As it is shown in Table 2, the output is subdivided into seven levels (constant numbers) which are labelled to correspond to seven levels of the Mamdani-based output.

5. Simulation Results

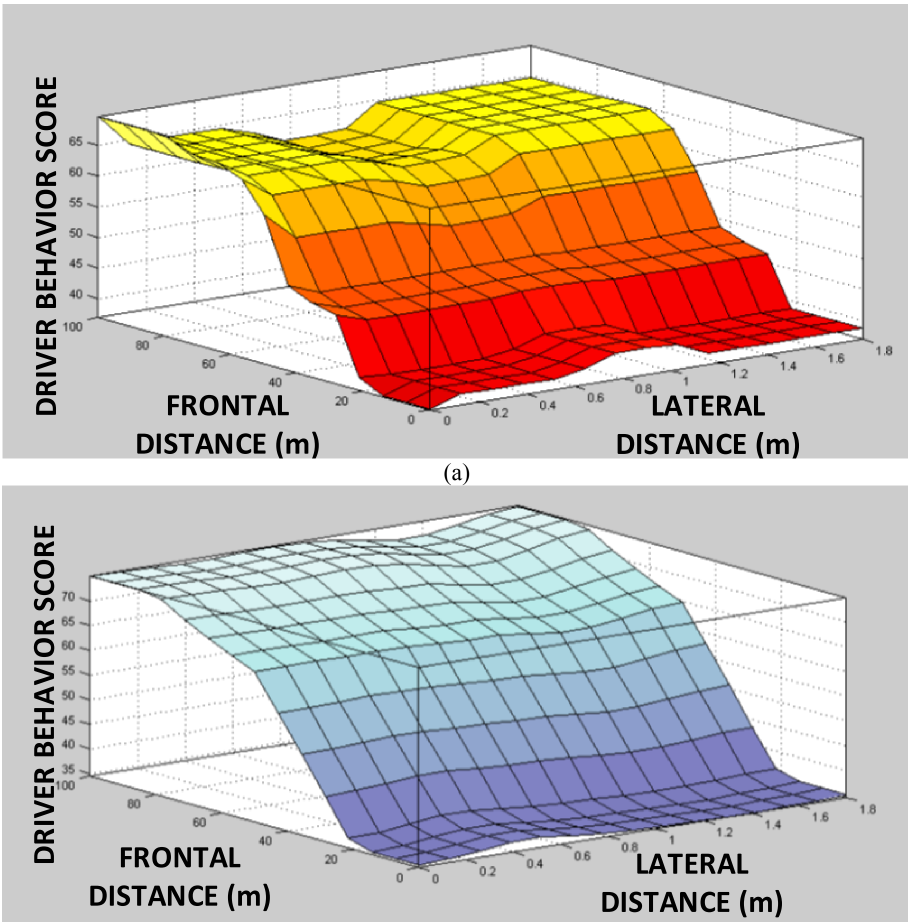
To evaluate the proposed algorithm, both Mamdani and Sugeno-TSK types were tested in MATLAB and fuzzy logic toolbox for displaying the results related to the driving behaviour. Figs. 6 and 7 show the driver behaviour scores for Mamdani and Sugeno-TSK types as two examples for the comparison of these two types. These figures present the variation of the driver behaviour scores based on the different parameters for both types.

Fig. 6 depicts the difference between Mamdani and Sugeno-TSK types in terms of driver behaviour scores based on the frontal and lateral distances. It shows that better driver behaviour scores are obtained by increasing the frontal distance for both types. When the lateral distance is considered, Mamdani type shows a little change from 0.5 m to 1.2 m; However, Sugeno-TSK type is relatively unchanged due to the utilization of the weighted average in fuzzification instead of the fuzzy set values.

Fig. 7 illustrates the comparison of driver-behaviour scores between both FIS types based on the vehicle deceleration and load. Deceleration of vehicle is shown in period (-0.5, 0.5) m/s^2 which is relied on the normal-part of Fig. 4f. Vehicle load is characterized in duration (0.2, 0.8) which is relied on the medium-part of Fig. 4b.

Table 2 Sugeno-TSK FIS output constants.

Level of driver	
Definition	Constant value
Excellent	100
Very Good	83.33
Good	66.64
Medium	49.98
Bad	33.33
Very Bad	16.66
Dangerous	0



(a)

(b)

Fig. 6 Driver behavior score based on frontal distance and lateral distance: (a) Mamdani type; (b) Sugeno-TSK type.

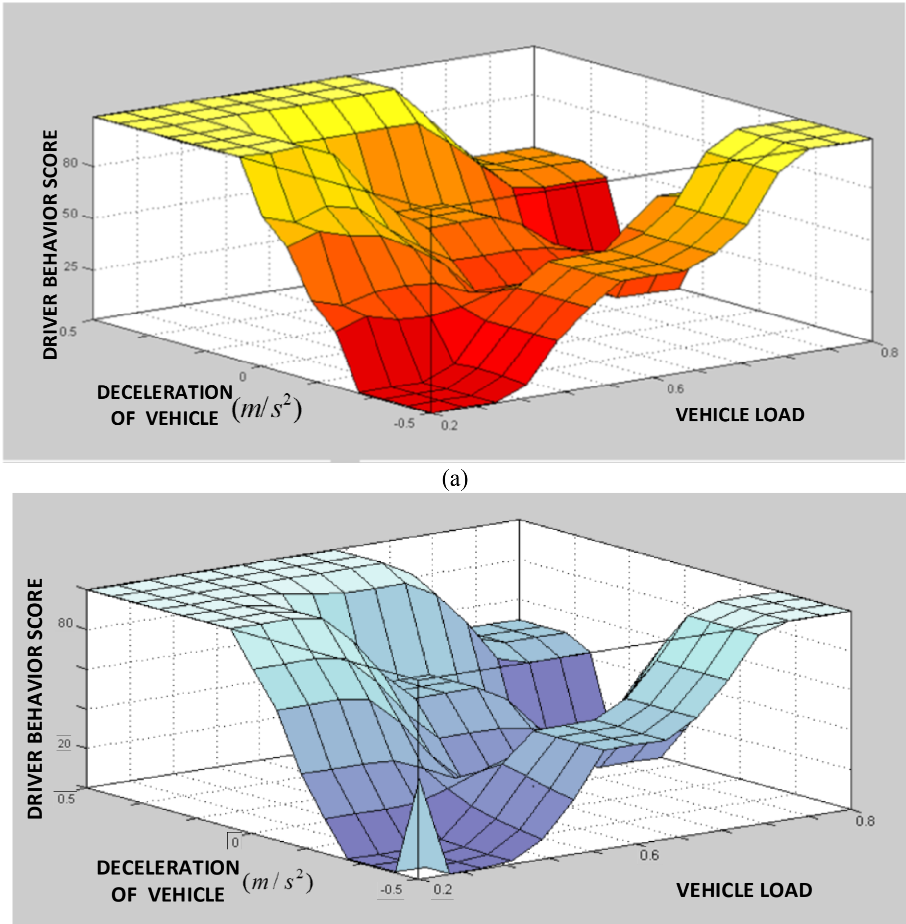


Fig. 7 Driver behavior score based on deceleration of vehicle and vehicle load: (a) Mamdani type; (b) Sugeno-TSK type.

The particular ranges of values are chosen for these parameters because they are most likely for driver behaviours. Where the normalized value of vehicle load is 0.2 and the deceleration of vehicle equals -0.5 m/s^2, the difference driver behaviour scores indicate the amount of changes between two FIS types. The reason for this difference is the loss of interpretability in Sugeno-TSK type which is caused by using weighted average of rule's consequent.

For better determining the differences between Mamdani and Sugeno-TSK types for driver characterization, cross-correlation is a proper method based on its potential performance benefits for surveying the similarities and the differences of these two FIS types. Cross-correlation is defined as a way to measure the similarity of two waveforms and is a function of a time-lag applied to one of them. This is also known as a sliding dot-product or sliding inner-product [19].

To calculate the cross-correlation of each parameter and determine the percent of similarity between two FIS types, the following steps have been considered: (1) choose one of input parameters as a reference variable; (2) fix the other input parameters in specific and constant values. These specific values are chosen because of most likely for driver behaviours; (3) change the reference variable in its particular ranges which are defined in previous section.

For example, when the frontal distance is reference variable, the value of speed is 100 m/s, the normalized value of the vehicle load is 0.5, the lateral distance is 0.8 m, the angle variation, acceleration and deceleration are zero. Also, the frontal distance is changed from 0 m to 100 m. The process of the

Table 3 Cross-correlation of Mamdani and Sugeno-TSK types.

Inputs parameters	Cross-correlation of both FIS types
Vehicle speed	0.9764
Vehicle load	0.9726
Lateral distance	0.9840
Angle variation	0.9875
Frontal distance	0.9738
Acceleration of the vehicle	0.9950
Deceleration of the vehicle	0.9961

calculation of the cross-correlation for the other parameters in the proposed FIS is similar to the mentioned example. As it is previously stated, during the calculation of each cross-correlation value, it is supposed that only one variable was changed and the other parameters were constant. The cross-correlation of the two FIS types is defined by:

$$r(d) = \frac{\sum_{i=0}^{N}[(x(i)-mx)\times(y(i-d)-my)]}{\sqrt{\sum_{i=0}^{N}(x(i)-mx)^2}\sqrt{\sum_{i=0}^{N}(y(i-d)-my)^2}} \quad (2)$$

where: *r*: cross-correlation;

d: delay for $i = 0, 1, 2, \ldots, N-1$;

x(*i*): the Mamdani FIS results;

y(*i*): the Sugeno-TSK FIS results;

mx: the mean of the *x*(*i*);

my: the mean of the *y*(*i*).

The results of cross-correlation between Mamdani and Sugeno-TSK types for various parameters are shown in Table 3. All cross-correlation values which are listed in Table 3, are larger than 0.9. It confirms that all the input variables of the proposed FIS have the high cross-correlation for both FIS types. Also, these results (the high cross-correlation for the variables) present the stability and reliability of the proposed FIS in both FIS types for estimating the driving behaviour.

6. Conclusions

This paper provided a solution for the analysis and the diagnosis of the driving behaviour based on FIS. The solution uses the functions of vehicle dynamics and human behaviour, expressed by a set of raw measurements. These raw measurements are obtained from various sensors and human signals. This solution can characterize the driving behaviour based on the capabilities of intelligent systems.

The proposed solution was based on an advanced model of driving behaviours in order to identify the quality of driving using two popular FIS. The results confirmed that higher accuracy and high dynamic behaviour can be achieved using the Sugeno-TSK type compared to the Mamdani type. The high cross-correlation values of the two FIS types validate the stability and reliability of the adopted FIS types for estimating the driving behaviour without any unusual exception in the results.

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References

[1] Consulting, R.S.C. 2011. *Road Safety in Canada*. Montreal: Public Health Agency of Canada.

[2] Landry, R. J. 2012. *Vehicle Tracking and Accident Diagnostic System (VTADS)*.

[3] Jung, T.-P., Makeig, S., Stensmo, M., and Sejnowski, T. J. 1997. “Estimating Alertness from the EEG Power Spectrum.” EEE Transactions on *Biomedical Engineering* 44 (1): 60-9.

[4] D’Orazio, T., Leo, M., Guaragnella, C., and Distante, A. 2007. “A Visual Approach for Driver Inattention Detection.” *Pattern Recognition* 40 (8): 2341-55.

[5] Bergasa, L. M., Nuevo, J., and Sotelo, M. A. 2006. “Real-Time System for Monitoring Driver Vigilance.” *IEEE Transactions on Intelligent Transportation Systems* 7 (1): 63-77.

[6] Zheng, J., Suzuki, K., and Fujita, M. 2013. “Car-Following Behavior with Instantaneous Driver-Vehicle Reaction Delay: A Neural-Network-Based Methodology.” *Transportation Research Part C: Emerging Technologies* 36: 339-51.

[7] Bhatt, D., Aggarwal, P., Devabhaktuni, V., and Bhattacharya, P. 2012. “A New Source Difference

Artificial Neural Network for Enhanced Positioning Accuracy." *Measurement Science and Technology* 23 (10): 105101.

[8] Zhou, F., and Wang, W. 2009. "A New SVM Algorithm and AMR Sensor Based Vehicle Classification." Presented at Intelligent Computation Technology and Automation, 2009. Second International Conference on. 2009.

[9] Jazayeri, A., Cai, H., Zheng, J. Y., and Tuceryan, M. 2011. "Vehicle Detection and Tracking in Car Video Based on Motion Model." *IEEE Transactions on Intelligent Transportation Systems* 12 (2): 583-95.

[10] He, L., Zong, C.-F., and Wang, C. 2012. "Driving Intention Recognition and Behaviour Prediction Based on a Double-Layer Hidden Markov Model." *Journal of Zhejiang University SCIENCE C* 13 (3): 208-17.

[11] Ross, T. J. 2009. *Fuzzy Logic with Engineering Applications*. Hoboken: John Wiley & Sons.

[12] Chan, S., Miranda-Moreno, L. F., Patterson, Z. R., and Barla, P..2013. "Spatial Analysis of Demand for Hybrid Electric Vehicles and Its Potential Impact on Greenhouse Gases in Montreal and Quebec City, Canada." Presented at Transportation Research Board 92nd Annual Meeting.

[13] Sivanandam, S., Sumathi, S., and Deepa, S. 2007. *Introduction to Fuzzy Logic Using MATLAB*. Vol. 1. Springer.

[14] Carlson, R., Lohse-Busch, H., Diez, J., and Gibbs, J. 2013. "The Measured Impact of Vehicle Mass on Road Load Forces and Energy Consumption for a BEV, HEV, and ICE Vehicle." *SAE International Journal of Alternative Powertrains* 2 (1): 105-14.

[15] Kean, A. J., Harley, R. A., and Kendall, G. R. 2003. "Effects of Vehicle Speed and Engine Load on Motor Vehicle Emissions." *Environmental Science & Technology* 37 (17): 3739-46.

[16] Quintero, M. C. G, López, J. O., and Pinilla, A. C. C. 2012. "Driver Behavior Classification Model Based on an Intelligent Driving Diagnosis System." In *IEEE Conf Intell Transport Syst Proc ITSC IEEE Conference on Intelligent Transportation Systems, Proceedings,* 894-9.

[17] Hamam, A., and Georganas, N. D. 2008. "A Comparison of Mamdani and Sugeno Fuzzy Inference Systems for Evaluating the Quality of Experience of Hapto-Audio-Visual Applications." Presented at Haptic Audio visual Environments and Games, 2008.

[18] Ying, H., Ding, Y., Li, S., and Shao, S. 1999. "*Comparison of necessary conditions for typical Takagi-Sugeno and Mamdani fuzzy systems as universal approximators." Systems, Man and Cybernetics, Part A: Systems and Humans* 29 (5): 508-14.

[19] Wei, W.W.-S. 1994. *Time Series Analysis*. Redwood City, California: Addison-Wesley.