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Detection of driver cognitive distraction: an SVM based real-time algorithm and its comparison study in typical driving scenarios*

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***Abstract*— Detection of driver cognitive distraction is critical for active safety systems of road vehicles. Compared with visual distraction, cognitive distraction is more challenging for detection due to the lack of apparent exterior features. This paper presents a novel real-time detection algorithm for driver cognitive distraction by using support vector machine (SVM). Data are collected from 26 subjects, driving in typical urban and highway scenarios in a simulator. The chosen urban scenario is the stop-controlled intersection and the highway scenario is the speed-limited highway. Driver cognitive distraction while driving is induced by clock tasks which compete with the main driving tasks for visuospatial short working memory. For each subject, distracted driving instances and the equal number of non-distracted driving instances were collected (24 for urban scenario and 20 for highway scenario in total). Features concerning both driving performance and eye movement are used for training and validation. The proposed algorithm have correct rate of 93.0% and 98.5% for highway and urban scenarios respectively. Results also show that driver distraction can be recognized 6.5 s to 9.0 s after its happening, indicating good performance of the detection algorithm.**

***Index Terms*—Road vehicle, active safety, cognitive distraction, support vector machine (SVM)**

I. INTRODUCTION

Driver distraction is a major cause of road traffic accidents, which has become a growing public safety hazard [1]. Up to 25% of crashes involved driver distraction in some extent according to the police reported accident data [2]. Suggested by a study based on a survey of 1367 drivers, 14% to 33% of all serious crashes may be attributed to driver distraction [3]. Driver distraction occurs when a driver's attention is diverted away from driving by a secondary task that is not related to the driving task [4]. Driving is a complex task, requiring the concurrent execution of various cognitive, physical, sensory and psychomotor skills [5]. Driver distraction competes for driver attention paid on the driving task; it potentially causes decrease on driver awareness to critical information for safe driving which makes them prone to cause severe car accidents.

Cognitive secondary tasks, such as talking through a hand-free cellphone, reading auditory e-mails, being lost in thought may happen during driving and would competes for cognitive resources with main tasks. Proper distraction like simple conversation can mitigate driving boredom and fatigue. However, driving safety will be threatened when cognitive workload is too high or driving environment changes dramatically. Even though significantly delaying drivers' response to unexpected incidents, cognitive distraction happens inside brain without apparent exterior features [6]. Therefore, compared with visual distraction, cognitive distraction is more challenging to be detected.

According to the traffic data in the US, distraction-related crashes happened in urban environment are increasing, which increases from 32.7% to 39.8% from 1999 to 2008 [1]. The cognition workload level changes with the driving scenarios. Urban scenarios with high traffic density, e.g., stop-controlled intersections, require higher cognition workload than such speed limited highway scenarios with low traffic density [7]. Increased roadway complexity compounds the decrement in performance caused by concurrent cognitive tasks [8]. Compared with abiding by varying speed limit signs, approaching a stop-controlled intersection demands higher cognitive workload. Moreover, the basic cognitive workload difference between those two scenarios may lead to different detection performance.

The detection of driver distraction is a question of driver attention status classification. The widely used features include driving performance and eye movement. It is indicated by our previous study that the fusion of driving performance and eye movement is promising for the cognitive distraction detection and we have extracted the most important features from a huge amount of candidate features for the cognitive distraction detection [9]. Driver cognition can hardly be presented by a linear model, and hence, nonlinear modeling techniques are adopted in the cognitive distraction detection [10]. Following distance and steering angle as the classifier inputs, Farid et al. [11] constructed a real-time model, using Hidden Markov Models (HMMs) with Gaussian mixtures. Torkkola et al. [12] have employed random forest (RF) to construct classifier (with accuracy of 80%) with steering angle, accelerator pedal position, lane boundaries and upcoming road curvature as inputs. Liang et al. [13] have applied fixation, saccade, smoothing pursuit of the eye, steering-wheel angle, lane position, and steering error as

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inputs to real-time Support Vector Machine (SVM) classifiers to detect the driver cognitive distraction caused by interacting with in-vehicle information systems (IVISs). Their SVM classifier reached the average accuracy of 81.1%.

The SVM model is applied in this study as the core component of proposed algorithm for real-time cognitive distraction detection. SVMs are insensitive to the curse of dimensionality and are efficient to handle large-scale problems [14]. It can avoid over-fitting by minimizing the upper bound of the generalization error to produce more robust models than traditional ones [15]. To avoid over repetition during data collection, the number of collected events for each participant is highly restricted which leads to small sample size. Data over-fitting arises due to large number of features compounding with comparatively small number of training instances.

This paper presents a novel algorithm for the real-time detection of driver cognitive distraction happened at stop-controlled intersections and speed-limited highway. The classification accuracy, detection rapidity and optimal parameters of the proposed algorithm are compared between two driving scenarios. A driving simulator was used for the data collection under two typical driving scenarios, in which the clock task was selected to generate cognitive distraction. The cognitive distraction here is defined as driving with concurrent clock task while the non-distraction is defined as normal driving without secondary task. The proposed algorithm is trained and cross validated by using that collected data.

The proposed algorithm consists of three main components; feature vector calculation, SVM classification and filtering recognizer. The moving window size is tested shorter than previous studies to make sure higher detection rapidity. Moreover, a consistency tester is designed to eliminate the result of "recognizing correctly by accident" from the performance of proposed algorithm. The results show that the proposed algorithm performs well in the two driving scenarios for both detection accuracy and rapidity.

The main contributions of this paper include: (1) An novel algorithm is proposed for real-time detection of driver cognitive distraction, from the system architecture to the parameter optimization; (2) The correct rate and the detection rapidity are both considered as the performance indicators to optimize the algorithm parameters; (3) The average performance of proposed algorithm is better than the previous related studies indicatively in correct rate. The detection rapidity in the proposed algorithm is tested across different typical driving scenarios, yielding similarly good results.

The rest of this paper is structured as follows: section II describes the data collection; section III presents the proposed algorithm; section IV shows the main results, followed by a discussion in section V. Section VI concludes this paper.

II. Description of Data Collection

A. Subjects

Twenty-six drivers (16 male and 10 female) aged from 20 to 53 with normal or corrected to normal vision participated in the experiment among which 11 of them were involved in the scenario of stop-controlled intersections and 15 of them were asked to drive in the scenario of speed limited highway. Each groups contained participants of different genders and ages as shown in TABLE I.

TABLE I. SUBJECT NUMBER

Scenario	Number in types		
	Male	*Female*	*Age (year)*
Urban	7	4	20~35 (mean = 24.5, SD = 4.4) 46~53 (mean = 49.7, SD = 1.8)
Highway	9	6	20~30 (mean = 24.1, SD = 3.7) 46~53 (mean = 49.8, SD = 2.0)

B. Apparatus

The motion-based driving simulator used in this study was composed by a visual simulation unit, an audio simulation unit and a motion simulation unit [16]. Location of vehicles and driving behaviors data (speed, acceleration/deceleration, steering angle, etc.) were automatically recorded. Smart Eye Pro 5.8 was used to collect eye movement data. The eye-tracker consists of three video cameras that located on the dashboard on either side of steer wheel and above it on the center. The cognitive secondary tasks were realized by an in-vehicle tablet speaker and they were automatically triggered by the serial communication between the tablet and the control computer of driving simulator. All the data were logged at 60Hz during the experiment.

C. Driving scenarios

1) Urban driving- Stop-controlled intersection

The subjects involved in the scenario of stop-controlled intersection were instructed to drive along a straight, flat and non-priority road as shown in Fig. 1. There were four vehicles driving at 40 km/h on the crossed priority road. To reduce the learning effect of subjects, the time headway between each two vehicles on the priority road randomly changed from 1 s to 3 s. The appearance of these four vehicles was triggered by the location of the ego vehicle passing 60 m before the center of intersection. The covered distance, 130 m before to 30m after the center of the intersection, was extracted as one trial of intersection crossing. Each subject requires driving the experimental road map twice to encounter 24 intersections in total with distracted trial and non-distracted trial half-to-half. Subjects were told to keep their speed around 40 km/h between two intersections and follow traffic rules giving way to the vehicles on the priority road.

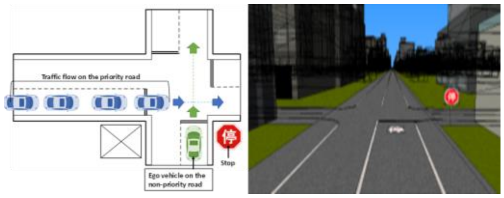


Figure 1. Stop-controlled intersection.

2) Highway driving – Speed limited highway

The subjects involved in the scenario of speed-limited highway were asked to drive along the middle lane of a straight and flat road as shown in Fig. 2. The ego vehicle drove along the middle lane towards only one direction and lane changing was not permitted. These subjects were required to control the speed to comply with variable speed limits; the required minimum speed were 60 km/h, 70 km/h, 80 km/h and the required maximum speed was always 20 km/h higher than the minimum one. The process of crossing the speed limit sign was extracted from 300 m before to 150 m after the center of the sign. Each subject had to drive going through 20 of speed limit sign in total with distracted trial and non-distracted trial half-to-half. Subjects were instructed to comply with the speed range indicated by previously encountered speed limit sign and meanwhile drive as fast as they could.

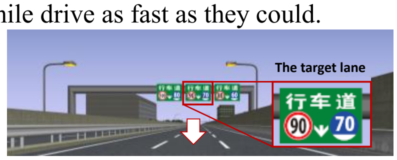


Figure 2. Speed limited highway (max – 90km/h, min – 70km/h).

D. *Cognitive secondary task*

Considering easy implementation, task repeatability, and measurability of workload level, the clock task, a kind of surrogate secondary task was adopted in this study [17]. It calls for the visualization of the clock hands and consumes visuospatial short working memory [18]. In the clock task, subjects listened to a series of three randomized clock times (1:00 – 12:59) with an interval of 5 s between two times. Upon hearing a clock time (e.g., 10:30), the subject should visualize the location of this time's hour and minute hands on the face of an imaginary analog clock in mind and orally indicate whether the hands of the clock would form an acute angle as shown in Fig. 3. In each trial of the secondary task, subjects would be presented a prompt of the incoming task and have 2 s to get prepared [18]. It was required for all the involved subjects to try to provide accurate answer to each stimulus as quickly as possible.

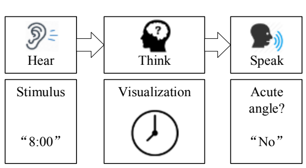


Figure 3. Illustration of the cognitive secondary task – clock task.

E. *Experiment Design*

For both driving scenarios, one within-subject factor, attention status, was applied, rendering a repeated measures design. Attention status has two levels; distracted driving concurrent with the clock task and non-distracted driving. To control learning effects, the presence order of attention status conditions was counterbalanced across repeated measures. For distracted driving, it was confirmed that the cognitively distracted status was realized during the whole event. Before data collection, training of the clock task and simulator driving was conducted to ensure subjects' familiarity with all experimental procedures. For each subject, 12 distracted driving instances and 12 non-distracted driving instances were collected in the experiment of stop-controlled intersection scenario; while in the scenario of speed limited highway, 10 distracted driving instances and 10 non-distracted driving instances were collected.

III. ALGORITHM

The architecture of the proposed algorithm is shown in Fig. 4. The original signals include the steering angle (°, *Str*) and speed (km/h, *V*) from the driving simulator and the gaze location x (°, G_x), gaze location y (°, G_y), and head heading angle (rad, H_g) collected from the eye tracker. Considering the needs of detection rapidity and low dimension, some significant features were selected in the proposed algorithm under both driving scenarios based on our previous study [9]. The moving windows have the size of T_w (s) and the overlap rate of O_p (%) every adjacent two of them. The feature vector calculation component transits observations in each moving window into a feature vector *D* including features of driving performance and eye movement. Each feature vector as the input, the SVM classifier generates an output for a preliminary classification of driver attention status (*ds* or *dn*). A series of preliminary classification results are pushed into a buffer with the size of L_b (s). The filtering recognizer generates the final classification result of the driver attention status based on each buffer (*ds* or *dn*). To better validate the proposed algorithm, a consistency tester is designed to eliminate the result of "recognizing correctly by accident" from the performance of proposed algorithm.

A. *Selected Features*

The employed statistical functions to calculate features are shown in Table II. Extracted from five original signals used for cognitive distraction recognition, 35 statistical features are proposed to describe driver attention status.

B. *The SVM Classifier Component*

The classifier is individually constructed based on the half distracted driving instances and half non-distracted driving instances (24 in total for urban driving and 20 in total for highway driving). The feature data were normalized by min-max method mapping into the range of [-1, 1] within each subject [20]. Leave-one-out cross validation was applied to generate the reported values of classifier performance. The radial basis function (RBF) was adopted as the kernel function for the SVM models. The SVM classifier was trained and tested via "LIBSVM" Matlab toolbox [21]. Correct rate (*CR*) is one indicator of the classifier performance; defined as the rate of instances correctly classified. *F* measure is the harmonic average of precision and recall which comprehensively reflects the performance of SVM classifier.

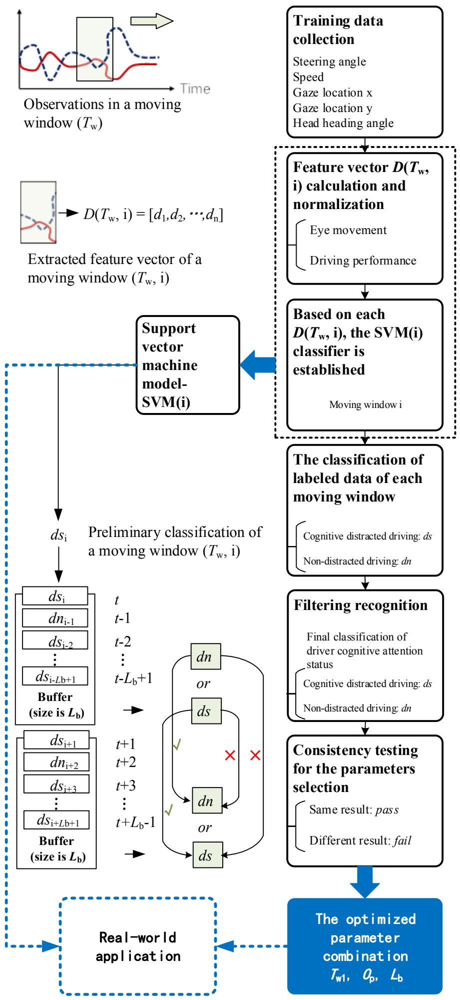


Figure 4. System architecture of proposed algorithm.

C. The Filtering Recognizer Component

The filtering recognizer generates the final classification result based on the data in the buffer with size of L_b. Once all the preliminary classification results in the buffer are the same (*ds* or *dn*), e.g. *ds*, the filtering recognizer delivers the final classification result as *ds*. If the preliminary results in the buffer have not reached the same attention status till the end of the event, the proposed algorithm fails in that case.

During the process of parameter optimization, the test instance is marked as incorrectly classified when the final classification result is different from its label, namely the proposed algorithm fails. For those test instances with the same final classification result and annotated label, the consistency tester component is applied to further performance discussion (seen in Section III-D).

D. The Consistency Tester Component

The whole process of driver cognitive distraction detection is completed after delivering the final classification result by the filtering recognizer.

During the process of modeling and parameter optimization, to better validate the performance of proposed algorithm, the consistency tester keeps generating the classification result under the same rule of the filtering recognizer after the final classification delivered; the proposed algorithm fails if the consistency tester generates the classification result in contrast with the delivered driver attention status and passes if it generates the same result with the delivered one. The consistency tester detects the risk of "recognizing correctly by accident" therefore ensuring that the performance of proposed algorithm is validated comprehensively.

TABLE II. SELECTED FEATURES [9, 19]

#	Function	Description	
		Applied signals	***Meaning***
1	*Mean*	All[a]	Mean of a signal
2	*Std*	All[a]	Standard deviation of a signal
3	*Cov*	*V*, *Str*	Coefficient of variation
4	*Max*	*V*, *Str*	Maximum value of a signal
5	*Amp*	*V*, *Str*	Difference between the Max and Mean
6	*Rms*	*V*, *Str*	Root mean square
7	*Q1*	*V*, *Str*	The 25th percentile
8	*Q2*	*V*, *Str*	The 50th percentile
9	*Q3*	*V*, *Str*	The 75th percentile
10	*MeanQ1*	*V*, *Str*	Mean of a signal below the 25th percentile
11	*MeanQ3*	*V*, *Str*	Mean of a signal above the 75th percentile
12	*NeuPerc*	*Str*	Percentage of neutral steering (θ = 0 deg)
13	*LarTime*	*Str*	Maximum large amplitude steering keeping time (|θ| ≥ 2 deg)
14	*LarPerc*	*Str*	Percentage of large amplitude steering (|θ| ≥ 2 deg)
15	*PeakFrq*	*V*, *Str*	The frequency of peak value
16	*PeakAmpl*	*V*, *Str*	Difference between the maximum and minimum value of the signal

a. V, Str, G_x, G_y, H_g

E. Algorithm Parameters and Performance Indicators

Real-time algorithm design should consider the balance between the detection rapidity and correct rate. High rapidity with low correct rate tends to cause miss alarm; high correct rate without good performance on the detection rapidity also impairs the efficacy of algorithm. The real-time recognition of driver cognitive distraction should detect the change of driver attention status with high performance on both detection rapidity and correct rate. As for the indicator of detection rapidity, two time ranges are defined first. Time range one (T_{r1}) is defined as the time gap between the start time window of the event instance and delivering time window start of final classification result. Time range two (T_{r2}) is defined as the time gap between delivering time window end of final classification result and the end timing of the event instance as shown in Fig. 5.

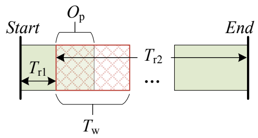


Figure 5. Illustration of detection rapidity pre-definition.

As previously described, the system architecture of proposed algorithm has three parameters and three performance indicators as shown in TABLE III. High S indicates good performance on the detection rapidity. Liang *et al.* [13] have applied 5s to 40s as the length of moving window. To enhance the detection rapidity, shorter time window size (2s and 5s) was selected to test the performance of proposed algorithm in this study.

TABLE III. ALGORITHM PARAMETERS AND PERFORMANCE INDICATORS

Type	#	Name	Unit	Abb.	Test range / Meaning
Algorithm parameters	1	Moving window size	s	T_w	2, 5
	2	Overlap rate	%	O_p	5, 25, 50, 75, 95
	3	Buffer size	s	L_b	3-12
Performance indicators	1	F measure	-	F	Harmonic average of precision and recall
	2	Correct rate	%	CR	Rate of instances correctly classified
	3	Detection rapidity	%	S	T_{r2} / (T_{r1}+T_{r2}) [a]

a. S = 0 means that the algorithm fails

IV. RESULTS

The performance of proposed algorithm under two driving scenarios with different algorithm parameter combinations are shown in Fig. 6.

A. Optimal Algorithm Parameters

As shown in Figure 6, the performance of proposed algorithm changed with different values of T_w and O_p for both scenarios. The combination of T_w = 5 s and O_p = 75% yielded the best performance considering both detection rapidity and correct rate.

The performance of proposed algorithm is highly influenced by the parameters as shown in TABLE IV. The interaction effect of O_p and T_w strongly impacts on the performance of proposed algorithm.

The proposed algorithm with optimal parameters have CR = 93.0% ± 5.3% with S = 88.7% ± 3.9% for highway driving and CR = 98.5% ± 2.1% with S = 91.9% ± 2.8% for urban driving. There is no significant difference between those two driving scenarios on the optimal algorithm performance which indicates that the performance of proposed algorithm is reliable on both driving scenarios.

TABLE IV. IMPACTS OF ALGORITM PARAMETERS ON CR (ANOVA)

Scenario	Main effects		Interaction effect
	O_p	T_w	$O_p * T_w$
Highway driving	$F_{4,149} = 3.37$ $p = 0.012^{**}$	$F_{1,149} = 5.10$ $p = 0.025^{**}$	$F_{4,149} = 24.0$ $p < 0.001^{**}$
Urban driving	$F_{4,109} = 1.84$ $p = 0.13$	$F_{1,109} = 0.60$ $p = 0.44$	$F_{4,109} = 4.38$ $p = 0.003^{**}$

**. The tests obtained significant difference at α = 0.05

B. Scenario Impacts on the Proposed Algorithm Performance

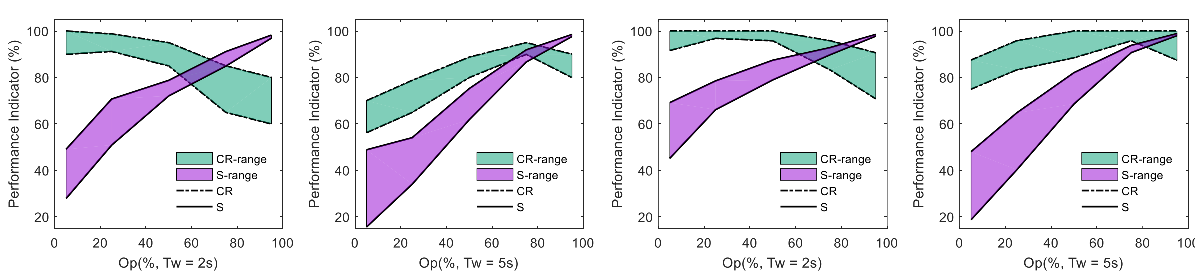
The CR of urban driving is significantly higher than highway driving ($p < 0.001$, $F_{1,259} = 20.53$). The S value shows slight difference between two driving scenarios ($p = 0.099$, $F_{1,259} = 2.74$). As shown in TABLE IV, the performance of proposed algorithm is more sensitive to the changing of algorithm parameters in the speed limited highway than in the stop-controlled intersection.

Seen from the scenario difference, the performance of proposed algorithm including detection rapidity and accuracy is better for stop-controlled intersections than speed limited highway. However, as for the algorithm with optimal combination of parameters, there is no significant difference between those two driving scenarios.

V. DISCUSSIONS

In this paper, a novel SVM-based real-time cognitive distraction detection algorithm with both driving performance and eye movement features as inputs is proposed and cross validated.

The proposed algorithm performs well in both correct rate and detection rapidity, which is also adaptive to different driving scenarios. The length of moving window (T_w) and the overlap rate of each two of them (O_p) are two parameters of the proposed algorithm. The optimal combination of these parameters, T_w = 5 s with O_p = 75%, is determined by the best comprehensive performance of cognitive distraction detection



(a) Speed limited highway (b) Stop-controlled intersection

Figure 6. Algorithm performance of different parameters (25% - 75%, 3-order polynomial smoothing).

considering both correct rate and detection rapidity. The algorithm gets correct rates on average between 93.0% and 98.5% while the detection rapidity (S) reaches 88.7% to 91.9%. Being more specific, with 30s as the length of extracted event sample, the distracted status of the driver can be recognized 6.5s to 9.0s after the happening of cognitive distraction that indicates the good performance of detection rapidity. Liang *et al*. got 81.1% as the average accuracy of the SVM classifier [13]. The best case was above 98% in this study, which is comparable with the best case above 96% in the study of Tango *et al*. [14]. It is shown that the comprehensive performance of proposed algorithm is better than the previous related studies indicatively (considering different settings of collected data and system architecture).

Seen from the varying tendency of algorithm performance along with increasing O_p, there exists a trade-off relationship between detection rapidity and accuracy. When the overlap rate and the length of moving window are small, the preliminary classification results distribute sparsely in the time domain. It takes long time to have the same results in one buffer that impairs the detection rapidity. Along with the increasing of O_p, for one specific event there will be more feature vectors included. It takes short time to reach the same classification result in one buffer. However, it is difficult to pass the consistency tester due to higher fluctuation in the preliminary classification result.

The overall performance of proposed algorithm is better for the urban driving than the highway driving which can be explained by the driving environment complexity. Urban scenarios have high traffic density that impose higher cognitive workload on drivers. Therefore, cognitive distraction tends to cause obvious changes on the driving performance and eye movement in urban driving. These more obvious changes make the cognitive distraction easy to be detected compared with highway driving condition. This explanation is confirmed in our previous study on the feature extraction of cognitive distraction detection [9]. For the real-time detection of driver cognitive distraction, the fusion of driving context is important for achieving reasonable and good detection performance.

VI. CONCLUSIONS

A SVM-based real-time cognitive distraction detection algorithm using both driving performance and eye movement features is proposed and cross validated, from the system architecture to the parameter optimization. The following conclusions are obtained:

(1) With optimal parameters combination, the algorithm achieves correct rate between 93.0% and 98.5% on average. The detection rapidity reaches 88.7% to 91.9% namely the distracted status can be recognized in 6.5s to 9.0s after it happens.

(2) The proposed algorithm is tested across different typical driving scenarios, yielding similarly good results.

Our future study will focus on building an improved driver distraction recognition method with online normalization, dynamic moving window and smaller size of selected features. To further assess the generality and functionalities required in active safety systems, naturalistic driving data will be collected for the construction of improved algorithm.

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