Novel Adaptive Detection Approach for Monitoring Drivers' Eye Movement During Vehicle Movement

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Abstract*-The increase in vehicle accidents due to the driver drowsiness over the last years highlights the need for developing reliable drowsiness assistant systems by a reference drowsiness measure. Therefore, the paper at hand is aimed at classifying the driver vigilance state based on eye movements using electrooculography (EOG). In order to give an insight into the states of driving, which lead to critical safety situations, first, driver drowsiness, distraction and different terminologies in this context are described. Afterwards, countermeasures as techniques for keeping a driver awake and consequently preventing car crashes are reviewed. Since countermeasures do not have a long-lasting effect on the driver vigilance, intelligent driver drowsiness detection systems are needed. Driver state is quantifiable by objective and subjective measures. The objective measures monitor the driver either directly or indirectly. For indirect monitoring of the driver, one uses the driving performance measures such as the lane keeping behavior or steering wheel movements. On the contrary, direct monitoring mainly comprises the driver's physiological measures such as the brain activities, heart rate and eye movements. In order to assess these objective measures, subjective measures such as self-rating scores are required. This study introduces these measures and discusses the concerns about their interpretation and reliability. EOG as a tool to measure the driver eye movements allows us to distinguish between drowsiness- or distraction-related and driving situation dependent eye movements. In order to cover all relevant eye movement patterns during awake and drowsy driving, different experiments are conducted in this work including daytime and nighttime experiments under real road and simulated driving conditions. Based on the measured signals in the experiments, investigate the conventional blink detection method based on the median filtering and show its drawback in detecting slow blinks and saccades. Afterwards, an adaptive detection approach is proposed based on the derivative of the EOG signal to simultaneously detect not only the eye blinks, but also other driving-relevant eye movements such as saccades and microsleep events. Finally, feature dimension reduction approaches to determine the applicability of extracted features for in-vehicle warning systems. On this account, filter and wrapper approaches are introduced and compared with each other. Our comparison results show that wrapper approaches outperform the filter-based methods.

Keywords - Electrooculography, Driving, Eye Movement, k-NN classifier, Support Vector Machine, ANN Classifier.

1. INTRODUCTION

The states of driving, which lead to critical safety situations, have been described and distinguished by a variety of terminologies such as distraction, inattention, fatigue, exhaustion, sleepiness, and drowsiness. In addition, the proper states of driving are also referred to as awareness, vigilance and alertness. This Paper introduces driver drowsiness detection systems available on the market by car companies and explains the idea behind their detection methods based on the review provided by Colic et al. (2014).

Mercedes-Benz In 2009, Daimler AG introduced the *Attention Assist* to warn drowsy drivers. This system is mainly based on steering wheel movements and their velocities (Daimler AG, 2008). The idea behind the Attention Assist is that an alert driver steers with small corrections

Regan et al. (2011) suggested distinguishing between driver distraction and driver inattention for a better comparison of research findings. Oxford dictionary (Oxford, 2014) defines distraction as *"a thing that prevents someone from concentrating on something else"*.

Regan et al. (2011) also summarized following points for defining distraction in the driving context:

- “There is a diversion of attention away from driving or safe driving.”
- *“*Attention is diverted toward a competing activity, inside or outside the vehicle, which may or may not be driving-related.”
- “The competing activity may compel or induce the driver to divert attention toward it.”
- “There is an implicit, or explicit, assumption that safe driving is adversely effected.”

On the other hand, is defined as *“lack of attention; failure to attend to one’s responsibilities; negligence”*(Oxford, 2014). Hoel et al. (2010) categorized attentional dysfunction as: *“inattention, attentional competition and distraction”.* Similar to distraction, inattentive situations also involve the interference in the driving task. Thus, inattention in terms of the driving task occurs, while performing a secondary non-driving-related task such as text messaging. On the contrary, Hoel et al. (2010) linked distraction to *personal concerns* like daydreaming. Finally, performing secondary driving-related tasks in addition to the primary driving task is considered as attentional competition (e.g. driving and navigating). Unlike Hoel et al. (2010), Wallen Warner et al. (2008) (as cited by Regan et al., 2011) decomposed inattention as:

- *“*driving-related distractors inside vehicle”: *e.g. navigation system*
- “driving-related distractors outside vehicle”: *e.g. road signs*
- “non driving-related distractors inside vehicle”: *e.g. speaking to a passenger*
- “non driving-related distractors outside vehicle”: *e.g. a passenger on the pavement*
- “thoughts/daydreaming”: e.g. personal problems.

This work targets the full coverage of requirements to be fulfilled during the development of the camera and the warning system for timely detection of the onset of drowsiness. Therefore, studying, implementation and evaluation of drowsiness-related eye movement features are on the central focus. To this account, well-known methods for event detection, feature extraction and classification need to be investigated along with providing new ideas and approaches. These goals can be achieved by designing daytime and night time experiments with representative driving scenarios.

In the following, the main contributions of this thesis towards driver drowsiness detection are summarized.

- Based on a thorough literature review on the terminologies related to drowsiness, a suitable term among many terminologies e.g. fatigue, sleepiness, etc. is targeted which best describes the driver state during driving.
- A new approach for enhancing the calculation of the alpha spindle rate is suggested and evaluated against the initial calculation method. This idea benefits from the fusion of eye movement activity information into the calculation of the alpha spindle rate.
- Most of the previous studies collected eye movement data with the eye movement measurement system used in this work (electrooculography) in laboratories or in fixed-base driving simulators. However, in this work, the reliability and robustness of this system.
- The results and findings of this thesis are evaluated based on different experiments on both real roads and driving simulators with a total number of 43 subjects. Moreover, by designing both daytime and nighttime experiments, the collected data set contained all vigilance levels during driving
- In an experiment on the real road, where secondary tasks have been performed along with the primary driving task, eye blink behavior is analyzed. Based on the findings, a recommendation about task-induced blinks is made.
- For the detection of blink and distinguishing them from other eye movements, two novel algorithms are proposed. The first algorithm is based on derivative signal and is suitable for detection of fast eye movements. The seconds approach is based on continuous wavelet transform and covers the detection of both fast and slow eye movements. Therefore, in contrast to other studies, this work addresses the detection of all relevant eye movements to drowsiness.
- This work is the most comprehensive study on eye blink features for in-vehicle applications and under real driving conditions. By considering all inconsistent definitions of features in previous studies, 19 features are well-defined and extracted per blink. Afterwards, their evolution due to drowsiness is studied individually.

2. DRIVER STATE MEASUREMENT

Driver objective measures, as their name implies, are measures which are collected by a measurement technique such as sensors, electrodes, etc. with no deliberate interference of the driver in them. An objective measure is developed based on either driving performance measures, driver physiological measures or their fusion which is called hybrid measures.

2.1. *Driving Performance Measures*

Colic et al. (2014) summarized car crashes due to drowsy driving with the following characteristics which were based on reports by the police or the driver himself:

- "*Higher speed with little or no breaking*" which means the combination of high speed with low reaction time due to drowsiness.
- "A vehicle leaves the roadway" *which is also called* single-vehicle crash *due to lane departure.*
- " *The crash occurs on a high-speed road*" which might be due to monotonicity of such roads.
- " *The driver does not attempt to avoid crashing*" which is the result of severe drowsiness and falling asleep.
- *"* The driver is alone in the vehicle".

The common point in these characteristics is that they all lead to degraded driving performance. As a result, by quantifying them by means of sensors installed in the car, it is possible to develop a drowsiness indicator measure to prevent car crashes. These measures are called driving performance measures.

Another very common method for an indirect observation of the driver is the analysis of steering wheel movements in terms of amplitude and velocity i.e Driver's lane keeping behavior, Driver physiological measures, in general, are measures based on the direct observation of the driver which can be either intrusive like *electrophysiological* ones or non-intrusive like cameras. Unlike the latter, the former requires a direct contact of the electrodes to the driver's skin.-Driver's steering wheel movement behavior, Driver physiological measures

2.2. *Subjective Estimation of the Drowsiness*

Subjective estimation of the drowsiness, as its name says, is based on the rating of subjects about their vigilance or drowsiness level before, during and at the end of the experiment. This estimation can be done either by the subject himself or by an investigator.

2.3. Human Visual System and Attention

The material in this section is taken from Duchowski (2007). He explained visual attention based on *"where"* and *"what*". The idea of "where" defines visual attention as roaming eyes in the space (von Helmholtz, 1925). On the contrary, with the definition of James (1981), visual attention means *"focus of attention",* i.e. "what". At the first glance, these two ideas seem to be independent. However, they support each other in a way that visual attention is only understandable, if both definitions are considered. The idea of "where" occurs *parafoveally* which means, at first, something roughly attracts our attention as a whole in the entire visual field. It is similar to a low resolution image. Then, the idea of "what" leads to the collection of more detailed information through the *foveal* visioni. In fact, during the second step, the image will be perceived as a high resolution image.

3. DRIVER STATE DETECTION BY MACHINE LEARNING METHODS

Artificial Neural Network (ANN), Support Vector Machine (SVM) and K-nearest neighbors are the sophisticated classifiers used here. In order to evaluate the classification results, different metrics are also introduced. In addition, we consider different data division approaches to study the generalization aspects of the classifiers

3.1. Supervised classification

Supervised classification is defined as a classification problem with available information about class membership for each sample in the feature matrix. In our work, the KSS inputs collected during the experiments are the class labels. Therefore, for each sample N of the feature matrix F, namely R^D, there exists a corresponding discrete-valued class label C_n. The total data set S is then expressed as follows

$$S = j(X_1, C_1), (X_2, C_2), \dots \dots (X_N, C_N) \quad (1)$$

The task of supervised classification begins with the division of the data set into two sets called *training* and *test* sets. Based on the features and the corresponding classes belonging to the training set $S_{tra}i_n$, the classifier is trained by learning rules. Afterwards, the rules will be applied to the features of the test set $S_{tes}t$, which is unknown to the classifier, in order to estimate the class of its samples. Finally, the performance of the classifier is evaluated by comparing the estimated class C with the true class c of each sample.

3.2. Artificial neural network classifier

Inspired by the human nervous system and more specific the human brain, which is capable not only to learn and to generalize rules, but also to perform parallel tasks, the A*rtificial Neural Network* (ANN) also consists of elements called *neurons.* As a machine learning method, it is also capable to perform similar tasks. The first mathematical model of a simple neuron was originally introduced by McCulloch and Pitts in 1943 (McCulloch and Pitts, 1943). Eskandarian et al.(2007) and Friedrichs and Yang (2010a) also used this classifier for driver state classification.
Another variant of the network architecture discussed in Duda et al. (2012) is the *recurrent* or *feed-back* network.

3.3. Classification results of subject-dependent data sets

The classification results based on the ANN classifier for the subject- dependent data division. Moreover, results of different classification issues such as feature aggregation types and imbalanced data sets are discussed. Here, applied a feed-forward ANN classifier with scaled conjugate gradient back-propagation algorithm for adjusting the weights in one hidden layer for hidden and output layer.

4. CLASSIFICATION RESULTS OF SUBJECT-DEPENDENT DATA SETS

Results of different classification issues such as feature aggregation types and imbalanced data sets are discussed. Here, applied a feed-forward ANN classifier with scaled conjugate gradient back-propagation algorithm for adjusting the weights in one hidden layer.

4.1. Comparison of the supervised classifiers for driver state classification

Review them in terms of different aspects such as the performance, subject-dependent versus subject-independent classification, simulation runtime, etc.
Regarding subject-independent classification, the performance of all classifiers degrade as expected. The *k*-NN method also seems not to be a suitable classifier for a data set with large between subject differences due to its poorer performance in the classification of the drowsy class. The ANN and SVM classifiers interpret the features in a similar way in this case. Nevertheless, a more effective feature baselining method might improve the results of subject-independent classification.

4.2. Features of the driving simulator versus real road driving

As mentioned before, due to safety concerns, driving simulators are required for data collection with higher drowsy-related characteristics. However, this makes the collected data less applicable for the comparison with real driving conditions. In this context, Hallvig et al. (2013) reported longer blink duration in the driving simulator compared to real driving and believes that due to safety aspects of driving simulators higher level of drowsiness is generally achieved in them. Philip et al. (2005), who also compared real driving with driving in simulators, reported slower reaction time and higher KSS values in the driving simulator. Therefore, all good classification results based on driving simulator data might suffer from the fact that very deep phases of drowsiness are included in the data set which sharpens the discrimination of classes. In general, under real driving conditions, drowsiness should be detected at a time that the warning of the corresponding assistance system can still be perceived by the driver for a timely correcting reaction.
To address the mentioned issues, two approaches are considered here. The first approach generalizes the driving simulator to real driving conditions by discarding very drowsy parts of the drives. Unlike the first approach, the second approach uses all valuable features collected in both driving simulator and under real driving conditions to investigate whether unseen drowsy data collected under real driving conditions can be classified correctly.

5. CONCLUSION

Considering the results of the GSRD approach provided by all classifiers for the subject-dependent data division, removing samples from the very drowsy parts of the drive degrades the performance of the classifiers. Nevertheless, it is still possible to correctly detect both classes over 70%. An interesting finding is that regardless of the data division type, namely subject-dependent versus subject-independent, the removed drowsy samples are crucial not only for the correct classification of the drowsy samples, but also for the correct classification of the awake samples. The DR value of the drowsy class by the subject-independent k-NN classifier, as an example, varies only 2% (57.4% vs. 55.1%), while for the awake class, it drops by about 15% (80% vs. 65.7%). Finally, we discussed approaches for feature dimension reduction in order to address the issues of an in-vehicle warning system. According to the SFFS method fused with the ANN classifier, four features were determined to be sufficient. The trained ANN classifier, however, did not perform as good as a classifier trained with all 19 features in the detection of the drowsy class. As a result, we conclude that for the correct detection of the drowsy class, which seems overall to be more challenging, more than four features are needed.

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