Driver sleepiness detection in real driving situations, a pre-study

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FFI Trafiksäkerhet och automatiserade fordon

FFI Fordonsstrategisk Forskning och Innovation
VINNOVA Energimyndigheten TRAFIKVERKET FKG VOLVO SCANIA VOLVO

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1 Sammanfattning

Förartrötthet har fått ökad uppmärksamhet under de senaste åren och anses vara en viktig orsak till ca 15-30% av alla trafikolyckor. Ett sätt att upptäcka sömnighet är med hjälp av fysiologiska mätningar. Av den anledningen är hjärtfrekvensvariabilitet (HRV) och dess relation till förares sömnighet i fokus i denna studie, där förhållandet mellan hjärtfrekvensvariation och förares sömnighet har studerats. Baserat på denna studie och med hjälp av maskinlärande metoder har en algoritm för att identifiera förarens sömnighet utvecklats. Denna algoritm baseras på en klassificerare som har förmåga att diskriminera mellan vaken och sömnig förare. Studien genomfördes i en grupp på 80 förare som kör på en offentlig motorväg 3 gånger om dagen - morgon, eftermiddag och kväll. Subjektiv sömnighet utvärderas var 5:e minut, vilket leder till över 3500 epoker att analysera. Innan beräkning av HRV index, görs ´outlier detection´ på hjärtats slag-till slag variation (interbeat intervall; IBI) genom ett godtyckligt val. För HRV indexen i frekvensplanet, representerar spektral omvandling ett godtyckligt andrahandsval. Alla potentiellt lämpliga metoder testades för att utvärdera att val av metod inte skulle ha en betydande inverkan. Slutlig ´outlier detection´ baserades på att IBI skiljer sig med mer än 30% från medelvärdet av de fyra föregående intervallerna, och spektrala omvandlingen baserades på fouriertransform. Som klassificerare användes en stödvektormaskin (SVM) med radiell kärna. Algoritmen för detektion av förares sömnighet uppnådde en mycket hög noggrannhet på tio gånger kors-validering. Prestanda, mätt som ´area under kurvan´ (AUC) hos ROC (receiving operating characteristic) var över 0,93.

2 Executive summary

Driver fatigue has received increased attention during recent years and it is now considered to be a major contributor to approximately 15-30% of all crashes. One way to detect sleepiness is with help of physiological measurements. For that reason heart rate variability (HRV) and its relation to drivers´ sleepiness is in focus of this study.

The relationship between heart rate variability and drivers´ sleepiness have been studied. Based on this study and using machine learning methods an algorithm to detect driver sleepiness was developed. This algorithm was based on a classifier that discriminate between alert and sleepy driver. The study, was conducted on a population of 80 drivers driving on a public motorway 3 times a day -morning, afternoon and night, with subjective sleepiness evaluations every 5 minutes, leading to over 3500 epochs.

Prior to deriving HRV indices, outlier detection on the heart interbeat intervals (IBI) signal constitute an arbitrary choice. For the HRV indices in the frequency domain, spectral transformation represent a second arbitrary choice. All potentially suitable methods were tested determining that the methods of choice would

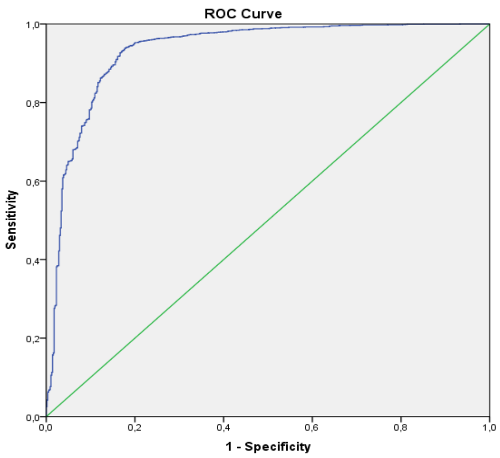

Figure 1 Best classifier, AUC>0.93

not have a significant impact. Finally outliers' detection was based on a heart IBI differing in more than 30% from the mean value of the four previous intervals and spectral transformation was based on the Fourier transform.

As classifier, a support vector machine with radial kernel was used. The best classifier was achieved using 12 HRV indices, time of the day and time driving, the parameter for adjustment γ was fixed to 1. The performance measured as area under the receiving operating characteristic (ROC) curve (AUC) was over 0.93, see ROC in Figure 1. Examples of Sensitivity and Specificity at certain costs are, Sensitivity=95% & Specificity=80%, Sensitivity=99% & Specificity=50%, or Specificity=90% & Sensitivity=78%, Specificity=97% & Sensitivity=50%.

The algorithm achieved in this project together with unobtrusive accurate HR detection are the two necessary pieces for implementing a driver sleepiness detection system based on physiological measurements.

3 Background

Driver fatigue is one of the main contributing factors to road crashes (Connor et al 2002; Horne & Reyner 1995). Nevertheless incidence of fatigue on vehicle crashes and injuries vary depending on the characteristics of each study. In US, NHTSA (US National Highway Traffic Safety Administration) has estimated Drowsy driving in 2013 caused about 72,000 crashes, 800 fatalities and 44,000 injuries (NHTSA 2015). In EU, driver fatigue accounts for 20-35% of serious accidents depending on the study (Herman et al. 2013; Williamson et al. 2011; Klauer et al 2006; Connor et al. 2002; Horne & Reyner 1995). Major contributing factors to driver fatigue are sleep loss, being awake for too long, and driving under circadian low. Furthermore, driving at night as well as low speeds and long driving tasks was proven to increase driver fatigue (Åkerstedt 2008). Finally, high risk groups for driver fatigue are for example young drivers and professional shift workers (Filtness et al 2012).

There are different attempts to measure driver sleepiness and they might be categorized into physiological-, vehicle- or behavioral based measurements. Whereas they have all pros and cons, it has been argued that physiological measurements start changing at the earliest stage of sleepiness (Sahayadhas et al 2013; Barr et al., 2009). This observation speaks in favor of physiological measurements because early detection is crucial for crash avoidance (Evans et al 1995). Moreover, driver behavior alone may underestimate the loss of ability to respond to sudden risks (Lal and Craig 2001).

Physiological measures of driver sleepiness includes normally EEG, EOG or ECG among others. Based on those measurements different indicators are calculated. EEG is most often consider to be the golden standard, at least in laboratory settings and simulators (Anund et al 2008). ECG based indicators based on HRV analysis have been used for detection of driver sleepiness (Patel et al 2011; Sato et al 2001; Atsumi 1995). Finally, the recent advances of smart textiles and contactless sensors enable unobtrusive HR detection, what motivate increased efforts to detect drivers' sleepiness using HRV.

4 Purpose, issues and method

The project has been the collaboration between Chalmers University of Technology, Autoliv and VTI in the frame of the SAFER center for traffic safety research; more specifically in the Pre-crash reference group. Apart from that, this project is the first one resulting from the youngest competence area in SAFER, i.e. Human Monitoring.

Two steps were clearly differentiable; firstly a study to choose outlier detection and spectral transformation methods in which strength of association between individual HRV indices and driver sleepiness was also pointed out. In a second step the sleepiness detection algorithm was developed.

5 Objective

The purpose stated on the application was:

The objective of this project is to investigate the relationship between physiological signals that potentially can be contactless measured in real driving situations, i.e. HR, HRV and RR, and driver sleepiness. The relationship will be used to develop algorithms to detect driver sleepiness.

And the fulfilled goals are:

The relationship between heart rate variability and drivers´ sleepiness have been studied. Based on this study and using machine learning methods a classifier that discriminate between awake and sleepy driver have been achieved. This classifier achieve a very good performance.

6 Results and goals fulfillment

The results of the first step are statistical tests and Bland-Altman plots in order to evaluate agreement between outlier detection and spectral transformation methods as well as their suitability for drivers' sleepiness detection. Those results lead to the following conclusions.

- *Outlier detection methods are not interchangeable.*
- *Spectral transformation methods are not interchangeable.*
- *No method showed superiority for HRV association to driver sleepiness. This is also true for combinations of methods in the case of frequency domain indices.*

Regarding the classifier, its performance dependency on the Gamma factor of the radial kernel was evaluated. Gamma (γ) is an adjusting parameter to regulate the compromise between overfitting and under –fitting. Figure 2 shows the ROCs of the classifier using different values of γ followed by a table showing corresponding AUCs values. It can be appreciated that γ=1 offer the highest performance.

Finally, Figure 3 and subsequent table show how both, HRV indices and time of the day + time driving, achieve high performance separately. Nevertheless their combination outperform both individual sets of features.

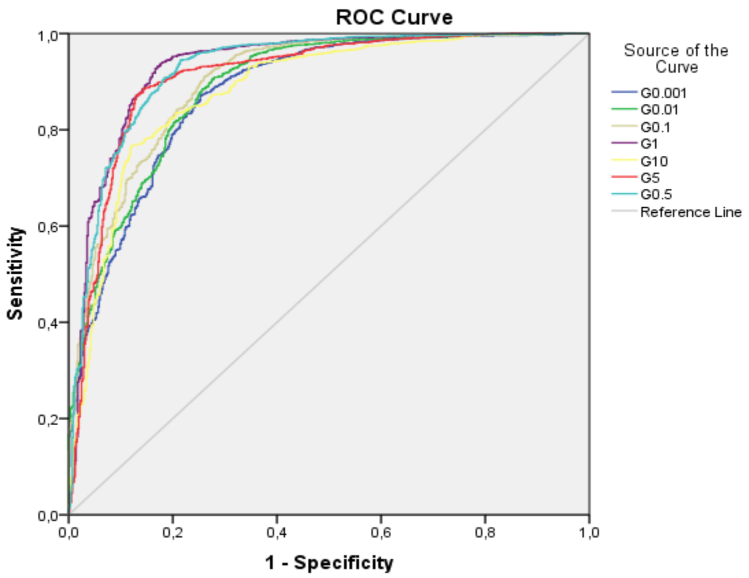

Figure 2 Classifier using a wide range of Gammas.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval Lower Bound	Upper Bound
G0.001	,878	,008	,000	,861	,895
G0.01	,889	,008	,000	,873	,905
G0.1	,903	,008	,000	,888	,917
G1	**,932**	**,007**	**,000**	**,919**	**,946**
G10	,883	,008	,000	,866	,899
G5	,912	,008	,000	,896	,927
G0.5	,928	,007	,000	,914	,941

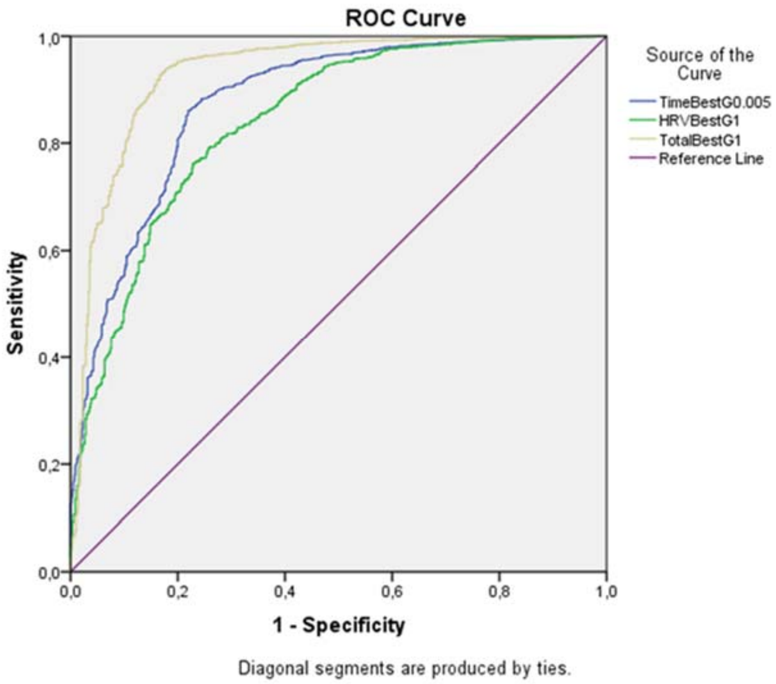

Figure 2 Best models Comparison

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval Lower Bound	Upper Bound
Time only	**,876**	,009	,000	,859	,893
HRV Only	**,841**	,010	,000	,822	,860
Combination	**,932**	,007	,000	,919	,946

The sub-program has two specific objectives, technology development with the potential to account for a third of the reduction in the number of traffic fatalities and the Swedish automotive companies remain world leader in the development of safe vehicles. This project suit perfectly both specific goals as driver sleepiness accounts for 20-35% of serious accidents (Hell et al., 1997, Horne and Reyner, 2000, Sagberg, 1999) in EU and its detection could prevent many of these fatalities.

Traffic safety analysis as well as driver support are the sub-program research fields that are most relevant to the project. Besides it relates to the sub-program road map in the stage of “supporting and protective vehicle” and more specifically in the “alert the driver” part.

7 Dissemination and publications

The results of this project motivate increased efforts towards unobtrusive vitals monitoring. The way to a commercial drivers’ sleepiness detection system based on vital signs might result in multiple high impact publications.

7.1 Knowledge and results dissemination

How has / planned project results will be used and disseminated?	Marx with X	Comments
Increase knowledge in the field	X	The relation between driver sleepiness and HRV have been under study for over 30 years. However this is the first time that a high performance prediction algorithm is developed.
Passed on to other advanced technological development	X	A project to achieve non-obtrusive vitals monitoring is needed. Afterwards combining the results achieved in this project and non-obtrusive vitals monitoring a project to develop a driver sleepiness detection system based on physiological measurements will be highly feasible.
Passed on to product development projects		
Introduced on the market		
Used in investigations / regulatory / licensing / political decisions		

7.2 Publications

So far the Master Thesis of Fabio Forcolin have been published as a Chalmers master thesis in the department of signal and systems. Moreover VINNOVA reports have been produced.
Regarding scientific publications one journal article is in proof reading phase prior submission probably to the *European Journal of Applied Physiology*. Moreover a second journal article probably targeting the journal *Sleep* is being drafted. Due to the short duration of the project, scientific publications will be finalized after the project final date.

8 Conclusions and future research

A classifier that accurately discriminate between alert and sleepy driver have been achieved.
As future work an analysis of the misclassifications as well as a usability study need to be performed.
Furthermore, as there are several suitable machine learning algorithms available other that SVMs, logistic regression, artificial neural networks and tree based methods could be approached in case any of them outperform SVM algorithms.

9 Participating parties and contact person

Chalmers contact person is Ruben Buendia
Autoliv Contact person is Cecilia Sunnevång
VTI contact person is Anna Anund

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