Online Learning for an Individualized Lane-Change Situation Recognition System Applied to Driving Assistance

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***Abstract*—Situation recognition is a significant part of supervision to advance human operator decision making. It is a process for identification of occurred situations as the result of a sequence of actions. Situation recognition process could be individualized for an assistance system by considering exclusive behaviors of human operators individually. Accordingly, the assistance system should be provided with an online learning process to explore new experiences by modeling and labeling the occurred situations and adapt the knowledge base.**

In this paper, an improved Case-Based Reasoning (CBR) approach is proposed and applied for lane-change driving situation recognition. The proposed CBR is able to model event-discrete situations using Situation-Operator Modeling (SOM) approach. In addition, human operator experiences are learned online and reused for situation recognition by integration of fuzzy logic. Additional processes need to be carried out in the proposed fuzzy-SOM based CBR to support online learning for data reduction and knowledge indexing. As an experiment, the proposed approach is implemented to recognize lane-change situations for a driving assistance system. According to fundamental evaluation results, the proposed approach is able to improve lane-change situations recognition performance for individual human operators.

***Keywords*—Individualized situation recognition, driving assistance system, learning, Case-Based Reasoning, Situation-Operator Modeling.**

I. Introduction

Recent developments in cognitive systems as well as increasing the detection options for human errors in decision making in critical moments highlight the need for supervision of human operators. Real-time situation recognition is a challenging problem especially in the case of supervision of operators in unplanned and ambiguous situations.

A situation is stated as "a complete state of the universe at an instant of time" [3]. It is generated with the actions performed by human operator or other agents. It could be defined using a set of features and relation between the features [10]. The features could denote a situation resulting from a sequence of actions. Therefore, a situation is introduced as an event-discrete knowledge for cognitive systems. A situation could be identified by finding the similarity between the features of a situation as well as a relation between situations [1].

Real-time recognition of situations by considering operator goals enhances situation awareness of human operators [4]. Using a recognition assistance system, it will be possible to identify specific situation patterns resulting from a set of actions performed through the interaction with the environment. Situation recognition may be individualized for human drivers by considering exclusive behaviors of human operators in different situations. Here, the structure of related situations as well as related features are remarked for each human operator.

To realize the proposed situation recognition, an online learning process is applied to adapt the knowledge base using experienced sequential orders of performed actions. One of the challenges in online learning process is dynamic adaptation of knowledge base based on the new experiences [5]. Assigning situation patterns to new experienced situations (labeling) is an important task of dynamic adaptation. When a defined situation rises, the set of initial and middle situations are remarked as related situation pattern. Through an offline learning process, the knowledge base could be adapted and labeled over an entire data set while a complete sequence of actions and the resulting situations is available. However, labeling situations through online learning is challenge since the sequence of actions may not have been completed.

In this contribution, the developed CBR [8] is applied for situation recognition. In the proposed approach, knowledge about situations is modeled and represented in CBR by applying SOM approach [10] to support event-discrete situation recognition. In addition, fuzzy logic is applied for data structuring, knowledge generalization, and inferring experienced knowledge. Online learning is applied to CBR for knowledge base adaptation by means of on-line acquisition of cases and adaptation for further situation recognition.

Here, the implemented CBR in [8] is adapted and proposed for individualized situation recognition with application to assistance systems. Accordingly, some processes and the related knowledge base are adapted. In this paper, the ability of

SOM in modeling the event-discrete knowledge is considered through online learning. The sequence of situations and actions modeled using SOM (SOM-based knowledge) for individual human operators, is used to label and adapt event-based situations when specific situation is occurred. In addition, an indexing process is implemented for improving the retrieval process.

The paper is divided into several sections. In Section 2, an overview of fuzzy SOM-based CBR approach is given. In Section 3, online learning process and related tasks applied to fuzzy SOM-based CBR are introduced. The concepts are applied to a driving assistance system. In Section 4, a lane-change situation recognition process is developed for evaluation. Finally, the effects of online learning for individualized situation recognition assistance system are pointed out.

II. Fuzzy SOM-based Case-Based Reasoning

Case-Based Reasoning is a methodology to model human reasoning for solving cognitive problems such as decision making, planning, etc. It has been successfully applied for problem solving to a wide range of real-world applications [11]. The Fuzzy SOM-based CBR approach proposed by [8] is an improved CBR approach establishing an integrated case representation approach for modeling event-discrete knowledge and handling uncertainties. Case representation is the problem of deciding about case contents and finding a suitable structure for describing the contents as well as organizing the case in memory [2].

The proposed Fuzzy SOM-based CBR applies SOM approach for representing cases as a sequence of situation, operator, and upcoming situation. The SOM approach models events in a real world as a sequence of scenes, related causes (actions), and their effects, with initial situation, operator, and upcoming situation respectively [10]. A graphical illustration of these terms is given in Figure 1. A situation models a scene and illustrates the internal structure of a system. Situation S_i consists of a set of characteristics C and relations R between the characteristics. Characteristics are quantities combining the features of a scene. Relations indicate an internal structure of a situation by using function-oriented connections between the characteristics. Additionally, an operator models an action which changes scenes. The item operator O applies function f to transfer the situation S_i to $S_{\text{i}+1}$ with possibly a new set of characteristics' values and the relations. A sequence of situations and actions modeled by SOM is represented in Figure 2.

Fuzzy logic is a logical system dealing with uncertain knowledge and able to formalize approximate reasoning. In this approach, quantitative values U of characteristics demonstrating the environment are transferred to fuzzy sets. A fuzzy set (F, μ_F) indicates a set of membership grades F which is calculated by membership function $\mu_\text{F} : F[0,1]$ and labeled by linguistic terms. Accordingly, a similarity assessment is applied on fuzzy values instead of discrete or continuous values of characteristics. This improves the generalization of comparable cases. The knowledge complexity in the case base is decreased [8].

III. Online learning in fuzzy SOM-based CBR

Here, the proposed fuzzy SOM-based CBR [8] is improved to support online learning for individualized situation recognition. The cycling of the proposed fuzzy SOM-based CBR process with the ability of online learning is illustrated in Figure 3. Online learning in fuzzy SOM-based CBR carries out different tasks including case labeling, fuzzification, data reduction, and case indexing. This process could be able to model and learn event-discrete knowledge using SOM approach. The main tasks of online learning are detailed in the following sections.

A. New case detection

As described in Section II, the SOM approach is used to model knowledge using a sequence of situations and operators for event-discrete systems.

A sequence starts with an occurred situation defining initial situation of a pattern. The initial situation is followed with a sequence of performed actions and upcoming situations and is ended when a defined situation pattern occurs. Then, the situations registered in the sequence from the last situation up to the initial situation are labeled as that situation pattern. The sequence shows a series of actions resulting to a specific situation pattern. Each set of situation, operator, and upcoming situation in the generated sequence is considered as a new case.

B. Reconfiguration of fuzzy membership function

A reconfiguration process is applied to the learning process for updating the membership functions and supporting the new experienced values of characteristics. In this contribution, a density-based algorithm is applied for automatic generation of fuzzy sets and related membership functions. Through this algorithm, at first a distribution of the quantitative values for each characteristic is calculated. Membership functions based on new distributions of the values are then reconfigured to cover new cases. In this step, any changes of the membership functions (number and design parameters of membership

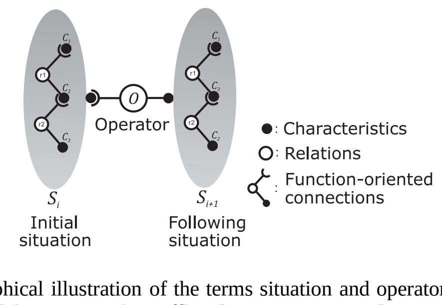

Fig. 1. Graphical illustration of the terms situation and operator in Situation-Opertor Modeling approach (Söffker [1997, 2001, 2008])

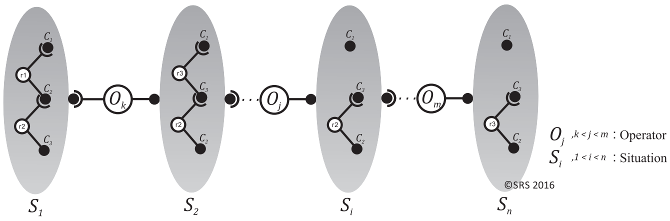

Fig. 2. Graphical illustration of a sequence of situations and operators in Situation-Opertor Modeling approach

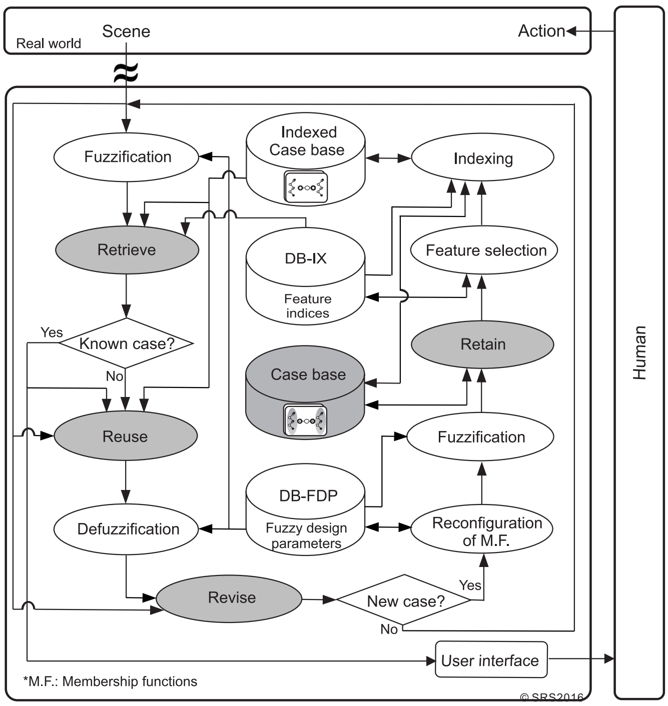

Fig. 3. Fuzzy SOM-based CBR cycle applied to human-machine assistance system

functions) are recorded in a data base called DB-FDP. This data base is used for the fuzzification of cases.

C. Case fuzzification

Quantitative characteristics of a new case could be fuzzified with a set of membership functions which are parameterized in DB-FDP. Each membership function returns a fuzzy value for a characteristic. Thus, the actual situation may be addressed as one or more sets of fuzzy values described by the characteristics.

D. Retain

In this step, the case base is scanned to find if the new fuzzified cases are representing similar old cases. If there is a new case for the case base, it is saved as a new experience.

E. Feature selection

Feature selection is a quite efficient method for data reduction. Here, a set of relevant features specifying the situation pattern is selected using a feature selection approach. This set is updated by learning new cases during online learning. In each update, an optimal set of relevant features is selected and stored in DB-IX. This data base is used for classification of cases.

F. Indexing

Stored cases in the case base could be indexed for fast retrieval of the similar cases. In this step, the stored and labeled cases in the case base are classified based on the defined situation patterns. The classified cases are stored in an indexed case base. The indexed case base is used further for case retrieval. Here, similarity of occurred situations is measured with the cases in the indexed case base.

IV. Experimental application

In this section, the proposed situation recognition approach is developed and examined for recognizing driving situations including lane-change to left and lane-change to right maneuvers. The proposed CBR is developed using a Java-based platform and Matlab. K-Nearest Neighbor algorithm is applied for classification of the cases as well as case indexing. Gaussian function is considered as membership function to transfer the crisp values to fuzzy values. Moreover, a fuzzy density clustering method [6] is applied to define design parameters of membership functions. A selection approach based on Rough-Set Theory [9] is used for feature selection in learning process.

A. Description

Here, the proposed approach is developed and experimented for 6 drivers. The drivers performed different driving tests.

In the implemented driving scenario, the drivers are invited to drive in a winding highway with 4 lanes of two directions and simulated traffic environment. During driving, the participants could perform overtaking maneuvers when the preceding vehicle drives slowly. After overtaking the participants could also drive back to the initial lane. Here, the driving data sets are comprised of different characteristics including ego-vehicle and its environment status as listed in [8]. Accordingly, the related internal connecting structure of a situation is addressed using a set of those characteristics which have the same importance weight initially. The characteristic weights will be changed through feature selection process. Each single recorded data could be labeled (classified) as lane-change to right, lane-change to left, and lane-keeping.

In each experiment, the assistance system is initialized with a set of lane-change maneuvers performed by each driver (around 30 minutes driving). The collected data set after the first driving test is used to initialize the case base and other related data bases in the proposed approach. The number of lane-change maneuvers experienced by each driver for initialization of the case base is shown in Table I.

TABLE I
DETAILS OF THE DRIVING TESTS (6 TEST DRIVERS)

Test driver	No. of lane-change experiences to left	to right	Driving duration time [m:s] online learning	offline test
#1	34	33	31:30	56:19
#2	30	28	28:15	38:44
#3	25	26	30:41	45:21
#4	20	22	30:33	42:17
#5	35	33	29:20	52:11
#6	28	29	32:21	39:22

By analyzing the lane-change maneuvers experienced by the drivers, the test drivers could be classified into the groups A and B. The classification is based on the average distance, velocity, and time to collision to the vehicle in front (for a lane-change to left) and to the vehicle right-behind (for a lane-change to right). Some classified lane-change maneuvers are shown using a 2-dimensional perspective of the ego-vehicle trajectories during lane-change maneuvers in Figure 4. In this experiment, drivers #1, #2, and #5 are included in group A and the rest are included in group B. The grouped test drivers are considered to evaluate the proposed individualized situation recognition.

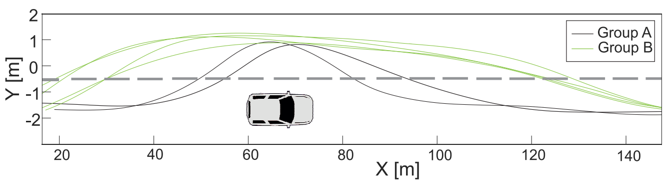

Fig. 4. 2-dimensional representation of ego-vehicle trajectories samples during lane-change maneuvers done by drivers

To evaluate online learning process, the initialized assistance system for each driver is applied for further learning. Here, the drivers use the assistance system to train it online with new experiences. The driving time for evaluation of online learning for each driver is given in Table I.

Afterwards, another driving test without online learning is done to evaluate the efficiency of the proposed individualized situation recognition. In this test, the individualized assistance system for one drivers in Group A is used by other drivers in Group A and the drivers in Group B separately. Driving time for offline test of individualized situation recognition is shown in Table I.

B. *Evaluation of online learning*

An initial assistance system is applied for the drivers to show online learning performance. In this step, each driver uses their personalized assistance system. The knowledge base is updated for each new lane-change experience when the occurred situation is not similar to the experienced cases and therefore is recognized incorrectly.

Here, situation recognition performance is evaluated in terms of detection rate, false alarm rate, and recognition accuracy. The evaluation metrics are calculated based on True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP) classification results.

Evaluation results of the online learning process for a test driver of group A is illustrated in Figure 5(a). The plots are representing the accuracy, detection rate, and false alarm of situation recognition in 30 minutes driving with online learning. The situation recognition results in the first 15 minutes of driving confirms the importance of the online learning. Considerable changes in the measured situation recognition accuracy can be detected.. However, the situation recognition performance is improved significantly in the next minutes. Moreover, it notes the effectiveness of online learning in learning new cases. The result demonstrates low performance of the situation recognition in the last minutes during new case learning. The obtained results emphasize the significance of online learning. Although the obtained accuracy in the last 15 minutes is high, the new experiences may decrease the performance of the system afterwards.

The same test is done for an online learning applied to the assistance system for a test driver of group B. The test results illustrated in Figure 5(b) demonstrate that learning is frequently done in the first minutes of driving. Afterwards, the average accuracy of situation recognition is improved to 0.98.

The evaluation results measured for all test drivers are presented in Table II. The average accuracy of the situation recognition is given in two time periods of test driving: first 15 minutes and rest test time.

TABLE II
AVERAGE SITUATION RECOGNITION ACCURACY DURING ONLINE LEARNING IN TWO TIME PERIODS DONE BY 6 TEST DRIVERS

Test driver	Average recognition accuracy First 15 minutes	Last 15 minutes
#1	0.822	0.981
#2	0.852	0.978
#3	0.752	0.988
#4	0.792	0.986
#5	0.942	0.982
#6	0.822	0.990

C. *Evaluation of individualized situation recognition*

In this section, the effectiveness of assistance system by applying individualized lane-change situation recognition is expressed. Here, the individualized assistance systems trained (during online learning) by drivers of Group A is used by the drivers of Groups A and B separately. These is an attempt to answer the question, ”Can the performance of situation recognition be improved by consideration of individual behaviors of drivers?”.

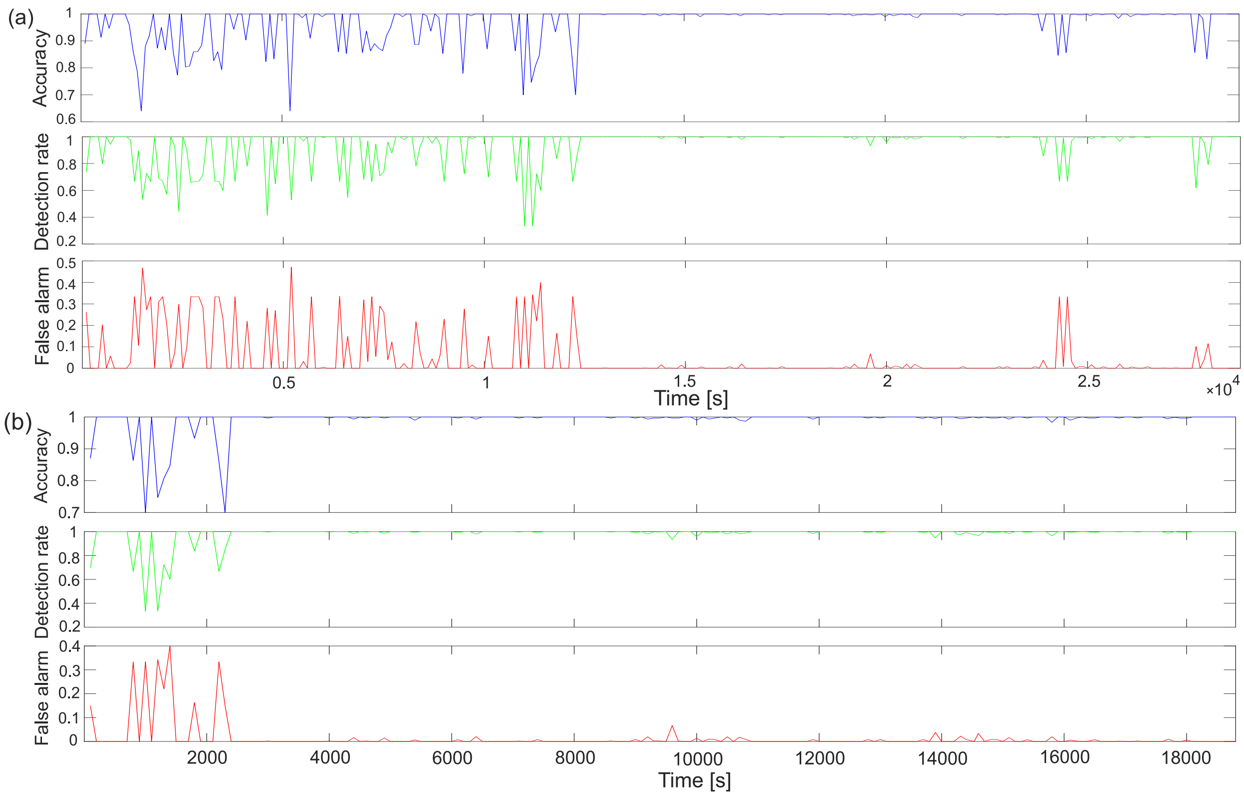

Fig. 5. Evaluation results obtained during online learning; (a) for a driver of Group A, (b) for a driver of Group B

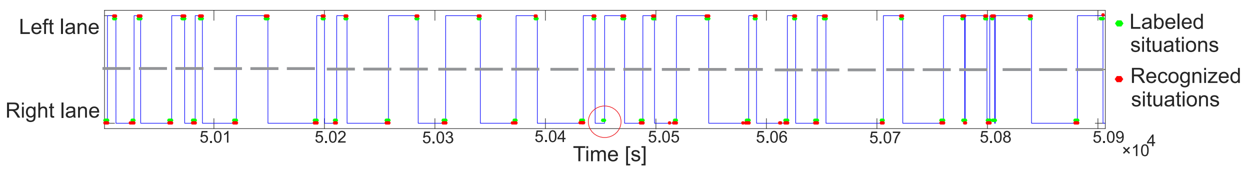

Fig. 6. The lane-change situations recognized for a driver of group A using the assistance system trained for the same drivers group

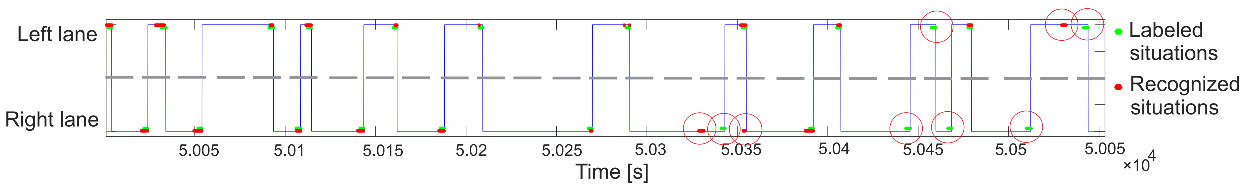

Fig. 7. The lane-change situations recognized for a driver of group B using the assistance system trained for drivers of group A

To approach this goal, the assistance system trained for a driver of group A is used at first by another driver of group A and then by one driver of group B. Results of the recognized lane-change situations in the first and second tests (around 40 minutes driving) are shown in Figure 6 and Figure 7. The blue lines show the driving lane of ego-vehicle at time. The points marked as green and blue indicate the labeled lane-change situations and recognized lane-change situations alternatively. The red circles in the figures could obviously highlight the visible situations which are recognized incorrectly as well as the situations which are not detected correctly. The results presented in Figure 6 state that the recognized situations nearly overlap the labeled situations. However, the recognized situations illustrated in Figure 7 confirm the inconsistency between the recognized and labeled situations. Using an unrelated situation recognition could increase false alarm rate.

V. Summary and conclusion

In this contribution, an individualized situation recognition has been successfully developed and applied to an assistance system. The approach uses a fuzzy SOM-based CBR approach to identify event-discrete knowledge about situations. Individualization of situation recognition has been actualized by applying an online learning process in the CBR approach. The online learning benefits the ability of SOM in modeling event-discrete knowledge in run-time.

An experimental application using driving maneuver was considered to evaluate the proposed approach. The results obtained from different driving tests states that online learning from new driving experiences could improve the accuracy of situation recognition for the drivers. In addition, online learning with the ability of dynamic adaption of knowledge base based on new human-operator behaviors could support situation recognition.

The experimental results of individualized situation recognition indicates that individualization may improve detection rate and decrease false alarm rate. Overall, the experimental results on the proposed approach show the importance of online learning and individualized situation recognition in driving assistance systems.

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