Driver Mirror-Checking Action Detection Using Multi-Modal Signals

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Abstract Studies on driver distraction aim to identify features extracted from various sensory signals that can be used to distinguish between normal and distracted driving behaviors. A major challenge in these studies is to determine whether the observed behaviors are associated with the primary driving tasks (checking mirrors, monitoring speed, changing lines) or secondary tasks that deviate the attention of the drivers. This study focuses on detecting the important driving task of checking the mirrors. The study compares the duration and frequency of mirror checking actions observed when the drivers are engaged in secondary tasks with the ones observed in normal driving conditions. The analysis reveals that the drivers reduce the frequency of checking the mirrors when they are engaged in secondary tasks, which affects their situational awareness. Based on real world driving data, we extracted multimodal features associated with the driver and vehicle behaviors. We train binary classifiers to detect mirror checking actions. Even though the classes are highly unbalanced (most of the samples do not have mirror checking actions), the proposed system achieves an F-score of 0.65 (recall 73%, precision 68%) using the extracted features. This promising result suggests that it is possible to detect mirror-checking actions, which can be used to signal alarms, preventing collisions and improving the overall driving experience.

Keywords Driver mirror checking detection, driver distraction, machine learning

1. INTRODUCTION

Detecting driver distraction has become an important research problem given the increasing usage of infotainment systems and hand-held devices on vehicles. Although these devices are popular, they use manual, visual and cognitive resources affecting the driving performance, and reducing the driver's situational awareness. According to a recent report from the U.S. Department of Transportation, over 17% of police-reported crashes involved a distracted driver, where distraction was defined as inattentions from the primary driving task due to secondary tasks [16]. Another study showed that over 65% of near crashes and 78% of crashes involve distracted drivers [15]. These alarming statistics highlight the importance of detecting distraction caused by secondary tasks.

Studies on driver distraction aim to identify features extracted from various sensory signals that can be used to distinguish between normal and distracted driving behaviors [9, 13]. Some of these signals include direct measurements from the driving activity such as lateral and longitudinal control [6, 8], secondary task performance such as driver accuracy and response time [4, 14], and features from *electroencephalography* (EEG) and eye movement [3, 17]. A major challenge in these studies is to determine whether the observed behaviors are associated with the primary driving tasks (e.g., checking mirrors, monitoring speed, and changing lines) or secondary tasks that deviate the attention of the drivers. A context-aware monitoring system that can reliably make these distinctions will be more effective in alerting inattentive drivers. This study focuses on detecting the important driving task of checking the mirrors.

The purpose of mirror-checking detection is twofold. First, mirror-checking action is an essential part of safe driving that helps drivers to maintain their situation awareness. By regularly checking the mirrors, drivers can monitor the activity of adjacent vehicles. The information perceived through checking the mirrors can change the driver's driving plan. In some cases, it can make the driver to delay or abandon the actual intended maneuver to avoid accidents. This action, however, is closely related to the driver's attention level [7, 10]. It can be influenced by elements such as fatigue, cognitive workload, and road conditions. When affected by fatigue or high cognitive workload (day-dreaming, thinking, etc), drivers are likely to reduce the mirror-checking frequency [8]. In these cases, monitoring lack of mirror-checking can facilitate the detection of driver fatigue or cognitive distractions. Second, mirror-checking by itself is a task that forces the driver to take their eyes off the road, and can be regarded as a type of a visual distraction. When drivers check mirrors, they may miss important road events, such as unexpected brakes or other vehicles changing lanes. These scenarios can lead to accidents that can be avoided if a monitoring system is aware of the drivers' actions. Therefore, detecting driver mirror-checking can increase the effectiveness of in-vehicle active safety system.

This study aims to detect driver mirror-checking actions using multimodal information extracted from CAN-Bus and cameras. The database used in this study is collected using

Fig. 1. UTDrive car.

Fig. 2. Driving Route

the UTDrive car, over real driving recordings [2]. We record our corpus from 20 different drivers under both normal and secondary task conditions. The tasks include secondary activities that are commonly performed while driving: operating a radio (*Radio*), operating and following a navigation system (*GPS - Operating* and *GPS - Following*), operating and talking on a cellphone (*Phone - Operating* and *Phone - Talking*), describing pictures (*Pictures*) and talking to a fellow passenger (*Conversation*). Using this real-world data, we analyze the mirror checking actions under both normal and task driving conditions. The result shows that the frequency of mirror checking action tends to reduce when drivers are involved in secondary tasks. This finding suggests that detecting mirror checking actions can be used to signal distractions. This study evaluate the feasibility of detecting mirror checking actions using the CAN-Bus signal and cameras. We extracted multimodal features describing the drivers' eye openness, head pose, vehicle speed, brake value and steering angle. Using mirror checking annotations, we conducted binary classification in which one class includes segments with mirror checking actions and the second class includes the remaining segments. We achieve an F-score of 0.65 in this challenging, highly unbalanced problem. This promising result suggests that it is possible to detect mirror-checking actions, which can be used to signal alarms, preventing collisions and improving the overall driving experience.

2. DATA COLLECTION

This study relies on real-world driving recordings that includes numerous uncontrollable factors such as traffic, road condition and weather. All these challenging but important conditions are not easily replicated in simulated environments. This section describes the database used for this study, and the protocol used to annotate mirror checking actions.

2.1. UTDrive platform and Database

The UTDrive platform is used to collect the real-world database (see Fig. 1). The UTDrive car is a customized 2006 Toyota RAV4 equipped with various sensors that record the driver, road, vehicle activity and audio [1, 2]. A video camera (320×240 pixels, 30 fps) is mounted on the dashboard facing the driver to capture the driver facial behavior. Another video camera is placed on the dashboard facing the road (320×240 pixels, 15 fps) to capture the road activity. The CAN-Bus signal provides the vehicle speed, steering wheel angle, brake value, and acceleration. Two additional pressure sensors are separately placed on the gas pedal and brake pedal. A microphone array records the sound in the car.

Twenty drivers (10 male and 10 female) participated in the data collection. All of them were 18 years old or older, and had a valid driving license at the time of the recordings. The average and standard deviation of the participants' age are 25 and 7, respectively. Each participant drove the vehicle through a predefined 5.6-mile route twice, as shown in Figure 2. On average, each lap takes about 15 minutes. During the first lap, we asked the participants to perform seven tasks that are commonly performed in the car (e.g., operating radio, phone and GPS, describing pictures and conversation with another passenger – see Table 1). During the second lap, we asked the participants to drive along the same route without performing the aforementioned tasks. We use this recording as a reference of normal driving behaviors. A detailed description of the protocol and recording settings of the corpus is provided in Li et al. [13].

Table 1. Seven secondary tasks considered in this study. The tasks phone and GPS were split, since we observed different driver behaviors while operating and using the devices.

Task Name	Description
Radio (red-route)	Driver tunes the radio to predetermined stations
GPS-Operating (green-route)	Driver inputs predetermined address into GPS
GPS-Following (green-route)	Driver follows the GPS instruction to the destination
Phone-Operating (blue-route)	Driver dials the airline automatic flight information system using a cellphone
Phone-Talking (blue-route)	Driver interacts with the flight information system to retreive flight information
Picture (orange-route)	Driver describes the A4 size pictures shown by the passenger to reflect the distraction caused by road sighs and billboard
Conversation (black-route)	Driver discusses the driving experience with the passengers and answers general questions to the passenger

2.2. Mirror Checking Annotation

Using the videos facing the driver and the road, the mirror checking actions are manually annotated by external observers. Mirror checking actions are defined as the primary driving task of looking at the right, left or center mirrors to increase road situational awareness. Both videos are used by the external observers to distinguish between mirror checking actions and similar gaze behaviors not related to mirror checking actions (i.e., road scanning and traffic sign checking). We annotate the entire corpus including normal and task driving conditions (20 drivers $\times$ 2 driving conditions). Two external observers participated in the evaluation who annotated non-overlapped set of the corpus.

We annotate the starting and ending frame of each mirror-checking action, in both normal and task driving sessions. Each mirror checking action consists of three steps: It starts with the head rotation and eye movement that allow the driver to focus his/her visual attention on the mirror. The second step is a short period of eye fixation on the mirror, during which the driver can perceive the reflected scene. The process finishes when the driver brings his/her visual attention back to the road. To consider the whole process, the annotation starts with the frame where the head/eye is about to move, and ends with the frame where the driver brings his/her visual attention back to the road. Fig. 3 shows examples of frames where the driver is identified by the external observer in the process of checking different mirrors. In addition to the timing of the mirror checking action, the annotation also includes the particular mirror that the drivers were looking. There are four types of mirror checking actions in our database: left mirror checking, rear-view mirror checking, right mirror checking and combined right and rear-view mirror checking. The combined right and rear-view mirror checking is the action where the driver checks both right and rear-view mirrors before bringing his/her visual attention back to the road. It usually happens when the driver has the intention of changing lanes to the right.

3. ANALYSIS OF MIRROR CHECKING ACTIONS

With the annotations, we analyze the duration and frequency of the mirror-checking actions under both normal and task driving conditions. The analysis aims to identify differences in mirror checking actions when the driver is engaged in secondary tasks. We only consider mirror checking actions when the vehicle speed is above 2km/h, since the driver behaviors are different when the car is not moving. The vehicle speed is derived from the CAN-Bus information.

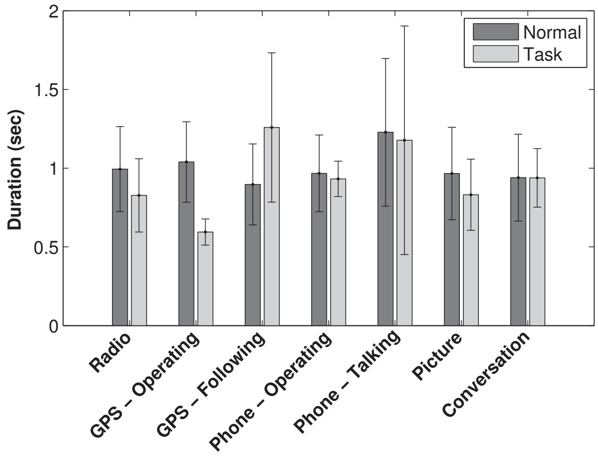
The secondary tasks considered in this study induce different distraction levels since they require varying manual, cognitive and visual resources. Therefore, we expect that mirror checking actions will be affected by these tasks. To get a better understanding of the relationship between secondary tasks and mirror checking behaviors, we compare mirror checking actions observed during normal and each of the seven task conditions listed in Table 1. Notice that checking mirror actions depend on the underlying road and traffic condition (e.g., street signs, intersections, other cars). Therefore, we compare the behaviors during normal and task conditions observed during the corresponding route segments (see Fig. 2). Notice that the drivers drove this predefined route twice with and without performing tasks. Since the time between both recordings was less than 30 minutes, it is expected that the traffic conditions will be similar. Thus, the mirror checking actions that happened over the same route segment between normal and task conditions can be directly compared.

We define two parameters to measure the mirror checking behaviors between normal and task conditions: mirror checking duration and mirror checking frequency. Mirror checking duration is defined as the time interval between the first and last frame of each annotation. The mirror checking frequency is defined as the number of mirror checking actions per minute. We calculate the number of mirror checking actions for each route segment corresponding to a task (see Fig. 2). Then, we normalize the total number mirror checking actions by the time duration (in minutes) of the task. Therefore, both metrics are not affected by the differences in duration of the secondary tasks.

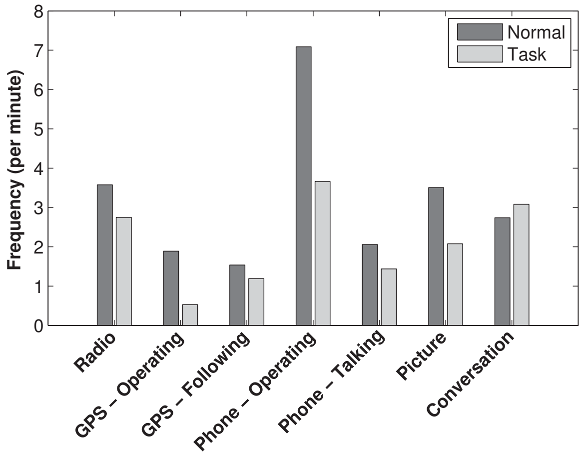
Figure 4 shows the statistics of mirror checking behaviors.

(a) Left mirror checking (b) Rear mirror checking (c) Right mirror checking

Fig. 3. Sample frames identified by external observers as mirror checking actions.



(a) Mirror checking duration



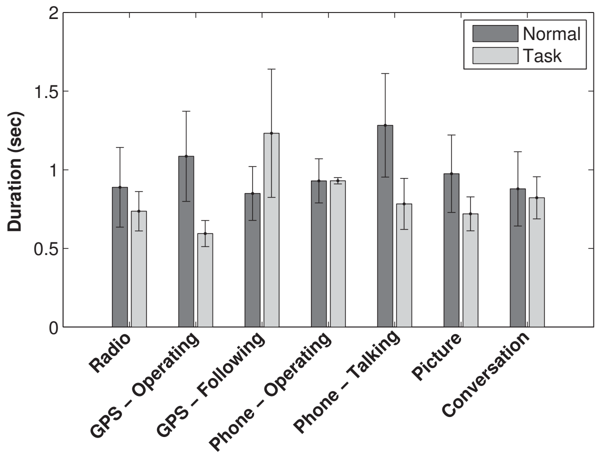
(b) Mirror checking frequency

Fig. 4. Comparison of mirror checking actions during normal and task conditions (left, rear and right mirrors). The normal data was collected during the second lap over the same route segment used to collect the secondary tasks (see Fig. 2).

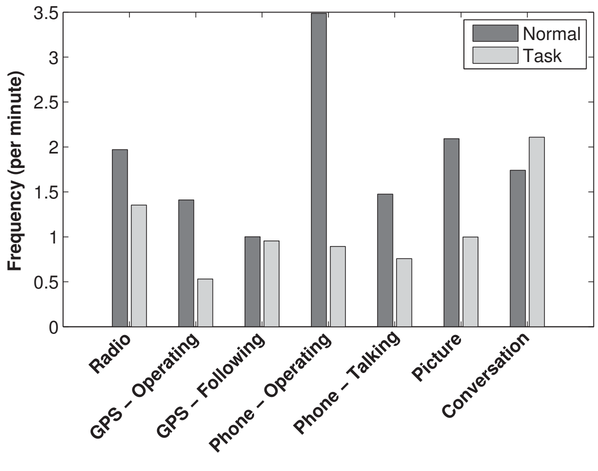
Figure 4(a) shows the mean and standard deviation of the mirror checking duration for left, right and rear mirrors. With the exception of *GPS - Following*, the duration of mirror checking action is slightly shorter for task conditions. We observe significant differences for *GPS - Operating* task. In fact, this is the task identified by external observers as the most distracting task in terms of both visual and cognitive distractions [11, 12]. This suggests that mirror checking duration may be affected when the manual, cognitive or visual demand increases. In these cases, the driver may compromise the attention assigned to the primary driving tasks, including the time used to check the mirrors.

Figure 4(b) shows the comparison of the mirror checking frequencies between the normal and task conditions for all mirrors. The figure shows important differences between both conditions. The frequency of mirror-checking actions reduces when the driver is engaged in most of the secondary tasks. We conduct a matched-pairs hypothesis t-test to assess whether the differences in mirror checking frequencies between each task and the corresponding normal condition are statistically significant (the paired conditions is the drivers). As expected, the mirror checking frequencies during *GPS-Operating*, *Phone-Operating* and *Picture* are found significantly different from the one under normal condition ($p-value$= 0.05). These findings highlight the detrimental effects of secondary tasks on the situational awareness of the driver.

Figure 4 describes the aggregated mirror checking statistics across all mirrors. However, we expect that these patterns are different across right, left and rear mirrors. Since some of the left, right and combined right and rear-view mirror checking actions are related to the driver's intention to switch lane or making turns, they are more dependent on the traffic and road conditions. In contrast, checking the rear mirror is important for situational awareness even when the driver does not intend to perform any of the aforementioned maneuvers. Therefore, we hypothesize that the patterns for checking rear mirrors is more affected by secondary tasks. To verify this assumption, we replicate the analysis focusing only on rear mirror checking actions. Figure 5 shows the duration and



(a) Mirror checking duration



(b) Mirror checking frequency

Fig. 5. Comparison of rear mirror checking actions during normal and task conditions (left and right mirrors excluded).

frequency of rear mirror checking actions. The figure describes interesting differences compared to the results observed across all mirrors. Figure 5(a) shows a large difference in rear mirror checking duration not only in *GPS-Operating*, but also in *Phone-Talking* task. Figure 5(b) shows that the reduction in rear mirror checking frequency is more evident than the ones observed across all mirrors. The matched-pair t-test shows that the mirror checking frequency under *GPS-Operating*, *Phone-Operating*, *Phone-Talking* and *Pictures* are significantly lower than the one under normal condition ($p-value$= 0.05). This result suggests that rear mirror checking actions are more affected by the secondary tasks.

The only secondary task that has higher frequency than the corresponding normal condition is *Conversation*. However, a closer look at the database reveals that this unexpected result is an artifact of the data recording. In many of the recording sessions, the second passenger sit in the back seat to control the equipments. In these cases, the drivers used the rear mirror to establish eye contact. Therefore, these rear mirror checking actions are not associated with the primary driving task. Since it is difficult for external observers to identify the purpose of each rear mirror checking action, the result for the task *Conversation* may not reflect the actual effects of this task on the drivers' mirror checking actions.

4. DETECTION OF MIRROR CHECKING ACTIONS USING MULTIMODAL FEATURES

The results in Section 3 suggest that mirror checking actions are useful indicators for driver distraction detection. In particular, the rear mirror checking actions are highly affected by the secondary tasks. Detecting whether glance behaviors are associated with the primary driving tasks is important in the design of context-aware monitoring systems. This section explores the use of multimodal features from noninvasive sensors to detect the drivers' mirror checking actions.

4.1. Preprocessing Steps

We address the detection of mirror checking actions as a binary classification problem. Using the mirror checking annotation (Sec. 2.2), we create videos containing the mirror checking actions under both normal and task conditions. The duration of these segments varies according to the durations of mirror checking actions. The study considers these videos as the positive class. The rest of the data is also segmented into short videos. These videos convey non-mirror checking actions and are regarded as the negative class. The duration of these videos is similar to the duration of the positive class. Since drivers present different mirror checking behaviors (i.e., some drivers finish the mirror checking actions faster than others), we calculate the average duration of mirror checking actions per driver. For each driver, the non-mirror checking videos are segmented such that their duration match his/her average duration of mirror checking actions.

The definition of positive (mirror checking actions) and negative (non-mirror checking actions) classes generates highly unbalanced partitions. Most of the samples belong to the negative class. (see Table 2). The average ratio between the size of positive and negative classes across all drivers is 1 to 26.7, since different drivers have different mirror checking habit (some are more frequent than others).

4.2. Feature Extraction

As described in Section 2, the database used for this study includes recordings with various sensors: a camera facing the driver, a camera recording the road, a microphone array, and

CAN-Bus data. For mirror checking action detection, we consider the data from two modalities: the driver's camera and CAN-Bus. The frontal camera captures the movement of drivers' head and eye glances. The CAN-Bus signals capture the vehicle activities that may signal mirror checking actions such as steering wheel jitter and vehicle's speed.

We extract features describing the driver's facial behaviors from the frontal camera with the *computer expression recognition toolbox* (CERT). CERT extracts was developed by Bartlett et al. [5], and it provides frame-by-frame estimation of head pose and facial *action units* (AUs) under various illumination conditions. The toolkit has been used for driver drowsy detection [20]. We use CERT to estimate both head pose (yaw, pitch and roll angles) and eye openness (AU 45). For the CAN-Bus data, we consider three important signals: steering wheel angle in degrees, the vehicle's speed in kilometers per hour (km/h), and the brake value. These time series signals are regarded as low level features. While they describe detailed aspects of driver behavior, global patterns in these features are expected to provide discriminant information about mirror checking actions. Therefore, we consider global statistics of these signals. We calculate eight statistics for each of the signals over the predefined segments: mean, standard deviation, maximum, minimum, range, interquartile range, skewness and kurtosis. This approach generates a 56D feature vector for each data segment (7 signals $\times$ 8 statistics).

In addition, we use facial signals extracted with CERT to derive four additional gaze related features. The first feature is the total *eye-off-the-road* (EOR) duration, which corresponds to the total time that the drivers take their eyes off the road during the given segment. The second feature corresponds to the *longest eye-off-the-road* (LEOR) duration, which provides the duration of the longest glance during the segments. It is less than or equal to the EOR duration. The third gaze features is the eye-off-the-road frequency, which gives the number of glances per segment. The last gaze feature is eye blink frequency, which estimates the number of blinks in the segment. We have used these features in our previous work to study driver distraction [12, 13]. They have provided useful information about visual and cognitive distractions. The details on the estimation of these features can be found in Li et al. [13].

Due to hand occlusions, extreme glance behaviors or adverse illumination conditions, CERT may fail to recognize the face in the frame producing empty values. For each preprocessed data segment, we interpolated the missing value when the number of frames with missing values is less than one third of the total number of frames. Otherwise, the data segment are excluded from the analysis. Overall, a 60D feature vector is generated for each data segment (56 statistics plus 4 gaze related features). These features are used to train the classifiers to distinguish between the mirror and non-mirror checking actions.

Table 2. Binary classification for mirror checking actions.

Classifier	Precision	Recall	F-score
LDC	57%	53%	0.54
KNN	68%	51%	0.57
QDC	62%	73%	0.65

4.3. Detecting of Mirror Checking Actions

Given the high dimension of our feature vector, we reduce the set using forward feature selection. We implement the feature reduction technique using the inter/intra class distance ratio criterion. With this technique, the forward feature selection algorithm chooses the feature set that maximizes this criterion until a given number of features is selected. We considered three machine learning algorithms: *K-Nearest Neighbor* (k-NN) classifier, *linear discriminant classifier* (LDC) and *quadratic discriminant classifiers* (QDC). Notice that the feature selection scheme is independent of the machine learning algorithm, thus generates consistent features across classifiers.

Due to the highly unbalanced classes (i.e., most of the segments do not have mirror-checking actions), we report the precision, recall and the F-score to evaluate the performance. The precision rate (also called positive predictive value) is the fraction of classified instances that are correct. The recall rate (also known as sensitivity) is the fraction of instances that are correctly classified. The F-score combines the precision and recall rate using the equation 1:

$$F = 2 * \frac{precision * recall}{precision + recall} \tag{1}$$

We use a 20-fold driver independent cross-validation scheme to evaluate the performance. In each fold, the data from 19 drivers are used for training and the data from the remaining driver is used for testing. The feature selection process is performed over the training data. The number of selected features is changed from 1 to 30. For each setting, we evaluate the performance using the selected features in both training and testing data. The best performance among the 30 settings is averaged across the 20 folds. Table 2 reports the average results.

QDC provides the best performance among the classifiers in term of F-score (0.65). Table 3 shows the confusion matrix achieved by the QDC classifier. The reported performance is clearly affected by the unbalanced classes. Although the precision of the QDC is still low, we achieve a recall rate of 73 percent, which indicates that we identified most of the mirror checking actions. This result suggests that the proposed multimodal features can capture the mirror checking actions.

Notice that the data in the positive class consists of all the mirror checking actions that were annotated, including the ones that happened when the car is stopped at the traffic lights or intersections. In these cases, the CAN-Bus features are not

Table 3. Confusion matrix of QDC for mirror checking actions.

	Predicted Mirror Checking	**Predicted Non Mirror Checking**
Actual Miror Checking	612	442
Actual Non Miror Checking	3282	21091

very effective in detecting mirror checking actions. Also, we expect that the drivers glance behaviors change when the car is not moving. For example, their head movement, and the duration of the glance patterns can be significantly different from the ones observed when the car is moving. In our future work, we will consider a model that considers the vehicle speed. For example, we can add speed constraints such that data segments where the vehicle speed is low are processed with different classifiers trained with similar data.

5. CONCLUSIONS

This paper used a real-world driving database to study the drivers' mirror checking actions, which were carefully annotated. The study presents a comparison of the mirror checking actions under both normal and task driving conditions, in terms of both duration and frequency. The results suggested that mirror checking frequency is affected when the driver is engaged in secondary tasks. The drivers reduce the number of mirror checking actions to cope with the cognitive, visual and manual demand of the tasks. This result clearly highlights the detrimental effect of secondary tasks on the situational awareness of the drivers. Leveraging the results of the analysis, the paper proposed to detect mirror checking actions using multimodal features. We aimed to detect mirror checking actions to distinguish glance behaviors that are related to the primary driving task and to identify deviations from mirror checking patterns observed under normal driving conditions. We extracted multimodal features describing the driver eye openness, head pose, vehicle speed, brake value and steering angle. We used the manual annotations to define the classes for binary classification of mirror-checking actions. One class includes the segments with mirror checking actions, and everything else is grouped into a separate class. We use a leave-one-driver-out cross-validation approach, where the data of one driver is used to test the performance of the system trained with the data of remaining drivers. We achieved an F-score of 0.65 (recall 73%, precision 68%) using the extracted features. This promising result suggests that it is possible to detect mirror-checking actions, which can be used to signal alarms, preventing collision and improving the overall driving experience.

For our future work, we are planning to include features from the road camera. We are also considering using extra information from the camera facing the driver and the CAN-Bus data. We expect to improve the performance of the classifiers with these extra features. During the annotation of the mirror checking actions, we noticed that the mirror checking behaviors vary across drivers. For example, some drivers tend to check the mirrors with less obvious head movement. Drivers also show different behaviors while involved in the secondary tasks. Some of the drivers are more cautious than others. They perform mirror checking actions more often when engaged in secondary tasks. In fact, previous studies suggested that drivers' mirror checking behaviors are related to the drivers' experience [18, 19]. Given these observations, we are planning to build driver dependent classifiers to detect the mirror checking actions based on personalized models.

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