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Citation for the original published paper (version of record):
Buendia, R., Forcolin, F., Karlsson, J. et al (2019). Deriving heart rate variability indices from cardiac monitoring—An indicator of driver
sleepiness. Traffic Injury Prevention, 20(3): 249-254.
http://dx.doi.org/10.1080/15389588.2018.1548766

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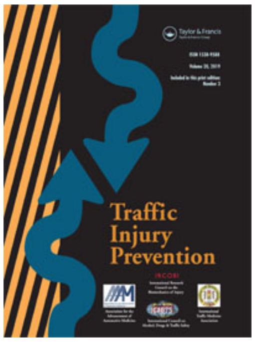

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Traffic Injury Prevention

ISSN: 1538-9588 (Print) 1538-957X (Online) Journal homepage: https://www.tandfonline.com/loi/gcpi20

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To cite this article: Ruben Buendia, Fabio Forcolin, Johan Karlsson, Bengt Arne Sjöqvist, Anna Anund & Stefan Candefjord (2019) Deriving heart rate variability indices from cardiac monitoring—An indicator of driver sleepiness, Traffic Injury Prevention, 20:3, 249-254, DOI: 10.1080/15389588.2018.1548766

To link to this article: https://doi.org/10.1080/15389588.2018.1548766

TRAFFIC INJURY PREVENTION
2019, VOL. 20, NO. 3, 249–254
https://doi.org/10.1080/15389588.2018.1548766

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Deriving heart rate variability indices from cardiac monitoring—An indicator of driver sleepiness

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ABSTRACT

Objective: Driver fatigue is considered to be a major contributor to road traffic crashes. Cardiac monitoring and heart rate variability (HRV) analysis is a candidate method for early and accurate detection of driver sleepiness. This study has 2 objectives: to evaluate the (1) suitability of different preprocessing strategies for detecting and removing outlier heartbeats and spectral transformation of HRV signals and their impact of driver sleepiness assessment and (2) relation between common HRV indices and subjective sleepiness reported by a large number of drivers in real driving situations, for the first time.
Methods: The study analyzed >3,500 5-min driving epochs from 76 drivers on a public motorway in Sweden. The electrocardiograph (ECG) data were recorded in 3 studies designed to evaluate the physiological differences between awake and sleepy drivers. The drivers reported their perceived level of sleepiness according to the Karolinska Sleepiness Scale (KSS) every 5 min. Two standard methods were used for identifying outlier heartbeats: (1) percentage change (PC), where outliers were defined as interbeat intervals deviating >30% from the mean of the four previous intervals and (2) standard deviation (SD), where outliers were defined as interbeat interval deviating >4 SD from the mean interval duration in the current epoch. Three standard methods were used for spectral transformation, which is needed for deriving HRV indices in the frequency domain: (1) Fourier transform; (2) autoregressive model; and (3) Lomb-Scargle periodogram. Different preprocessing strategies were compared regarding their impact on derivation of common HRV indices and their relation to KSS data distribution, using box plots and statistical tests such as analysis of variance (ANOVA) and Student's *t* test.
Results: The ability of HRV indices to discriminate between alert and sleepy drivers does not differ significantly depending on which outlier detection and spectral transformation methods are used. As expected, with increasing sleepiness, the heart rate decreased, whereas heart rate variability overall increased. Furthermore, HRV parameters representing the parasympathetic branch of the autonomous nervous system increased. An unexpected finding was that parameters representing the sympathetic branch of the autonomous nervous system also increased with increasing KSS level. We hypothesize that this increment was due to stress induced by trying to avoid an incident, because the drivers were in real driving situations.
Conclusions: The association of HRV indices to KSS did not depend on the preprocessing strategy. No preprocessing method showed superiority for HRV association to driver sleepiness. This was also true for combinations of methods for frequency domain HRV indices. The results prove clear relationships between HRV indices and perceived sleepiness. Thus, HRV analysis shows promise for driver sleepiness detection.

ARTICLE HISTORY
Received 17 April 2018
Accepted 12 November 2018

KEYWORDS
Heart rate variability; driver sleepiness; outlier detection; spectral transformation

Introduction

Driver sleepiness is a major factor contributing to road crashes (Connor et al. 2002; Horne and Reyner 1995). There is a need for countermeasures to reduce the number of crashes caused by driver fatigue (Abe et al. 2010). This study focuses on physiological measurements for detecting sleepiness, more specifically on the relation between heart rate variability (HRV) and driver sleepiness. HRV is the physiological phenomenon of the beat-to-beat temporal variation of the heart. HRV indices are derived from the heart interbeat interval (IBI) signal (Forcolin et al. 2018).

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Buendia and Forcolin are co-first authors.
Associate Editor Matthew R. Maltese oversaw the review of this article.
Supplemental material for this article can be accessed on the publisher's website.

Different approaches to measure driver sleepiness can be classified as physiological-, vehicle-, or behavioral-based measurements. In Sahayadhas et al. (2012) and Barr et al. (2009), physiological measurements were reported to start changing at an earlier stage of sleepiness compared to other methods. This observation speaks in favor of physiological measurements because early detection is crucial for crash avoidance (Evans 1991). Physiological measures of driver sleepiness include measurement of the brain's electrical activity (electroencephalography, EEG), eyelid movements (electrooculography), muscle tonus (electromyogram), and electrical activity of the heart (electrocardiography, ECG). A few studies on a small number of drivers have evaluated ECG-based indicators like heart rate and HRV with promising results, especially for HRV (Patel et al. 2011; Sato et al. 2001; Vicente et al. 2016). Using indicators based on the heart rate signal can open up possibilities to use nonintrusive measurement devices that can be suitable for real-life sleepy driver alert systems, in contrast to EEG/electromyogram/ECG measurements that are suitable only in experimental settings, although progress is being made for improving wearability by, for example, combining EEG and ECG using only 2 electrodes (Awais et al. 2017). Heart rate could be measured by sensors in the driving wheel, wristbands, and sensors mounted in the seat using techniques such as bioimpedance, contactless recordings of ECG, and microwave technology (Macias et al. 2013; Wartzek et al. 2011).

In order to obtain good estimations of HRV indices, it is essential to employ effective preprocessing algorithms. Outlier heartbeats are common and, when recording drivers, motion artefacts may increase the number of outliers. Thus, prior to deriving HRV indices, detecting and removing outlier heartbeats is essential (Lippman et al. 1994). In this study, 2 methods to detect outliers were considered. The first method, percentage change (PC), defines an outlier as having an interbeat interval deviating >30% from the mean of the 4 previous accepted intervals. The second method, standard deviation (SD), defines outliers as an interbeat interval deviating >4 SD. After removing heartbeat outliers, spectral transformation is applied to estimate HRV indices in the frequency domain. The choice of spectral transformation method has a large influence (Clifford 2002). Commonly used methods are the autoregressive model, Fourier transform (FT), and the Lomb-Scargle (LS) periodogram. These 3 methods were considered in the present study. In Forcolin et al. (2018), a more comprehensive background of the preprocessing methods considered here can be found. Forcolin and colleagues evaluated the level of agreement between these methods, using the same data as in the present study. The study concluded that the standard preprocessing methods for HRV data—that is, the aforementioned outlier heartbeat detection and spectral transformation methods—show low levels of agreement. Therefore, studying the impact of different preprocessing strategies on HRV indices and their relation to sleepiness level is a fundamental step in the implementation of systems for detecting a sleepy driver based on HRV analysis.

The 2 objectives of this study are to evaluate the (1) suitability of different preprocessing strategies for detecting and removing outlier heartbeats and spectral transformation of HRV signals and their impact of driver sleepiness assessment and (2) relation between common HRV indices and subjective sleepiness reported by a large number of drivers in real driving situations. The rationale of the study is to support the development of machine learning algorithms for driver sleepiness detection and to increase the knowledge of how HRV is related to sleepiness. By reporting quantified information about the suitability of available preprocessing methods and predictive value of individual HRV indices, flexible support to sleepiness detection algorithms is provided; that is, the analysis is not restricted to particular cases where several HRV indices are combined or used in conjunction with information of different nature such as duration of driving. The hypothesis is that significant differences in the reported level of sleepiness are associated with significant changes in different HRV indices. To fulfill the objectives, the suitability of different outlier detection and spectral transformation methods to discriminate between alert and sleepy drivers is quantified. Further, the relationship between common HRV indices and the level of perceived driver sleepiness is evaluated. This is the first time that common HRV indices are related to driver sleepiness using a large database of drivers in real driving situations.

Methods

Experimental design

ECG data were recorded in 3 studies designed to evaluate the physiological differences between alert and sleepy drivers, with a total of 81 participants. The inclusion criteria were healthy, experienced drivers between 25 and 65 years of age. A comprehensive description of the participants is provided in Forcolin et al. (2018). All studies were ethically approved (EPN 142-07; EPN 142-07 T34-09). Data from 5 subjects were disregarded due to the high number of outliers; the remaining 76 participants were included.

Test drives were performed on a Swedish public motorway. Drivers were accompanied by a test leader and reported subjective sleepiness according to the Karolinska Sleepiness Scale (KSS; Åkerstedt and Gillberg 1990) every 5 min. The driver reported a number from 1 to 9 corresponding to perceived sleepiness according to the KSS. Otherwise, the test leader did not interact with the driver during the experiment. Each subject performed 3 drives, of approximately the same duration, in the morning, evening, and night. The drivers were monitored by a 12-lead ECG commercial Holter system (Vitaport 2 and Vitaport 3, Temec, The Netherlands) during the complete driving session. A comprehensive explanation of the design and procedure of the 3 studies on which the current work is based can be found in Forcolin et al. (2018).

Table 1. HRV indices summary.

Domain/Feature	Label	Unit
Time		
Average heart rate	HR	Beats/minute
SD of NN intervals	SDNN	ms
RMS of succ. diff.	RMSSD	ms
Frequency		
LF spectral power	LF	ms^2
HF spectral power	HF	ms^2
Ratio between LF and HF, LF/HF	LF/HF	—
LF norm. spectral power	LFnu	Norm. units
HF norm. spectral power	HFnu	Norm. units
Geometrical		
Triangular interp. index	TINN	ms
Log. Index	LogId	—
Nonlinear		
Poincaré	SD1 and SD2	—

Note: R is a point corresponding to the peak of the QRS complex of the ECG wave; and RR is the interval between successive Rs. The term "NN" is used in place of RR to emphasize the fact that the processed beats are "normal" beats.

Data preparation

The IBI signal was extracted by applying peak detection to the ECG data. For this purpose, the Pan-Tompkins algorithm (Pan and Tompkins 1985) was used. The ECG sampling frequency was 256 Hz. Each test drive was processed separately and divided into epochs of 5 min, as recommended by the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology ("Heart Rate Variability" 1996). In total over 3,500 5-min driving epochs were analyzed, including almost 1.3 million IBI samples.

Two standard methods were used for identifying outlier heartbeats: The PC method and the SD method. In the PC method, outliers were defined as an interbeat interval deviating >30% from the mean of the 4 previous accepted intervals. In the SD method, outliers were defined as an interbeat interval deviating >4 SD from the mean interval duration in the current epoch. Three standard methods were used for spectral transformation, which is needed to derive HRV indices in the frequency domain. These methods were FT, an autoregressive model, and the LS periodogram. The study was performed on the most commonly used HRV indices in the different information domains; these are summarized in Table 1 and further explained in "Heart Rate Variability" (1996). Details of the preprocessing methods are described in Forcolin et al. (2018).

The first and second epochs of each drive were discarded. This was done because, for most HRV indices, the first 2 epochs presented a very high variability. As an example, the high-frequency (HF) index is illustrative. Figure 1 shows the evolution of HF with duration of driving, where each value represents the average of all epochs for a certain duration of driving; for example, the ninth point is the mean of all ninth epochs after 40 min of driving. The high variability of the first 2 epochs was probably due to the stress load induced by performing a new task; that is the start of the test drive. After discarding the first and second epochs, HRV indices were normalized in order to avoid the influence of individual differences. Normalization was done using the average of epochs 3–5 (min 10 to 25 of driving) for each driver's morning drive. The rationale is that every driver is expected to be alert during this time and that using 3 epochs is more stable than using 1.

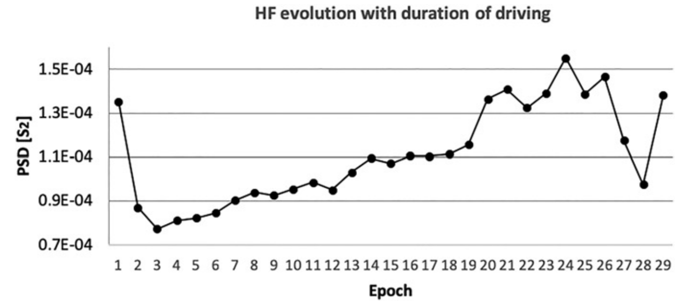

Figure 1. Evolution with duration of driving with the HF index as an example. Each value represents the average value of all epochs for that duration of driving. The HF index was calculated using SD and LS methods.

Statistical testing

Analyses of variance (ANOVA) and box plots (Massart et al. 2005) were used to evaluate the association between each HRV index and KSS. All epochs were grouped by KSS level; that is, from 1 to 9. Both ANOVAs and box plots were repeated for indices estimated using different preprocessing strategies so that the influence of different preprocessing methods could be compared. To obtain a measure of which preprocessing methods and combination of methods enabled a higher separation between alert and sleepy drivers, box plots and Student's t tests were used. Because a large number of statistical tests were performed—that is, a total of 88 summing all ANOVAs and t tests—the likelihood of a test being positive by chance increases. In order to avoid that limitation, Bonferroni correction was applied. The desired overall level of statistical significance was .05; therefore, a significance level for each test of $P < .0005$ was chosen. All statistical tests were implemented using Matlab (Ver. R2013b, MathWorks Inc., Natick, MA).

Dichotomization between alert and sleepy drivers was done according to the KSS, where an alert driver was defined as having a KSS level of 1–6 and a sleepy driver was classified as having a KSS level of 8–9. Epochs classified as 7 were discarded. This dichotomization was chosen because, though it is clear that 8 and 9 need to be classified as sleepy driver, level 7 is ambiguous. Literature supporting this includes, for example, Ingre and colleagues (2006), who found that high crash risk in a driving simulator is associated with KSS levels 8 and 9, and Hallvig and associates (2014), who showed that a KSS of 8 is related to risky situations due to driver sleepiness. Driving on real roads, a driver with a KSS level of 7 could potentially be classified as sleepy because the transition from level 7 to level 8 can occur quickly (Åkerstedt et al. 2013; Mahachandra et al. 2009). However, including level 7 in a driver sleepiness alarm system would likely produce unnecessary alarms.

Results

In this section, the association between each HRV index and subjective driver sleepiness evaluated according to the KSS is presented. After the 2 methods for outlier detection were applied, 0.28% of epochs were identified as outliers by the PC method and 0.065% by the SD method; these outliers were removed. A histogram of the KSS levels for all retained epochs ($n > 3{,}500$) can be found in Appendix A, Figure A1 (see online supplement). In that histogram the bins of levels 8 and 9 represent sleepy drivers. Further, the most common KSS level was 5.

ANOVA tests were performed to compare the estimations of each HRV index using different preprocessing strategies, grouping epochs by KSS value (1–9). Results of these tests are included in Table B1 in Appendix B (see online supplement). In addition, Figure 2 shows notched box plots for each KSS group for 2 indices—that is, HR and low-frequency (LF)/HF ratio estimated using the PC and FT methods—as examples. Outliers as defined by the box plot function were removed from the plots for better visualization. The whiskers extend to 1.5 times the interquartile range away from the top or bottom of the box or to the furthest observations from the box; for a normal distribution this means that epochs falling outside 99.3% of the distribution are considered outliers. Notched box plots for all HRV indices are shown in Appendix C, Figures C1–C12 (see online supplement).

To study alert versus sleepy driver, epochs were classified into only 2 groups, alert (KSS from 1 to 6) or sleepy (KSS 8 or 9) drivers. KSS level 7 epochs were excluded. Box plot analysis, ANOVA tests, and independent *t* tests of association were performed. Results of the *t* tests and summaries of the box plots for all HRV indices are included in Table B1 in Appendix B. Figure 3 shows notched box plots of the 2 groups for the HR and LF/HF ratio HRV indices. Notched box plots for all HRV indices are shown in Appendix C, Figures C1–C12.

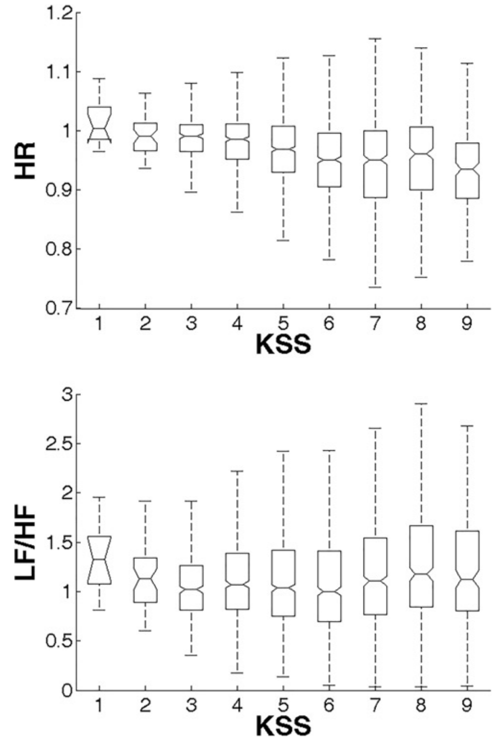

Figure 2. Notched box plots of all epochs regarding KSS for HR and LF/HF ratio HRV indices, which were estimated using PC and FT methods.

Discussion

In this study, the suitability of different outlier detection and spectral transformation methods to discriminate between alert and sleepy drivers was evaluated. Further, the association between the most common HRV indices and subjective driver sleepiness was evaluated.

Suitability of different preprocessing strategies

Results show that, for HRV indices in all domains, both outlier detection methods allow the estimation of HRV indices that can potentially discriminate between alert and sleepy drivers. Further, the potential ability of estimated HRV indices does not depend on the outlier detection methods; for both methods HRV indices relate similarly to alert and sleepy drivers. The influence of the outlier detection method on the ability to tap into sleepiness is higher in the parameters of the frequency domain, but the difference is not substantial.

Spectral transformation methods apply only to the frequency domain and their influence is similar to the outlier detection methods. Thus, the potential ability of estimated HRV indices does not depend on the spectral transformation methods.

Relation between HRV and driver sleepiness

Hypothetically, the parasympathetic branch is dominating the Autonomic Nervous System (ANS) of a person falling asleep. The parasympathetic influence would slow down the heart and make its beating less regular; that is, increasing overall HRV. Heart rate was proven to decrease with driver sleepiness in a simulator (Xiong 2012) and in real driving situations (Milosevic 1997). In Egelund (1982), overall HRV increased with increasing sleepiness in real driving. In the present study, the heart rate was lower when drivers were feeling sleepy, which is in line with the expectation. Moreover, HRV was higher overall in sleepy drivers, as represented by the HRV indices Standard deviation of NN (SDNN) intervals and Triangular index of NN (TINN) intervals.

The frequency domain is expected to more precisely represent both branches of the ANS (Burr 2007). The high-frequency band represented by HF and HFnu is considered as the index of modulation of the parasympathetic branch because it influences the sinoatrial node of the heart. This is because, although HF power cannot be solely attributed to changes in cardiac vagal efferent nerve traffic, numerous studies have reported a strong association between HF power and cardiac parasympathetic activity (Billman 2013). Analogously, the low-frequency band represented by LF and LFnu is usually viewed as an index of modulation of the sympathetic branch, although some researchers prefer to view LFnu as a general indicator of aggregate modulation of both the sympathetic and parasympathetic branches. In a comprehensive review by Billman (2013), it was concluded that the LF band reflects a complex mix of sympathetic, parasympathetic, and other unidentified factors, with parasympathetic factors contributing most to the variability. In applied research reports describing sleep studies, both normalized spectral HRV power band measures—that is, LFnu and HFnu—are often presented together and usually in conjunction with the LF/HF ratio.

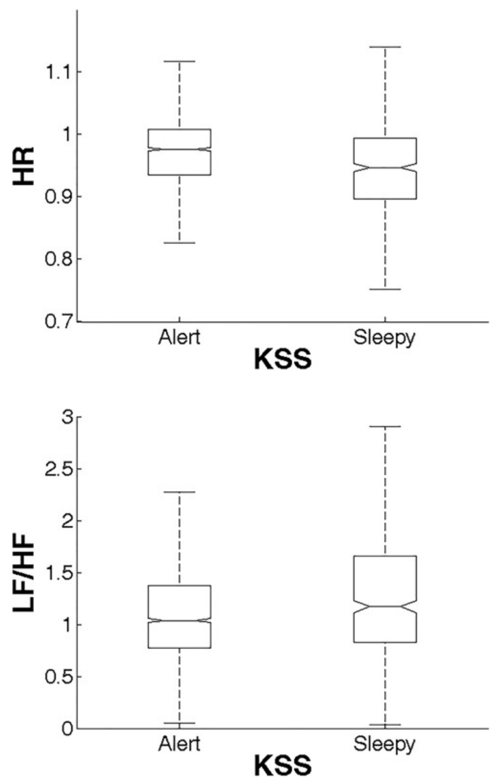

Figure 3. Box plots of epochs classified into 2 groups, alert (KSS from 1 to 6) or sleepy (KSS 8 or 9) drivers.

This LF/HF ratio is a widely used HRV index of sympathovagal balance between both branches of the ANS. However, Billman (2013) demonstrated that LF/HF cannot accurately quantify cardiac sympathovagal balance. Driver sleepiness in sleep-deprived subjects exposed to real driving conditions was studied in Michail et al. (2008). That study reported lower LF/HF values during driving errors. However, the study presented by Michail et al. (2008) had important limitations as the number of participants was few (4) and they only drove for an hour. Further, LF/HF was found to decrease with sleepiness in 8 out of 12 subjects in a driver simulator in Patel et al. (2011). Additionally, in Elsenbruch et al. (1999), LF/HF was found to decrease between awake and stage 2 sleep. In the present study, HF was higher in sleepy drivers. However, LF and the LF/HF ratio were also higher in sleepy drivers. This is in contradiction with Michail et al. (2008) and Patel et al. (2011). Vicente et al. (2016) hypothesized that in the process of a driver falling asleep, the Power spectral density (PSD) in the HF band would rise as a result of parasympathetic activation; similarly, the PSD in the LF band would rise as a consequence of sympathetic activation because the driver is trying to stay awake. Results of the present work fulfill that hypothesis, with LF rising higher than HF. Possibly, the rise in the LF band was due to both sympathetic and parasympathetic activity.

In the nonlinear domain, the parameters SD1 and SD2 were derived from the Poincaré plot. The parameter SD1 represents the short-term component and it is related to parasympathetic activity, similar to HF. The parameter SD2 is influenced by both parasympathetic and sympathetic tones (De Vito et al. 2002), similar to LF. In Hoshi et al. (2013), for healthy adults, correlations of 0.93 and 0.99 were found between SD1 and HF and the root mean square of successive differences (RMSSD), respectively; in the same study, correlations of 0.80 and 0.95 were found between SD2 and LF and SDNN, respectively. In this work, SD1 and SD2 exhibit behavior similar to HF and LF, respectively. In Mahachandra et al. (2012), a substantial decrement in SD1 was found among sleepy drivers in simulator driving, which is a surprising finding.

Other indices considered were RMSSD and LogId. RMSSD is related to the short-term component and the parasympathetic branch. It is expected to rise with sleepiness, similar to SD1 or HF, which was confirmed by the present study. In Mahachandra et al. (2012), as in the case of SD1, a substantial decrement in RMSSD was found among sleepy drivers in simulator driving, which also is a surprising finding. Finally, LogId related poorly to driver sleepiness. Previously, this parameter has received little attention regarding driver sleepiness.

Most HRV indices showed statistically significant different averages for alert and sleepy drivers. However, according to the box plots, the distribution of HRV index values between alert and sleepy drivers overlap substantially. Nevertheless, most indices show a significant separation between alert and sleepy drivers (LF showed the highest separation). For this reason, the possibility of implementing a machine learning classifier to discriminate between alert and sleepy drivers based on HRV seems promising. Such a classifier should make use of all HRV indices considered except LogId.

Limitations

Different thresholds for the outlier detection methods were not tested; instead, threshold values were taken from the literature. Similarly, several different choices were made when applying each spectral transformation method, which may affect the values of estimated HRV indices. The lack of these analyses limits the precision of the results.

An analysis of the influence of driving task time and circadian cycle was not performed. HRV was considered to act the same regardless of the reason behind sleepiness. This is a limitation and might be of interest in future studies. Nevertheless, in future work, in order to choose outlier detection and spectral transformation methods for a machine learning classifier that discriminates between alert and sleepy conditions in drivers, accounting for the influence of task time and circadian cycle is not necessary. Both can be used as covariates in that hypothetic classifier, which then can account for that influence.

The high average value of the index HF when drivers are sleepy is mainly due to few very high values that may or may not be outliers. Therefore, this high average is not reflected in the median, the box plots, or the average of HFnu. Moreover, it is important to be aware that all parameters in the frequency domain are interrelated; note that Ratio = LF/HF = LFnu/HFnu.

In conclusion, the results prove a clear relationship between HRV and the KSS. Accordingly, we conclude that

HRV shows promise for driver sleepiness detection. The association of HRV indices to the KSS was found to be independent of the preprocessing strategy. No preprocessing method showed superiority for HRV association to driver sleepiness. This was also true for combinations of methods in the case of frequency domain indices.

Acknowledgments

We thank Cecilia Sunnevång for her help in the project, as well as all who helped collect the data and the individuals who participated in the study.

Funding

This study was possible due to funding from the Swedish research program Vinnova FFI–Strategic Vehicle Research and Innovation. It was performed in the frame of the Human Monitoring competence area within the SAFER Vehicle and Traffic Safety Centre at Chalmers University of Technology. Autoliv Development AB and the Swedish National Road and Transport Research Institute (VTI) participated in the study.

The data that support the findings of this study are proprietary and were used under license for this study. Data requests should be addressed to Autoliv Research and availability is subject to additional permission of Veoneer Inc. and VTI.

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