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Situated and personalized monitoring of human operators during complex situations

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Human behavior monitoring classically refers to the detection of human movements or a simple recognition of activities in limited known space. The monitoring of human activities in the context of concrete operating tasks often focuses on the detection of operating errors, unauthorized actions, or implicitly on the violation of protection goals. This contribution uses a qualitative description approach (situation-operator-modeling(SOM)) with which the logic of human interaction in given formalized context as action sequences as well as the situational, i.e. contextual, application of individual single actions can be realized. However, human performance reliability in action sequences is not clear and the optimal action sequence can not be defined. To solve this problem, the concept of human performance reliability score (HPRS) proposed in previous works is calculated with the modified fuzzy-based CREAM (cognitive reliability and error analysis method) approach. Therefore, situated and personalized HPRS values could be assigned to the action sequences in SOM action space. In this case, an event-discretized behavior model situated and personalized monitoring human performance with human reliability values could be generated. Using the example of human driving behavior for driving situations on highways, the application of the method is presented in detail. The monitoring of concrete example driver in real time will be demonstrated. The examples show that a direct warning or assistance will be helpful.

Keywords: Situation-operator-modeling (SOM), human reliability analysis, situated driving context, modified CREAM, FN-DBSCAN algorithm, personalized monitoring.

1. Introduction

With the increased proportion of human-related accidents in industry and traffic fields, the interest in using assistance systems for supervision of human operators is increasing Sarkheyli-Hägele and Söffker (2018). Supervision of human behaviors often focuses on the detection of operating errors, unauthorized actions, or implicitly on the violation of protection goals Fridman et al. (2019). Many assistance systems are developed to monitor human operator behaviors and states in different application fields. In Farjadian et al. (2020), an architecture for human supervision of automation in aviation is proposed which includes the actions of both a human pilot and an autopilot to ensure resilient tracking performance when anomalies occur. In maritime surveillance, a user study conceptualizing knowledge is implemented to support operators' situation awareness for enabling the possibility to detect anomalous behaviors Nilsson et al. (2008). In dynamic driving context, driver distractions are monitored to assess the driver's ability to take over the vehicle in critical scenarios based on machine learning and deep learning approaches Gjoreski et al. (2020).

The architecture of situation-operation-modeling (SOM) for interaction of intelligent and autonomous systems is developed to realize the automated supervision of human-machine-interaction Ahle and Söffker (2008). In the past this approach has been applied to dynamic driving context. In Fu and Söffker (2012), the lane changing maneuver is supervised with SOM approach by interpreting the driving scene and driver action with 'situation' and 'operator'. The main result of this paper is defining individualizable criteria for the decision moment when individuals as deciding to pass (start overtaking maneuver), so initializing a new action changing the upcoming action options. In Sarkheyli-Hägele and Söffker (2018), a fuzzy SOM approach is developed for modeling interaction-based knowledge structures to handle event-discrete situations in a simulated driving environment and to automatically generate a full and individualized knowledge space of sets of situations and actions and related individualized conditions. Using the SOM approach, action space could be generated with possible actions the operator could make considering available options Ertle et al. (2010). The research gap in the existing SOM-based monitoring approach is to automatically integrate individualized criteria for the evaluation of action sequences into the situationally generated action space. In this way, it would be possible to automatically evaluate whether specific action sequences are safe or rather unsafe for this person, e.g., because the action sequence is particularly familiar to this person or because actions/constellations foreseeably occur in the intended action or in the action space that are unsafe or with which the person is not familiar or which he or she demonstrably cannot master. Such an additional option would improve assistance in human-machine interaction and lead to more reliable human-machine systems.

The human performance reliability estimation approach applied in this contribution is the modified fuzzy-based CREAM (cognitive reliability and error analysis method) developed in He et al. (2021). This approach could situational and personalized calculate the reliability of human performance in dynamic contexts. With features selected in driving context, this approach is applied to situated driving context and the human performance reliability score (HPRS) is calculated in real time. It is promising to combine the SOM approach with the modified fuzzy-based CREAM approach to monitor human operators in complex situations and define the optimal action sequence in action space of operating tasks. In this contribution, the driving task of overtaking is taken as an example to explain this method.

The following sections make up this contribution: In section 2, the SOM-based human reliability evaluation approach is detailed explained including the SOM approach and modified fuzzy-based CREAM approach. In section 3, the data-based HPRS calculation is presented with driving data. The SOM-based human performance reliability evaluation is applied to the driving task of overtaking in section 4. The conclusion is provided in section 5.

2. The SOM-based human reliability evaluation approach

2.1. *Situation-operator-modeling*

A situation-operator-modeling approach is developed in Söffker (2001) allowing the modeling of human-machine-interaction and to map the changes and scenes from the real world to a graph-based-model. Changes are modeled as sequences consisting of items scenes and items actions. A scene is modeled as a situation and an action as an operator. In Fig. 1 a SOM-based sequence is shown consisting of an actual situation S_i, a current operator O_i and the following situation S_{i+1}. An operator is represented as a white ellipse. A situation is described as a situation vector represented as gray ellipse.

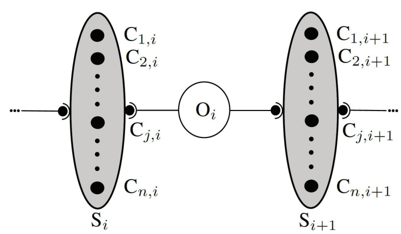

Fig. 1. Action sequence modeled as situation-operator-situation sequence Söffker (2001)

A situation S_i includes a set of characteristics $C_{j,i}$, can be physical, logical, functional, or informational terms and is expressed by its related values. A situation is related to a fix problem configuration.

Using the SOM-approach actions in the real world are modeled as operators. An operator is related to its functionality F, which depends of explicit and implicit assumptions. The assumptions are described by suitable mathematical, logical, or textual expressions. A current situation S_i and the following situation S_{i+1} are connected by an operator, so that an operator can effect the structure and the values related to the characteristics in the following situation.

2.2. *Modified fuzzy-based CREAM approach*

The modified fuzzy-based CREAM approach established in He et al. (2021) is applied for automatic generation of membership functions and calculation of human performance reliability score (HPRS) to realize the individualized human reliability evaluation in real time.

2.2.1. *CREAM*

The CREAM approach as a so called "second generation" of HRA approach is applied for retrospective analysis of historic events and a prospective analysis for the design of high-risk systems or processes Di Pasquale et al. (2013). It provides the human cognition model to illustrate the information processing which is denoted as contextual control mode (COCOM) assuming that the degree of human operator's control on context is the most significant index for human performance reliability estimation.

Common performance conditions (CPCs) represents the most vital factors in operation context, which are similar with the concept of performance shaping factors Park et al. (2020). There are nine CPCs defined in CREAM. Each CPC includes several levels and related expected effects on performance reliability which are improved, not significant and reduced. The CPC score could be calculated as $[\sum$ reduced, $\sum$ improved$]$. In this case, human performance reliability is determined with control mode map Hollnagel (1998).

To apply CREAM into other domain, it is advised to generate a new list of CPCs Taga et al. (2012). In dynamic driving context, a new CPC list has to be defined which includes the number of surrounding vehicles, time to collision (TTC), ego-vehicle speed, longitudinal acceleration, lateral acceleration, traffic density, and general visibility He et al. (2021).

2.2.2. *Automatic generation of membership functions*

Fuzzy logic: Fuzzy logic is used for modeling the imprecise modes of reasoning that play an essential role in human decision ability in an environment of uncertainty and imprecision Zadeh (1988). It considers the degree of truth of statements continuously between true (1) and false (0). To define the related membership function, the core and support points and membership function shape should be known. In this contribution, trapezoidal shape is selected.

FN-DBSCAN algorithm: To define the core and support points in membership functions, the fuzzy density clustering method Ulutagay and Nasibov (2008) fuzzy neighborhood density-based spatial clustering of application with noise (FN-DBSCAN) is applied.

Genetic algorithm: In FN-DBSCAN, the parameter of fuzzy cardinality threshold needs to be predefined, therefore, genetic algorithm is applied for the optimization of the parameter McCall (2005).

2.2.3. *Human performance reliability score (HPRS)*

The CPC levels are divided by data clustering. When membership functions of CPCs are generated, they will be assigned to different levels with corresponding expected effects on performance reliability. In this case, each CPC score is calculated and human performance reliability score is generated with the sum of each CPC score.

In general, the steps to calculate HPRS are following: i) Execute genetic algorithm to obtain optimal value of fuzzy cardinality threshold. ii) Apply the FN-DBSCAN to calculate cores and supports of membership functions of CPCs. iii) Assign CPC levels and related effects on reliability ot membership functions to calculate CPC scores. iv) Add up all CPC scores to get the final HPRS.

3. Data-based HPRS calculation

3.1. *Data generation platform*

A driving simulator (SCANeR^{TM} studio, Fig. 2) is applied to collect driving data. Data with ego-vehicle dynamics (speed, steering angles, etc.) and surrounding vehicle status (TTC, lateral shift, etc.)

relative to ego-vehicle are collected to evaluate driving behavior and human driver reliability.

Fig. 2. Driving simulator laboratory, Chair of Dynamics and Control, U DuE

3.2. *Experimental results*

In this contribution, an example data set is contributed by a human driver with a valid driving license for eight years with approximately 250 kilometers per weekly driving. The driving data between 400 s and 520 s are selected to generate the membership functions and the HPRS.

Four CPC data including ego-vehicle speed, TTC, longitudinal acceleration, and lateral acceleration are clustered and membership functions are generated for each CPCs. The CPC scores of traffic density and general visibility are defaulted to 1 as the scenario is simple with normal daytime weather condition and the lane are relatively empty.

The membership functions of the clustered CPC data are shown in Fig. 3. For the CPC of speed, three membership functions are generated. Therefore, the first membership function (green) could be assigned to improved effects, the second membership function (blue) could be assigned to not significant effects, and the last one (red) is assigned to reduced effects. On the contrary, for the CPC of TTC, the assignment should be the opposite, where the first membership function (green) is assigned to reduced effects and the third membership function (red) is assigned to improved effects as lower TTC indicates higher time pressure for human driver to recognize the situations and take actions. There is only one membership function in CPCs of longitudinal acceleration and lateral acceleration. In this case, the membership function with membership degree of 1 is assigned to not significant effects and the other part is reduced effects.

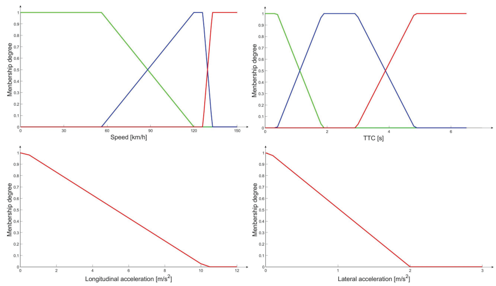

Fig. 3. Membership functions of CPCs

After the assignment of expected human performance effects, the CPC scores could be calculated. The final HPRS values is the sum of all CPCs scores. By evaluating the continuously determined HPRS values, human driving performance can be quantitatively monitored in real time.

4. SOM-based human performance reliability evaluation

4.1. *Operators and characteristics*

In the Table 1 the characteristics included in a situation vector are shown.

Table 1. List of characteristics including in the situation vector

Characteristic	Unit
C_1 : Longitudinal speed	[km/h]
C_2 : Lateral speed	[km/h]
C_3 : Longitudinal acceleration	$[m/s^2]$
C_4 : Lateral acceleration	$[m/s^2]$
C_5 : Yaw angle	[°]
C_6 : Steering wheel angle	[°]
C_7 : Direction indicator to the left	[-]
C_8 : Direction indicator to the right	[-]
C_9 : Lane number	[-]
C_{10}: TTC to front vehicle	[s]
C_{11}: Driving area in the left lane	[-]
C_{12}: Driving area in the right lane	[-]
C_{13}: Distance to front vehicle	[m]

The characteristics C_7 and C_8 provide the statement about the direction indicator and have a Boolean type. If the direction indicator to any direction (left or right) is on, the value of the related characteristic (C_7 or C_8) changes from 'False' to 'True'. The characteristic C_9 gives the number, in which lane the ego-vehicle is driving in the current moment. The characteristics C_{11} and C_{12} provide a statement about the availability of the driving area in the left and right lanes close to the ego-vehicle, which are Boolean.

A sequence consisting of items operators and situations, which describes a sequence of actions, can be replaced as a meta-operator. An example of a meta-operator is 'changing to the left lane' shown in the Fig. 4. This meta-operator consists of the basic operators 'Turn on the left direction indicator' O_4, 'Operate steering wheel to the left' O_8 ,'Turn off left direction indicator' O_5, 'Steering to the right' O_9 ,and 'Turn off left direction indicator' O_5 (cf. Table 2), so describes the 'Changing to left lane' sequence (cf. Fig. 4).

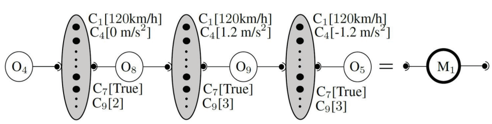

Fig. 4. Meta-operator 'Changing to the left lane'

The operators describing the actions of the driver are shown in the Table 2.

Table 2. List of characteristics of the situation vector

Operator	Description
O_1	Acceleration
O_2	Deceleration
O_3	Keeping the actual speed
O_4	Turn on the left direction indicator
O_5	Turn off left direction indicator
O_6	Turn on right direction indicator
O_7	Turn off the right direction indicator
O_8	Steering to the left
O_9	Steering to the right

In this work an overtaking maneuver is considered (cf. Fig. 5). The ego-vehicle is the red vehicle and the vehicle, which has to be overtaken, is the blue vehicle. Possible vehicles driving in the left lane are represented with white color. The final desired situation is, that the ego-vehicle overtakes the blue vehicle considering the environment, and so other vehicles. More than one possibility lead to the final desired situation. Using the situation-operator-modeling an action space consisting of possible driver's behaviors allowing to reach the final desired situation of overtaking the blue vehicle is proposed in the next section.

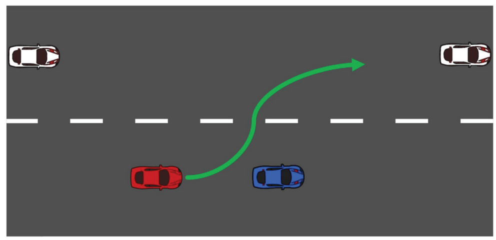

Fig. 5. Overtaking maneuver on a highway (2 lanes for one direction): Ego-vehicle (red)

4.2. *Action space*

For every action taking or decision making moment in time a SOM-based action can be established to map the individual and situated action options for this moment in time. The intended safety evaluation is based on this continuously changing discrete events. Beside the continuous evaluation of realized actions (section 4.3) also the options in specific moments in time can be evaluated establishing a new safety-related performance measure or decision making (section 4.2).

4.2.1. *Evaluation of driver's options*

A SOM-based action space consisting of permissible operator sequences, which lead to the desired final situation of overtaking the blue vehicle, is developed and shown in Fig. 6. In the concrete example, four possible paths lead to the desired final situation and are explained as follows:

Path I: In this case the driver keeps the current speed and waits of the passing of vehicle(s) in the left lane (C_{11} = 'False'). After the left lane is free, the driver changes to the left lane (cf. meta-operator ’Changing to the left lane’ in Fig. 4). The vehicle, which has to be overtaken, accelerates (C_{12} = ’False’), so that the driver of the ego-vehicle has to decelerate and then to keep the current speed. After the vehicle in the right lane do not accelerate and vehicles in the front keep the speed, the driver of the ego-vehicle can overtake by accelerating.

Path II: In this case the driver keeps the current speed and waits of the passing of vehicle(s) in the left lane (C_{11} = ’False’). After the left lane is free, the driver changes to the left lane (cf. meta-operator ’Changing to the left lane’ in Fig. 4). The vehicle in the right lane do not accelerate and vehicles in the front keep the speed, the driver of the ego-vehicle can overtake by accelerating.

Path III: This case is the optimal driving behavior to reach the final desired situation of overtaking the blue vehicle. The left lane is free (C_{12} = ’True’), the driver changes to the left lane (cf. meta-operator ’Changing to the left lane’ in Fig. 4). The vehicle in the right lane do not accelerate and vehicles in the front keep the speed, the driver of the ego-vehicle can overtake by accelerating.

Path IV: The left lane is free (C_{12} = ’True’), the driver changes to the left lane (cf. meta-operator ’Changing to the left lane’ in Fig. 4). The vehicle, which has to be overtaken, accelerates (C_{12} = ’False’), so the driver of the ego-Vehicle has to decelerate and then to keep the current speed. After the vehicle in the right lane do not accelerate and vehicles in the front keep the speed, driver of the ego-vehicle can overtake by accelerating.

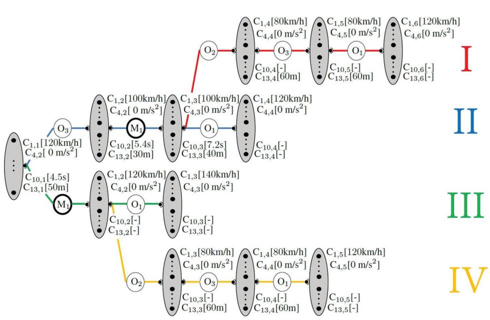

Fig. 6. SOM-based action space for overtaking

4.2.2. *Evaluating options by summarizing safety-related performance scores*

To quantitatively evaluate different options and define the optimal action sequence in action space, the group of artificial values of characteristics for the situations in Fig. 4 and 6 are defined. It is assumed that the vehicle speed in front (vehicles in blue and white in front) maintains the fixed speed of 80 km/h, the ego-vehicle speed is varying between 80 and 140 km/h. The distance between the front vehicles and ego-vehicle is from 30 to 60 m considering the traffic rules. In this case, the TTC of front vehicle and ego-vehicle is defined. When the time for lane changing and acceleration is artificially defined as 10 s, the lateral and longitudinal accelerations could be calculated with the relationship of speed and time. With the artificial defined values of characteristics in action space for the driving task of overtaking maneuver described in Fig. 4 and 6, the HPRS of each situation could be calculated with the membership functions generated from real driving data. The results is presented in Table. 3 and Table. 4.

Table 3. The HPRS of situations in meta-operator

Operators	HPRS
O_4	3.83
O_8	3.42
O_9	3.42

Different operators result in the changes of CPCs values in the modified CREAM, leading to the HPRS values fluctuation. From Table 3, it can be detected that HPRS is decreasing during lane change maneuver as the lateral acceleration is fluctuating. It can be observed in Table 4 that path III is the optimal action sequence as it has less action sequences which indicating less cognition requirement and the values of situation related HPRS is lower than other paths. Path I dominates most action sequences presenting human driver has more information processing and action implementation, and the mean HPRS is higher than other paths.

Table 4. The HPRS of situations in action space

Path	Operators	HPRS
Path I	O_3	2.88
	M_1	3.31
	O_2	3.43
	O_3	3.63
	O_1	2.63
Path II	O_3	2.88
	M_1	3.31
	O_1	2.83
Path III	M_1	3.00
	O_1	2.83
Path IV	M_1	3.00
	O_2	3.32
	O_3	3.63
	O_1	2.63

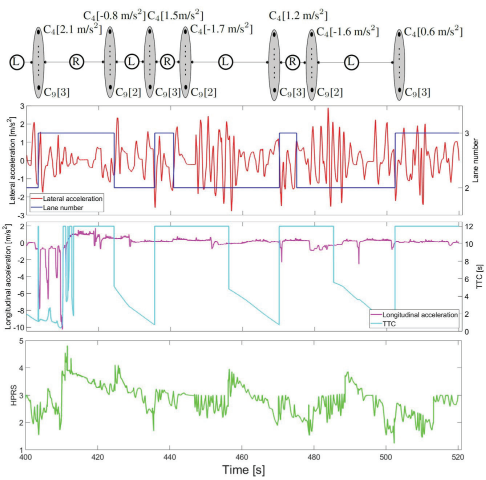

Fig. 7. Synchronization of SOM-based action sequence and HPRS in lane changing maneuver

4.3. *Real-time applicable SOM-based HPRS for real time driver safety evaluation*

The SOM approach applying to real driving data in lane changing maneuver is considered. Totally seven lane changing maneuvers including changing to left lane and changing to right lane in the selected data are considered. The changes of lateral acceleration can indicate the time of lane changing as the lateral acceleration is maintaining

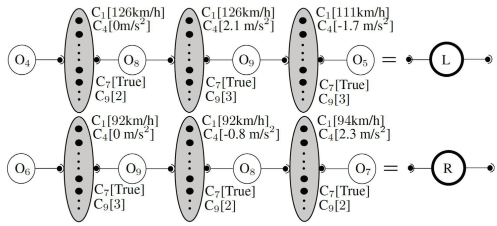

Fig. 8. Meta-operator of lane changing to left and right in simulated driving

around 0 m/s^2 when it is lane keeping. The lane changing is a continuous process which start when the lateral acceleration begins to change and ends with the lateral acceleration returning to around 0 m/s^2 and in between the lane number is changed. In this contribution, the top and bottom points in lateral acceleration near the lane number changing are selected as the time of starting and ending of the lane changing maneuver to present the HPRS varying. In this case, the synchronization map of SOM based action sequence and HPRS in lane changing maneuver is presented in Fig. 7.

In Fig. 7, the HPRS in the selected time synchronizing with the action sequence of lane changing is presented. With the meta-operator of lane changing to left and lane changing to right and the related situations as shown in Fig. 8, the action sequence of lane changing is illustrated. Meanwhile, the corresponding HPRS during the lane changing period is presented synchronously. In this case, the driver's lane changing behavior is monitored and evaluated with the SOM-based HPRS approach in real time.

5. Conclusion

In this contribution, a SOM-based human reliability evaluation approach is developed to calculate human performance reliability of situations driven by operators in action space. Within the SOM approach processes in the real world are considered as sequences of scenes and actions, which are modeled as situations and operators, respectively. To define human performance reliability of human driver in each situation, the modified CREAM approach is applied for the calculation of HPRS. The driving data collected from driving simulator are clustered with FN-DBSCAN to generate personalized membership functions of CPCs. An action space of overtaking maneuver is generated to describe different possible action sequences and options human driver available. For illustration as example artificial CPC values are defined for HPRS calculation, so that the optimal path can be determined. The SOM-based action sequence of lane changing maneuver is presented with the HPRS synchronously. Finally as result the approach developed shows that human driver's lane changing behavior can be evaluated in real time. This will allow in future work to use this information in combinations with experienced thresholds to warn the driver or to intervene from the vehicle side. This approach can be also applied to other applications, such as captain behavior monitoring in maritime.

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