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Heart on the road: HRV analysis for monitoring a driver's affective state

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ABSTRACT

Driving a vehicle is a task affected by an increasing number and a rising complexity of Driver Assistance Systems (DAS) resulting in a raised cognitive load of the driver, and in consequence to the distraction from the main activity of driving. A number of potential solutions have been proposed so far, however, although these techniques broaden the perception horizon (e. g. the introduction of the sense of touch as additional information modality or the utilization of multimodal instead of unimodal interfaces), they demand the attention of the driver too. In order to cope with the issues of workload and/or distraction, it would be essential to find a non-distracting and noninvasive solution for the emergence of information.

In this work we have investigated the application of heart rate variability (HRV) analysis to electrocardiography (ECG) data for identifying driving situations of possible threat by monitoring and recording the autonomic arousal states of the driver. For verification we have collected ECG and global positioning system (GPS) data in more than 20 test journeys on two regularly driven routes during a period of two weeks.

The first results have shown that an indicated difference of the arousal state of the driver for a dedicated point on a route, compared to its usual state, can be interpreted as a warning sign and used to notify the driver about this, perhaps safety critical, change. To provide evidence for this hypothesis it would be essential in the next step to conduct a large number of journeys on different times of the day, using different drivers and various roadways.

Categories and Subject Descriptors

H [**Information Systems**]: H.5 Information Interfaces and Presentation—*H.5.2 User Interfaces*

General Terms

User-centered design, Affective state recognition

Keywords

On-the-road studies, Driver-Vehicle interface, Electrocardiography (ECG), Emotional state recognition, HRV analysis

1. STATE-OF-THE-ART INTERFACES

The provision of a safe and a comfortable driving experience is a major concern of motor vehicle manufacturers. As the motor vehicle industry develops, more entertainment and information systems are integrated in new vehicles. These systems are aimed to make the driving experience more enjoyable and as safe as possible. However, a driver is expected to focus all his attention on road events at all times. Any activity that a driver engages in other than that is considered to be a distraction. A study conducted by Ranney et. al [25] shows that any form of distraction can cause a crash. 25 percent of the police reported crashes were due to distractions. The study classifies sources of distractions into four different categories; visual (e. g. looking away from the roadway), auditory (e. g. responding to a mobile phone), bio-mechanical (e. g. typing in a destination on a navigation device), and cognitive (e. g. daydreaming or being lost in thought).

Current car systems interfaces have a lot of disadvantages. For instance, the driver must have previous knowledge about the operation of these interfaces. Rydström *et al.* [31] reported that the operation of vehicles using different systems such as the BMW iDrive, Audi MMI or Jaguar touch screen interface took up to four times longer to use for persons unfamiliar with the interfaces than for the drivers knowing them. Additionally, the driver must pay some attention during driving to control these interfaces, which in term is a source of distraction. Another drawback of common driver assistance systems (DAS) is that they get very little or no input about the driver's emotional (or affective) state. Very little attention has been given for studying emotions in the context of driving. Nevertheless, one can envision that affective interfaces might be essential in automotive safety critical and driver assistance applications.

In an attempt to research alternative automotive interfaces, we thought about investigating the relationship between the driver's affective state and routes that are being regularly driven by him. The idea was inspired by the fact that different people feel and react differently to different roads at various times of the day. For example, we assume that most people will feel more stressed on a road with more traffic jams than a road that has a moderate traffic flow. In this paper we investigate our hypothesized claim. We present our first experiments using physiological data acquired from electrocardiography (ECG) and location data obtained using a global positioning system (GPS) device.

1.1 Attention-free Driver-Vehicle Interaction

Current vehicular interfaces are operating on a combination of either haptic, visual, or vocal modalities (Mauter and Katzki [19, p. 78], Bernsen [4, p. 2], Riener [26, p. 61f.]). These interfaces require a lot of knowledge and attention from the driver in order to interact with different car systems. Furthermore, there has been no or only little information considered about the affective state of the driver which can be gathered almost for free. Feeding the driver's affective state into different vehicular control systems might help to provide many possibilities for new vehicular applications dealing with safety, information, navigation, and entertainment. In a study conducted by Green [10], the following recommendations are made to help overcome crashes induced by in-car information systems:

(i) application and extension of driver interface regulations and design guidelines,

(ii) utilization of human factor experts, data, and methods to develop new driver-vehicle interfaces,

(iii) making greater use of usability testing,

(iv) conduction of research on and development of a workload manager which measures driving demands of a road required from the driver.

These are very important remarks that indicate that a lot of research work is yet to be done for improving the safety and usability of driver-vehicle interfaces.

As pointed out before, cognitive distractions can make the driver prone to accidents. Moreover, one can state that the emotional state of the driver falls under the category of cognitive distractions. Studying the driver's emotional state in relation to driving performance had an increasing interest from several researchers. Grimm *et al.* [11] researched on the importance and feasibility of detecting the driver's emotional state. The assumption of their study, based on cited evidence, is that different emotional states affect driving performance. Some of the emotional states were described as being positively improving the driving performance, and others as adversely affecting. A similar study was done by Cai *et al.* [17] on the feasibility of detecting driver emotions using driving simulators. Other studies by Nass *et al.* [21], Jones *et al.* [13], and Jonsson *et al.* [14] showed evidence that automotive safety can be improved by pairing an in-car voice interface output with the emotional state of the driver. Wang and Gong [34] showed the feasibility of emotion recognition in vehicular environments. In the study a driving simulator was used to elicit various emotions using driving courses and guidance voices. Most studies in this area claim that little attention has been given towards studying emotions encountered by drivers throughout the driving process.

Outline

The paper is organized as follows. In section 2 an overview of related work in emotion research and a short background on ECG is presented, in section 3 we present the experimental setting, conducted studies and a discussion of initial results. Finally, section 4 concludes the work and gives some directions for our future research.

2. AFFECTIVE STATE RECOGNITION

2.1 Emotion Research

To the best of our knowledge, there exists no scientifically agreed on definition for the notion of emotions. Finding an accepted working definition of emotions is an important issue and still under research. Understanding emotional components and their generation are made difficult by a lot of factors; describing emotions (or tagging emotions with adjectives) and interference problems (due to social pressures and expectations) are some of these factors.

The widely used definition for emotion recognition in computer disciplines was introduced by Picard [23] in the 1990s. Emotion recognition is defined as *"measuring observations of motor system behavior that correspond with high probability to an underlying emotion or combination of emotions"*. This definition is based on the fact that measuring cognitive influences is currently impossible. Nevertheless, we are able to measure physiological responses that can reflect an emotional state. This definition of emotion recognition simplifies the problem of understanding what an emotional state is. Furthermore, it is suggested to use the terms "emotional state", "affective state", and "sentic state" interchangeably in the context of emotion reasoning and computation.

Body Expressions

Affective computing is not aimed at measuring cognitive influences but to detect emotions from what is referred to as "sentic modulation". The body expresses (or modulates) an emotional state through many channels. What to be considered as a reliable source for understanding sentic expressions seems to be also debatable. A variety of motor system outputs and physiological responses have been studied with respect to emotional influence. Categorization of the main classes or the reliable sources for the purpose of emotion recognition is still debatable. Mauss and Robinson [18] classify the widely investigated channels as follows:

(i) facial expressions and whole body behavior,

(ii) vocal characteristics using features like quality, utterance timing, and utterance pitch contour,

(iii) physiological responses and other motor outputs (arising from biosignals like heart rate, blood volume pressure (BVP), pulse, pupillary dilation, respiration, skin conductance, and temperature),

(iv) subjective experience (based on self report).

Various interpretations and definitions from disciplines like psychology and philosophy are given about the notion of emotions. The recommended definition by Picard gives us a stricter domain for understanding emotions in the field of computer science. Given this definition we need to understand *(i)* what are the causes for emotions or emotion elicitation, *(ii)* what are the channels for expressing emotions, and *(iii)* how to measure emotional responses. We also need a computational model for interpreting the measured responses. Two of the widely used models in emotion research are the discrete emotion model (a basic set of emotions are assumed), see Zinck *et al.* [35, p. 2], and the dimensional model (describes different categories of emotions in three or fewer dimensions; such dimensions include arousal, valence, and control/attention), see Sebe *et al.* [32] or Barrett [2]. Arousal indicates the strength of the emotion (calmness/excitement), valence shows the pleasantness of an emotion (positive or negative), and control/attention addresses the internal or external source of emotion. Nevertheless, the names of the dimensions vary across the literature. For the convenience of mapping dimensional models to discrete emotions, Russel [30] proposed a model which is widely used by researchers in this area.

Emotion Recognition from Biosignals

Facial expressions and the voice are bodily signals that we can control. Emotions that are being conveyed through these channels can be deceiving as they can be faked by the person. For example, think about how good actors can show certain emotions in films or in the theater. Although emotions appear to be realistic, their truthfulness is debatable. The other problem with relying on such signals is the setup needed for data acquisition. Such setups rely on sensors like cameras or microphones which are, particularly in the car, constrained by factors like placement and environment conditions (like lighting, background noise, etc.), see Riener [26, p. 93f.]. For this reason, researchers currently tend to investigate other signals that can also convey an affective state such that a person can have less influence on. Such signals are commonly known as biosignals (or physiological signals) and, according to Benovoy *et al.* [3], are believed to provide more reliable means for determining emotions.

Biosignals are widely related to the autonomic nervous system (ANS), the limbic system, and other parts of the central nervous system (CNS). These systems are responsible for controlling a lot of vital activities and involuntary muscles, and are furthermore known to respond to emotional stimuli. Despite the fact that a lot of sensors exist for the acquisition of biosignals, the usage of data from such signals for emotion recognition is neither an easy nor a direct task. In relation to other approaches there are no "golden rules" yet established for the usage of biosignals for emotion recognition.

2.2 Electrocardiography (ECG)

The ANS controls smooth muscles, cardiac muscles, and secretions from various glands. Two branches of the ANS are the sympathetic and the parasympathetic system. The sympathetic system is needed for "fear, flight, fright" response (high arousal state). It is responsible to prepare the body for a stressful condition. The parasympathetic system works in the opposite way. It is responsible to put the body in a "calmer state" (low arousal state). For the normal activity, a balance is maintained between the sympathetic and the parasympathetic activities. Such variations of ANS activity can be measured using several channels. The following list by Mendes [20] represents a summary of the most widely used noninvasive methods for measuring ANS activity:

(i) electrodermal activity using skin conductance and skin potential,

(ii) cardiovascular activity using electrocardiogram, impedance cardiography, blood pressure, respiration,

(iii) pupillary responses (measurement of pupil diameter),

(iv) skin temperature,

(v) skin blood flow (volume of blood flowing in skin).

Cardiovascular activity has been used by a lot of researchers in emotion research and related fields [16, 29, 5, 28, 8, 24, 33, 12]. Electrocardiography (ECG) is one of the most common ways of measurement. The ECG records these cardiac electrical currents (voltages, potentials) by means of metal electrodes placed on the body (the recording is visualized by means of an electrocardiogram). Normally, the cardiac stimulus is produced in the sinoatrial (SA) node, that is present in the right atrium (RA). The stimulus then is passed through the RA and left atrium (LA). After that the stimulus is passed through the atrioventricular (AV) node and the bundle of His. The stimulus then passes into the left and right ventricles (LV and RV) by way of the left and right bundle branches. Finally, and according to Goldberger *et al.* [9], the stimulus is transferred to the ventricular muscle cells.

For normal cases the process of cardiac stimulus generates patterns as shown in Figure 1. The time interval between two heart beats can be calculated by observing the time between two consecutive R peaks using a QRS detector. This R-R interval is known as the inter-beat time and is used for the measurement of the heart rate.

Heart Rate Variability (HRV)

On the shortest time scale, the time between each heartbeat is irregular (unless the heart is paced by an artificial electrical source such as a pacemaker or due to medical conditions). An important tool to measure this irregularity is heart rate variability (HRV). HRV is a promising tool for applications involving medical diagnoses and stress detection. Kim *et al.* [15, 5] have reported the use of HRV statistics as to estimate mental stress. This can be applied to vehicular applications where the estimation of emotional state is required.

The tool relies on the analysis of the series of R-R interval differences. Time and frequency domain measures provide means for HRV analysis. Measures of time domain include mean, standard deviation, and root mean square of differences of consecutive R-R intervals. Frequency domain analysis represents deviations with respect to frequency. For that, several interesting frequency bands can be analyzed like the very low frequency (VLF) ($< 0.04Hz$), low frequency (LF) ($0.04 - 0.15Hz$), and high frequency (HF) ($0.15 - 0.4Hz$). VLF was indicated as being unreliable for short time intervals. The LF/HF ratio is an indicator for autonomic balance. High values are thought to indicate the dominance of sympathetic activity with vagal modulation and low values indicate dominance of parasympathetic activity. Typically, HRV analysis is done for time windows of 5 minutes or for longer periods like 24 hours. However, there is no standard mentioned for an ideal time window frame (Clifford *et al.* [6, p. 71–83]). For a dimensional model of emotions, this parameter could be a good indicator for arousal but not valence.

Mobile ECG Measurement

One might think that the measurement of ECG can be very tedious as compared to a setup available in hospitals which is mostly based on a standard 12-lead ECG. Today most mobile ECG devices used for measuring heart (or pulse) rate, heart rate variability and other biorhythm related parameters operate with three conductively coupled electrodes ("Einthoven ECG"), attached to the skin of the person and providing direct resistive contact (see Figure 2). But also their application in vehicles is almost unfeasible due to the inconvenience and lack of user friendliness (even the "ultimate" DASs necessitating the driving person to attach three electrodes every time prior boarding would not be accepted).

However, using a system operating on capacitively coupled electrodes, as for instance presented by Aleksandrowicz *et al.* [1], could avoid these restrictions. The introduced system is able to measure ECGs through the clothes, without a direct skin contact. Although the measurement system is, compared to a conventional conductive ECG measurement device, more sensitive to moving artifacts and is furthermore strongly dependent on the subject's clothing, it seems useful for at least high convenient heart rate detection in mobile fields of application. The measurement device additionally avoids skin irritation often evoked by the contact gel between skin and the electrodes. The proposed capacitive measurement system could be for example integrated into a vehicle seat with two electrodes embedded into the back, and the reference electrode integrated into the seat. This system would then operate fully autonomously and attention-free, and thus would be the missing building block for the class of implicit operating sensing systems.

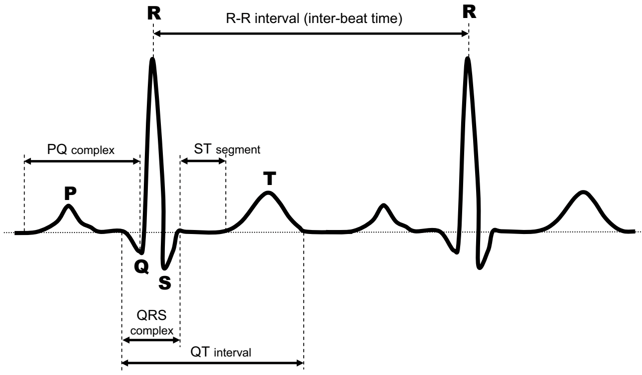

Figure 1: A normal electrocardiogram.

3. FIELD TESTS

In order to study the relationship between the driver's emotional (or affective, arousal) state and a driven route and to test the proposed framework, we conducted experiments measuring pairs of ECG/GPS for a specific route and a fixed daytime (a small variation in driver time is indispensable according to environmental parameters such as weather or traffic jams). Based on this data a "personal affective profile" for a route and a specific daytime can be compiled, indicating the "normal, balanced" state of that person for each position on the (regularly driven) track (=training set). The assumption of the research is that differing affective state values identified during a trip (testing set) represents some kind of abnormality and should be immediately forwarded to the driver as a kind of proactive notification to avoid danger situations.

A second field of application for the emotional profiles would be the utilization for any service provider. For instance, streets or road segments can be classified according to the arousal state of the collection of all drivers using this road on a certain day or at a certain time of the day regularly in order to identify the "danger-level" (or "stress-impact") of a route. For a car insurance company the aggregated state values could be used to calculate the insurance rate for this trip.

3.1 Geographic Regions of the Experiments

The on-the-road driving tests have been conducted in the greater Linz area. In order to avoid the general areas of traffic congestions, two different driving routes (inbound via the city of Altenberg, outbound via Glasau) – according to the personal preference of the test person – have been used for data acquisition. All of the test runs have been processed on these predefined courses with a distance of $20.47km$ (inbound) and $19.53km$ (outbound). Figure 3 illustrates maps of the routes driven in the experiments.

3.2 Data Acquisition

GPS traces and ECG data have been acquired in on-the-road experiments on two predetermined routes (morning and evening route) driven by a single identical person for a period of two weeks (the subject was commuting from his home to work; we only consider the workdays in our experiments). A total of 22 trips with more than 500 kilometers driven were logged and employed in this research study.

For recording electrocardiograms we used a common 3-lead ECG device "HeartMan 301" from HeartBalance AG[1]. This appliance can be easily attached to a human's body, is small-sized, light-weight and records up to 24 hours with one battery pack. Figure 2 illustrates the setup of the device on the subject. The device operates reliably and delivers high precise data in real-time at a sampling rate of $50Hz$. Data sets are either transmitted via a Bluetooth communication interface or stored in the European data format (EDF)[2] on an integrated SmartMedia memory card.

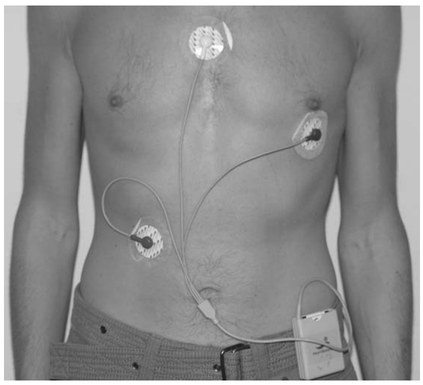

Figure 2: A 3-lead mobile ECG device "Heartman 301" attached to the test driver.

A GPS receiver ATR062x[3] with ANTARIS 4 GPS chipset, mounted nearby the front window, was used to get the vehi-

[1] `http://www.heartbalance.com/hb2/index.php?content=home`, last retrieved July 30, 2009.
[2] `http://www.edfplus.info/`, last retrieved July 30, 2009.
[3] For details on ANTARIS 4 GPS Chipsets and Sin-

Figure 3: GPS traces of the two pre-defined driving routes with subjacent maps. Tthe left image shows the morning journey (20.47km), the right one indicates the evening trip (19.53km).

cle geo-locations. The ATR062x is optimized for automotive and mobile terminal applications. GPS data is logged in the National Marine Electronics Association (NMEA) 1083 format at a rate of $1Hz$. Furthermore, the GPS time field was consulted as external synchronization basis.

3.3 Signal Processing and Feature Extraction

The ECG signal was preprocessed with a high-pass filter of $1Hz$ followed by a low-pass filter of $1,000Hz$. For the next processing steps we used BioSig[4](an open source toolkit for biomedical signal processing) in Matlab. In the beginning we analyzed the dataset mapping between raw ECG and GPS logs but no significant correlation was noticed. Therefore, we decided on using HRV analysis. In order to calculate the R-R interval series, we first must detect the R peaks throughout the entire ECG signal. For that we used a QRS complex detector provided by the toolkit and as described by Nygards *et al.* [22]. The detector returns the fiducial points of R peaks. We then used the integrated heart rate variability toolkit to calculate the LF/HF ratios as an index for autonomic balance.

GPS data was converted from the NMEA format to a simplified comma separated values (CSV) file format. This was done using GPSBabel[5] (an open source toolkit for the conversion between multiple GPS device formats). Transformed data consisted of the car latitude, longitude, speed, course, and a time stamp. The time needed to travel a route varied every day. This is due to factors like driving speed, road conditions, and traffic congestions. Therefore synchronizing data based on exact time was not possible.

In order to overcome the synchronization problem, reference routes for the morning and the evening trips were defined. These reference routes were manually plotted using Google Earth[6]. Moreover, we had to choose a good time window for segmenting and analyzing the data. We experimented with several time window sizes ranging from 1 to 5 minutes. The least time window we can use, that provided us with the best resolution, was 60 seconds (since a journey lasted between 20 to 30 minutes, a large time frame was not able to provide us with variations of LF/HF ratios over distance). With a time window of $60sec.$, the lowest frequency that can be resolved is $1/60 = 0.016Hz$ which is below the lower limit of the LF region. The highest frequency that can be resolved is calculated by applying the Nyquist constraint of $N/2T >= 0.4$, where N is the number of beats and T is the time in seconds [6, p. 79]. Applying this formula leads to a lower limit of $N = 48beats$. Our subject is a healthy adult with an average of 75 beats per minute (bpm), and since we are interested in analyzing the LF and HF bands this time window choice was appropriate.

The distance ranges (with respect to the final destination) traveled within every division were stored along with the corresponding LF/HF ratio. By the end of the experiment we had different distance ranges of $60secs.$ overlapping with each other. Finally, to calculate the corresponding LF/HF ratios of any point of the route the following was done. The distance ranges in which a route point falls were first detected (the distance of a point to the final destination was calculated and the corresponding ranges which it falls in were known by a simple comparison). Figure 4 illustrates the various 60 second ranges for a driver on two different days. Given the known ranges and the LF/HF pairs, the corresponding LF/HF ratio of a point was the mean of the LF/HF ratios across the ranges.

3.4 Discussion

After collecting and processing the datasets, we visualized the aggregated LF/HF ratios along the routes. This was done by means of a quantitative visualization on Google Earth (an illustration of the morning route visualized can be seen in Figure 7) over the driven tracks, and as simple graphs generated by Matlab. Figure 5 and Figure 6 show the corresponding ratios in relation to the distance to destination of the morning and the evening journeys respectively. As described before, we use LF/HF ratios as indicators for autonomic balance. Higher values are thought to exhibit

gle Chip GPS Receivers see `http://www.u-blox.com/products/a4chipsets.html`, last retrieved May 13, 2009.

[4]The BioSig Project, URL: `http://biosig.sourceforge.net/`, last retrieved July 30, 2009.

[5]GPSBabel, URL: `http://www.gpsbabel.org/`, last retrieved July 30, 2009.

[6]Google Earth, URL: `http://earth.google.com/`, last retrieved July 30, 2009.

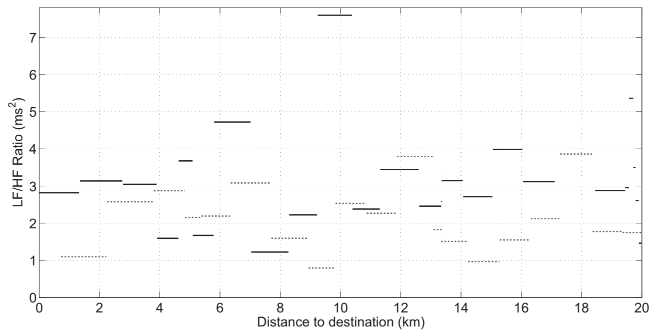

Figure 4: Morning route distance ranges and corresponding LF/HF ratios for two days.

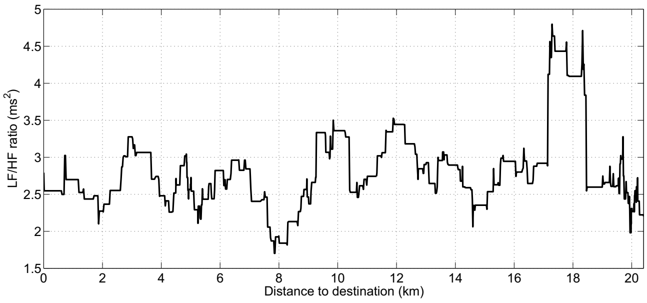

Figure 5: Morning route distance ranges and aggregated LF/HF ratios for two weeks.

higher levels of arousal (implied by increased sympathetic activity) and lower values are opt to demonstrate lower levels of arousal (as a result of the dominance of parasympathetic activity).When calculating the mean of LF/HF ratios for a span of two weeks, we get a characteristic gradient of the curves as depicted in the figures. After analyzing the routes driven and the ratios we came to some interesting observations. In fact we have no means to proof the reasons behind the phenomenon in the data. However, we try to give reasons that might be likely to exhibit the observed measurements. The analysis is done based on road characteristics noted throughout the experiment.

HRV is known to vary according to age, gender, activity, medications, and health [6, p. 71]. It is rather unclear how to differentiate between this causes, e. g. when driving at high speed. Therefore, it is not clear whether the high LF/HF ratios are caused by an increased mental load (attention on the road) or the raised activity of steering the vehicle (braking and accelerating, changing gears, steering).

The Morning Journey

At the beginning of the journey (morning, starting from home) the level of arousal is with a value of $2.6ms^2$ relatively low. The value increases for a short time, probably caused by several dangerous road crossings, and decreases again while driving at low speed in the municipality. The following section (from kilometers 2 to 4), driven on an interurban road with a speed limit of $100km/h$, directs to an LF/HF ratio between 2.5 and $3.3ms^2$. Similar curve shapes can be indicated for the other interurban road sections on the route (regions from kilometers 9.0 to 10.5 and 11.5 to 13.0). The region 4.5 to 6.0 corresponds to the city of "Hellmonsödt", driven at a speed limit of $50km/h$. The $8km$ mark between the city "Hellmonsödt" and the small town "Pelmberg" (long straight street section through a forest) corresponds to the lowest value of arousal for the entire trip ($1.7ms^2$). The road there has very light traffic at that time of the day. The most significant road segment is the distance from kilometers 17.0 to 18.6, the state of arousal here, varying between 4.2 and $4.8ms^2$, is much higher than in any other region of the curve. The reason for this is probably the incipient traffic congestion (dense traffic, but vehicles are still moving) on the borders of Linz (inbound). Driving on workdays and at the same time each day (at around 7:30AM) a traffic jam (standstill) will appear every day between the kilometers 18.6 and 20.1. This behavior is also noticeable in the Google Earth representation in Figure 7 (please note that the labels of the bar graph stands for the LF/HF value scaled by a factor of 1000 – due to a restriction of the utilized software tool). The final segment (low to very-low LF/HF ratio) is driven at walking-speed on the university parking lot, which is almost empty at this time (neither cars nor pedestrians/students).

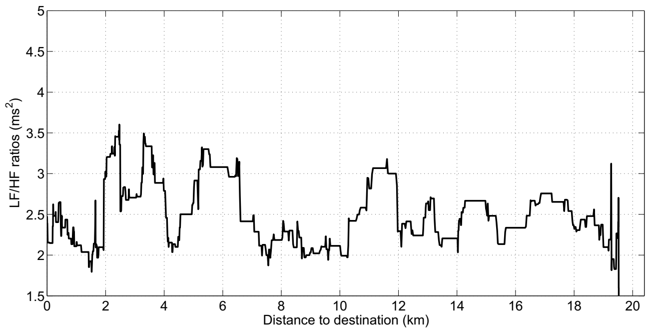

Figure 6: Evening route distance ranges and aggregated LF/HF ratios for two weeks.

The Evening Journey

The LF/HF ratios for the evening route fundamentally follow that of the morning route. The first $1.5km$ of the route, indicated by a very low state of arousal around $2ms^2$, are driven on the parking lot and a following $30km/h$ zone. It is connected to a common "city-traffic" region (route kilometers 2.0 to 6.5), showing a high LF/HF ratio of up to $3.6ms^2$. The reason for this is probably due to city traffic (outbound, around 6:30PM, high traffic density but in general no traffic jam). The region of 7.5 to $12.0km$ indicating the lowest LF/HF ratio is represented by permanent road works ($50km/h$ zone, narrow roads), but at the time of driving regular work has already been stopped for the day. The remaining route (kilometers 12.0 to 19.53) shows no more distinctive features. It can be mentioned that the apex at the end of the route (at kilometer 19.3), where the value of arousal increases from 1.8 to $3.2ms^2$, might be due to a number of hazardous curves that require maneuvering just before reaching the end point.

4. CONCLUSION AND FUTURE WORK

It is undoubted that the cognitive workload of a car driver is increasingly demanded by modern vehicular interfaces and driver assistance systems. The consequence is a possible

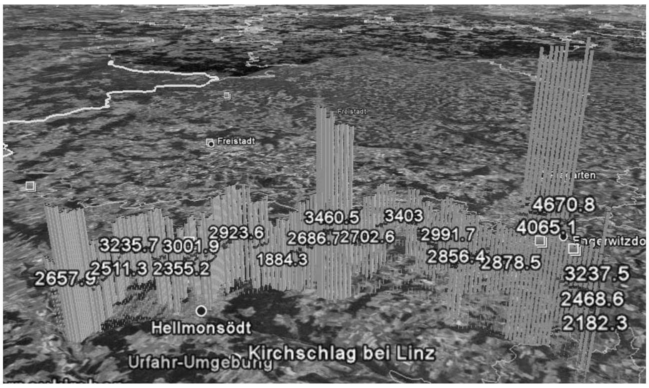

Figure 7: Visualization of the morning route using Google Earth. The values are representations for the arousal state of the driver.

threat, mainly caused by distraction (from the task of driving) due to information overload. In this study we have investigated the proof-of-possibility for the application of heart rate variability (HRV) analysis for representing the driver's affective state in terms of autonomic arousal levels in a noninvasive and a non-distractive way. The experiments we conducted lasted for 2 weeks using one driver commuting every day from his home to work place. We calculated LF/HF values from ECG data, partitioned them into $60sec.$ segments, and mapped them to the corresponding GPS coordinates. This curve, denominated as "personal affective profile", can be used to identify differences for further trips of that driver on the same route in order to notify him (or the driver assistance system) of that change.

In short, the results of the initial tests can be summarized as follows.

(i) The here presented and used metric is only a good measure for arousal. For emotion recognition a metric for representing valence is still required.

(ii) A disadvantage of using ECG (or in particular HRV) is that we had to take larger time intervals (we used $60sec.$ segments). For realtime applications this would be unfeasible (a measure with a quicker response will be needed).

(iii) We presented the potential for using one type of biosignals (ECG) as an indicator for arousal. We might consider comparing it to other ANS measures in future studies.

(iv) Using an ECG device with a sampling rate of $50Hz$ was not feasible for usage with advanced ECG analysis techniques in short time intervals.

(v) We cannot back our observed phenomenons in relation to the road characteristics with a proof. Nevertheless, the stated observations are only remarks on what we think is significant.

(vi) The subject was not feeling stressed during the experiment, which indicates that the LF/HF ratios can be used as an indicator for subconscious stress.

(vii) Higher arousal levels were noticed at roads of higher traffic volume.

As our research is still in progress, a lot of issues are still open and should be covered in the future. Our focus of research will be segmented into two directions. One part is aimed to continue the recording of ECG/GPS data on different driving routes with a larger number of recordings each (e. g. ≥ 10). For these tests it is planned to integrate, apart from ECG and GPS, other biosensors to improve data set quality. We will then repeat the conducted on-the-road studies for a certain driving route with at least one different driver in order to provide evidence for person-related differences. In addition to the "real" driving studies we will conduct tests on a predefined simulated track, e. g. by using a trace-driven experiment as described in [27] or a driving simulator. On the other hand, but concurrently in time, we will use more effort in the mapping of data and selection of algorithms with respect to improving the computational model for emotion representation and interpretation.

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