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COMMONLY USED METHODS TO MONITOR DRIVER'S DROWSINESS AND FATIGUE WITH A FOCUS ON THE INTERIOR CAMERA

Filip Kotas*, Jan Leistner

Czech Technical University in Prague, Faculty of Transportation Sciences, Konviktská 20, 110 00 Prague 1, Czech Republic

* corresponding author: kotasfil@cvut.cz

Abstract. Some of the main causes of road accidents nowadays are fatigue, drowsiness and driver inattention. In many cases, these accidents are fatal and can cause significant financial loss. Most of these accidents happen between midnight and 6am. One way to reduce the number of accidents caused by these causes is to use an interior camera. This camera can detect fatigue or drowsiness and alert the driver in time, and in the worst case, take over the car and stop safely at the side of the road. The aim of this article is to provide a comprehensive overview of the methods used to detect driver fatigue, drowsiness and inattention. A further objective is then to develop and process a survey that focuses on public awareness and opinions on the integration of interior cameras in vehicles across Europe.

Keywords: ADAS, driver drowsiness, driver fatigue, driver attention system, vehicle interior camera.

1. Introduction

In the last few years, traffic safety has become an increasingly popular topic in the automotive industry. The main goal of this research is to reduce the number of accidents related to driver fatigue and distraction. According to [1], from 2022, the number of fatal accidents on the roads in the United States, was 693, which is 1.6 % of all fatal accidents in that year. In Europe, the number of accidents caused by driver fatigue is around 20 % [2]. This situation increases the pressure to develop technologies to prevent those kinds of accidents from happening. This pressure is evidenced by the European Parliament regulations that require car manufacturers in Europe to incorporate these systems in their vehicles to pass the homologation.

One of the latest approaches in accident prevention is the integration of interior cameras that have the ability to monitor driver behaviour and detect early signs of fatigue, drowsiness and inattention. There are several approaches used for this detection: facial and eye movement analysis, detection of the position of the head and the rest of the body or monitoring physiological signs of fatigue such as falling heart and respiratory rates. However, it has not yet been possible to develop a system that is 100 % reliable under all operating conditions.

The introduction of interior cameras brings a lot of benefits on one hand, but they can raise questions about privacy and ethics on the other. Public awareness will play an important role in the successful implementation of these systems. In order to get a better idea of public opinion towards these technologies, a survey has been created with a focus on public awareness and views on the deployment of interior cameras in vehicles in Europe.

The aim of this article is to provide an overview of methods for detecting driver fatigue, drowsiness and inattention using an interior camera. It also focuses on the analysis of the results of a survey that maps public awareness and opinions towards these technologies. This research aims to contribute to a better understanding of how the public perceives these new technologies and to offer recommendations for the effective implementation of these technologies within the European Union.

2. Methods of monitoring the driver's state

2.1. Classification of methods to detect driver fatigue and drowsiness

Methods to detect driver fatigue and drowsiness can be divided into two categories: invasive and non-invasive. Invasive methods monitor physiological parameters and often require sensors to be in contact with the body. Examples of such methods are the EEG (electroencephalogram), which monitors brain activity, or the ECG (electrocardiogram), which monitors the electrical activity of the heart. These methods often provide more accurate information but are difficult to use and can cause discomfort to the driver. Non-invasive methods are preferred for their convenience and less intervention for the user. They can, for example, analyse facial expressions, eye movements or detect changes in driving. Methods are based on sensing using external technology such as an interior camera or sensors in the vehicle.

Another division that can be used is based on the observed parameters: behavioural, psychological and vehicle parameters. Behavioural parameters include monitoring changes in driver behaviour, changes in driving style or increased blinking frequency. Psychological parameters include tests of attention and concentration that attempt to detect cognitive decline. Vehicular parameters monitor technical aspects of the vehicle, such as distance from lanes, changes in speed or sudden course corrections.

2.2. Common methods for monitoring driver health

There are many methods used nowadays to detect driver state. In this paper, authors will focus on the most used methods and their accuracy in use.

2.2.1. PERCLOS

PERCLOS (Percentage of Eyelid Closure) is a method based on tracking the movement of eyes, specifically their closure time over a period of time. The main idea is that as fatigue increases, the frequency and total time of eye closure increases. The method analyzes how long during a certain time interval the eyelids are closed above a certain threshold. Most often, an eye is considered closed when the eyelid covers about 70–80 % of the eye. The measurement is most often made using camera systems that monitor a person's face and eyes. The following formula 1 is used to calculated PERCLOS [3].

$$\text{PERCLOS} = 100 \times \left(\frac{\text{Number of Eye Closure Events}}{\text{Total Number of Frames}}\right) \quad (1)$$

A higher percentage of PERCLOS means that the eye was closed a greater proportion of the time, indicating greater fatigue. Typically a threshold must be set which, if exceeded, indicates driver fatigue. The threshold value is usually between 20 and 40 %.

2.2.2. EAR

EAR (Eye Aspect Ratio) is an algorithm based on geometric analysis of the eyes (Figure 1). Typically, several points are tracked around the eye to determine its shape.

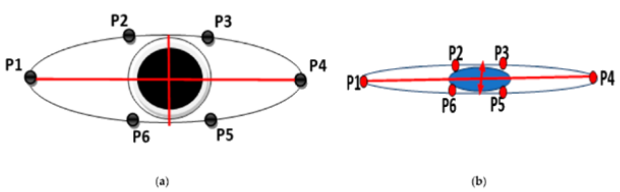

Figure 1. Facial points (P1–P6) while the eye is a) open and b) closed [4].

Points P1 and P4 determine the width of the eye, the remaining four points determine the vertical dimensions of the eye. The EAR ratio is then calculated using the following formula 2.

$$\text{EAR} = \frac{|P_2 - P_6| + |P_3 - P_5|}{2|P_1 - P_4|} \quad (2)$$

If the eye is open, the EAR reaches higher values because there is a greater distance between points P2, P3 and P5, P6. The threshold is often set to 0.2, lower values, for example for more than 0.5 seconds, indicate a closed eye. The MAR (Mouth Aspect Ratio) method works on the same principle, which monitors the driver's mouth and focuses on yawning analysis, one of the typical signs of fatigue.

2.2.3. Machine learning

Machine learning is another frequently used option for driver state recognition. The principle is a model that is trained on a set of historical datasets to determine desired states based on more complex patterns of behaviour.

General procedure for use:

(1.) Data collection: Machine learning models are dependent on quality and large amounts of data. This data can be obtained, for example, from a camera that captures a face and registers visual signs of drowsiness. It can also be various sensors that monitor heart rate, head movements or skin resistance. In general, the driver's behaviour, reaction time, accuracy and errors in performing tasks are then monitored.

(2.) Data processing: The data collected often contains noise and unnecessary information. The data therefore needs to be filtered and normalised. Then, key signs are extracted from the data, which may be, for example, head drops, eye closure, etc. This data can then be used to train the model and to test the accuracy of prediction and detection.

(3.) Model training: The model is trained on the previously mentioned processed data, where the desired states ("sleepy", "tired", ...) have already been labelled. It then uses various algorithms to partition the data, such as classifiers (Support Vector Machine or K-Nearest Neighbors) or deep learning (Neural Networks).

(4.) Prediction and detection: once the model is trained, it can be used to monitor the actual data in real time. Again, already processed data (different from the data on which the model was trained) is then used to determine the accuracy of the model, where the model results are compared to the data processing results.

2.2.4. Other methods

There are many other methods that are used to detect driver fatigue and distraction. However, they often cause discomfort (invasive methods such as EEG) or are not accurate enough compared to the methods already mentioned in this article. Still, it is a good idea to use these methods to obtain additional data that may indicate, driver fatigue. Different correlations between the signals of the different methods support the recognition of fatigue and attention. These methods can focus on heart or breathing rate, as well as depth of breathing. As driver fatigue increases, the heart rate typically decreases, breathing becomes shallow, and the breathing rate decreases. Fatigue can also be determined by monitoring facial temperature with an infrared camera, where a drop in temperature, particularly around the eyes, can indicate drowsiness and fatigue. All of these signals can be measured and may indicate fatigue or drowsiness, but their accuracy is usually not as high as it would need to be. It is therefore a good idea to use them in combination with more accurate methods and then look for correlations between the results of each method.

2.3. Accuracy of commonly used methods

In a 2012 paper [5], the authors compared several methods to determine fatigue. The experiment was conducted over several days, with test subjects being tested every two hours. Testing consisted of completing a 10-minute PVT (Psychomotor vigilance task) test, during which EEG signals, RR interval (time between consecutive heartbeats) and fatigue were measured simultaneously using the PERCLOS method. At the same time, subjects completed a questionnaire that determined their subjective feeling of fatigue on the KSS (Karolina sleepiness scale). Subjective feeling of fatigue graded around 4 to 10 a.m. In terms of accuracy of the methods, the PERCLOS method showed the best results, achieving an accuracy of around 90 %. The RR interval achieved an accuracy of around 86 % and the accuracy of the delta power EEG signal was determined to be around 82 %.

To get a better idea of the extent to which fatigue and drowsiness affect driver reaction time, in [6] the authors measured reaction time in two age groups. The first group was around 20 years old and the second around 50 years old. The difference in reaction time between the first and second groups was on average 0.04 seconds. Verbal ratings of levels of drowsiness and fatigue are shown in the Table 1.

Dimension	Level	Status of the Driver
Fatigue	Level 0	Adequate rest, short driving time, no fatigue
	Level 1	Driving for more than 2.5 hours, obvious fatigue
	Level 2	Driving for more than 4 hours, very tired
Sleepiness	Level 0	Enough sleep, good energy, very awake
	Level 1	Feel sleepy and have a certain desire to sleep and rest
	Level 2	Feel very sleepy, especially eager to sleep and rest

Table 1. A verbal evaluation of different levels of fatigue and sleepiness.

The experiment was conducted by having the system generate a random interval, after this interval a simple command (e.g., turn left, stop, or turn right) was announced to the driver, and then the reaction time was measured. In the Figures 2 and 3, a reaction time comparison of different levels of fatigue and sleepiness can be seen.

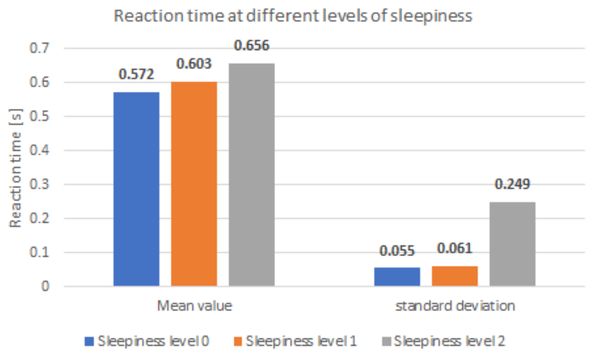

Figure 2. How sleepiness affects the driver's reaction time. Based on data published by [6].

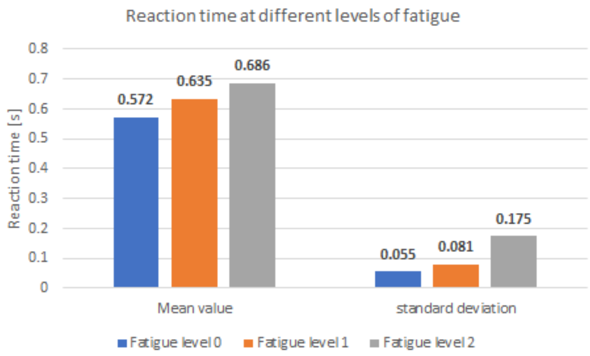

Figure 3. How fatigue affects the driver's reaction time. Based on data published by [6].

These results ideally demonstrate the effect of fatigue and drowsiness on driver reaction time.

An interesting approach to measuring fatigue is proposed in [7], where the authors detect fatigue by tracking chest movement with a camera. The first phase consisted of laboratory testing to find the optimal position for camera placement. In the second phase, they already measured the data in a driving simulator, in order to train the model to recognize fatigue. The method achieved 90 % correlation of results with measurements from a plethysmography band (used to measure changes in chest volume). During the testing the expected premises were confirmed. The loose clothing and poor lighting brought down the measurement accuracy.

The authors in [8] use EAR, MAR and hand gesture recognition to determine driver fatigue. The authors encountered a problem where the system reported a false positive when the driver put his hand to his head but did not cover his mouth (a typical reaction when yawning). They solved the problem by additionally training the model for this particular situation and thus achieved an overall yawning recognition accuracy of 92.75 %.

In [9], the authors propose a modification of the PERCLOS method, to which they added a method of image analysis, edge detection, in which the image is converted to a greal-scale image and then edge pixels are detected. By setting the tresholding of the PERCLOS method to 80 %, the proposed modification achieved more accurate results, and in addition, compared to the RGB image, it needs 1/3 memory. In the following Table 2 an overview of three states can be seen.

	Eyes Closed	Eyes Open < 50%	Eyes Open > 50%
Glasses	84.29%	72.66%	92.67%
No Glasses	86.35%	77.84%	94.36%

Table 2. Performance of PERCLOS with and without Glasses for all three stages.

The paper [10] presents the Cascaded ConvNet Framework, which achieves a success rate of 98.1 % in detecting eye conditions to determine driver fatigue, with varying image quality. 84 898 images were used to train this model. The model makes decisions based on: blink rate, maximum time for eye closure, PERCLOS, EAR, Yawning and Head pose. It uses an infrared camera as hardware.

The authors in [11], focus on the effect of contrast and lighting conditions on the accuracy of eye state determination using PERCLOS method. Their results achieved an accuracy of over 95 %.

In [12], the authors developed a method based on deep learning of face video from which they recognize PERCLOS, FOM (frequency of open mouth) and EM (eye-mouth state). Based on the recognized parameters, the model then detected fatigue with 98.3 % accuracy.

A wearable bracelet to measure fatigue that converts the results to the KSS is presented in [13]. The bracelet measures GSR (galvanic skin response) signal, drowsy level, heart rate, pulse rate variability and respiration rate. It uses a trained SVM model as a classifier to determine the fatigue level, which achieves an accuracy of 98.3 %.

Driver behavior/attention recognition is measured in a different way. Often a so-called two-stream, or a shot of the driver and the road in front of the vehicle at the same time, is used. In the driver shot, Eye-Tracking tracks where the driver is looking and then looks for correlations in what is happening on the road. An example is the work of [14], in which the authors use a neural network that recognizes vehicles, cyclists, etc. in front of a vehicle and then compares this data with data from EyeTracker. The model achieved an accuracy of 99.68 %. The authors in [15] used a similar approach. They tried to find a correlation between the data from the EyeTracker and the driving of the vehicle, for example, when looking to the left or overtaking, they monitor whether the driver is looking in the appropriate direction. The accuracy of the results (87.2 %) is reduced by the impaired camera view from the vehicle, where the side view is not properly visible.

3. Public awareness questionnaire

The questionnaire is aimed at mapping public awareness of the deployment of interior cameras in passenger cars within the EU. The main objective is to find out the public's awareness of the mandatory introduction of interior cameras, their opinion on this technology and whether they would like to have it in their vehicle. The questionnaire asks the respondent for basic information such as age, driving experience or whether they plan to buy a new vehicle in the near future in which a camera may already be implemented.

The anonymous questionnaire aimed at gauging the public's opinion on the enactment of interior cameras in passenger cars produced in the EU. The main objective was to find out what respondent's awareness and opinion on the deployment of interior cameras is.

4. Results

4.1. Summary of methods

There are methods to determine fatigue and drowsiness. There is a number of symptoms that can be measured, some of which are common and quite obvious and some of which are less well known and harder to detect. For example, those that can be detected by image recognition, such as yawning, blinking, closing the eyes or head position, can be described as common. The less easily detectable ones include a decreasing RR interval, reduced respiratory rate, reduced skin conductance or even a slightly lower body temperature.

For attention recognition, correlations are most often sought between images from cameras on the driver and on the road in front of the vehicle. Deep learning models (neural networks) are often used to detect vehicles and road events in general. These models can be very reliable, but good model training is required.

In the measurement process, the influence of elements that may have a negative impact on the accuracy of the measurement results should be minimized or, better still, eliminated altogether. Examples include the use of hardware with sufficient image quality or the preference for infrared over RGB cameras when measuring at night. From the research carried out, it appears that methods based on multiple data sources are generally more accurate and, more importantly, more robust. The Table 3 lists and ranks the methods found according to their accuracy.

Some methods achieve high accuracy, but not all of these methods directly detect fatigue levels, but focus on the correlation between subjective and objective results, which is usually simpler and less complex. Another factor that has a large impact on accuracy is the influence of the environment. There is a huge difference between measuring in laboratory “ideal” conditions versus measuring in real-world conditions.

Method	Accuracy	Measurement Target	Source
EyeTracking, Neural Network	99.68 %	Two-stream, finding correlations between the driver and the road	[14]
Deep learning – Perclos, FOM, EM	98.3 %	Recognising fatigue with deep learning	[12]
SVM	98.3 %	Measuring fatigue on the KSS scale using a wearable bracelet	[13]
Cascaded Network Framework	98.1 %	Eye condition detection with different image quality	[10]
Perclos	95 %	Effect of contrast and lighting conditions on eye condition detection	[11]
Perclos, Edge detection	72.66–94.36 %	Recognition of three eye conditions for people with and without glasses	[9]
EAR, MAR, hand gestures	92.75 %	Recognition of yawning even if the hand is in front of the face	[8]
Perclos	90 %	Correlation with the PVT and the subjective fatigue questionnaire	[5]
Monitoring of respiration rate	90 %	Camera tracking of chest movement – correlation with plethysmography band results	[7]
RR interval	86 %	Correlation with the PVT and the subjective fatigue questionnaire	[5]
EyeTracking, monitoring of vehicle parameters	87.2 %	Finding the correlation between EyeTracking and driving (e.g. turning)	[15]
Response time monitoring	–	Monitoring the effect of fatigue and drowsiness on driver reaction time	[6]

Table 3. Methods and their accuracies expressed as a percentage in measuring fatigue.

4.2. Results of the questionnaire

The questionnaire got answers from 108 respondents, with a distribution of 46 women and 62 men. Figure 4 shows the gender division of respondents. 53 % of respondents belong into the age group 18–27, the second most populated group is 28–37 years old. Figure 5 shows the representation of age groups.

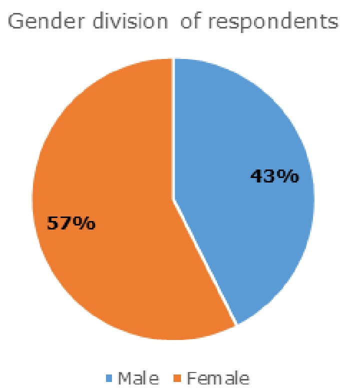

Figure 4. Gender division of participants.

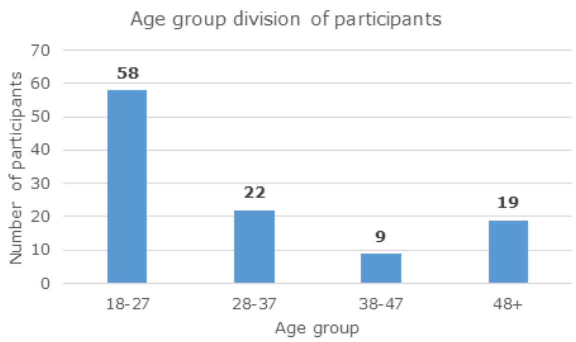

Figure 5. The strongest represented age group of respondents is 18–27.

Important experience indicator in drivers is their annual kilometres driven. Contrary to expectations that come form the age group division (Figure 5), most respondents replied, that their annual mileage is more than 10 000 kilometres. Annual kilometres driven overview can be found in the Figure 6.

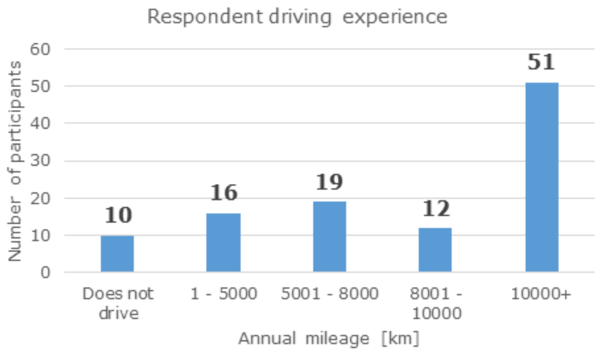

Figure 6. Majority of respondents drive more than 10 000 km annually.

When looking at Figure 7, one can see that 55 % of the respondents knew about interior camera prior to the questionnaire. When asked about the source of the information, most of them stated that they got their information on the internet (Figure 8).

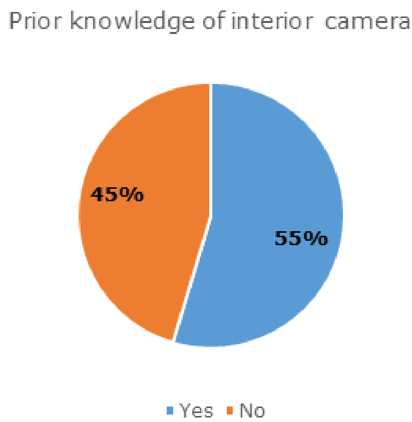

Figure 7. More than half of the respondents had some prior knowledge about the interior camera.

The vehicle age could indicate whether the respondent is planning on buying a new vehicle, 51 % indicated that their vehicle is older than 8 years (Figure 9). The new vehicle, will be most probably equipped with the interior camera. In relation to this question, respondents were asked whether the presence of the

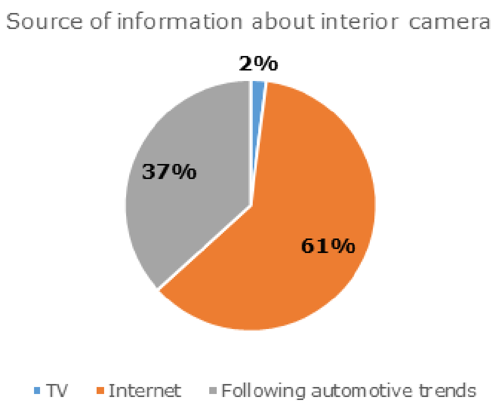

Figure 8. Source of information about the interior camera.

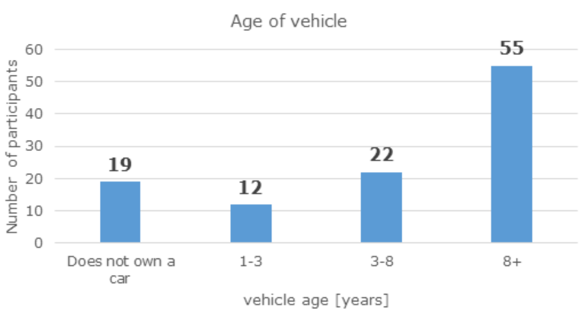

Figure 9. Almost a half of respondents have a car that is 8 years or older.

interior camera would affect their choice. As Figure 10 depicts, only 8 % of respondents said, that they would have not any problem with the presence of interior camera. The rest of the respondents said they would rather buy an old car instead or the presence of interior camera would not be a factor when choosing a new vehicle.

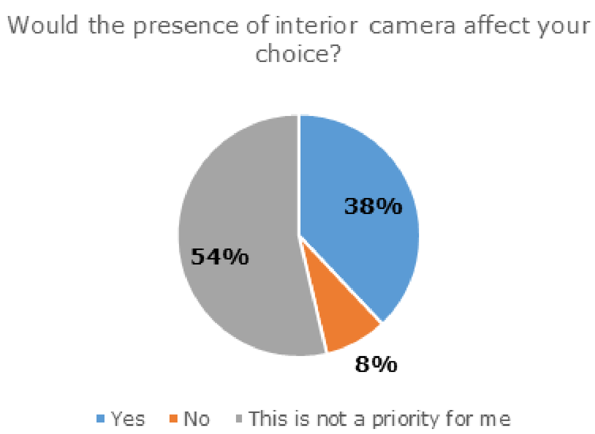

Figure 10. The presence of interior camera would make a significant factor for 46 % of respondents when picking a new car.

Along with the increased safety on the road while using interior camera, the question of one's privacy comes to mind. The respondents were asked to rate on a scale from one to ten, whether they felt their privacy would be invaded. Figure 11 shows respondents' rating of privacy risks when interior camera is installed.

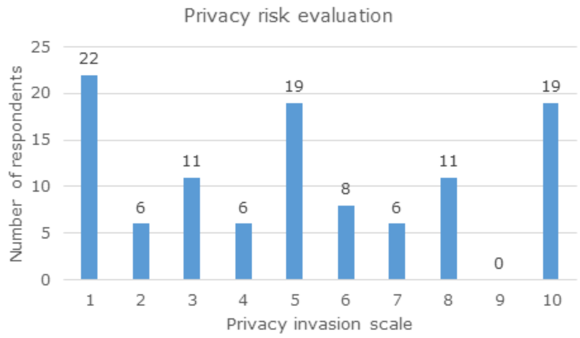

Figure 11. Number 1 on the scale suggests the respondents find interior camera as an invasion of privacy while number 10 suggests the opposite.

Respondents were also asked to evaluate on scale from 1 to 10 the increase of their safety they fell would interior camera deliver. Figure 12 depicts the respondents' answers to this question.

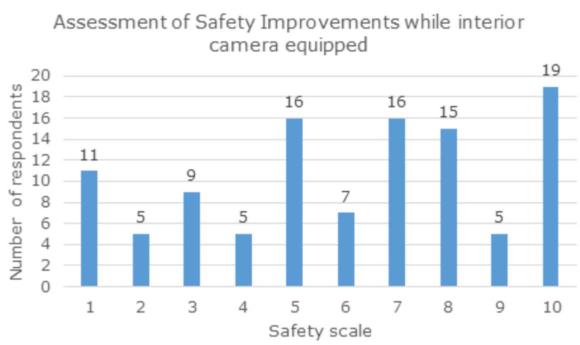

Figure 12. Number 1 on the scale suggests the respondents believe there would be no increase in their safety when interior camera is installed, number 10 suggests otherwise.

5. Conclusion

The results of the research suggest that more data sources are needed to be used in moving towards the development of methods for the recognition of fatigue, sleepiness and attention. The method then becomes more accurate and robust when applied. When selecting data sources, the compactness of each measurement method needs to be considered so that the correlations sought between them are as unambiguous as possible.

The questionnaire received responses from 108 respondents, with a mix of 42.6 % female and 57.4 % male across all age groups. When asked about their driving experience, almost half of the respondents reported driving more than 10 000 kilometres per year.

This pool of respondents, with a majority of experienced drivers, provided a unique insight into the opinion on an interior camera. When asked about drivers' privacy and security concerns, the average privacy risk rating was 5.13 out of 10, where 10 means respondents were not at all concerned about privacy intrusion. Regarding the increase of security of passengers while using the interior camera the average rating was 6.1 out of 10 where 10 means the respondents felt that interior camera would greatly increase their safety while driving. The final part of this questionnaire was aimed at those who were likely to buy a new car soon. The main question was whether the presence of an interior camera would influence respondents' choice of vehicle. Most respondents said that the presence of an interior camera would not be a priority when choosing a new car, while 38 % said that the presence of the camera would bother them and that they would rather choose an older car without this feature. Only 8 % of respondents said they would not mind having an interior camera in their new car.

Although the majority part of respondents knew about the interior camera prior to this questionnaire, the overall level of information seems to be only scratching the surface. In order to prevent some misinformation about the data privacy, which seems to be the biggest issue with the respondents, the car manufacturers ought to spread the information among customers with advertising campaigns or through social media. The lack of this information can lead to a negative view on the technology.

The next step in this topic could be to develop a method to recognize desired states and test it in both laboratory and real-world conditions. Regarding public awareness, the next approach could be to create another questionnaire for the public, but this time focusing on the interest and opinion about the different features of the system that will be implemented in the vehicles.

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