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Eye Gesture Analysis with Head Movement for Advanced Driver Assistance Systems

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***Abstract*—**Road traffic accidents are a major cause of death worldwide. In an attempt to reduce accidents, some research efforts have focused on creating Advanced Driver Assistance Systems (ADAS) able to detect vehicle, driver and environmental conditions and to use this information to identify cues for potential accidents. This paper presents continued work on a novel Non-intrusive Intelligent Driver Assistance and Safety System (Ni-DASS) for assessing driver point of regard within vehicles. It uses an on-board CCD camera to observe the driver's face. A template matching approach is used to compare the driver's eye-gaze pattern with a set of eye-gesture templates of the driver looking at different focal points within the vehicle. The windscreen is divided into cells and comparison of the driver's eye-gaze pattern with templates of a driver's eyes looking at each cell is used to determine the driver's point of regard on the windscreen. Results indicate that the proposed technique could be useful in situations where low resolution estimates of driver point of regard are adequate. For instance, To allow ADAS systems to alert the driver if he/she has positively failed to observe a hazard.

***Keywords*—**Head rotation, Eye-gestures,Windscreen, Template matching.

I. Introduction

ROAD traffic accidents represent a major cause of fatalities worldwide. A report commissioned by the World Health Organisation [1], states that road accidents cause one million deaths each year and fifty million serious injuries. Road accidents represent the main cause of death for males under the age of 25 within the Organization for Economic Co-operation and Development (OECD) countries [2]. The United Kingdom's Department for Transport published a report entitled 'Reported Road Casualties Great Britain: 2008'[3] which looked at accident causation factors. The findings were that speed was a major contributory factor in road traffic accidents with 14% of accidents linked to exceeding the speed limit or driving too fast for the road conditions. The report also states that this rate rises to 24% when considering only fatal accidents. In the USA, the Department of Transportation published a report,[4], which investigates pre-crash causation factors for light passenger vehicles that took place between2005 to 2007. The report studied 6,950 crashes and states that 22% of the vehicles ran off the edge of the road and 11% of the vehicles failed to maintain proper lane keeping.Recent research investigating the factors contributing to road accidents have suggested that momentary lack of attention featured in as much as 78% of road accidents [5].

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Other researchers have claimed that poor attention is the main cause of accidents because factors such as fatigue, alcohol or drug use, distraction and speeding all impair the driver's capacity to pay attention to the vehicle and road conditions (Fletcher and Zelinsky, 2009).

These factors have motivated research efforts that aim to improve driver performance and thus help to reduce accidents. This research has led to the development of Advanced Driver Assistance Systems (ADAS). ADAS systems are on-board computer systems that attempt to reduce the risk of accidents by monitoring the driver, vehicle and environmental conditions and taking some action when a risk is identified. However, there is comparatively little published work that tackles the problem of driver attention with much of the work focusing upon detecting and responding tovehicle and environmental state. Some recent work has attempted to create ADAS systems able to determine the driver's level of attention [6]. In order to have reliable and accurate assessment of the driver's condition and his/her fitness to drive, a number of factors need to be considered such as vehicle behaviour (speed, lane changes, manoeuvresetc), driver's eye gaze (to determine the driver's focus of attention), other road users and road conditions.In the proposed Non-intrusive Intelligent Driver Assistance and Safety System (Ni-DASS), a video of the driver's eyes is processed to determine the driver's point of regard on the windscreen. The overall aim of this process is to determine whether the driver has seen the hazard. Because of the 'look but not see' phenomenon, it is very difficult to determine if the driver has actually observed a hazard. However, it is often possible to determine if the driver has failed to observe the hazard simply because he/she has been looking at something else. The main contribution of this paper is an extension our earlier introductory work on eye-gesture recognition for mirror observations [7] to point of regard determination on windscreens. In this paper, eye-gesture templates are matched with the driver's eye to determine the driver's point of regard on the windscreen. Results have shown that it is possible to use gesture recognition techniques to determine point of regard with sufficient accuracy to be used for hazard awareness.

II. Previous Work

Advanced Driver Assistance Systems (ADAS) have been designed to assist the driver within a vehicle and to help avoid traffic accidents by improving driving performance. For this reason, it is necessary to understand the main pre-crash causal and contributing factors.

Factors that contribute to traffic accidents include driver behaviour, driving context and vehicle performance. For instance, police crashes reports have shown that the driver following too closely to the vehicle in front is one of the main causes of rear-end collisions. Studies have shown that as much as 78 per cent of fatal accidents are a result of poor driver observational behavior [5].

[6] suggest that sub-optimal driver attention may be the major causation factor in road accidents as other factors such as speeding, fatigue, drink driving etc all impair the driver's ability to pay attention to the vehicle and environment.

Driver fatigue is also one of the main causation factors in road traffic accidents. In Great Britain, statistics have shown that 20 per cent of serious accidents on motorways are caused by the driver being drowsy and not fit to drive [8]. For this reason, researchers [9] have developed drowsiness detection systems based upon measurement of the percentage of eye closure so as to detect when the driver is fatigued and help avoid road accidents. Other researchers [10,11]have focused on driver distraction as a main contributing factor in many accidents. This research has found that in-car technology is a factor in causing driver distraction. For instance, if the driver is using a telephone or resetting the route within a satellite guidance system. However, there are other factors that contribute to distraction such as eating, conversing with a passenger etc. Driver distraction is claimed to be a contributing factor in over half of non-vigilance crashes. Researchers [10, 6] have use simulators and test track studies in order to assess the importance of driver distraction in road accidents. Changes to the speed of the vehicle are also a crucial factor that causes car accidents. Researchers have found that people who have been distracted may decrease or increase the pressure on the acceleration pedal. A report has shown that speeding is also an important factor in traffic accidents. Around 430 people are killed in crashes in the United Kingdom in which someone exceeds the speed limit or drives too fast for the road conditions [12].

Based upon the factors described above, ADAS systems have been proposed by researchers as an initiative to avoid road accidents and reduce death. The following sections will look at work related to driver state that affects driver performance.

1) Fatigue/Drowsiness

[9] have used visual information to detect driver drowsiness. The visual cues are; yawn frequency, eye-blinking frequency, eye gaze movement, head movement and facial expressions. To localize the face, this system uses the VJ object detector (this is a machine learning approach for object detection). It uses three important aspects to make an efficient object detector based on the integral image, AdaBoost technique and cascade classifier. They then use the face region of interest to minimise the search area when finding the eyes. The technique used to find the eyes is based on anthropometric properties proposed by [13]. Then the exact position of the eye is searched by incorporating information from grey level pixels. After that the mathematical equation is used to generate the random samples of eyes (elliptic model) which indicate the state of the eye (closed or opened). The classification technique (support Vector Machine) has been used to identify whether they eyes being closed or opened.

Then Gabor filter has been used to extract the features to analyse the eyes by changing the orientation and scale. The percentage of eye closure initially used by [4] is used to determine the drowsiness and the driver's face orientation was determined using mathematical formula based on eye position.

Meanwhile [14] has used sensor approach to determine the driver's drowsiness. The adaptive cruise control fuse with driver vigilance and lane departure warning system information has been employed to indicate the driver's drowsiness. ACC systems use either radar (radio detection and ranging) or LIDAR (light detection and ranging), and the latter is the more precise distance-measuring sensor. Both systems are utilised to measure the speed and distance relative to the vehicle in front and automatically applies deceleration when necessary. They used image processing technique to access the driver's alertness by measuring driver's vigilance using unobtrusive camera to infer the driver is looking ahead and taking an appropriate action if necessary.

2) Driver Attention/ Vigilance

[15] has implemented facial features and eyelid movement detection to identify poor vigilance to assess driver behavior. A statistically anthropometric face model has been used to find the important features on face. Combination of image processing technique has been employed to make it robust. Kalman filter has been used to robustly detect the facial features point over a sequence of human face images taken from different head pose. The author used technique proposed by [16] to automatically select the face skin pixels on the image. The technique called colour skin histogram that used to take sample from different scenarios. They then choose face skin region manually which is performed on a sequence of learning frames to compute a (normalised) skin colour histogram model in RGB-space. After all they find the probability of pixel value in RGB space is drawn from the predefined skin histogram model.

[17] have used driver's vigilance based technique by implementing fuzzy logic to infer inattentiveness of the driver. The information of the driver's behaviors like duration and percentage of eye closure, blink and nodding frequency, face positions and fixed gaze is obtained from PERCLOS in order to measure the driver drowsiness. The device is being developed by Seeing Machine which has three drowsiness metrics. They are proportion of time the eyes were closed at least 70%; the time the eyes were closed at least 80% and EYEMEAS (EM) where mean square percentage of eye closure rating measured [18]. All the parameters have been fused using fuzzy classifier to differentiate level of driver's inattentiveness plus to increase the performance of detection.

3) Driver Distraction

Driver distraction may occur during driving period due to driver picking up phone, texting or using entertainment facilities such as music players, PDA devices, mobile phones, etc. There are a few approaches that have been employed to indicate the driver distraction. They are based on visual information like eye gaze, lips detection, head position etc.

[10] used to reveal driver's distraction using rules based on gaze, head lane tracking data by fusing them together with support vector machine classification technique. The FaceLab of Seeing Machines has been applied to extract the eye features of the driver. FaceLab is a device to calculate head rotation and analyse eye states (e.g. saccades, eye blinking, eye gaze direction etc.). The gaze direction and head position (output mapping) is being used to determine the driver's

attention especially when the driver is not looking on the road. Beside the output mapping also assist to indicate when the driver is continuously dividing his attention with something else. Lastly the mapping output is used to generate driver's intent to change the lane. A kernel function is used for mapping and the Support Vector Machine algorithm to classify the driver's behavior due to better adaptation of momentary changes. The result shows the eye gaze and head rotation achieved a good enough performance to be employed in driver distraction system.

III. Eye-Gesture Analysis for Windscreen Observations

The proposed system is an extension of the Ni-DASS system outlined in our introductory work on eye-gesture analysis for mirror observations [7] to include general eye-gaze determinations within vehicles. As such, there are two primary contributions: the extension of eye-gesture analysis to include general driver point of regard determinations within vehicles and the extension of eye-gesture analysis to include driver head movements. Eye-gesture templates are captured of the driver looking at each point of regard element and are compared with the driver's eyes during driving situations in order to determine if the driver is looking at any of the point of regard elements. To determine the driver's point of regard on the windscreen, the windscreen is divided into a grid of evenly spaced cells and eye-gesture templates are captured of the driver looking at each cell. The number of cells used is important but it has been found empirically that using four rows of six cells per row is an adequate cell resolution for the template matching.

To deal with movements of the head, three situations must be considered:

- Rotations of the head
- Forward and backward displacements.
- Horizontal and vertical displacements.

Each of these cases will be addressed below.

A. Head Rotation

When making observations, the driver may rotate her head to look at a focal point in the vehicle. If the driver's head is considered to be at the origin of the coordinate axes and aligned so that the x-axis is horizontal with respect to the head, then rotating about the x-axis represents an up and down movement of the head. If the y-axis runs vertically with respect to the head then rotation about the y-axis represents a left and right turning of the head. Lastly, if the z-axis projects out from the head in a forward direction then rotation about the z-axis represents a left, right tilting motion of the head. During routine road observations, rotations about the x-axis and y-axis are more common as these represent natural head rotations that take place during normal observations. Head tilting rotations about the z-axis are less common. For this reason, the following section will deal with x-axis and y-axis rotations. To do this, it is proposed to capture eye-gesture templates of the driver in different head poses and to select the appropriate template set based upon an estimate of the rotation of the head. To do this, a calibration driver rotates her head to face each of the 24 windscreen cells and a full set of eye-gesture templates are captured for each head pose. For instance, the calibration driver rotates her head to face a windscreen celland eye-gesture templates are captured of the driver looking at all 24 windscreen cells while keeping her head pose fixed. With 24 focal-points, there will be 24 different sets of eye-gesture templates with each set containing 24 templates.

During normal driving situations, the driver's head rotation is estimated using the approach presented by [19] based upon estimating the 3D rotation of the head from the relative positions of facial feature points in the 2D video image of the face. The present work tracks the outer corners of the left and right eye and the outer corners of the mouth. The reader is referred to [19] for a full discussion of the approach. Once the head rotation is estimated, it is then possible to determine the eye-gesture template set to use for point of regard determinations. This is done by comparing the calculated head rotation with the rotation used while capturing the templates and selecting the nearest match.

B. Forward and Backward Displacements

Since the driver's seat can be adjusted, the distance of the driver from the point of regard elements can vary and this can impact upon the accuracy of the point of regard determinations. Given a particular eye gaze vector, forward or backward movement of the driver will displace the actual point of regard by (Δx, Δy). The value of the Δx and Δy will depend upon the change in distance Δd of the drivers head from the point-of-regard element with respect to the calibration distance *d* and the viewing angle θ. In Figure 1, the pink head represents the calibration head position with *d* being the distance of the pink head from the windscreen. The blue head represents a backward displacement of Δ*d*. The horizontal position x represents the distance of the point of regard from the neutral, forward facing eye-gaze position and Δx represents the change in the point of regard resulting from the backward displacement of the driver's head. The eye-gaze viewing angle remains the same in both the pink head position and the blue head position.

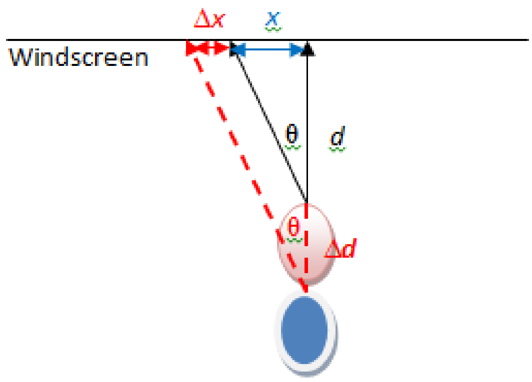

Fig. 1 2D representation of a backward displacement of the head (blue) from the calibration head position (pink)

From the trigonometric rule for right-angled triangles, we know that

$$\tan(\theta) = x/d \quad (1)$$

$$\tan(\theta)=(x+\Delta x)/(d+\Delta d) \quad (2)$$

Combining these two equations gives us

$$x/d=(x+\Delta x)/(d+\Delta d) \quad (3)$$

and rearranging gives us

$$\Delta x=x\Delta d/d \quad (4)$$

From the calibration of the templates, we know *x* and *d*. Therefore, if we can measure Δd, then we can calculate Δx and determine the driver's actual point of regard on the windscreen. Δd can be determined in a number of ways. For instance, the value of Δd often depends upon the seat adjustment relative to the calibration seat position. It would also be possible to estimate the change in distance from the camera from the change in scale of the driver's head. However, experimental results in a Ford Focus car have shown that if the eye-gesture templates are captured at the mid-point of the seat adjustments and the forward and backward displacements are in the order of 10cm in each direction then the maximum point of regard displacements are less half the width and height of the windscreen cells when the windscreen is divided into 4 rows of 6 cells. This means that for a given eye-gaze pattern, the maximum forward or backward seat position will not change the cell upon which the driver is focused.

C. Horizontal and Vertical Displacements

To handle horizontal and vertical displacements of the head from the calibration position, it is imagined that the driver's head is contained within a 2D mapping grid. Figure 2 shows an eye-gesture mapping grid used to determine the mapping between eye-gesture templates and the point-of-regard elements within the vehicle as the driver shifts position horizontally or vertically. In the diagram, a grid of 64 cells is used and two drivers are shown. The pink driver is the shorter of the two drivers. Her right eye is located in cell(4,5).

Suppose the pink driver is in the calibration position and her head is in a neutral, forward facing pose. Eye-gesture templates are created from the pink driver's left eye as she looks at the centre of the point-of-regard element while keeping her head stationary. With 24 point-of-regard elements (windscreen cells), there would be 24 corresponding eye-gesture templates calibrated for the pink driver's left eye located in cell(4,5) in the forward facing head pose.

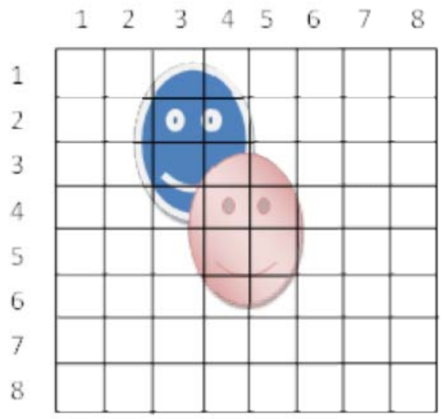

Fig. 2 Eye Gesture Mapping Grid

Provided the pink driver does not move, a match between the pink driver's left eye and an eye-gesture template looking at a particular windscreen cell would indicate that the pink driver is looking at that windscreen cell. However, this is not the case for the blue driver who is taller and is positioned to the left of the pink driver. His left eye is located within cell (2, 4). A match between the blue driver's left eye and an eye-gesture template looking at a particular windscreen cell need not indicate that the blue driver is actually looking at that windscreen cell due to the fact that his left eye is displaced one cell to the left and two cells above the calibration cell.

If the driver's left eye moves horizontally by Δx and vertically by Δy from the calibration position then the driver's point of regard on the windscreen or mirror will also move by Δx and Δy providing the drivers head movement is constrained within the XY plane and the gaze direction has not changed. The Ni-DASS system will measure Δx and Δy in pixels in the video image from the on-board CCD camera observing the driver's face. In order to calculate the real-world displacement values, it is necessary to determine the scaling between the real-world head displacements and the pixel displacements within video. This can be achieved simply by measuring the height of the calibration driver's head in real-world units and dividing by the length of the calibration driver's head in pixels within the video.

IV. Evaluation

A. Experiment One

The windscreen of a Ford Focus car was divided up into 24 cells consisting of 4 rows of 6 columns. Figure 3 shows an image of the car with the windscreen cells marked out with masking tape.

Fig. 3 Marking out 24 windscreen cells

A CCD camera was placed on the centre of the dashboard and aligned to capture the driver's face. The camera used was a Sentient 540TVL IR CCTV Camera. This is a dual visible spectrum and infra-red camera with a variable focal length and a sensor size of 1/3 inch. A focal length of 4mm was used during the experiment. The camera was positioned so as to be able to capture the driver's head in the full range of driving positions. To create the eye-gesture templates, a calibration driver was asked to sit in the normal driving position with the driver seat position at the mid-way point of the forward and backward adjustments.

The calibration driver was asked to rotate her head to face each windscreen cell. When the calibration driver's head was rotated to face a windscreen cell, eye-gesture templates were captured of the calibration driver's left eye looking at each of the 24 windscreen cells while keeping her head pose fixed. This process was repeated with the calibration driver's head rotated to face each cell. This produced 24 sets of eye-gesture templates with each set having 24 templates. These eye-gesture templates were then cropped to approximately the same size and show the calibration driver's left eye with a small portion of skin surrounding the eye. A video of a test driver was captured repeating the same head pose and eye pose observations used when capturing the templates. The test driver's head pose was estimated using the 2D approach proposed by [19]. Once the head rotation about the x-axis (up-down) and y-axis (left-right) was estimated, the nearest matching gesture-template set was used to match with the driver's eye.

1) Result of Experiment One

Table I shows the results of the test driver rotating her head to face windscreen cell(1,6) (top right) while looking at windscreen cell(1,1) (top left). As can been seen the highest matching eye-gesture template was for template (1,1). The matching results gradually decrease going from left to right along the table to reflect the movement of the driver's pupil as she scans the top row of windscreen cells and thus increasing the disparity between the templates and the driver's eye-gaze pattern. The same pattern is observed for subsequent rows with the left most templates obtaining the highest matching result in each case and gradually decreasing. Within each column in Table I, the top row achieves the highest match with subsequent rows being lower to reflect the movements of the eye gaze from the top of the windscreen to the bottom.

TABLE I
TEMPLATE MATCHING RESULT FOR TEST DRIVER HEAD ROTATED TO FACE WINDSCREEN CELL(1,6) WHILE LOOKING AT WINDSCREEN CELL(1,1)

Template	1	2	3	4	5	6
1	76.141 %	71.917 %	75.230 %	57.563 %	51.002 %	43.656 %
2	73.493 %	70.651 %	66.186 %	57.580 %	55.479 %	54.641 %
3	72.868 %	66.032 %	61.290 %	64.210 %	58.387 %	49.175 %
4	63.126 %	61.131 %	57.279 %	56.589 %	54.533 %	53.272 %

B. Experiment two

The same experimental setup as in Experiment One was followed to divide the windscreen into 24 cells and to capture the eye-gesture templates. If the camera lens is considered to be at the origin of a Cartesian coordinate axis with the positive x-axis pointing to the right of the driver, the positive y-axis pointing up and the positive z-axis pointing out the windscreen then the calibration driver's left eye was measured to be at coordinate (40.6cm, 17.8cm, -91.4cm). The driver's car seat was move forward to the maximum extent and the coordinates of the driver's left eye measure then the car seat was moved backward to the maximum extent and the coordinates of the driver's left eye were recorded once again. Table 2 shows the coordinates of the left eye in the forward, calibration and backward seat positions. The coordinates of the centres of the windscreen cells were recorded and are presented in Table 3 and the dimensions of the windscreen cells are presented in Table IV.

TABLE II
COORDINATES OF THE DRIVER'S LEFT EYE WHEN THE DRIVER'S SEAT IS MOVE FORWARD AND BACKWARD TO THE FULL EXTENT AND AT THE CALIBRATION POSITION

	x	y	Z
Forward	40.64cm	17.78cm	-81.28cm
Calibration	40.64cm	17.78cm	-91.44cm
Backward	40.64cm	17.78cm	-101.6cm

Using Equation 4, Δx was calculated for the forward and backward seat positions where x is the distance between the centre of each windscreen cell and the driver's point of regard in the neutral forward facing position measured along the x-axis, d is the distance of the driver's eye along the z-axis at the calibration position and Δd is the displacement of the driver's left eye along the z-axis with respect to the calibration position at the forward and backward seat positions. An analogous calculation was performed for Δy. Table 5 shows the calculated Δx and Δy for the forward seat position and Table 6 shows the calculated Δx and Δy for the backward seat position.

1) Results of Experiments Two

Table V shows the displacement of the driver's point of regard within each cell based upon the forward seat position with the driver's head fixed in a forward neutral position. Examining the values of Δx and Δy shows that the change in the driver's point of regard never exceeds half the width or height of the cell. This means that, if the driver focuses her eye-gaze on the centre of a cell, then the driver's point of regard in the forward and backward seat position remain in the cell. This suggests that the impact of small forward and backward movements associated with adjustments of the driver's seat will have a limited impact upon point of regard determinations. In the cell(1, 1) (top left windscreen cell) when the driver moves forward toward to the maximum seat position, the point of regard is displaced 9.17cm to the right The coordinates of the point of regard will decrease 5.08cm along the y-axis as the driver moves forward. This means that the driver's point of regard will stay within the horizontal and vertical bounds of the cell. This is true for all 24 cells. Similar results are obtained for backward seat positions presented in Table VI.

CONCLUSION

This paper presents continued work to develop the Ni-DASS system which aims to monitor driver eye-gaze and to

TABLE III
COORDINATES OF THE CENTRE OF EACH WINDSCREEN CELL WITH THE CAMERA AT THE ORIGIN WITH COORDINATES IN CM

Cell	1	2	3	4	5	6
1	(-41.9, 63.5, -54.6)	(-21.6, 63.5, -54.6)	(0, 63.5, -54.6)	(19.0, 63.5, -54.6)	(36.8, 63.5, -54.6)	(55.9, 63.5, -54.6)
2	(-44.5, 41.9, 38.1)	(-21.6, 41.9, 38.1)	(0, 41.9, -38.1)	(21.59 41.91 -38.1)	(39.37 41.91 -38.1)	(60.9, 41.9, -38.1)
3	(-45.7, 24.1, 19.0)	(-21.6, 24.1, 19.0)	(0, 24.1, -19.0)	(21.6 24.1 -19.0)	(39.424.1 -19.0)	(63.5, 24.1, -19.0)
4	(-46.9 , 0, 0)	(-21.6, 0, 0)	(0 , 0, 0)	(21.6, 0, 0)	(41.9, 0, 0)	(64.8, 0, 0)

TABLE IV
DIMENSIONS (WIDTH, HEIGHT) OF EACH WINDSCREEN CELL IN CM

Cell	1	2	3	4	5	6
1	22W, 21H	19W, 20H	21W, 20.5H	18W, 21H	19W, 21H	21W, 18H
2	24W, 20H	20W, 20H	21W, 20H	19W, 19.5H	19W, 20H	23W, 19.5H
3	27W, 20H	21W, 19H	21.5W, 19H	22W, 19.5H	19.5W, 19.5H	26W, 18H
4	29.5W, 19H	21.5W. 23H	22W, 23.5H	23W, 23.5H	19.5W, 22H	28W, 19.5H

TABLE V
POINT OF REGARD DISPLACEMENT IN FORWARD SEAT POSITION

Cell	1		2		3		4		5		6	
	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy
1	9.17	-5.08	6.91	-5.08	4.52	-5.08	2.40	-5.08	0.42	-5.08	-1.69	-5.08
2	9.45	-2.68	6.91	-2.68	4.52	-2.68	2.12	-2.68	0.14	-2.68	-2.26	-2.68
3	9.60	-0.71	6.91	-0.71	4.52	-0.71	2.12	-0.71	0.14	-0.71	-2.54	-0.71
4	9.74	1.98	6.91	1.98	4.52	1.98	2.12	1.98	-0.14	1.98	-2.68	1.98

TABLE VI
POINT OF REGARD DISPLACEMENT IN BACKWARD SEAT POSITION

Cell	1		2		3		4		5		6	
	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy	Δx	Δy
1	-9.17	5.08	-6.91	5.08	-4.52	5.08	-2.40	5.08	-0.42	5.08	1.69	5.08
2	-9.45	2.68	-6.91	2.68	-4.52	2.68	-2.12	2.68	-0.14	2.68	2.26	2.68
3	-9.60	0.71	-6.91	0.71	-4.52	0.71	-2.12	0.71	-0.14	0.71	2.54	0.71
4	-9.74	-1.98	-6.91	-1.98	-4.52	-1.98	-2.12	-1.98	0.14	-1.98	2.68	-1.98

alert the driver in situations where attention is lacking. The work presented here use eye-gesture templates to provide low-resolution point of regard determinations with natural head movements that take place in the vehicle.

The results indicate that the approach might be suitable for point of regard determinations in situation when high accuracy is not required. Such situations would be hazard awareness systems where the ADAS system would alert the driver if he or she is failing to observe a hazard on the road by detecting situations when the driver is positively looking elsewhere.

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