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Human reliability estimation based on fuzzy logic-modified CREAM approach

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***Abstract*—Human reliability is one of the key issues in driver-vehicle systems as human-related accidents accounts for the highest proportion of total accidents. Furthermore, the behaviors of drivers become increasingly essential for driving safety as the driving context is of increasing complexity. 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. In this contribution, a modified fuzzy-based CREAM approach is introduced to evaluate human driver reliability in situated driving context using the data collected from driving simulator. Firstly, a new list of common performance conditions (CPCs) characterizing the situated driving context is generated due to the application limits of CPCs in CREAM. Secondly, to determine the levels in the 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, which reduces reliance on expert knowledge and can better characterize human behaviors individually. Next, a new evaluation index, human performance reliability score (HPRS), is proposed for the quantitative and dynamic evaluation of human reliability. The results show that the new proposed method could quantify and evaluate human driver reliability in real time.**

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

I. Introduction

In driver-vehicle systems, the role played by human drivers is increasing important, as most of the accidents are related to human errors. The national highway traffic safety administration (NHTSA) states that 94 % of traffic accidents are related to human factors [1]. With the increasingly complex road traffic system, driving context is becoming complicated, which requires the driver to maintain a high level of reliability at all times while driving. Although some advanced driver assistance systems (ADAS), such as forward collision warning system and lane keeping assistance system, have been developed to assist driver and therefore to make driving safer, human driver is still the key to ensure driving safety [2].

Human reliability is a common concept in probability assessment context, for example, marine engineering [3] and spaceflight application [4]. Human reliability analysis (HRA) is a sophisticated method to calculate human error probability (HEP), which is quantified by the ratio of occurrences of errors to number of opportunities for errors. Human reliability analysis methods have been proposed to systematically incorporate for the analysis, prediction, and prevention of human errors. Over the years, HRA methods have developed various changes. These changes are often categorized into generations, the so-called ”first generation”-HEART, THERP, SPAR-H, etc., and the so-called ”second generation”-ATHEANA, MERMOS, CREAM, etc [5]. The first generation of HRA methods are developed based on the idea that human naturally fails to perform tasks because of inherent deficiencies, just like mechanical or electrical components. Therefore, human reliability is characterized by the characteristics of the performed tasks [6]. The core assumption of the second generation of HRA methods, however, is that environment or context is considered as the most significant factor affecting human reliability. 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 denotation as static approaches. When detailed dynamic context must be considered, these methods are not suitable, an adaption should be generated to characterize the dynamic features.

As the likelihood of human error occurrences and the possibilities of gathering relevant data are much more promising in road traffic than other human-in-loop related industry, driving data could be used for HRA. The driving context is dynamically changing in real time, which is significantly different from other industrial scenarios, determines human driver reliability is also changing in real time. Even with the widespread use of ADAS, the role of humans in the driving process has not diminished, and human reliability still needs to be considered seriously. For example, when driver assistance systems in a highly automated vehicle fail, take-over action from the driver is needed to avoid accidents. A suitable level of human driver reliability is required in exactly that moment of requested human performance of a specific take-over situation. Different take-over conditions may have impacts on human driver reliability. From [7], it can be concluded that it is inappropriate using one general take-over request (TOR) time regardless the individual drivers and critical takeover situations. In this contribution the problem description is prepared related to the dynamic driving context and the existing approaches, as the performance shaping factors (PSFs), such as training or state of stress, in the existing approaches are designed for static operating situation, when it is applied to dynamic driving context, the existing approaches are not useful any more, as PSFs in dynamic driving context are totally different where factors like ego-vehicle speed and acceleration mainly affecting human driver reliability.

In this contribution, human reliability in situated driving context is analyzed with the so called "second generation" approach, CREAM [8]. However, reports on human driver reliability analysis in situated or dynamic driving context are limited as how to characterize the situated driving context in HRA is less considered. Therefore, a fuzzy logic-modified CREAM approach is generated for human reliability quantification and evaluation in situated driving context. Actually, integrating fuzzy logic into CREAM has been also discussed in other works [9]. This contribution is organized as follows: in Section II, theoretical backgrounds including CREAM and fuzzy logic are introduced. In Section III, the modified fuzzy-based CREAM is proposed, the FN-DBSCAN method is applied to cluster driving data for the determination of CPCs levels, meanwhile, in order to automatically determine the related parameters in FN-DBCAN, Genet algorithm is applied. The experiment and results are discussed in Section IV, human performance reliability score (HPRS) is generated to evaluate human driver reliability in situated driving context. The conclusion is provided in Section V.

II. Theoretical Background

A. CREAM

The CREAM approach is a practical approach for performance analysis as well as attendant prediction. This approach is able to conduct a retrospective analysis of historic events and a prospective analysis for the design of high-risk systems or processes. The core idea of CREAM is that human error is shaped by both context and human nature [8], although both are assumed as static.

Contextual control mode

Human cognition model used in CREAM methodology to model human behaviors is denoted as contextual control mode (COCOM). It is assumed that the degree of control that human operators on situations or context is the most important index to estimate human performance and human reliability. Meanwhile, the degree of control can be determined by the context under which human operators perform their tasks. Finally, the degree of control is the core mechanism to determine the relations between context and human reliability [10]. Four control modes are defined in CREAM, which are scrambled control, opportunistic control, tactical control, and strategic control. Each control mode corresponds to different human reliability interval in which strategic control has the highest reliability and scrambled control is related to lowest reliability.

Common performance conditions (CPCs)

Nine CPCs are defined as the most significant factors representing the operation context. 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.

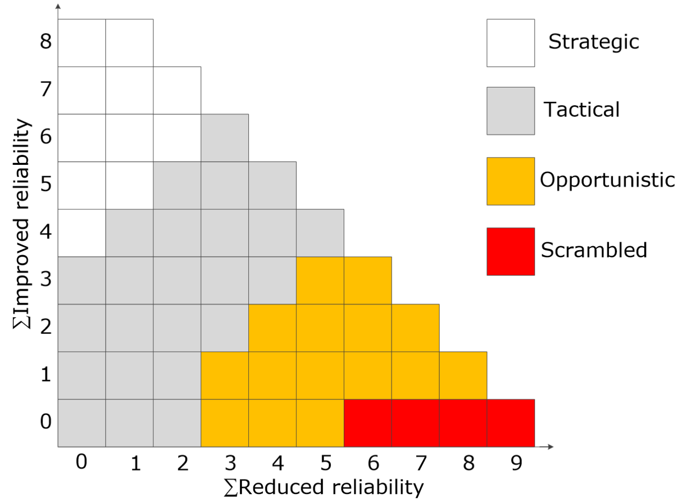

Fig. 1. Relations between CPC score and control modes (adapted from [8])

When the effect on performance reliability of each CPC is determined, CPC score can be identified as [$\sum$reduced, $\sum$improved], where $\sum$reduced represents the sum of reduced effects on performance reliability and $\sum$improved means the sum of improved effects on performance reliability. The control mode is then identified with a relation map between CPC score and control modes which is shown in Fig. 1. Therefore, human error probability (HEP) interval is defined with the determination of control mode. The original CREAM approach is mainly applied in human reliability analysis in industry fields. It is advised to generate new CPC lists adequate for application domains [11].

B. Fuzzy logic

Fuzzy logic is an approach intended to model the imprecise modes of reasoning that play an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and imprecision [12]. It is established on the degree of truth of a logically compound proposition which can obtain any value between 0 and 1 rather than assuming an extremity value of truth (1) or false (0) found in standard Boolean logic.

Fuzzy logic was generated by Lotfi Zadeh based on his earlier work on fuzzy set theory [13]. In [13], 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 main features of a membership function are the height, core, and support parameters. 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. The domain of height can be any value in the range of 0 to 1.

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.

Membership functions of fuzzy sets can be in various shapes, and the three widely used shape of membership functions are triangular function, trapezoidal function, and Gaussian function. Trapezoidal membership functions are chosen in this contribution to describe the membership degree of CPCs. The advantages of using trapezoidal membership functions are mainly due to its simplicity and popularity [14]. The reliability of a trapezoidal membership function is also higher compared to the reliability of a triangular membership function [15].

III. Modified Fuzzy-based CREAM Approach

In this contribution the CREAM approach is modified to implement the approach to dynamic and situated contexts. This is done by proposing a new set of CPCs describing the main features affecting human performance reliability in a dynamic or situated driving context [16]. However, in [16], the levels of CPCs are determined by literature research and expert experience which can not properly distinguish the characteristics of driving behaviors of different drivers to some extent. For example, when determining the levels of time to collision (TTC), two thresholds of 2.5 s and 5.5 s are determined. When TTC $\geq$ 5.5 s, human driver has enough time to complete different options, like lane changing, or braking, so the effect on on performance reliability is improved. The case TTC of 2.5 s could be regarded as the lower threshold that should be avoided in normal traffic conditions [17]. When TTC $\leq$ 2.5 s, driver abilities to handle the situation are limited, so the effect on performance reliability is reduced [16].

Therefore, to avoid the effects of expert experience on results, at the same time, to reflect the driving behavior characteristics of different drivers, with the introduction of fuzzy logic, the driving data of drivers are clustered using a density-based clustering algorithm with fuzzy neighborhood relation, fuzzy neighborhood density-based spatial clustering of application with noise (FN-DBSCAN) [18]. The automatically generated membership functions are corresponding to their respective levels and expected effects on performance reliability of CPCs. Finally, the human driver performance reliability is evaluated using human performance reliability score (HPRS) [16]. Therefore, section III is the part introducing applied methods to obtain HPRS.

A. New List of CPCs

When applying CREAM into another domain, a new list of CPCs adapting the new application domain has to be generated. To evaluate human reliability in a driving domain, a new list of CPCs is introduced based on [10] and [16]. 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. In this contribution, number of available lanes and actual lane are not considered as effecting the performance reliability. The driving data can be clustered according to the FN-DBSCAN algorithm, and different clusters relate to the effects on performance reliability. In this case, the levels in CREAM approach is only determined by obtained driving data, which could represent driving behaviors individually.

B. Automatic generation of membership function

In the standard DBSCAN approach, classical neighborhood density analysis is applied to determine the core points (and noise points) of clusters. A core point is defined if the number of points in a specific radius is larger than a certain threshold [19]. On the other hand, FN-DBSCAN implements fuzzy neighborhood cardinality to generate core points. For the generation of membership function, the core and support parameters of a trapezoidal membership function are determined using the core and support points based on the fuzzy density-neighborhood of the centroid of clusters.

FN-DBSCAN algorithm

The fuzzy neighborhood membership function could be defined as

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

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 with different distances to the neighbor points, the neighborhood membership functions dependent on the parameter k is expressed as

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

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

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

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

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

Nonetheless, the parameters ϵ_1, ϵ_2, and k must still be defined using expert knowledge. Further details regarding ϵ_1 and ϵ_2 are given in [20]. To decrease the dependency of parameters on expert knowledge, it is suggested a way to reduce the pre-defined parameters from 3 to 1. ϵ is defined as the average distance between adjacent data

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

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. Therefore, if a data point y is closer to a data point x than the average distance between adjacent data, data point y then has a neighborhood degree of $N_x(y) > 0$.

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

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

Furthermore, parameter ϵ_1 defines the radius of the membership threshold of data points to be included in the fuzzy cardinality is given the value of 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 algorithm is generally utilized as a way to produce efficient solutions to optimization and search problems by introducing biologically inspired operators like mutation, crossover, and selection [21]. This algorithm represents the process of natural selection where only fittest individuals are chosen from a population to produce offspring of the next generation.

Generally, a population of random generated individuals to an optimization problem is first initialized. Each individual has chromosomes (or genotypes) which can be mutated and altered [22]. These chromosomes contain solutions to an optimization problem and are generally represented by binary strings. In each generation, individuals go through selection and are modified or mutated to produce new offspring for the next iteration. The algorithm ends when maximum number of generation is reached or suitable fitness level of the population has been obtained.

The standard selection method used is roulette wheel selection. The selection is based proportional to its relative fitness value, which is proportion to the sum of all fitness values in the population. In this contribution, individuals that have the five highest fitness value in the population are selected via roulette to undergo crossover and mutation, thus increasing the probability of the algorithm to obtain an optimum ϵ_2 value. In genetic terminology, individual selected to undergo mutation or crossover is known as parent while the offspring is known as child. The ϵ_2 value of the individuals is also called a gene.

If the parent is selected for mutation, a random value within the range of [0,1] will be added or subtracted to the parent gene. On the other hand, two parents are selected using roulette to undergo crossover. Instead of exchanging genes between chromosomes, the mean value of the parent's gene will be selected as the child. In both cases, if the child has a higher fitness level than at least one of the individual in the population, the child replaces the individual that has the lowest fitness value in the population. This cycle repeats until the generation size is reached.

Application of genetic algorithm and FN-DBSCAN

To generate membership function automatically with FN-DBSCAN, the value of parameter ϵ_2 is estimated by genetic algorithm. The ϵ_2 values of the population are taken as the sole parameter for the clustering algorithm FN-DBSCAN to define the core and support parameters of the membership functions. The training data is normalized and clustered using the parameter ϵ_2. The centroid of the cluster, or the closest point to the mean value of all data point is then found. Direct and dense neighbors of each centroid are then obtained to derive the core and support points of the membership functions.

C. Human performance reliability score (HPRS)

In the original CREAM approach, the CPC score is based on the sum of reduced and improved expected effects on performance reliability [$\sum$reduced, $\sum$improved]. Then the control mode can be identified.

In this contribution, new CPCs are described in III *A*. The CPC levels are determined by data clustering, when membership functions are generated, they will be assigned to different levels and their corresponding expected effects on performance reliability could be determined. Therefore, each CPC score is calculated. The human performance reliability score is the sum of each CPC score, but it is different from the HPRS calculation method in [16] as the weight λ in [16] is switching between the discrete -1 and the discrete +1. Therefore, HPRS values fluctuate between integer values. Due to the application of fuzzy logic in this contribution, the CPC score could be any value from -1 to +1, so HPRS fluctuates smoother compared with the results in [16].

With the crisp data, the membership functions of four CPCs, ego-vehicle speed, time to collision, lateral acceleration, and longitudinal acceleration are automatically generated, the membership functions of traffic density and general visibility conditions in both scenarios are not considered as the traffic density is low, and general visibility condition is constant, so their effects on performance reliability is considered as improved, no membership functions are needed. For the CPC of number of surrounding vehicles, the CPC score can be directly translated using the crisp data.

For the validation of the generated membership functions, 5-fold cross validation method is applied. The data set is first divided into 5 randomly generated folds of equivalent sizes. One fold is then taken as test data while four of the remaining folds are used as training data. This process repeats for a total of 5 times, where each fold is used as test data once. The membership functions that best describe the data set of each CPCs are chosen to calculate the CPC scores. Each membership function is then labeled to represent an expected effect on performance reliability of the driver. The CPC score for the entire duration of driving simulation is then calculated according to the membership degree of each data point. The final HPRS can then be calculated by adding up all seven CPC scores relative to time.

In general, the steps to obtain HPRS are as follows: Step I: Execute genetic algorithm to generate optimal value of ϵ_2. Step II: FN-DBSCAN algorithm is applied to obtain core and support values of membership functions of each CPC. Step III: Assign membership functions to different CPC levels to calculate each CPC score. Step IV: Add up all seven CPC scores to generate final HPRS. In this contribution, genetic algorithm and FN-DBSCAN are used as tools for ordering and classifying behaviors and situations.

IV. Experiments and Results

A. Description of data generation platform

A professional driving simulator SCANeR^{TM} studio as shown in Fig. 2 is used to collect driving data. The simulator realizes a 270° view of the driving environment, a rear view mirror, and two side mirrors. For controlling ego-vehicle, a base-fixed driver seat, steering wheel, and pedals are used. Data describing ego-vehicle dynamics (e.g. speed, steering angles, etc.) and surronding interacting vehicles status (e.g. lateral shift, TTC, etc.) relative to ego-vehicle are collected allowing evaluation driver interaction behaviors as well as to be used for human driver reliability analysis.

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

B. Experimental results analysis

Example data sets from two scenarios (scenario_1 and scenario_2) are contributed by a participant that has a driving license for 8 years. The participant drives approximately 250 kilometers weekly and has experience in driving simulator.

The membership functions of the four CPCs (ego-vehicle speed, time to collision, longitudinal acceleration, and lateral acceleration) of both scenarios are generated, here the membership functions of four CPCs in scenario_1 are plotted as shown in Fig. 3. There are three membership functions in Fig. 3, which could be assigned to three different levels, and these levels relate to different expected effects, which are improved (score of 1), not significant (score of 0), and reduced (score of -1). The CPC score of ego-vehicle speed is calculated based on the core and support points, and the membership degree of each data points on the membership functions.

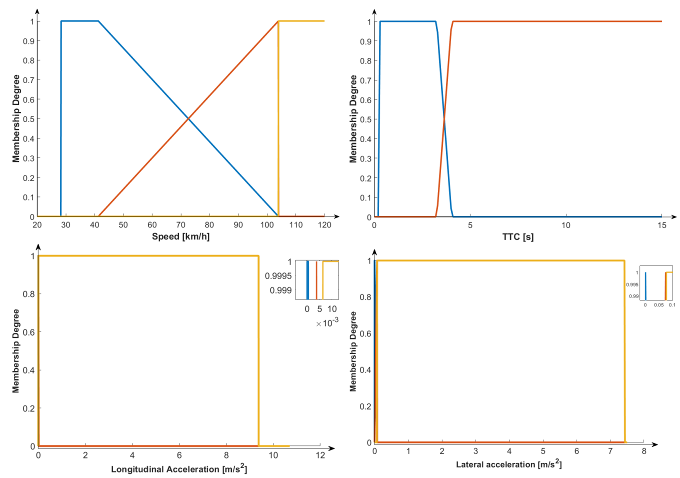

Fig. 3. Menbership functions of four CPCs in scenario_1

The human performance reliability score (HPRS) is then calculated by using the summation of all seven CPC score with respect to time. The HPRS of scenario_1 and scenario_2 are then plotted in Fig. 4 and Fig. 5. It can be observed that HPRS are above tactical level in both scenarios, only for a very short time in scenario_1, HPRS are below tactical level.To analyze what actually happened at that moment, the status of each CPC at that moment should be considered. It is found that at 779 s, the scores of the other six CPCs are rough the same except for the CPC score of surrounding vehicle decreasing from 1 to 0, which leads HPRS to decrease below the tactical level.

In [16], the HPRS is also presented, but the CPC levels in [16] are determined by literature research and expert knowledge. In this contribution, the new HPRS is obtained by fuzzy logic-based data clustering method. In order to compare the difference between these two HPRS based on different methods, the HPRS obtained from the same data (scenario_1) in [16] is presented as shown in Fig. 6. It can be observed that the fluctuation of new HPRS generated in this contribution is more smoothly than the results in [16], which indicates more realistic changes in human reliability during driving.

V. Conclusion

In this contribution, a new approach defining the situated and dynamic human reliability measure is established. Based on the CREAM approach, a fuzzy logic-modified CREAM approach is generated to characterize the situated driving

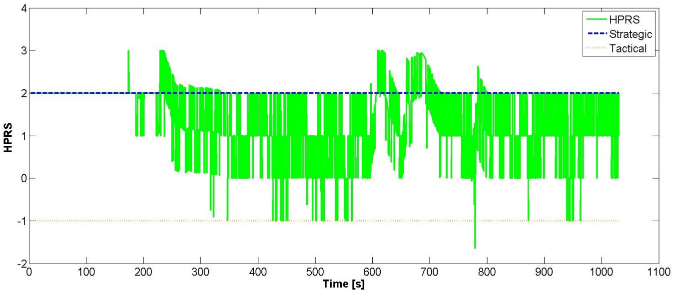

Fig. 4. HPRS of scenario_1

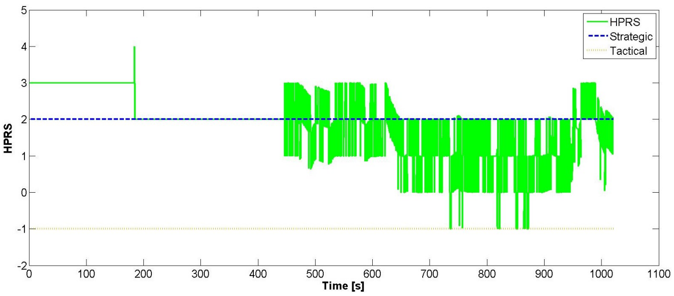

Fig. 5. HPRS of scenario_2

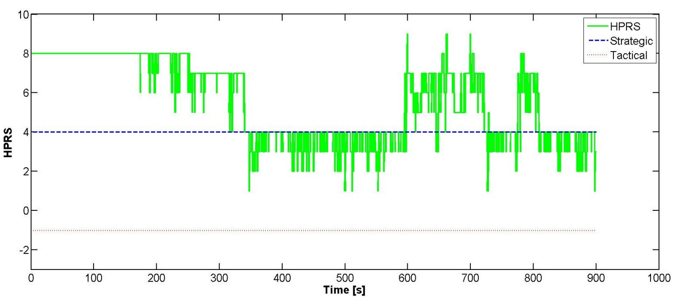

Fig. 6. Unfuzzified HPRS of scenario_1 [16]

context and to quantify human driver reliability. The results show that the HPRS obtained based on fuzzy logic-based data clustering method can properly evaluate human driver's reliability in real time. The HPRS generated with the new approach in this contribution indicates more realistic changes in human reliability during driving compared with the HPRS in [16]. The main innovation of this contribution is the modeling of the human reliability dynamization. In the next steps, some other data clustering methods, like clustering-based method with expectation-maximization (EM) and genetic-based membership function parameter-estimation (GMFPE) could be applied with CREAM. The approach will allow future automation systems including warnings, assistance, or fully automated control to be established for the avoidance of human errors.

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References

[1] 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.

[2] T. A. Dingus, F. Guo, S. Lee, J. F. Antin, M. Perez, M. Buchanan-King, and J. Hankey, "Driver crash risk factors and prevalence evaluation using naturalistic driving data," *Proceedings of the National Academy of Sciences*, vol. 113, no. 10, pp. 2636–2641, 2016.

[3] S.-T. Ung, "A weighted cream model for maritime human reliability analysis," *Safety science*, vol. 72, pp. 144–152, 2015.

[4] J. Calhoun, C. Savoie, M. Randolph-Gips, and I. Bozkurt, "Human reliability analysis in spaceflight applications," *Quality and reliability engineering international*, vol. 29, no. 6, pp. 869–882, 2013.

[5] 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.

[6] Q. Zhou, Y. D. Wong, H. Xu, V. Van Thai, H. S. Loh, and K. F. Yuen, "An enhanced cream with stakeholder-graded protocols for tanker shipping safety application," *Safety science*, vol. 95, pp. 140–147, 2017.

[7] 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.

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

[9] 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.

[10] C. He and D. Söffker, "Establishing a modified cream approach for reliability evaluation," in *2020 IEEE International Conference on Human-Machine Systems (ICHMS)*, pp. 1–6, IEEE, 2020.

[11] H. Taga, K. Furuta, and T. Kanno, "Human reliability analysis of car drivers in urban intersections," *Cognition, Technology & Work*, vol. 14, no. 4, pp. 365–377, 2012.

[12] L. A. Zadeh, "Fuzzy logic," *Computer*, vol. 21, no. 4, pp. 83–93, 1988.

[13] 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.

[14] I. Derbel, N. Hachani, and H. Ounelli, "Membership functions generation based on density function," in *2008 International Conference on Computational Intelligence and Security*, vol. 1, pp. 96–101, IEEE, 2008.

[15] J. Paetz, "A note on core regions of membership functions," in *European Symposium on Intelligent Technologies, Hybrid Systems and their implementation on Smart Adaptive Systems*, 2002.

[16] 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.

[17] R. Van Der Horst and J. Hogema, "Time-to-collision and collision avoidance systems," in *Proceedings of the 6th ICTCT workshop: Safety evaluation of traffic systems: Traffic conflicts and other measures*, pp. 109–121, Citeseer, 1993.

[18] 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.

[19] 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.

[20] 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.

[21] M. Mitchell, *An introduction to genetic algorithms*. MIT press, 1998.

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