An Enhancement of the Driver Distraction Detection and Evaluation Method Based on Computational Intelligence Algorithms

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Abstract—Driver distraction is a fundamental problem for human safety, because the number of traffic accidents due to distracted driving does not decrease. In this paper, an enhancement of previously proposed driver distraction detection and evaluation methodology is introduced. The method is composed of computational intelligence algorithms: a driver performance prediction algorithm with nearest neighbor regression and an intelligent fuzzy logic evaluation algorithm. Thanks to the improvement, an additional variable for driver performance prediction and an additional performance-based indicator were introduced. To verify the novelty, the series of thirty driver-in-the-loop experiments has been delivered on an industrial vehicle simulator. At this, an interaction with a vehicle on-board computer was exploited as a distractive activity. Finally, the enhanced method is compared to the previously described one.

Keywords—computational intelligence; nearest neighbor methods; fuzzy logic; human computer interaction; vehicle safety

I. INTRODUCTION

Driver distraction (DD) is a serious problem for the safety of ground vehicles. Its negative impact is measured not only by paid insurances, but also by humans' and animals' injuries and lives. In 2016, only in the EU almost 20 % of drivers ended abruptly in vehicle crashes caused by DD [1]. In the USA, this number is even higher [2]. Therefore, detection and further minimization of DD induced by an interaction with on-board equipment is a significant challenge for all vehicle manufacturers. A development of a practical tool for evaluation of in-vehicle information systems (IVIS) for minimum DD before their installation in series products is an inevitable task.

DD is defined as "anything that delays the recognition of information necessary to safety maintain the lateral and longitudinal control of the vehicle (driver's primary task) due to some event, activity, object or person, within or outside the vehicle that compels or tends to induce the driver's shifting attention away from the fundamental driving task by compromising the driver's auditory, biomechanical, cognitive or visual faculties or combinations thereof" [2]. The secondary task is an activity not related to primary task that drivers perform while controlling a vehicle.

In the literature, there are no standard procedures to test IVIS on the DD level. Several proposed methods rely on surveys and questionnaires of experiment participants [3], [4]. These DD assessment ideas cannot be accepted as objective valuations since they are based on individual opinions. Consequently, the researchers decided to implement computational intelligence (CI) algorithms for replacement of subjective evaluations by artificial intelligence systems.

To detect DD, scholars have proposed applying support vector machines (SVM) [5], fuzzy logic (FL) [6], and artificial neural networks (ANN) with gradient boosting machines [7]. Some authors trusted such driver's behavior measures as gaze and head movement tracking. Others promoted psychological attributes (e.g. driver electrocardio- and electroencephalographical methods) also applying CI approaches [8], [9]. Despite an accurate DD detection, behavioral and psychological measures always require supplementary equipment, such as cameras and neuroscan systems. Furthermore, some devices (e.g. eye-tracking goggles or neuroscan helmets) are often considered as a distraction source themselves. Also, these appliances increase system cost and complexity [10].

Most advantageous approaches consider vehicle dynamic performance (i.e. longitudinal and lateral control quality). Referring to the DD definition, these factors estimate the drivers' primary tasks that must not be worsened due to interaction with vehicle on-board equipment. In addition, these methods do not require supplementary hardware, and turn out to be more applicable in practice, because the data can be gathered using only the sensors available in passenger vehicles, such as steering wheel angle gauges, vehicle velocity transducers, etc. Using these signals, researchers designed different DD detection algorithms based on artificial and computational intelligence: FL [11], SVM [12], Gaussian mixture model (GMM) [13], and their combinations, such as hidden Markov model with GMM [14], ANN with GMM [15], and ANN with SVM [16].

Despite a vast variety of different DD detection solutions, they all have an essential limitation, namely, Boolean logic classification (i.e. distracted/non-distracted). Thus, the methods

are not feasible as a practical tool for different secondary tasks evaluation and comparative analysis on safe vehicle operation.

A novel DD detection and evaluation method using CI algorithms, which is capable not only to detect DD, but also to precisely measure its impact on safe vehicle control was developed in [17]. The method combines ANN for DD detection and FL for DD evaluation. In this paper, an improvement of this methodology is presented. To differentiate the improved approach from the previously proposed one, the earlier developed method [17] is further called “*old*”, while the last one is named “*new*” in this paper.

The new method is enhanced with additional performance-based indicator, namely, the steering wheel acceleration. Moreover, one more input is used in driver modelling, which is a road curve direction (i.e. left, straight or right). These innovations are called to improve an accuracy of the DD measurement. And besides, the new method uses a nearest neighbor regression (NNR) for driver modelling. The FL algorithm is also redesigned, because more variables are used now in DD assessment.

The paper is organized as follows. Next Section describes the new DD detection and assessment method. Section III is dedicated to the driver-in-the-loop experiment portfolio. In Section IV, the case study results are presented and discussed. The conclusion is reported in Section V.

II. DRIVER DISTRACTION DETECTION AND EVALUATION METHOD

In Fig. 1, the DD detection and evaluation method block scheme is presented. Parameters description is listed in Table I. Superscript “*t*” refers to the “training data” collected during the DD-free driving and used for driver performance prediction. Individual detection and evaluation is conducted for each experiment participant in three main steps described below.

A schematic explanation of the two main performance-based variables is shown in Fig. 2. To measure the lane keeping offset Δx_r (Fig. 2a), it is assumed that a transparent vehicle represents driver’s normal angle cutting. The white car represents cornering under DD. The pink surface between these two turns is considered as a difference between normal and distracted road middle line keeping ability.

Similarly, it is anticipated that the speed limit on current

TABLE I. PARAMETERS DESCRIPTION

Symbol	Description	Unit
v_l	Speed limit	km/h
c_r	Road curve radius	m
c_d	Road curve direction	Left/Right
Δx	Real lane keeping offset	m
Δv	Real vehicle speed deviation	km/h
a	Real steering wheel acceleration	$^\circ/\text{s}^2$
Δx_p	Predicted lane keeping offset	m
Δv_p	Predicted vehicle speed deviation	km/h
a_p	Predicted steering wheel acceleration	$^\circ/\text{s}^2$
Δx_r	Resultative lane keeping offset	m
Δv_r	Resultative vehicle speed deviation	km/h
a_r	Resultative steering wheel acceleration	$^\circ/\text{s}^2$
DD	Driver distraction level	%

road segment is 100 km/h (Fig. 2b). Normally, driver passes this segment with 105 km/h. However, when she/he is distracted, the speed rises to 115 km/h. Thus, the error between normal and distracted speed maintenances Δv_r is calculated as a second performance-based measure. The deviation is also depicted as a pink sector in Fig. 2b. The third variable is simply a difference between normal steering wheel acceleration and a steering wheel acceleration while performing a secondary task.

First, an information about the road segment is inserted inside the Driver model block. As the Driver model tends to forecast driver’s performance, it is called the *Predictor*. The road segment is described by three parameters: segment speed limitation v_l , road curve radius (curvature) c_r , and road curve direction c_d . The last one is a Boolean type with the crisp values: -1 meaning that the road curve goes to the left, 0 — it is straight, and 1 — it turns right.

Based on the received information about the road shape, direction, and speed limit, a predicted driver performance (i.e. Δv_p , Δx_p , and a_p) on this specific road segment appears on the Predictor output. An NNR is applied as a prediction algorithm, which stores a preprocessed training set, uses these data to look up the nearest entry in it, and, finally, returns the associate regression target as offered in [18]. The preprocessed data pass through a dimensional reduction for model simplification and data diminishment, what makes the algorithm more understandable, robust, and computationally cheaper [19].

The main advantage of the NNR learning algorithm comparing to the other CI methods used for prediction (e.g. ANN, fuzzy neural networks, etc.) is its ability to achieve the minimum possible training error on any regression dataset [18]. In principle, the NNR algorithm finds the shortest distance

Fig. 1. Driver distraction detection and evaluation block scheme.

Fig. 2. A schematic explanation of the main performance-based evaluation variables: (a) Δx_r ; (b) Δv_r .

TABLE II. RULE-BASE OF THE FL EVALUATOR

DD [%]		$a_r = \text{negative}$				
		Δx_r				
		<i>neg far</i>	<i>neg close</i>	<i>zero</i>	<i>pos close</i>	<i>pos far</i>
Δy_r	<i>neg high</i>	100	85.8	42.9	85.8	100
	<i>neg low</i>	100	57.2	14.3	57.2	100
	<i>zero</i>	57.2	28.6	0	28.6	57.2
	<i>pos low</i>	85.8	42.9	14.3	42.9	85.8
	<i>pos high</i>	100	85.8	42.9	85.8	100
DD [%]		$a_r = \text{zero}$				
		Δx_r				
		<i>neg far</i>	<i>neg close</i>	<i>zero</i>	<i>pos close</i>	<i>pos far</i>
Δy_r	<i>neg high</i>	100	71.5	42.9	71.5	100
	<i>neg low</i>	85.8	14.3	0	14.3	85.8
	<i>zero</i>	42.9	0	0	0	42.9
	<i>pos low</i>	71.5	14.3	0	14.3	71.5
	<i>pos high</i>	85.8	57.2	28.6	57.2	85.5
DD [%]		$a_r = \text{positive}$				
		Δx_r				
		<i>neg far</i>	<i>neg close</i>	<i>zero</i>	<i>pos close</i>	<i>pos far</i>
Δy_r	<i>neg high</i>	100	85.8	42.9	85.8	100
	<i>neg low</i>	100	57.2	14.3	57.2	100
	<i>zero</i>	57.2	28.6	0	28.6	57.2
	<i>pos low</i>	85.8	42.9	14.3	42.9	85.8
	<i>pos high</i>	100	85.8	42.9	85.8	100

between a sample point with coordinates (v_l, c_r, c_d) and a set of data points with coordinates (v_l^t, c_r^t, c_d^t) applying the Euclidean distance formula. Therefore, the Predictor assigns an output $(\Delta y_p, \Delta x_p, a_p)$ to a training set point $(\Delta y^t, \Delta x^t, a^t)$, which corresponds to an appropriate point with the shortest distance to the sample one.

Next, the driver's performance under interaction with a vehicle on-board computer is compared with the predicted in the previous step one and a resultative performance (i.e. $\Delta y_r, \Delta x_r, a_r$) is calculated. An example of the calculation is presented here for a lane keeping ability Δx_r :

$$\Delta x_r = \begin{cases} \Delta x - \Delta x_p, & \text{if } \Delta x > 0; \Delta x_p > 0; |\Delta x| > |\Delta x_p| \\ \Delta x - \Delta x_p, & \text{if } \Delta x < 0; \Delta x_p < 0; |\Delta x| > |\Delta x_p| \\ \Delta x + \Delta x_p, & \text{if } \Delta x > 0; \Delta x_p < 0; |\Delta x| > |\Delta x_p| \\ \Delta x + \Delta x_p, & \text{if } \Delta x < 0; \Delta x_p > 0; |\Delta x| > |\Delta x_p| \\ 0, & \text{if } |\Delta x| \leq |\Delta x_p| \end{cases} \quad (1)$$

For other variables, Δy_r and a_r , the same rules are applied. Summarily, when a predicted deviation is smaller comparing to a real one, the difference between two values is calculated and accepted as a resultative output, $\Delta y_r, \Delta x_r$, or a_r . Therefore, when the driver's performance due to DD becomes poorer from the viewpoint of safe vehicle operation, a worsened vehicle dynamic performance is counted. However, if a predicted deviation is greater than or equal to a real one, the output is zero. It means that a driver performs normally to her/his usual driving, the driving is not corrupted by secondary tasks, and, thus, she/he is not distracted.

Negative $\Delta y_r, \Delta x_r$, and a_r mean driving slower its speed limit, driving to the right from the middle of the lane, and turning a steering wheel to the right, respectively. Contrariwise,

TABLE III. IVIS SECONDARY TASKS

#	In-vehicle secondary task	
1.	Volume	Volume regulation
2.		Radio
3.	Context selection	Media
4.		Telephone
5.		Navigation
6.	Radio	Radio station selection from a primary list
7.		Radio station selection from an overall list
8.	Media	Media source selection (e.g. CD, SD-card)
9.		Media item selection
10.		Song shuffle
11.	Telephone	Call a number from the Favorite contact list
12.		Call a number from an overall contact list
13.	Navigation	Input location
14.		Input of a next target
15.		Zoom operation

positive $\Delta y_r, \Delta x_r$, and a_r represent speeding, driving towards opposite lane, and steering to the left, accordingly.

Finally, three resultative variables, $\Delta y_r, \Delta x_r$, and a_r , enter the FL Evaluator, which inferences the three inputs into a single variable represented as a DD level in percentage. A FL Sugeno's type inference mechanism based on matrix operations is used [20]. In this work, however, the FL Evaluator has three inputs and, thus, the fuzzification procedure constructs a three-dimensional matrix. Each layer of the matrix has its own rule-base.

Two inputs, Δy_r and Δx_r , have five, and a_r — three symmetrically dispersed and overlapped between each other over the universe of discourse (UOD) membership functions (MFs). The triangular shapes are preferred for MFs, because they are simple for programming and famous for fast response. The UOD of Δy_r is between $[-12, 12]$, while Δx_r is bounded in $[-1.5, 1.5]$. The last input is restricted inside $[-1500, 1500]$.

As the output DD represents a level of distraction in percentage, its UOD lays inside $[0, 100]$. Eight output MFs have singleton forms. They are dissipated on equal distance between each other starting from 0 to 100 with a step 14.3: $\{0, 14.3, 28.6, 42.9, 57.2, 71.5, 85.8, 100\}$. It gives an equal responsiveness for each output MF.

The inputs and output are mapped via modus-ponens-form rules "If-And-Then". The linguistic relation is determined in Table II. The inputs-output relation example may be presented as follows: **IF** the steering wheel acceleration is "*negative*", **AND** vehicle speed deviation is "*pos_low*", **AND** lane keeping offset is "*neg_close*", **THEN** driver distraction is 42.9 %.

III. METHODOLOGY OF EXPERIMENTATION

A. Subjects

The DD detection and evaluation driver-in-the-loop experiment was carried out with thirty drivers. Five experiment participants were female, the rest — male. The drivers' gender, age and driving experience influence on the DD level were out of the scope of this study. Every participant owned a valid driver license and was physically and mentally healthy for safe vehicle operation. The participants were rewarded for their contribution.

B. Apparatus

An advanced driver simulator for DD tests was provided by ŠKODA Auto a.s. (Mladá Boleslav, Czech Republic). It is a fixed-base passenger vehicle mockup, with a same cockpit as used in modern passenger vehicles. As the test rig has an automatic transmission, drivers operated the simulator by acting on a steering wheel and on the throttle and braking pedals. The mockup head-up instrumental panel displays vehicle speed. The participants drove the test bed in a virtual world projected on a wall screen in front of the simulator.

The vehicle together with the virtual world scene was modelled with an open source library for C++ programming language, Open Dynamics Engine™ v 0.5 [21]. The Škoda Yeti with 77 kW engine model configuration was used for vehicle model parameterization. This model includes a vehicle body, a suspension system, and four wheels with Pacejka's Magic Formula tire models [22].

The road used in the virtual world was identical to the one of the road segments in Czech Republic. It is a two-way lap with 3.5 m width lanes in each direction. Its total length is 10 626 m, what takes approximately 10 minutes to complete it, if all the traffic rules are respected. The road has two main parts: 50 km/h speed limit with frequent sharp turns and 90 km/h speed limit with almost straight road shape. The steering wheel acceleration was obtained from a signal provided by a steering-wheel sensor mounted on the shaft end of the steering axle. Lane keeping ability and vehicle velocity abnormality were calculated from x , y , and z coordinates received from the global positioning system of the virtual world. All the variables were saved with 10 Hz frequency.

C. Procedure

As the drivers were regular contributors to the experimental studies, they were familiar with the experiment's facilities. Nevertheless, before the experiment they were allowed to test

Fig. 3. Driver performance prediction versus real driver performance example for one of the experiment participants: gray background — secondary task accomplishment period; black line — real driver performance; purple line — predicted performance; green line — road information; (a) speed difference Δv and road speed limit v_l ; (b) center lane keeping offset Δx and curve radius c_r ; (c) steering wheel acceleration deviation a .

the simulator as long as they preferred. What is more, the participants were instructed to the exploited IVIS and secondary tasks before the driver-in-the-loop experiment.

The study procedure included two stages. During the first one, the participants were requested to drive two laps obeying all the traffic rules as good as possible. Namely, their only tasks were to stay in the middle of the lane and maintain the speed limit. The collected driver-performance results were utilized as the training data of the Predictor (Fig. 1) for each driver separately. During the second phase, the same traffic regulations fulfillment was again a priority. However, in this stage the drivers were obliged to accomplish the IVIS secondary tasks (Table III) while driving. The tasks were insisted randomly and several times during the phase.

IV. RESULTS

In this section, the results of the driver-in-the-loop experiment for a random driver are presented. During experimental DD evaluation, participants were given the opportunity to pass two or more full laps. However, for better observability, only the last lap of the studied driver is analyzed in this section. In Fig. 3, the gray background shows the period of secondary task accomplishment, while the white background is a normal driving between DD tasks. The predicted driver performance, Δv_p , Δx_p , and a_p , are shown together with the real one, Δv , Δx , and a . The black curve represents driving under distraction, the purple curve — the predicted performance, and the green curve — information about the road segment.

In Fig. 3a, driver's speed maintenance ability is delivered. On a 50 km/h speed limitation segment (Fig. 3a; green line), as predicted by the algorithm, the participant normally held the speed around 5 km/h higher than road's speed limit (Fig. 3a; purple line). However, in driving under the secondary task influence the driver tended to move slower (Fig. 3a; black line). For instance, submitting the tasks 13 and 7 (Table III), the speed deviation was significantly dropped down to -10

km/h. On the contrary, on a faster road segment, 90 km/h, the participant normally kept the speed lower its limit. In average, the vehicle drove 5 km/h slower. Though, some secondary tasks, such as 6, 7, and 10 (Table III), called the speed reduction.

In Fig. 3b, the centerline keeping ability is plotted. Taking into consideration the road lane and vehicle body widths (Section III.B), the vehicle drove out of the road lane bounds with exceeding x up to 1 or -1 m. However, based on performance prediction (Fig. 3b, purple curve), the driver was always staying inside of the road frontier during the free from the DD run. In fact, on a curvy road segment, when the curve radius c_r frequently changes (Fig. 3b, green line), the lane keeping ability while interacting with on-board computer (Fig. 3b, black line) was almost the same as it has been predicted. Nevertheless, while fulfilling task 7 (Table III), the driver was not able to keep the car inside of the road bounds and went off the road several times. On the straight road segment with higher speed limit (i.e. 90 km/h), the algorithm predicted smooth lane keeping offset (Fig. 3b, purple line). On this segment, despite the DD induced by secondary activities, the participant held a road line very well (Fig. 3b, black line). Yet, tasks 6 and 7 have forced the driver to cross the road lane dividing lines multiple times.

The steering wheel acceleration on a curvy road segment with 50 km/h speed limit was frequent in case of the DD performance (Fig. 3c, black curve). However, the Predictor forecasted almost the same frequent behavior for the free from the secondary activity driving (Fig. 3c, purple line). At this, as in the previous cases, the task 7 (Table III) motivated the driver to act on the steering wheel more frequently (Fig. 3c, black line). Consequently, it led to high steering wheel acceleration a oscillation comparing to the predicted one a_p . On a straight road with 90 km/h speed limit, a under DD (Fig. 3c, black line) was neither higher nor more frequent than during the normal driving (Fig. 3c, purple curve), except for the tasks 6 and 7

Fig. 4. Driver distraction evaluation results: gray background — the secondary task accomplishment period; red curve — new method; blue curve — old method.

again. A meaningful difference in driving performance can be observed during these tasks execution.

In Fig 4, the *DD* results for old and new methods are reported. The curves were obtained as a result of the fusion of the resultative performances Δv_r , Δx_r , and a_r in the FL Evaluator. The blue line symbolizes the *DD* evaluated only with two performance-based variables Δv_r and Δx_r , whereas the red curve constitutes the method enhanced by an additional variable, a_r . For comparison, both results are shown together.

The new FL Evaluator does not detect higher *DD* level without distraction. Contrariwise, when the experiment participant's performance was vitally burdened (Fig. 3), the FL Evaluator lodges a corresponding evaluation. This is especially noticeable, when driver performed tasks 6, 7, and 10 on a 90 km/h limit straight road segment (Fig. 4; inset). It has been mentioned that these tasks led to greater performance degradation, what was immediately detected by the improved FL Evaluator. Moreover, the evaluation of *DD* is higher than with the old Evaluator, which had only two performance-based indicators. It is worth to note that the tasks 7 and 6 also took more time than others, what multiplies their danger for the safe vehicle operation.

V. CONCLUSION

An improvement of the *DD* detection and evaluation method based on CI algorithms is suggested in this paper. Similarly, to the old method [17], the new one, first, predicts normal performance for every driver applying NNR algorithm. Second, it compares the predicted performance with the one submitted while accomplishing a secondary task, such as an interaction between the driver and the vehicle on-board computer. Finally, FL completes an evaluation of *DD* using the performance-based indicators. The newly proposed method uses three instead of two road characterization parameters for driver behavior prediction. What is more, the new method applies one additional performance-based variable for *DD* evaluation, namely steering wheel acceleration. The results proved that the new method does not raise *DD*, when the participant is not distracted or drives free from IVIS interaction. Contrariwise, when the driver is distracted, the new method detects greater level of *DD* comparing to the old one.

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