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Human reliability analysis in situated driving context considering human experience using a fuzzy-based clustering approach

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***Abstract*—Although more higher level advanced driver assistance systems (ADAS) are applied to driving, human driver reliability remains crucial for driving safety. Existing reliability approaches qualify human behaviors in a static manner. In this contribution dynamically changing situations are considered: as example dynamic and situated driving context is used for human reliability evaluation. The dynamic and situated driving context requires dynamic solutions for human reliability evaluation. Cognitive reliability and error analysis method (CREAM) provides the evaluation method for human reliability in industrial fields, when it is applied to situated context, adaption is required. Human-related accidents account for the highest proportion of total accidents. Human experience as an important factor for driving safety so should be considered when human driver reliability is evaluated. In this contribution, human driver experience (HDE) is quantitatively characterized for the first time. Three variables are selected to evaluate HDE in situated driving context. A new list of common performance conditions (CPCs) in CREAM to characterize the situated driving context is generated due to the application limits of CPCs in original CREAM. To determine the levels in HDE variables and new generated CPCs, fuzzy neighborhood density-based spatial clustering of application with noise (FN-DBSCAN) is applied to driving data defining the membership function parameters. Therefore, HDE and human driver reliability score (HDRS) in situated driving context are calculated quantitatively. In this contribution evaluation of HDE and HDRS is data-driven and the reliance on expert knowledge is reduced. Next, a new evaluation index, human performance reliability score (HPRS) is defined. The results show that the method could quantify and evaluate human driver reliability in real time.**

***Index Terms*—Human reliability analysis (HRA), modified CREAM, FN-DBSCAN, fuzzy logic, human experience, situated driving context**

I. Introduction

With the development of technology, automation has been applied in a wide variety of fields. In most safety-critical systems, such as power plants [1], aviation [2], and transportation [3], automation is applied. Automation has profoundly influenced human behaviors in human-machine systems. Following the application of automation in human-machine systems, the importance of humans is increasing as more and more accidents are related to human errors [4]. In several automated system transitions between human guidance and automated processes are possible, so takeover processes may occur. A reliable transition should be guaranteed to realize continuous and safe operation. For example, when driver assistance systems of a highly automated vehicle fail, the driver must take control to avoid an accident. A suitable level of human driver reliability is required in exactly that moment to handle a specific take-over situation. Human driver reliability may be affected by different take-over scenarios. It should be noted that continuous human operation could be also considered using similar approaches. From [5], it can be concluded that employing one common take-over request (TOR) time for all drivers and critical takeover situations is inappropriate.

The majority of accidents in driver-vehicle systems are caused by human errors. According to the national highway traffic safety administration (NHTSA), human factors are to blame for 94 % of traffic accidents [4]. The driving environment is increasingly sophisticated as the road traffic framework is becoming complex, requiring the driver to maintain a high reliability level at all times while driving. Meanwhile, human driver experience (HDE) also affects driving safety. For experienced drivers, the driving process is smooth, and aggressive driving behaviors are rarely observed. Human experience is a concept that is difficult to characterize quantitatively. In situated driving context, with the idea that human reliability could be evaluated based on dynamic driving variables, human driver experience estimating by some significant driving variables from situated driving context could be also considered. In this case, human driver experience could be evaluated quantitatively. In this contribution, human driver experience (HDE) is quantitatively characterized for the first time.

A. Human reliability

Human reliability analysis methods have been proposed to systematically incorporate for the analysis, prediction, and prevention of human errors. Over the years, human reliability analysis (HRA) methods have developed various changes. These changes are often categorized into generations, the so-called "first generation"-HEART, THERP, SPAR-H, etc.,

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and the so-called "second generation"-ATHEANA, MERMOS, CREAM, etc [6]. The first and second generation methods, by any definition, consider task analysis of operating events as the underlying basis of performance modeling, while time dimension is less involved. This characterization leads to the characterization as static approach. When dynamic context has to be considered, these methods are not suitable, an adaption should be generated to integrate dynamic features.

The authors of [7] propose that dynamic human reliability analysis (HRA) should consider the evolution of performance shaping factors (PSFs). More important, in dynamic HRA, influences of PSFs can change with time. In static HRA, events are analyzed for an assumed window of time. For continuous changing driving context, static HRA is not suitable, so a definition for dynamic HRA is required.

To integrate simulation data to HRA, one option to overcome this is to vary PSF to generate PSF levels dynamically. In the so-called "second generation" HRA approaches, cognitive reliability and error analysis method (CREAM) approach provides a list of common performance conditions (CPCs) which are the main factors describing operation context. The states of these CPCs do not evolve with time in original CREAM unless CPCs are adjusted. It is necessary to understand scenarios if CPCs need to be adjusted. A list of CPCs characterizing the main features in situated driving context was proposed in [8].

B. Human experience

Human experience comes in discontinuous blips. The parsing of experience naturally corresponds to the aggregates of the mindfulness/awareness practitioner as known from the description of brain researchers [9]. In general, human experience is related to the operator's familiarity with specific situations. Human experience of a specific task is measured by the amount of time a person devotes to that task. For example, driving mileage is used as criteria for experienced drivers. In [10], as criteria an experienced driver should have held a driver's license for at least 3 years, a minimum annual mileage of 15,000 km in the last year, and has to be very familiar with the experiment scenarios. For an inexperienced driver, a maximum annual mileage of 15,000 km and little or no experience of driving in experiment scenarios are applied. In [11], a quantitative method to calculate human experience in takeover task is proposed. According to the description, human experience is a suitable number, which is related to the individual's familiarity with takeover scenarios. It is an equation related to non-driving related tasks (NDRT), assessment of the moment of conflict (AMC), scenario development rate (SDR), and number of conflicting units (NCU). The approach to compute human experience is based on the idea that human experience can be quantified based on a number of variables that are closely related to the task.

In this contribution, the so-called "second generation" technique CREAM [12], is used to investigate human reliability in a situated driving context. On the other hand, human driver reliability analysis in a dynamic driving context is less studied and therefore the approach is restricted. A modified CREAM approach combining different driving experiences is generated. The fuzzy neighborhood density-based spatial clustering of application with noise (FN-DBSCAN) and genetic algorithms are applied for automatically generation of membership functions of CPCs and variables in human driver experience (HDE). Integration of fuzzy logic applied to CREAM has been considered also in other studies [13]. Another concept applied to this focus is situation awareness (SA). In SA the general focus is given to the humans ability to perceive relevant features from the situation and to predict comsequences fro the own actions. The related experience is implicitly addressed. The whole approach works as a description. The newly introduced approach in this contribution addresses similar aspects but introduces a formalized approach leading to numerical quantification. Due to the reliability-based approach can be expected that generating numerical values indicating the newly introduced approach is the adequate approach.

In this contribution, the approach applied is firstly published in [14]. Human driver experience (HDE) is considered and quantitatively estimated with some relevant variables from situated driving context for the first time. In addition, in this contribution, dynamic human reliability analysis and human experience is more detailed explained, the fluctuation of HDE with time in driving process is mapped, and the new human performance reliability score (HPRS) combining the result of HDE is discussed in detail.

The following sections make up this contribution: Section II introduces theoretical backgrounds such as CREAM and fuzzy logic. In Section III, the HDE and modified CREAM are proposed, the FN-DBSCAN method is applied to cluster driving data for the determination of CPCs levels, and a genetic algorithm is used to automatically find the relevant variables in FN-DBSCAN. The experiment and results are discussed in Section IV, human performance reliability score (HPRS) is generated to assess human driver reliability in situated driving context. The conclusion and outlook are provided in Section V.

II. Theoretical Background

A. CREAM

The CREAM approach is a practical approach for analyzing performance and forecasting outcomes.

Contextual control mode

Human cognition model utilized in CREAM methodology to show human behaviors is indicated as contextual control mode (COCOM). The degree of control that human operators have over situations or context is believed to be the most important criterion for evaluating human performance and reliability. The fundamental step for determining the relationships between context and human reliability is the degree of control [12]. Scrambled control, opportunistic control, tactical control, and strategic control are the four control modes specified in CREAM. Each control mode compares to distinctive human reliability interval with strategic control having the highest reliability and scrambled control having the lowest.

Common performance conditions (CPCs)

The operation context is represented by nine CPCs, which are the most important components. These are adequacy of organization, working conditions, adequacy of MMI and operational support, availability of procedures/plans, number of simultaneous goals, available time, time of day (circadian rhythm), adequacy of training and experience, and crew collaboration quality. Each CPC has several different levels, and corresponding expected effects on performance reliability which are improved, not significant, and reduced.

When the impact on performance reliability of each CPC is decided, CPC score can be recognized as [$\sum$ reduced, $\sum$ improved]. A relation map between CPC score and control modes is used to distinguish the control mode. As a result, human error probability (HEP) interval is defined with the determination of control mode.

B. Fuzzy logic

Lotfi Zadeh establishes fuzzy logic based on the previous work on fuzzy set theory [15]. In [15], a fuzzy set *A* in the universe of discourse *X*, is defined by a membership function μ_A, which correlates each element *x* in *X* to a real number in the interval [0,1], where the degree of membership of *x* in *A* is denoted by the value of μ_A.

The height, core, and support parameters are the most important aspects of a membership function. The height of a fuzzy set *A* can be represented with the mathematical function

$$height(A) = max\{\mu_A(x)|x \in X\}, \tag{1}$$

which indicates the highest value of the membership function. Any number between 0 and 1 can be the height domain.

The core of the membership function can be defined mathematically by

$$core(A) = max\{x|x \in X, \mu_A\text{=}1\}, \tag{2}$$

where the core contains all elements *x* which are characterized by full membership in the set, in this case with a value of 1.

The support of a membership function of a fuzzy set *A* can be expressed by

$$supp(A) = max\{x|x \in X, \mu_A(x) > 0\}, \tag{3}$$

where the support contains all elements *x* which are characterized by a nonzero membership in the set.

III. Novel Approach for Dynamic Modeling of Human Performance Reliability

As an example for the new approach in this work driving data are used and clustered using FN-DBSCAN to reduce the effects of expert knowledge on the results and to reflect the driving behavior characteristics of diverse drivers [16]. The automatically generated membership functions are corresponding to the related levels and expected effects on performance reliability of CPCs. As result, human driver reliability score (HDRS) is calculated. The fuzzy-based CREAM approach to evaluate human driver reliability was firstly established in [14]. With the consideration of HDE, the human driver performance reliability can be evaluated using human performance reliability score (HPRS) [8]. In section III, the methods to obtain HPRS are introduced.

A. New List of CPCs

A new list of CPCs for the new application domain must be generated when using CREAM in another domain. A new set of CPCs is offered, based on the results of [8], to assess human reliability in the driving domain. These nine CPCs are: number of surrounding vehicles, time to collision (TTC), ego-vehicle speed, longitudinal acceleration, lateral acceleration, traffic density, number of available lanes, actual lane, and general visibility conditions. Number of available lanes and actual lane are not taken into account in this contribution.

B. Human driver experience (HDE) variables

The selection of variables to characterize human driver experience (HDE) is critical due to the effect on the result calculation. In [10], driving mileage as a selection criteria is proposed for the evaluation of experienced and inexperienced driver. This criteria is appropriate for the qualitative classification, but for quantitation of HDE in specific situations, it is invalid. In [11], the idea that human experience could be calculated by variables related to specific scenario is generated. In continuous driving process, HDE is dynamically varying with situations driver encountered. Therefore, the variables which are able to characterize situated driving context and define driver's safe and unsafe driving behavior should be selected. In [17], the combination of speed and acceleration to define the safety aspects of the driver's behavior is chosen. It is assumed that this two variables can clearly describe the motion of ego-vehicle, and are fundamental to define the behavior of driver. A safety domain or threshold calculated by ego-vehicle speed and acceleration to distinguish between safe and unsafe driving conditions is determined. So within the thresholds, driving behavior is evaluated as safe, otherwise, it is unsafe.

In this contribution, three variables are selected to quantify HDE, which are ego-vehicle speed, longitudinal acceleration, and lateral acceleration.

C. Automatic generation of membership function

Classical neighborhood density analysis is used in standard DBSCAN approach to determine the core points (and noise points) of clusters. A core point is defined as the number of points in a specific radius larger than a certain threshold [18]. On the other hand, FN-DBSCAN generates core points using fuzzy neighborhood cardinality.

FN-DBSCAN algorithm

The fuzzy neighborhood membership function could be defined as

$$N_x(y) = \begin{cases} 1 - \frac{d(x,y)}{d^{max}} & \text{if} \quad d(x,y) \le \epsilon, \\ 0 & \quad otherwise, \end{cases} \tag{4}$$

where $d(x, y)$ represents the distance between any points x and y, whereas ϵ determines the maximal threshold of the distance between points.

To further improve the sensitivity of the points that are at various distances from their neighbors, the neighborhood membership functions dependent on the variable k is expressed as

$$N_x(y) = max\{1 - k\frac{d(x,y)}{d^{max}}\}. \quad (5)$$

The fuzzy neighborhood set of point $x \in X$ with parameter ϵ_1 is expressed as

$$FN(x;\epsilon_1) = \{< y, N_x(y) > \mid y \in X, N_x(y) \geq \epsilon_1\}, \quad (6)$$

where ϵ_1 defines the minimal threshold of the neighborhood membership degree, N_x refers to any membership function that describes the neighborhood relation between points.

A point x is defined as a fuzzy core point with parameters ϵ_1 and ϵ_2 if it fulfills the requirement of

$$cardFN(x;\epsilon_1,\epsilon_2) \equiv \sum_{y \in N(x;\epsilon_1)} N_x(y) \geq \epsilon_2, \quad (7)$$

Nonetheless, expert knowledge is inevitable to determine the value of the parameters variables ϵ_1, ϵ_2, and k. Further details regarding ϵ_1 and ϵ_2 are given in [19]. To lessen the reliance of parameters on expert knowledge, it is suggested that the number of preset parameters is reduced from 3 to 1. ϵ is defined as the average distance between adjacent data

$$\epsilon = \frac{\sum_{i=1}^{m-1} d(x_i, x_{i+1})}{m-1}, \quad (8)$$

where $d(x_i, x_{i+1})$ represents the distance between the i-th data point and its adjacent neighboring data point while m is the total number of data points. A data point y has a neighborhood degree of $N_x(y) > 0$ if it is closer to a data point x than the average distance between adjacent data.

The relation of variable k with respect to ϵ can be represented by

$$k = \frac{d^{max}}{\epsilon}. \quad (9)$$

The parameter ϵ_1, which specifies the radius of the membership threshold of data points to be included in the fuzzy cardinality, is set to 0. As a result of ϵ in Eq. 8, a neighborhood consisting of relatively close points is considered and therefore these data points could also be included in the fuzzy cardinality. Given that $\epsilon_1 > 0$, the density requirement towards the center of the neighborhood could be increased. Thus, only fuzzy cardinality threshold ϵ_2 needs to be determined.

Optimization of ϵ_2 using genetic-based algorithm

Genetic algorithms reflect the natural selection process in which only the fittest combinations are picked from a population to generate the following generation.

Generally, a population of random generated individuals to an optimization problem is first initialized. Each individual's chromosomes (or genotypes) can be mutated and altered [20]. Selection, genetic recombination, and replacement are key pahses in genetic algorithm.

The roulette wheel is the most common technique of selecting. The selection is proportional to its relative fitness value, which is proportional to the sum of the population's fitness values. Individuals with the five greatest fitness values are picked via roulette to undergo crossover and mutation in this contribution, boosting the algorithm's probability of obtaining an optimal ϵ_2 value.

Application of genetic algorithm and FN-DBSCAN

The value of parameter ϵ_2 is evaluated using genetic algorithm to automatically generate membership function with FN-DBSCAN. For the clustering algorithm FN-DBSCAN to define core and support parameters of the membership functions, the ϵ_2 is used as the sole parameter. When core and support parameters are calculated, the membership functions of driving data could be generated.

D. Human performance reliability score (HPRS)

The CPC score is calculated using the sum of reduced and improved expected effects on performance reliability [$\sum$ reduced, $\sum$ improved] in the original CREAM technique. The control mode can then be determined.

In this contribution, new CPCs are described in III *A*. The CPC levels are determined by data clustering. Here membership functions are generated assigning different levels and corresponding expected effects on performance reliability. Therefore, each CPC score is calculated.

The HDE is the sum of the mentioned three variables, including ego-vehicle speed, longitudinal acceleration, and lateral acceleration. The HDRS is the sum of all listed CPCs. The new human performance reliability score (HPRS) is the sum of HDRS and HDE.

Each membership function is labeled to represent the expected effect on the performance reliability of the driver. The CPC score for the entire duration of driving simulation is calculated according to the membership degree of each data point. The final HPRS can be calculated by adding up the seven CPC scores and three variables in HDE relative to time.

In general, the steps to obtain HPRS are as follows:

Step 1 Executing genetic algorithm to generate optimal ϵ_2

Step 2 Applying the FN-DBSCAN algorithm to obtain core and support values of membership functions

Step 3 Assigning membership functions to different CPCs and variables levels to determine each CPC score and HDE

Step 4 Adding all seven CPC scores together to generate HDRS

Step 5 Adding up HDRS and HDE to generate the final HPRS

IV. EXPERIMENTS AND RESULTS

A. Description of data generation platform

A driving simulator SCANeR^{TM} studio as shown in Fig. 1 is used to collect driving data. The simulator realizes a 270° view of the driving environment with five monitors, steering wheel, pedals, and base-fixed driver seat.

B. Experimental results analysis

Example data sets from two scenarios (scenario_1 and scenario_2) are contributed by a participant.

Fig. 1. Driving simulator laboratory, Chair of Dynamics and Control, U DuE

Both scenarios' membership functions (ego-vehicle speed, time to collision, longitudinal acceleration, and lateral acceleration) are generated, here the membership functions of four CPCs in scenario_1 are shown in Fig. 2. In Fig. 2, there are three membership functions that could be assigned to three different levels, and these levels correspond to different expected effects, which are improved (score of 1), not significant (score of 0), and reduced (score of -1). The CPC score is calculated based on the core and support points, and the membership degree of each data points on membership functions.

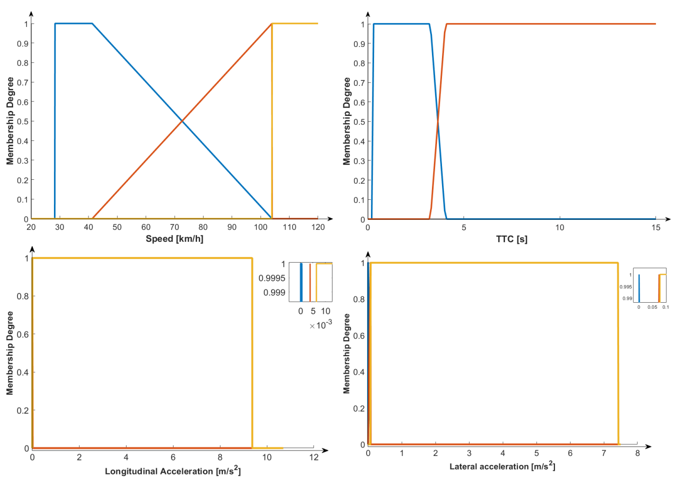

Fig. 2. Menbership functions of four CPCs in scenario_1

The human driver experience (HDE) is calculated by the sum of three parameter scores. The HDE of scenario_1 is plotted in Fig. 3. It is observed that HDE varies over time driving the driving process. The main reason is that slight changes in longitudinal and lateral acceleration during driving lead to very steep shape and close distance of membership functions.

The human driver reliability score (HDRS) is calculated by using the summation of all seven CPC scores with respect to time. The HDRS of scenario_1 is then plotted in Fig. 4.

The human performance reliability score (HPRS) is the sum of HDE and HDRS, therefore, the HPRS of scenario_1 and scenario_2 are plotted in Fig. 5 and Fig. 6.

To evaluate HPRS with time, the control mode determination system in the original CREAM method needs to be translated into a new time-related scaling system. From original CREAM approach, the CPC score is identified as [$\sum$ reduced, $\sum$ improved]. It can be concluded that each control mode is located in a specific interval when CPC score is indicated by the number in the manner as [$\sum$ improved - $\sum$ reduced]. The numbers of all strategic mode are larger than 4, tactical mode are between -1 and 4, most of opportunistic mode are between -5 and -1, and all scrambled control are less than -5. By this translation, HPRS could be evaluated with time.

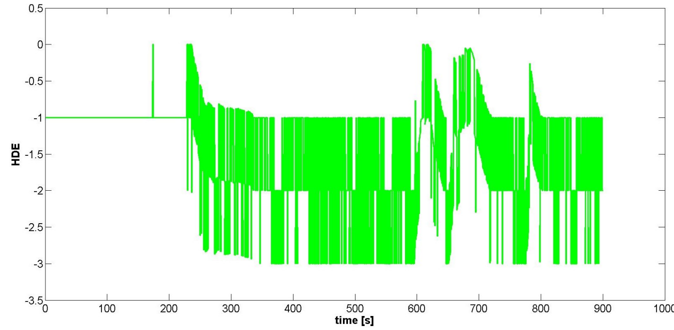

Fig. 3. HDE of scenario_1

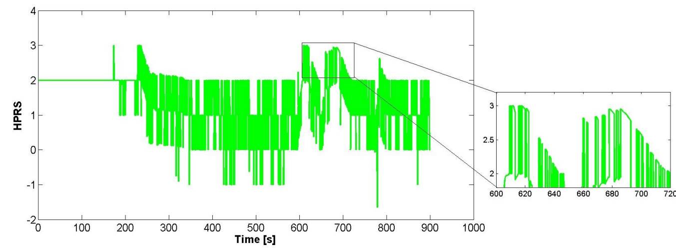

Fig. 4. HDRS of scenario_1

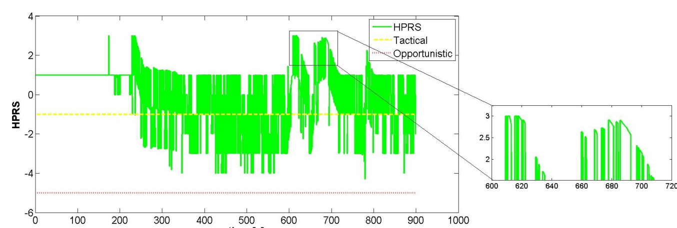

Fig. 5. HPRS of scenario_1

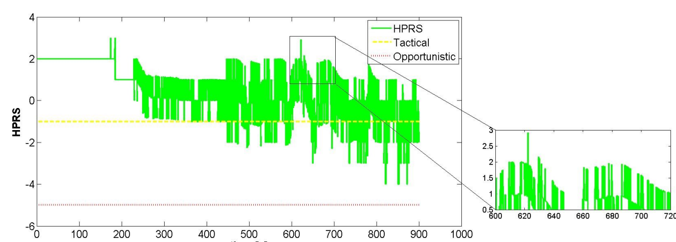

Fig. 6. HPRS of scenario_2

It can be observed that HPRS are above opportunistic level in both scenarios. The HPRS values corresponding to the level of different control modes are determined from [8]. For a more detailed discussion the differences for HDRS and HPRS, the results from 600 s to 720 s are magnified. It can be detected that although the changing trends of the two values are roughly similar, the related intervals are different. Meanwhile, it can also observed that the fluctuation trend of the HPRS curve is mainly affected by longitudinal and lateral acceleration by comparing HDE curve and HPRS curve.

In [8], the HPRS is presented in Fig. 7. The CPC levels in [8] are determined by literature research and expert knowledge. The human driver reliability score (HDRS) is the sum of CPC scores different from the HPRS calculation method in [8] as the weight λ in [8] is switching between the discrete -1 and the discrete +1. Therefore, HPRS values jump between integer values. Due to the application of fuzzy logic in this contribution, the CPC score could be any value from -1 to +1.

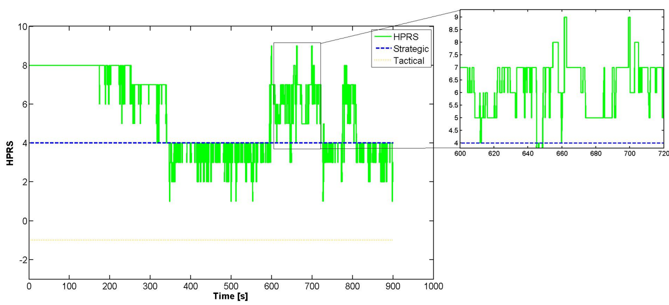

Fig. 7. Unfuzzified HPRS of scenario_1 [8]

V. Conclusion and Outlook

In this contribution, a new approach defining the situated and dynamic human reliability measure with the consideration of human driver reliability is used and extended. By combining human driver reliability into the established approach in [14], a new HPRS to evaluate human reliability in situated driving context is generated.

The main innovation of this contribution is quantitatively characterizing human driver experience with three variables in situated driving context for the first time and generating a new HPRS combining the effects of HDE for dynamic modeling of human reliability. This approach is the foundation for the realization of online estimation of human reliability, and the new concept HPRS becomes a visualization-oriented step for online estimation of human reliability. In the next steps, filter approach could be applied to acceleration data therefore to decrease the fluctuation of HPRS curve. This contribution establishes the foundation for further evaluation between automation and operator's takeover.

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References

[1] C. Zhang, P. Tang, N. Cooke, V. Buchanan, A. Yilmaz, S. W. S. Germain, R. L. Boring, S. Akca-Hobbins, and A. Gupta, "Human-centered automation for resilient nuclear power plant outage control," *Automation in Construction*, vol. 82, pp. 179–192, 2017.

[2] R. De Boer and S. Dekker, "Models of automation surprise: results of a field survey in aviation," *Safety*, vol. 3, no. 3, p. 20, 2017.

[3] M. N. Lees and J. D. Lee, "The influence of distraction and driving context on driver response to imperfect collision warning systems," *Ergonomics*, vol. 50, no. 8, pp. 1264–1286, 2007.

[4] B. Paden, M. Čáp, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Transactions on intelligent vehicles*, vol. 1, no. 1, pp. 33–55, 2016.

[5] J. Wang and D. Söffker, "Bridging gaps among human, assisted, and automated driving with dvis: a conceptional experimental study," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 6, pp. 2096–2108, 2018.

[6] S. Rangra, M. Sallak, W. Schön, and F. Vanderhaegen, "A graphical model based on performance shaping factors for assessing human reliability," *IEEE Transactions on Reliability*, vol. 66, no. 4, pp. 1120–1143, 2017.

[7] R. Boring and M. Rasmussen, "GOMS-HRA: A method for treating subtasks in dynamic human reliability analysis," in *Proceedings of the 2016 European Safety and Reliability Conference*, pp. 956–963, 2016.

[8] C. He, F. Tanshi, and D. Söffker, "Human online reliability estimation applied to real driving maneuvers," in *2020 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, pp. 149–154, IEEE, 2020.

[9] F. J. Varela, E. Thompson, and E. Rosch, *The Embodied Mind, revised edition: Cognitive Science and Human Experience*. MIT press, 2017.

[10] C. J. Patten, A. Kircher, J. Östlund, L. Nilsson, and O. Svenson, "Driver experience and cognitive workload in different traffic environments," *Accident Analysis & Prevention*, vol. 38, no. 5, pp. 887–894, 2006.

[11] F. Tanshi and D. Söffker, "Modeling of takeover variables with respect to driver situation awareness and workload for intelligent driver assistance," in *2019 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1667–1672, IEEE, 2019.

[12] E. Hollnagel, *Cognitive reliability and error analysis method (CREAM)*. Elsevier, 1998.

[13] M. Konstandinidou, Z. Nivolianitou, C. Kiranoudis, and N. Markatos, "A fuzzy modeling application of cream methodology for human reliability analysis," *Reliability Engineering & System Safety*, vol. 91, no. 6, pp. 706–716, 2006.

[14] C. He, Y. Y. Lum, K. Y. Lee, and D. Söffker, "Human reliability estimation based on fuzzy logic-modified cream approach," in *2021 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, pp. 45–50, IEEE, 2021.

[15] L. A. Zadeh, "Fuzzy sets as a basis for a theory of possibility," *Fuzzy sets and systems*, vol. 1, no. 1, pp. 3–28, 1978.

[16] A. C. Diker and E. Nasibov, "Estimation of traffic congestion level via fn-dbscan algorithm by using gps data," in *2012 IV International Conference" Problems of Cybernetics and Informatics"(PCI)*, pp. 1–4, IEEE, 2012.

[17] L. Eboli, G. Mazzulla, and G. Pungillo, "Combining speed and acceleration to define car users' safe or unsafe driving behaviour," *Transportation research part C: emerging technologies*, vol. 68, pp. 113–125, 2016.

[18] E. N. Nasibov and G. Ulutagay, "Robustness of density-based clustering methods with various neighborhood relations," *Fuzzy Sets and Systems*, vol. 160, no. 24, pp. 3601–3615, 2009.

[19] G. Ulutagay and E. Nasibov, "FN-DBSCAN: A novel density-based clustering method with fuzzy neighborhood relations," in *8th International Conference on Application of Fuzzy Systems and Soft Computing (ICAFS-2008)*, pp. 101–110, 2008.

[20] D. Whitley, "A genetic algorithm tutorial," *Statistics and computing*, vol. 4, no. 2, pp. 65–85, 1994.