Continuous Authentication Using Biometrics:

Data, Models, and Metrics

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Chapter 7
Sitting Postures and Electrocardiograms:
A Method for Continuous and Non-Disruptive Driver Authentication

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ABSTRACT

Travelling by car is the preferred method of everyday transportation by most of the people in the world. Individuals from different age groups (at least exceeding the minimum age limit of 16 or 18 years) and health condition (meeting safe mental and physiological requirements) are traveling by car more often and increasingly by themselves.

With a rising number of assistance systems and increasing complexity of information to be presented, drivers demand the automatic operation of driver assistance systems. One of the main interaction mediums between a driver and a car is the driver seat. Given that the seat is occupied all the time while driving, it can be a possible solution for unobtrusive recording of personal characteristics to be used for continuous driver authentication. In this work we focus on a discussion of design and implementation issues for authenticating a driver based on his/her sitting profile and/or contactless collected electrocardiogram data using in-seat electrodes.

This approach is novel in terms of "participation" – the driver has neither to operate something nor to attach a device. Furthermore he/she must not be aware of the continuous collection of his/her personal profile at all.

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INTRODUCTION

Identification and verification of drivers is a topic that is increasingly attracting attention for several reasons and for different fields of application in the transportation domain. It can be used for safety systems continuously monitoring the health condition and alertness of a driver (for example a biological state observation system checking if the driver is tired or drunken). With the emergence of car sharing vendors offering different account types for rental, a problem to be solved is the rate of insurance due for the driven route. The insurance rate should not only be bound to the car and calculated on a yearly basis, but should be linked to the driver and his/her personal skills. The amount payable by a driver can be dynamically calculated based on the driven kilometers and on his/her style of driving. Driven distance can be obtained from the CAN-bus of a car or calculated from available GPS data, and the profile of a driver can be formed from sensors continuously monitoring the emotional state of a driver and/or the on-board diagnostic functions of a vehicle. An important requirement for this system is that it has to be effective in operation all the time and can also be able to authenticate a driver as he/she might use different cars.

An example showing that the topic of authentication is relevant is given by the recent developments of (Yubico, 2010). Their "YubiKey" is a USB-key for secure, easy and affordable access to different applications which also includes an authentication service. Yubico suggests using the YubiKey as a stronger and better alternative to smart cards. Automobile manufacturer have tried smart cards as method for driver authentication in the past; unfortunately, their replacement is very expensive and, more important, cards are prone to hacking – the car domain is nowadays looking for improved, universal applicable solutions.

Identity Authentication

Long-established methods of human authentication are relying on "something you have" (tokens, access cards, identity document/passport, keys, etc.) or "something you know" (secret knowledge: passwords, pass phrases; non-secret: user ID, mother's maiden name, favorite color, birthday of the cat, etc.). Widely used methods, even in combined settings such as user ID or access card + password, are not sufficient for identity authentication – if an object used for identification was acquired or the required knowledge was attained, it can be relatively easy to forge an identity (IBIA, 2010; Revett, 2008). With advances in technology enabling precise measurement of human characteristics along with the availability of greater computational power to transfer measurements into representations that can be compared in real-time, biometrical identification as an effective and convenient way for verifying the identity of a person emerged. "Biometrics" comprises automated methods for recognizing a person based on physiological or behavioral characteristics (based on "what one is" or "how one behaves").

Driver Authentication

The transportation domain is one of the most complex sectors involving user interaction. An important interaction involves the authentication of drivers aimed at verifying if they are authorized to access a vehicle or service, or to transport sensitive goods (IBIA, 2010). Drivers who pick up rental or shared cars will be biometrically screened to authenticate their identities, ensure that they are holding a valid driving license and are also allowed to drive the type of taken car (by checking their driving license categories) (Riener and Ferscha, 2008). Furthermore, authentication techniques can also be used in the future to verify that truck drivers are not exceeding time limits on working hours, for calculating tax or personal insurance rates, and even for improving driving comfort.

A few biometric identification methods are applied in cars that are available today. However, most of them are based on physical attributes requiring active engagement by the involved person, e.g. by pressing sensors located in the car door handles, using fingerprint readers inside the car (Philips et al., 2000) (p. 60), or looking into iris scan systems.

Other physical attributes that can be more or less conveniently collected in a car (and converted into mathematical representations for later comparison) include faces, hand geometry, retinal patterns, thermal imaging (of face or wrist), vein patterns, voice patterns, and deoxyribonucleic acid (DNA). Recently, an exploratory work has been done to establish whether physical characteristics such as the fingernail bed, earlobes (Choras, 2009; Hurley et al., 2008; Ramesh & Rao, 2009) or body odor (Korotkaya, 2003; Rashed & Santos, 2010) can be used for electronic identity authentication (Bhattacharyya et al., 2009; Olden, 2009) (p. 24).

Behavioral attributes: Mathematical representations of an individual can be assigned to the physical traits mentioned above as well as to implicitly detectable behavioral traits. Traditionally the signature dynamics (writing speed, angle of the pen, applied pressure, etc.) of handwriting are used as a representative to describe behavioral traits. Others are keystroke dynamics or movement dynamics when walking (gait recognition). These techniques however are not suitable for in-car detection, especially while driving.

Nevertheless, behavioral traits must not be fully omitted in the car domain – after conducting long-lasting driving studies, we have discovered that a combination of dynamically captured pressure images from the driver seat and wirelessly collected electrocardiograms (ECG's) from the driver is a promising approach to continuously authenticate a driver operating a car in an inattentive, unobtrusive, and convenient way. The proposed system combining several implicit gathering techniques will allow activity recognition while driving.

Outline

In this chapter we elaborate authentication based on static/dynamic evaluation of pressure images from car seat and backrest together with contactless collected ECG signals. We start with individual traffic as a motivation for automatic and continuous driver authentication, and conclude this section with a definition of terms such as identification and authentication as used throughout this work. Subsequent to that we describe the individual building blocks of the proposed system including identified problems. In the section after that the single components are merged to a continuous driver authentication system and results of previous studies are indicated and elaborately discussed. The last two sections give an outlook to possible future research directions and finally conclude the chapter.

Background

Recently, a steadily *increasing volume of traffic* (most likely caused by a decreasing number of carpools due to more flexible work schedules, longer journeys to the place of work, and the desire of people for a more mobile lifestyle) has become evident – according to the U.S. Census Bureau 2000 report (Reschovsky, 2004), 88 percent of workers use a car to commute.

A second point to mention is that the *average travel time per route increased* to 25.5 minutes in 2000 from 21.7 minutes in 1990 with more than 5 percent spending between 60 and 89 minutes per direction in their cars; for nearly 3 percent of workers it takes more than 90 minutes to go to work every day. As expected, the trend for longer traveling times will not stagnate in the near future.

Thirdly, average vehicle occupancy rate (AVO), another measure useful to determine the mobility of persons in a specific area, has recently shown a *declining average number of persons per vehicle*. (The vehicle occupancy rate represents the average number of persons per vehicle, including the driver.) According to (Rimsley, 2003), the average number of persons/vehicle in Greater Lafayette decreased to 1.11 persons per vehicle in 2003, after 1.24 persons/vehicle in 1980. A similar study done in the Phoenix Metropolitan area (Maricopa Association of Governments, 2006) reported that the average occupancy rate has dropped from 1.34 (1992) to 1.23 (2006). A study presented by (Shafie et al., 2008) indicated average vehicle occupancy between 1.54 and 1.61 persons/vehicle. Latest data published by the (U.S. Department of Transportation, 2009) stated an AVO of 1.59 persons per car for the U.S.

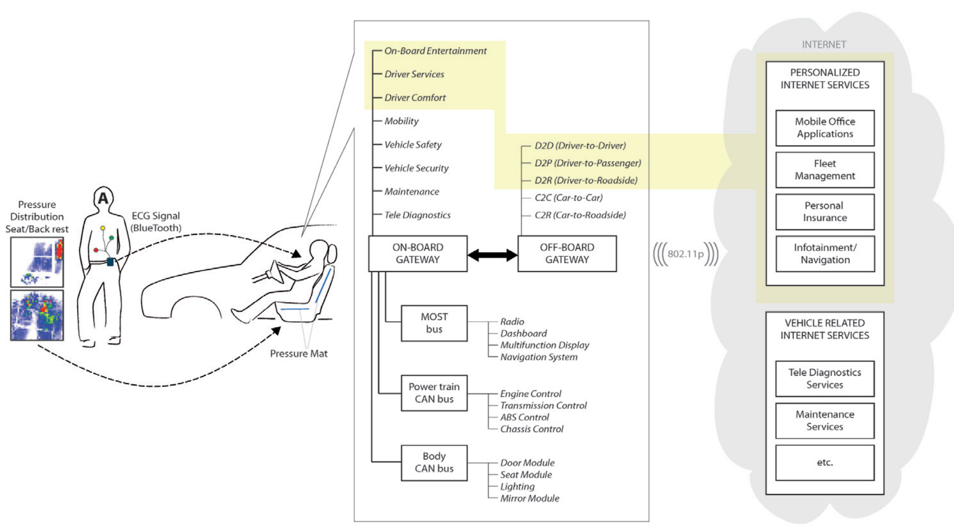
The conclusion to be drawn from these studies is the majority of workers use their car to reach their place of work, car drivers commute mostly alone and for continually longer traveling times a day. Individuals are solely responsible for operating not only the car but additionally for supervising all of its information and assistance systems, substantiating the necessity of attention-free authentication techniques.

The demand for rising personal mobility and individual traffic, together with information and communication technology present in cars at reasonable costs, have meanwhile led to a new generation of smart networked vehicles. In car-to-car (C2C) or car-to-infrastructure (C2I) networks, information about traditional system states like vehicle status, road occupancy or weather conditions is not only exchanged but more personal data of the driver is communicated to adopt individuality.

Individuality in Vehicle Operation

To achieve the goal of personal data exchange on one side and to avoid misuse on the other side, the spread of information between cars and infrastructure calls for continuous identification or authentication of the driver while operating a vehicle. Classical approaches, even if claiming to operate noninvasively, have to be withdrawn as vehicle drivers are often highly saturated in their regular task of steering; therefore, it is out of question that they can provide PIN codes, passwords, or pull their finger over a fingerprint reader to authenticate themselves. Fully automatic and at the same time safe solutions are required to fulfill the operational needs in cars – the car seat or contactless operating ECG devices as media for implicit data collection come into play (Figure 1).

Figure 1. A passive operating driver authentication system with several examples of personalized vehicular services



The application of biometric based implicit authentication of an individual will provide a new class of vehicular services such as personalization (once a driver is seated, he/she will be automatically identified while the vehicle will adjust seat position, AC, radio, mirrors, etc.) and safety functions (only authorized drivers are permitted to start the engine or drive the car while this privilege will be denied to others; posture pattern based identification, as an example for biometrics, is thought to be an effective method for car-theft protection).

Before discussing specific applications, it is also essential to critically examine possible limitations of such systems. Suppose, for instance, that the driver of a car gets injured or incapacitated to drive and someone else is asked to drive him/her to a hospital – can there be any chance for a driver to use his/her vehicle by skipping the authorization process, allowing the helping person to operate the vehicle in a “rescue mode” without a personalized profile (Riener, 2010) (p. 246)?

DEFINITION OF TERMS: IDENTIFICATION VS. AUTHENTICATION

Biometric identification refers to identifying a person based on his/her physiological or behavioral characteristics and biometric identifiers. Identification and authentication (also verification) are significantly different terms: Identification in a biometric system answers the question “who a specific person is” (this is a 1:N relationship, comparing the currently acquired pattern against biometric profiles from a database), whereas authentication attempts to answer the question “is this person A?” after the user claims to be A (Woodward et al., 2003) (p. 2). It has to be noted that the second case (authentication) is much more complex than identification; nevertheless, it can be solved in the designated automotive domain.

Authentication may be defined as “providing the right person with the right privileges the right access at the right time”. In general, in the security community three types of authentication methods (“proof of identity”) are distinguished (Woodward et al., 2003) (p. 6), (Liu, 2001) (p. 27):

- **Physical** or “something you have”, e.g. an access card, smart card, token, or key,
- **Mental**, cerebration or “something you know”, for instance a password, PIN-code, or piece of personal information (the birthday date of one’s mother or the name of one’s dog),
- **Personal** or “something you are”, which is a biometric characteristic dividable into an active (explicit) type, such as the interpretation of retina/iris, voice, face, or finger print, and a passive (implicit) type, comprising for instance sitting posture pattern or ECG signal evaluation.

Physical or mental systems have the disadvantage that they are not based on any inherited attributes of a person; from this point of view it should be clear that the remaining class (personal) is the most secure verification option – because it cannot be lost, stolen or borrowed (such as keys). Furthermore, it cannot be forgotten or guessed by an imposter (as for example a password), and forging of a biometric characteristic is in general very complex. Nevertheless, biometrical characteristics exhibit adverse properties legitimating its universal application, such as

- Some characteristics are dependent on the age or the gender of a person,
- Individuals lacking a specific characteristic may be excluded from the possibility of authentication,
- Correct authentication is always bound to probability levels. To rate the quality of a biometric system two metrics, False Accept Rate (FAR) and False Reject Rate

(FRR), are widely used. Both methods focus on the system's ability to allow limited entry to authorized users. FAR and FRR are interdependent and can vary significantly (Liu, 2001) (p. 32), thus both measures should always be given together, e.g. plotted one against the other.

Continuous and implicitly operating authentication methods based on biometric features can prevent the driver from additional cognitive load and distraction; that is particularly important for situations where the person is continuously highly challenged (for example during a city trip at rush hour). Another advantage of the proposed system can be seen in the fact that once a driver is authenticated using the pressure sensing system in the seat it can be assumed that the person remains the same unless the continuous data flow from the mat system tears off – only in this situation, the complex authentication process needs to be repeated.

Building Blocks for Continuous Driver Authentication

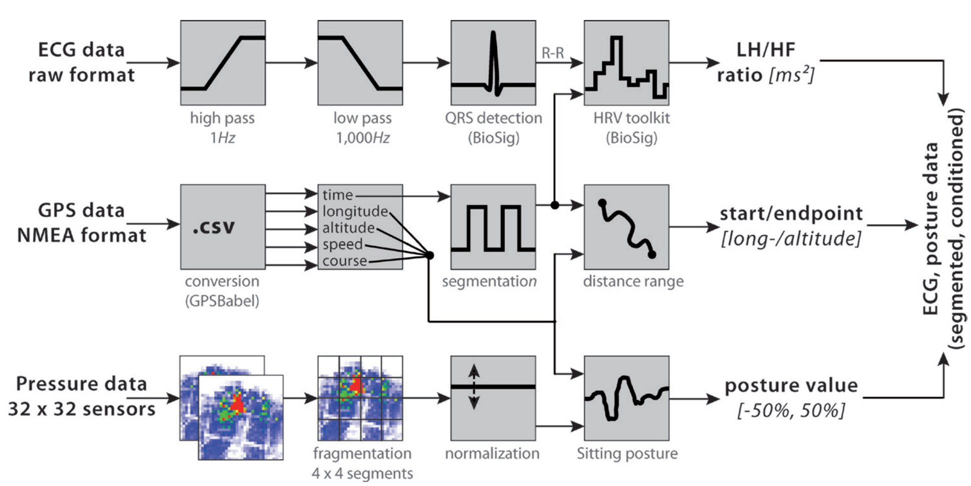
Sensor systems for continuously measuring signals from a person (a driver) must not be obtrusive or annoying as potential consequences can be caused by distraction or overlooked information. Considering this issue, we follow a fully implicit and attention-free approach to acquire the "state" of the driver using only the car seat.

According to a former review of sensors suitable for fulfilling this task, we selected a combination of ECG sensors and force-sensitive (pressure) sensor arrays as novel approach for implicit identification. As outlined in Figure 2, GPS data is gathered additionally for synchronization issues (GPS time) and for location estimation reasons (validation).

Permanent Seat Pressure Image Detection

The behavior of an individual in dynamic environments is dependent on numerous dimensions including context and time. (Bobick, 1997) divides the expression "behavior" into the three sub terms

Figure 2. Driver identification from continuously collected ECG and pressure sensor data. GPS position data is collected to relate sensor data to specific segments of the driven route (validity checking); the GPS time field is used as external basis for data synchronization.



(1) movements (these are the basic behaviors and they have no linkage to situational context or temporal structure), (2) activities (these are short sequences of movements combined with some temporal structure), and (3) actions (these are recognized from activities, and interpreted within the larger contexts of participants and environments).

Latest approaches to solve these issues are more user-centered. For example, analysis of a driver's body postures in real time (Cheng et al., 2005; Oliver & Pentland, 2000; Trivedi et al., 2007; Veeraraghavan et al., 2005). Unfortunately, most of the solutions presented to date are image or video based (tracking of roads, pedestrians/obstacles, and the driver) operating on a combination of color and thermal pictures and markers for pose estimation and are therefore subject to the known problems of image/video detection and processing. The utilization of sitting posture patterns to recognize a car driver's identity is a promising method operating totally implicit. Force-sensitive array mats are used for feature acquisition (Figure 3); acquired data is then analyzed and post-processed using novel algorithms. The sensors are (1) capable of being integrated into almost any type of seat (the mats are highly flexible and have a thickness of just above 1mm) and (2) not reliant on the attention of a person using the system. Finally, they are (3) requiring no active cooperation of the user, and are (4) continuously in operation while the person is seated.

The Seat as Medium for Collecting Pressure Data

The car seat is, in general, covered by the driver all the time while steering a car; it is therefore an optimal medium for collecting driver data in a fully unobtrusive and implicit way.

The application of continuous driver authentication is not limited to the car seat. Preliminary findings encourage an adaptation of the posture pattern acquisition system to operate in other domains like office, industry or at home. Pressure sensor mats have been used to detect sitting postures in a regular chair (Tessendorf et al., 2009), evaluate a driver's behavior (Riener & Ferscha, 2007) (Figure 4) or a person's stress level (Arnrich et al., 2010), as smart system for measuring health-related signals of airplane passengers (Schumm et al., 2010; Setz et al., 2010), and as a measure for comfort (De Looze et al., 2003) and physical wellness (Prado et al., 2002).

Figure 3. Continuous tracking of sitting postures for one person (seating only). The first line shows the pressure distributions as recorded, the second line indicates pressure images with applied zero pressure filter to identify differences between two consecutive readings. (Remark: Data analysis is done on raw data; images are only used for visual inspection.)

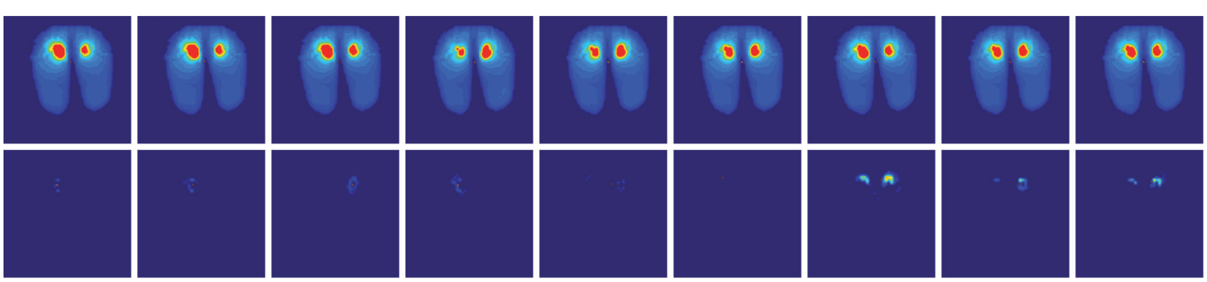
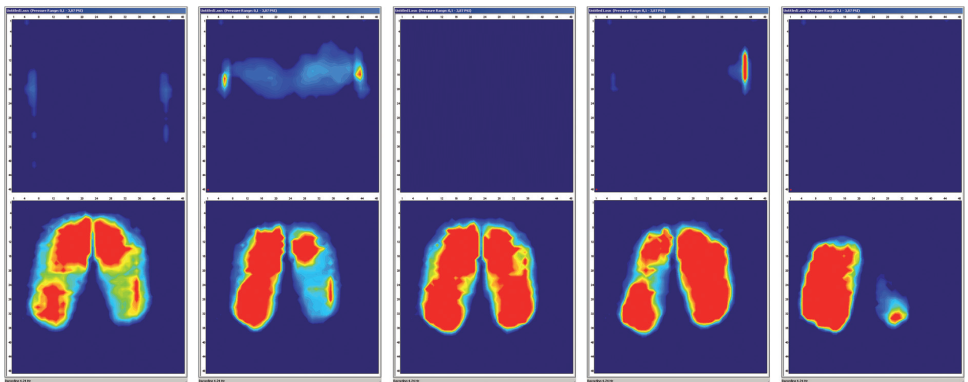


Figure 4. Dynamically collected pressure distributions from backrest (upper row) and seating (lower line) of a car seat. Pressure images show a person in different sitting postures/driving situations (from left to right): Driving normal (sitting upright), accelerating (increased pressure in clavicle region), braking (high pressure at thighs), driving a left curve, and switching gears.



Requirements of the Sensing System

A force-sensitive array system has at least to fulfill the following requirements to be usable for continuous driver authentication: (1) The area of common seats in a car is about 50 x 50cm^2, thus the size of the utilized pressure sensing system should be similar; the mat itself should be flexible and thin so that it is easy deployable in a car; (2) the system should be able to reliably collect data from any person possibly driving that car, e.g. persons ranging in age from 18 up to 80 years and weighing between ~50 and more than 130 kg; (3) the hardware interface should provide precise measurements at a high update rate (e.g. at least one measurement per second), and (4) data acquisition should be accurate (i.e. large number of sensors per mat, low inter-sensor distance, high sensing range and resolution).

System Selection and Setup

Two systems matching our requirements have been reviewed. We used a "FSA Dual High Resolution System" from (Vista Medical Ltd., 2010) (32 x 32 piezoresistive sensors = 1,024 sensing points) for preparatory studies, and a "X3 Pressure Mapping System PX100:48.48.02" (48 x 48 capacitive coupled sensors = 2,304 sensing points) from (XSENSOR Technology Corporation, 2010) for later productive application. Both systems employed for dynamic pressure distribution analysis allow the loads to be recorded on thin, flexible sensor mats. Each sensor covers a pressure range 0 to 26.67kPa (0-200mmHg), the mats are sized 430 x 430mm² (FSA) and 610 x 610mm² (X3). Initial studies have shown that even the smaller mat is virtually sufficient large for data acquisition; only exceptionally thick, heavy persons can exceed the sensing area (but, as indicated below, in not a single of our cases the pressure range). Both systems offer maximum sampling rates equal to (or higher than) 10Hz, while typical used refresh rates were in the order of magnitude of 1Hz (connection errors sometimes lead to an additional slight delay).

- **Calibration:** Prior to its initial use a calibration of the sensing system was required. The purpose is to compensate for any inevitable constructional heterogeneity of individual sensors. During the calibration process each sensor is matched with a determined weight factor in order to later obtain homogenous, similar pressure values. Repeated calibration would be required every four to ten weeks, depending on the frequency of use.

- **Maximum measurable weight:** The pressure range 0 to 26.67kPa (200mmHg, 26,664N/m²), detectable with both (FSA, X3) acquisition systems, seems to be high enough for posture detection in seats; this is true in the case of "normal" sitting (i.e. homogeneous pressure distribution), but may lead to problems in specific areas like around the pelvic bones (see "Problems" below). The analysis of a large number of posture patterns has shown that only about 35% of the sensing elements on the seat mat are covered when a driver is seated. This directly translates into a maximum weight of a person to be reliably measured of 180kg (35% of the maximum weight to be applied to the entire mat in case of uniform distribution). A loose forecast of the weight of a person can be computed from the accumulated force applied to all 1,024 (2,304) sensors; nevertheless, the exact weight of a particular test subject cannot be determined using this technique. The main reasons for that are unbalanced load sharing as well as dead space between the sensor elements.

Problems

The use of these pressure sensor arrays is, nevertheless, not always unproblematic. During our recent work with this type of interface placed in a driver seat, we identified several problems but also potentials for improvement. The most influential are:

- **Mat artifacts:** White noise in everyday life caused by different clothes worn by drivers' (season-specific, e.g. beach wear, jeans, ski-overall, etc.), trouser buttons or objects in the back-pockets (cell phone, small bunch of keys, wallet, coins) pressing on the mat, or even a changing weight of a person over time affect the results.
- **Fixation:** To further avoid faulty measurements and to increase system accuracy it is absolutely important to retain the sensor array mats to the car seat (if not integrated in the seat cushion). Problems were experienced in preliminary tests where the mats were only fixed on the seat with fabric tape: The quality of the test database was deteriorated by changes in the position of the mats, caused by the large number of seated persons in the data collection phase.
- **Unbalanced forces**: In some body regions, particularly around the pelvic bones, pressure forces much higher than on average occurs. These forces may exceed the maximum capable sensor value (26,664N/m²), resulting in a distortion of results. This problem is virtually unpredictable because it is not only dependent on a person's weight, but also on the shape of the back (e.g. pointed pelvic bone).
- **Gender discrimination:** As described by (Luo, 1995; Phenice, 1969) the pelvic bone distance is a suitable metric for accurate differentiation between female and male persons. Due to the low number of only 32 sensors per dimension used in the first experiment series (FSA sensory system) this distinction cannot be made reliably. Data evaluation revealed a mean distance between the two pelvic bones over all 34 test subjects of $\bar{x}=13.12$ and a median of $\tilde{x}=12$ sensors. More importantly, data analysis showed that there are only a few feasible distance-values (in the range 12 ±3 sensors), fostering the request for sensor mats with a higher resolution. Repeated tests with the more precise X3 sensory system

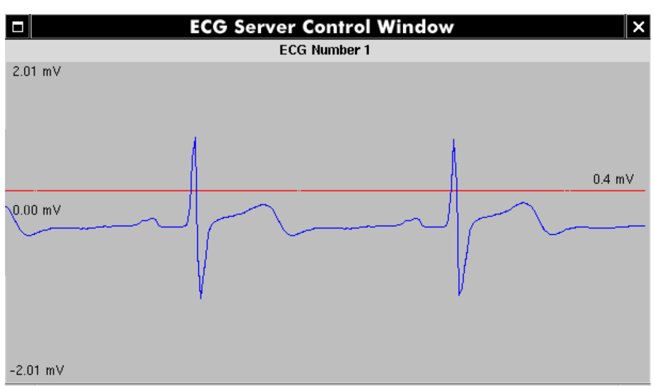
(48 by 48 pressure sensors) are promising, however still in progress.

Continuous ECG Measurement

Measurement and processing of ECG signals has been known for nearly 150 years – longer than for any other complex sensing technique. For a stable measurement of pulse rate, heart rate variability, and other biorhythm related parameters, devices normally demand a placement of the electrodes on the human body, i.e. three conductively coupled electrodes attached to the skin and providing direct resistive contact. The ECG records electrical potentials on the body (the visualized gradient of the curve is generally known as electrocardiogram). For normal cases the process of cardiac stimulus generates patterns as shown in Figure 5. 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. Some issues may have to be considered before employing electrocardiography in vehicular applications:

- **Infeasibility:** It is not surprising that the application of such a device is unfeasible in a twenty-four-seven operating authentication system due to lack of user friendliness and inconvenience (e.g. carrying the device, attaching electrodes, using a conductive gel, stowage of cables, changing batteries).
- **Interference factors:** Opposed to the technically mature ECG devices there are, according to (Mendes, 2009), several factors that can interfere with such an ECG recording:
    - Hairiness can make recording difficult when using adhesive disposable sensors (possible solutions: shaving, adjustment of sensor positions, usage of non-adhesive electrodes),
    - Person's skin characteristics (electrodes might slip on oily or sweat skin),
    - Changes in temperature during the course of the measurement (heating, stress) can make recordings unusable.
- **Drawbacks of emotion recognition:** Facial expression and the voice (e.g. pitch) are signals often used as input channels for human-computer interaction; however, they are not feasible for autonomic person authentication as information conveyed through these channels can be deceiving as they can be faked by the person. (For ex-

Figure 5. Electrocardiogram of a healthy person (driver) recorded wirelessly using a "Heartman" ECG device



ample, 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 (e.g. lighting, background noise), see (Riener, 2010) (p. 93f.). For these reasons, we recently focused our research on the use of bio signals derived from ECG, and conveying affective states to which a person has less influence on (Benovoy et al., 2008).

The Seat as Medium for Collecting ECG Data

(Aleksandrowicz & Leonhardt, 2007; Curio & Mueller, 2007) have independently developed ECG measurement systems operating on capacitive coupled electrodes (cECG). These systems record ECG signals through the clothes, without a direct skin contact. cECG measurements would be therefore insusceptible to interference from skin characteristics and, as skin irritation often evoked by the contact gel between skin and the electrodes can be avoided, it is also expected that these devices will increase user acceptance. Most of the other interference factors and restrictions mentioned before, in particular unfeasibility, will not occur.

Given the strong electrical activity of the heart (Mendes, 2009), a clear ECG signal should be in most cases obtainable with cECG devices. Moreover, cECG devices can immediately start recording once a driver is seated without wiring and distraction during the measurement. Although the measurement is, compared to that from the conventional conductive ECG devices, more sensitive to moving artifacts and is strongly dependent on the subject's clothing, it is supposed suitable for convenient heart rate detection and real-time evaluation in mobile fields of application.

(Schumm et al., 2010) have successfully shown its utilization for physiological monitoring of persons in airplane seats. Following their setting, a similar application in the vehicle seat, with two electrodes embedded into the backrest and the reference electrode integrated into the seating, should provide good results. It can operate fully autonomously and attention-free and thus can be one of the missing building blocks for implicit and continuously operating biometric sensing systems.

System Selection and Setup

In the research conducted in the scope of this work, a common body-mounted ECG device (type HeartMan 301, HeartBalance AG) was used (and not a measurement system with capacitive coupled electrodes similar to the one described above).

The choice for a wired in favor of a contactless operating device was made based on the criteria (1) higher accuracy; (2) more stable signal; and (3) increased resolution as well as the fact that potential restrictions for everyday use, like inconvenience, etc., are negligible in a prototype.

The HeartMan device as representative of wired ECG's was chosen based on the success criteria for ECG data analysis (sampling rate, signal-noise ratio, and data formats available for recording) introduced by (Clifford et al., 2006) (pp. 30-50). The HeartMan appliance is small-sized, lightweight, operates reliably, records up to 24 hours with one battery pack, and delivers highly precise data. Datasets are either transmitted wirelessly and in real time via a Bluetooth communication interface or stored in European Data Format (EDF) on the integrated SmartMedia memory card (space for up to 24 hours of data).

Results of the previous experiments highlighted some problems. Subsequently they are named together with potential improvement solutions.

- **Attribute combinations:** The quality of any biometric identification system can be improved when combining more than one technique. This knowledge has already been applied by adding the ECG signal to the posture pattern recognition system. Adding further measurement categories, such as for instance galvanic skin response (GSR), skin moisture, etc., for collecting person-related data is expected to further enhance the identification system performance.
- **Noise in ECG signals:** When carrying out experiments indoor (e.g. driving simulator studies), it has to be regarded that ECG signals might be influenced by noise from mains or power-lines (50-60Hz). Noise can in particular interfere with ECG data logged at low sampling rates; in such a case appropriate filters have to be applied to clean data from ripple voltage. This issue can be disregarded when using ECG devices in vehicular applications.
- **Sampling frequency:** Sample rate used for recording has to be chosen in order to suit the desired application. For accurate heart rate variability and R-R interval measurements a sampling rate of at least 500Hz is highly recommended; unfortunately, this suggestion cannot be fulfilled using HeartMan devices as they offer a maximum sampling rate of only 200Hz.
- **Data format and storage:** ECG devices either provide the facility to store data internally or by using an external device (e.g. a PC). Device selection, in terms of storage capacity, is dependent on (1) sampling rate; (2) projected recording time for an experiment; and (3) data format used to store ECG data (e.g. EDF/EDF+, WFDB, HL7, and ecgML (Clifford et al., 2006) (p. 36)). Problems with storage capacity shortage are not an issue when using HeartMan devices, as they offer both real time data transmission to a host computer using a Bluetooth communication interface and recording of up to 24 hours of data on the internal memory card.

GPS Data

A GPS receiver (type ATR062x3, ANTARIS 4 GPS chipset (u-blox, 2010); this receiver is optimized for automotive and mobile terminal applications) was carried in the test car and used to gather a vehicle's exact geo-location.

GPS position data was logged in the National Marine Electronics Association (NMEA) 1083 format at a rate of one hertz. GPS data was then converted from the NMEA format to a simplified comma separated values (CSV) file format using (GPSBabel, 2010) (an open source toolkit for the conversion between multiple GPS device formats). Transformed data consisted of a car's position data (latitude, longitude, speed, and course) and a time stamp. This information was later used for visual inspection of the driven route. The GPS time field was consulted as external synchronization basis for the different sensing systems. It has to be noted here, that due to factors like driving speed variation, changed road/traffic conditions, emerging and disappearing jams, etc., an exact synchronization of routes driven by the test participants based on driving time or GPS position only is not possible (we used route segmentation, as indicated in Figure 2, for dataset comparisons).

Environmental and On-Board Sensors

Modeling the interactions among a driver and the vehicle has to address two major aspects of complexity. First, on the driver side, it has to reflect the complex cognitive task of controlling the vehicle (which is determined by the four sub-processes (1) perception; (2) analysis; (3) decision; and (4) expression). Second, on the vehicle side and apart from biometric identification/authentication technologies, sensor values captured from acceleration or brake pedals, vehicles on board diagnostics (OBD) interface, the steering wheel, etc. should provide substantial added value towards personalized in-car applications (in particular, if possible to associate "sensor states" with driver behavior). (Erzin et al., 2006) conducted driving experiments utilizing the behavior of a driver (derived from speed variants and pedal pressures). They found out that the "vehicle context" allows verification and, in succession, reaction to the driver's physical or mental condition (alert, sleepy, drunk) to a certain degree.

Modeling the driver-vehicle interaction loop is a difficult task, as it may be influenced by reaction time discrepancies between vehicle and driver. Recording, instrumentation, and processing of vehicle-related data (=input) as well as actuator control (=output) by far excels the human perception-analysis-decision-expression process. This may cause steering mistakes due to unnecessary operation delays. This problem is not new – there are some solutions available to counteract this reaction-time issue: Driver Assistance Systems (DAS) have emerged, aiming to improve (power steering) or compensate (ABS breaking) driver performance, but potentially elevating cognitive load at the same time. In addition, on-board entertainment systems can lead to an overload of the visual or auditory channels of perception having a negative impact on reaction time. Last, but not at least vital parameters like fatigue, stress, attention, etc. crucially affect driver performance. All these essential aspects have been taken into consideration in the design phase of our feature-rich driver emotional state recognition system including identification and authentication components. The test bed used for studying continuous driver authentication while driving includes video data, accelerometers at all 4 axes of the vehicle, ECG data plus related measures (heart rate variability (HRV), standard deviation of all normal R-R intervals (SDNN)), pressure data, driving speed, as well as GPS information.

CONTINUOUS DRIVER AUTHENTICATION IN VEHICLES

Services that demand unambiguous, unmistakable, and continuous identification and/or authentication of drivers have recently attracted reasonable research interest. (DeLoney, 2008; Koenig, 2004) reported that most efforts have been directed to identification techniques based on face or pose recognition (using still or moving images) or acoustic analysis.

An overview of the characteristics of appropriate biometric identification technologies for vehicular use is presented in Table 1; a description of biometric security technologies in more detail is given for example in the underlying research study published in (Liu, 2001). It is assumed that all the explicit identification techniques used to date can be replaced by implicit identification methods. Sitting postures, the ECG, and also a person's voice are qualified biometrics for providing implicit acquisition.

For employing personalization from biometrics (appropriate for the vehicular domain), the identification demand can be divided into two main categories:

- **Personalized settings**, such as seat and mirror adjustments, radio station presets, calibration of the running gear, chassis setup, horsepower regulations, etc., where the adaptation to predefined settings requires an identification once at the time of boarding,
- **Personalized services,** such as a car insurance rate, road pricing, cause-based CO_2 taxation, etc., demands for continuous authentication of the driver while seated and/or operating the car.

Implicitly acquired biometrics, combined with additional sensors and processing capacity, can allow for new advanced fields of vehicular applications such as (1) automatic allowance/disallow-

Table 1. Comparison of biometrics (extension based on Liu's work (Liu, 2001))

		Fingerprint	Hand Geometry	Retina	Iris	Face	Signature	Voice	Sitting Posture	ECG
Characteristic	Ease of Use	high	high	low	medium	medium	high	high	high	high
	Error Incidence	dryness, dirt, age	hand injury, age	glasses	poor lighting	light, age glasses, hair	changing signatures	noise, colds, weather	age, weight	clothes, vibrations
	Accuracy	high	high	very high	very high	high	high	high	medium	high
	Cost	*)	*)	*)	*)	*)	*)	*)	*)	*)
	User Acceptance	medium	medium	medium	medium	medium	very high	high	very high	very high
	Required Level of Security	high	medium	high	very high	medium	medium	medium	medium	high
	Long-Term Stability	high	medium	high	high	medium	medium	medium	medium	low to medium
	Implicit Acquisition	no	no	no	no	no	no	yes	yes	yes

*) The large number of factors involved makes a simple cost comparison impractical.

ance of vehicle operation (e.g. by determining if the person sitting in the driver seat is authorized to steer the vehicle) or (2) increased safety functions (promoting safe driving by monitoring a driver's behavior to determine for example if the driver is sleepy or drunk and to prohibit further operation of the vehicle if a certain threshold is exceeded).

Recommendation: Authentication from Body Behavior and ECG

We propose an automatic driver authentication system based on personal characteristics or "something the driver is…" (Woodward et al., 2003) (p. 6), (Liu, 2001) (p. 27). The two characteristics body behavior and driver ECG are passive representatives of biometrics, thus assumed not to influence the driver in his/her regular task of steering a vehicle. Examples of application for the first type include (1) the analysis of movement trajectories of torso, limbs, and the head; (2) intentional gestures, e.g., with an arm or hand; and (3) the shift of a person's weight over the time, identifiable via pressure sensors in a chair/seat. A recorded ECG can be analyzed and interpreted in numerous ways, e.g. (1) dynamic developing of the signal from heartbeat to heartbeat; (2) progress of the R-peak value; (3) R-R interval; (4) power spectrum of the ECG signal; (5) HRV analysis (derived unit of measurement), etc.

The building blocks for the research presented in this article are (1) static body postures; (2) dynamic body postures recorded/analyzed while driving; and (3) ECG signals (in particular the derived unit HRV) evaluated in real time. Each of these subcomponents can be used fully autonomic (as the paragraphs on initial experiments below shows). Furthermore, there is evidence that a combination of several aspects may improve the overall (authentication) accuracy (Liu, 2001). This approach is feasible and can be noted from Table 1 – it relates the usability of sitting postures or ECG signals as biometric identification techniques for in-car usage to other known methods, such as retina or iris scan, face recognition, fingerprint, signature, etc.

Both sitting posture acquisition from a sensor matrix attached to the seat and contactless ECG recording convince by the key point that data gathering can be, opposed to most other biometric methods, completed fully implicit. But not only the possibility for implicit acquisition qualifies the use of sitting postures and ECG's for continuous driver authentication – other criteria like ease of application or a high expected user acceptance (both types of sensors are integrated into the seat cushion and are whether visible nor noticeable by the driver) furthermore promotes their application.

The continuity of measurement is also guaranteed all the time as the driver has to be seated while steering the car, providing pressure to the force sensors and electrical signals of the heart to the ECG measurement system.

Static Sitting Posture Evaluation

For data acquisition in our first prototype (Figure 6) we used force sensor arrays (FSA) connected via USB to a standard notebook computer. The system setup is universal, thus can be used in any type of car (e.g. utility-driven car, sports car with body-contoured seats, family van, comfort station wagon, etc.) and for arbitrary style of sitting or driving. Recently, we used the same setting in office chairs for authentication in a porter's lodge. We suppose that a combination of different features received from static sitting postures are unique, thus allowing driver (or in general person) authentication. For further verification, experiments have to be conducted in different types of cars, respectively seats, and with a large number of subjects.

Test Execution

To assess the quality and accuracy of the prototype, a database with pressure patterns from 34 volunteers has been created. All recordings have been processed in a comfort station wagon (type Audi A6) with pressure mats attached to both, seat and backrest. For initial evaluations, the Euclidian distance metric – a well-researched approach in the field of pattern recognition – was used to match a person's current sitting posture against earlier stored patterns. The experiment was conducted in two stages, (1) recording of the training set, and (2) system evaluation with a testing set.

- **Training set:** In the first phase, data samples were captured and the test subject features were extracted and stored in a relational database. For that, consecutive readings of sensor data alternating between seat and backrest mat, were written as raw-data into the database. Pressure data was completed by a timestamp and personal data (age, gender, size, weight). The duration for recording of one person was less

Figure 6. Dynamic pressure distribution acquired from different types of car seats: comfort station wagon, sports car, and race car (from left to right)

than 5 minutes, including introduction and briefing.
- **Testing set:** Samples of any acquired person have been compared in the "live system" to all stored datasets to detect the best matching dataset (that with most similar pressure dissemination).

To eliminate the impact of sudden movements during data acquisition on the driver seat, the median of each of the 1,024 pressure sensor values over a series of measurements was calculated. Initial tests confirmed that using five measurements is sufficient to create a stable matrix of pressure values. To ensure data integrity (Hamming distance), for each test participant four independent datasets were captured and stored.

Features

Feature vectors for a person were calculated using a weighted combination of several parameters extracted from the sitting posture matrix, and referred to as the personal sitting profile. The following features were utilized for evaluations regarding person identification from static sitting posture patterns.

- **Weight:** A weight approximation for the driving person was calculated as the sum of all pressure values on the seat mat (therefore, sensors were calibrated before to exhibit similar pressure distribution). The total weight cannot be exactly estimated from the charged sensors as already mentioned before.
- **High pressure area:** This attribute considers only high pressure values exceeding 90% of the maximum pressure.
- **Mid to high pressure area:** This parameter is similar to the "High pressure area", but calculated from sensor values exceeding 10% of the normalized pressure minimum.
- **Pelvic bones area:** This factor is more sophisticated, determined by the location as well as the distance of the thighs on the seat mat. It is relatively simple to identify the pelvic bones on the mat because they are responsible for two areas of very high pressure. The Euclidian distance between the midpoints (x and y coordinates) of left and right pelvic bone was calculated and used as fourth parameter for feature vector calculation. Using the pelvic bone area benefits from the following stability characteristics;
    - *Durability:* The feature is permanent as distance between the pelvic bones does not change if people gain weight or wear different clothes (in contrast, size/shape of the area indicating pelvic bone region does).
    - *Gender dependency:* It is established that pelvic bones of males and females are different (Phenice, 1969) and the feasibility of discrimination has been shown, e.g. by (Giles, 1970; Stewart, 1954).

Biometric Characteristics: Experiments and Results

Permanency: This characteristic specifies the potential of a feature to always stay the same. Sitting postures of a person, however, do not stay constant as persons wear, dependent on the season, different clothes (thick jacket in winter, beach wear in summer). Furthermore, objects like wallet, cell phone, bunch of keys, coins, etc. in the back-pockets as well as trouser buttons providing additional force to the sensor elements which adversely affect the measurements.

An experiment to investigate the susceptibility to "noise" (with different artifacts in the pockets) provided the following results (Table 2). All sitting posture variants[1] of a subject with objects (artifacts) in the back-pocket are compared to each other and to the underlying normal posture. The confusion matrix shows the distinction of postures with different artifacts in percent. The base quantity for differences in postures was defined as the maximum difference of any two regular sitting postures in the database of 34 subjects and set to 100% (independently for seat and back). As no artifacts have been applied on the backrest mat (i.e. placed on a person's back), there was no significant change in the backrest postures detected. On the seat, however, the maximum difference for pressure patterns between one subject in normal posture and the same person with applied artifacts in the back-pockets is, with 58.9%, high. Reliable person identification would therefore be not possible when using the actual feature vector calculation, particularly when compared to the maximum difference of any two persons which is 100%. Statistical analysis (Table 3) of the artifact-afflicted datasets is very similar to that of the normal datasets.

Uniqueness: For determining the accuracy and uniqueness of pressure patterns, this feature has been evaluated for two test subjects (Figure 7) with a large number of recordings. Candidates were seated in the car again, and larger series of consecutive readings were processed. For each of the trials, gathered postures were compared to all stored patterns in the database. Deviations were calculated and saved in a separate database table. Table 4 shows the results for the feature weight only (weights are normalized, i.e. factorized with the predetermined reference weight). The mean-value gives a relative precise estimation of a person's actual weight, but the deviation is rather large.

Table 2. Confusion matrix of normal postures compared to postures with applied artifacts for the seat (maximum differences in percent compared to database of regular postures)

-	N	KL	KR	CL	CR	DL	DR	DRKL
N	-	29.4	39.8	50.0	46.5	55.6	52.7	58.9
KL		-	38.3	42.6	43.0	48.4	49.9	51.0
KR			-	33.8	33.5	49.0	36.0	47.7
CL				-	34.0	37.0	37.6	45.4
CR					-	36.9	28.8	39.5
DL						-	41.8	34.3
DR							-	31.5
DRKL								-

Table 3. Statistical analysis of the feature "permanency"

Data Sets	Database	Min x_{min}	Max x_{max}	Mean $\overline{x}$	Median $\tilde{x}$	Std. Dev. σ	(P_{25})	(P_{75})
Seat mat (normalized)								
34	Normal	24.78	100.00*	54.79	52.93	12.39	46.45	62.08
8	Artifacts	28.82	58.55	41.89	40.79	8.13	35.59	48.75
Backrest mat (normalized)								
34	Normal	15.16	100.00*	41.10	38.43	12.00	32.21	45.56
8	Artifacts	11.61	28.27	20.02	19.47	4.16	17.37	2.45
** Maximum difference of any two normal datasets has been set to 100%*								

Figure 7. Two persons (both male, similar age and figure) sitting upright in a stopped car (right after boarding). Already the visual inspection of pressure images allows for clear differentiation.

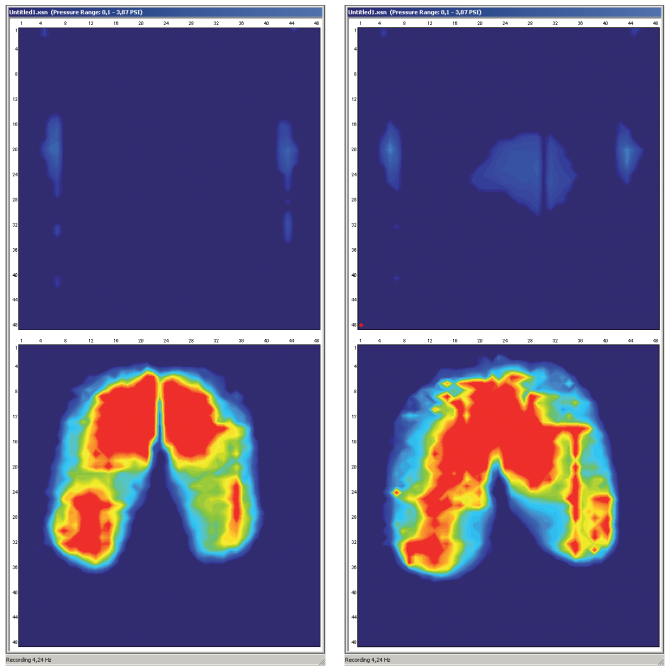


Table 4. Measurement accuracy for 2 subjects (parameter weight only)

Data Sets	Actual Weight	Min x_{min}	Max x_{max}	Mean $\bar{x}$	Median $\tilde{x}$	Std. Dev. σ	(P_{25})	(P_{90})
105	75.5	58.797	83.667	75.251	75.682	6.192	67.223	82.246
31	80.0	69.433	90.381	81.925	83.779	5.937	70.571	88.295

For the entire feature vector a rank was calculated and assigned in the order of minimal differences. For example rank 1 reads as least deviation between the current feature vector and the feature vector in the database currently checked against, thus represents the best match; rank 34, in a database with 34 datasets, is the largest difference or worst match.

Dataset matching for the drivers with 31 independent readings resulted in ranks 1 to 6. In worst case, that occurs in only 3.33%, the matching between measurements against all 34 postures in the database results in place 6. This stands for rather high stability of the sitting posture of that person. On the other hand, however, it can be seen that an exact match (= rank 1) is obtained in less than 25%, which, of course, is poor. The results for the 2nd test read divergent. An exact match is given here in 48.08%, but the remaining 51.92% are distributed to nearly all ranks (86.54% of readings are assigned to ranks 1-10, the absolute worst case, occurring in less than 1 percent, is an assignment to rank 30). From the results of these two tests it is not possible to draw generally acceptable conclusions (additional studies, using the more precise X3 mat system, are currently in progress).

Conclusion

Motivated by an ample emergence of in-car services going beyond the usual automatic customization of vehicle functions or services (which all are reliant on unambiguous, unmistakable, and continuous driver authentication), we have developed a driver identification method based on the biometrics of sitting.

Our approach is based on implicitly inspected sitting postures acquired from pressure sensor mats on the driver seat and backrest. Posture recognition does not suffer, opposed to vision detection techniques, from environmental conditions like brightness or weather; moreover, the measuring system itself is invisibly integrated into the vehicle seat and the unobtrusive disposition avoids driver distraction.

Experimental results showed that posture patterns are in some respect a feature suitable for describing an individual, and thus, applicable for identifying or authorizing a person in a vehicle seat. With the investigated method of feature vector calculation and its comparison against the "training set", at least persons usually sharing a car should be clearly differentiable.

The current accuracy of the prototype necessitates improvements: On-line analysis of a driver and a training data base containing 34 datasets resulted in authentication rates of 22.33% for one individual and 31 trials and 48.08% for the second test with another person and 105 readings. Conducted experiments showed further that the achieved authentication rate was prone to changed sitting postures for an individual (e.g. due to artifacts) to a stronger degree than initially expected.

Dynamic Sitting Posture Evaluation

Intelligent driver assistance can relieve the driver from manipulative and cognitive issues by e.g. adaptively controlling the vehicle before activities from the driver actually take place. The aim of the initial experiment was to prove the hypothesis of a visually detected phenomenon. Video analysis of dynamic sitting postures and steering behavior revealed that a driver has low or moderate ambition to compensate centripetal force in low speed driving while in high speed cornering situations the readiness to compensate lateral forces is high. If this behavior can be substantiated in real driving situations, it can be utilized to enhance intelligent driver assistance systems (e.g. to avoid over- and under-steering). The next step toward automatic driver authentication would be the investigation of driver's dynamic developing postures.

As an extension to the previously described static posture acquisition system, we deployed the system of 32 by 32 sensors per array in a dynamic environment. To increase system stability and to improve the quality of the measurements we added supplementary sensors. The parameters vehicle speed, steering angle, body posture, GPS position, vehicle acceleration forces, and driver's ECG were recorded. Video cameras were used for visual inspection and verification of obtained results. Vehicle-specific data were gathered via the vehicles On-Board Diagnostics (OBD) interface.

Experimental Setting

In common road traffic we can distinguish between a number of different types of turns, e.g. right-angled streets or crossings, freeway entrance and exit ramps, U-turns, banked corners or "regular" curves. In the first of a series of experiments reported here, we were focused on driving situations while cornering left or right (curves with different radii) in a closed environment. The field study was conducted in a driving safety center on a specified race course with a length of about 1,150 meters.

Reference weight: As the expected correlation body posture – cruising speed is dependent on the driver's weight (centrifugal force) it is also necessary to obtain a coarse estimation of the weight of the seated driver. Therefore, we initially applied a reference weight to it: A person with a given weight (74.80kg) was seated and 100 consecutive readings from the 32x32 sensor matrix were recorded. The mean value of the accumulated pressure has been set as reference factor for further weight estimations.

$$\overline{pressure} = \frac{1}{100}\sum_{j=1}^{100}\sum_{i=1}^{1024} sensor_i$$

$$factor_{pressure} = \frac{weight_{real}}{\overline{pressure}} = \frac{74.80kg}{176.589} = 0.4235$$

Data Processing

Data from different sensors was recorded and preprocessed (filtered and time-aligned using the GPS time field) to meet the requirements of the statistical analysis tool set. Table 5 presents five datasets out of the entire data table of 3,786 rows.

Accelerometer data: The utilized type of accelerometer (InertiaCube, (Intersense, 2010)) provides data at a high update rate of 180Hz. The car itself acts as a reference coordinate system, consequently all accelerometer readings had to be aligned to the vehicle coordinate system (x-coordinate is in vehicles direction of motion, y is oriented in the right angle of x, z face upwards). Although accelerometers were placed around each axis of the vehicle, for the present evaluation only the one accelerometer mounted near-by the front, left wheel was used.

Normalized accelerator data is, after time-synchronization, smoothed with a ramp function taking the current value and the previous 8 sensor values into account. (Remark: Using a Gaussian bell-shaped function instead may improve the results.)

Pressure mats: FSA11, FSA12, FSA13,… FSA44 indicate the aggregated pressure regions from the sensor matrix. Each value stands for the sum of 64 sensor values in a specific region. (To give an estimate for the "direction of leaning", the evaluation based on a single-sensor will be impossible.) As the pressure sensors are intended to reason about "leaning postures", we defined "leaning left" as a deviation from the initial symmetric pressure distribution (indicating an up-right sitting position of the driver) to the left. Analogously, "leaning right" is a deviation of the sitting pressure distribution towards right.

Vehicle speed, time, GPS: Vehicle specific parameters have been obtained from the OBD interface, the remaining attributes were provided by the GPS receiver. The GPS time field was used as external basis for data synchronization.

Results

Results for some of the experiments are presented in the subsequent Figures 9, 10. The plots contain three variables: vehicle lateral acceleration force (acc_y) in the range [−20, 40] m/s^2, vehicle speed (v) in the range [0, 125] km/h and driver's sitting

Table 5. Tabular specification of incorporated features

Time ms	FSA11 kPa	FSA12 kPa	... ...	FSA44 kPa	Accelerometer1			v km/h	GPS ϕ GRD	GPS λ GRD
					x	y	z			
540,687	5.444	19.144	...	0.000	-2.195	7.427	-3.456	118.648	1,519.736	4,812.780
540,890	5.420	19.026	...	0.004	-1.698	9.657	-0.201	119.528	1,519.739	4,812.781
541,109	10.086	24.365	...	0.004	-1.466	8.422	0.101	120.477	1,519.472	4,812.782
541,640	12.104	28.130	...	0.020	-0.368	8.729	3.824	122.778	1,519.778	4,812.786
541,828	12.081	28.277	...	0.000	-3.925	8.606	-3.213	123.593	1,519.751	4,812.786
...	...	...	...	...	...	...	...	...	...	...

posture (as "direction of leaning" to the left or right side) (pr_{right_norm}) in the range [−50, 50].

Figure 8 shows a clipping of 11 minutes of one experiment considering only sections driven at low speed (below the driver-dependent break-even speed v_{BE}). The weight-dependent value for the current driver was calculated at 75km/h. (The Euclidean distance between acceleration force and normalized mat pressure is smallest at this speed; evaluation for speed values between 0 and 120 km/h in steps of 1 km/h).

It has to be noted that the relation between leaning behavior and driving speed also depends on the geometry of the curve – a lower speed at a tight turn can probably produce the same result as high-speed driving in a wider turn or in a banked curve. As task for future improvement, the break-even speed v_{BE} has to be actualized dynamically

Figure 8. Incoherence of vehicle lateral acceleration force and driver's sitting posture while cruising at low speed (below person dependent break-even speed; here: 75km/h)

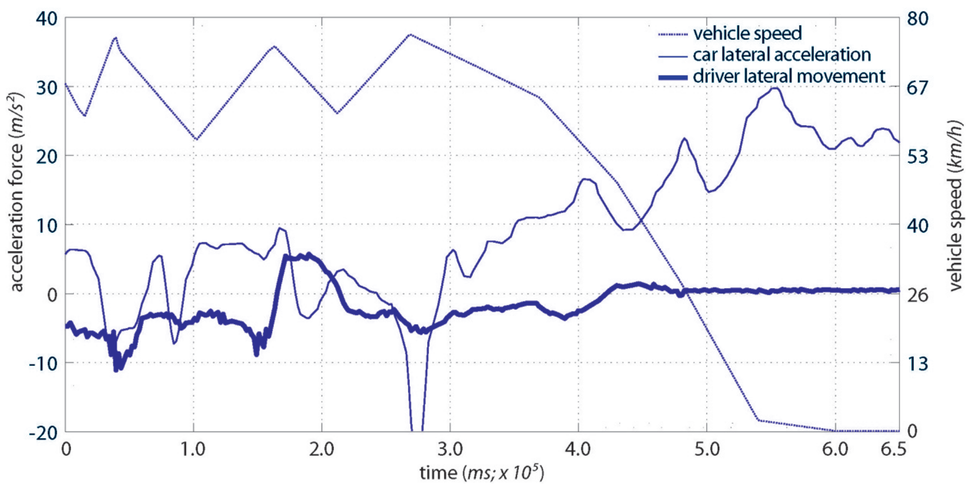


Figure 9. Dynamic sitting postures for high speed driving above a person-dependent break even speed (here: 75km/h) indicates a close relation to vehicle lateral acceleration force (shown as thin blue line)

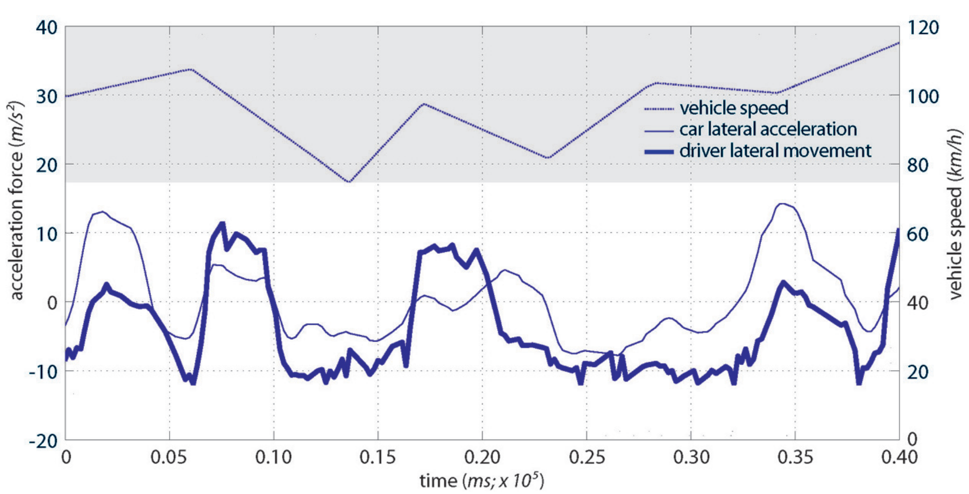
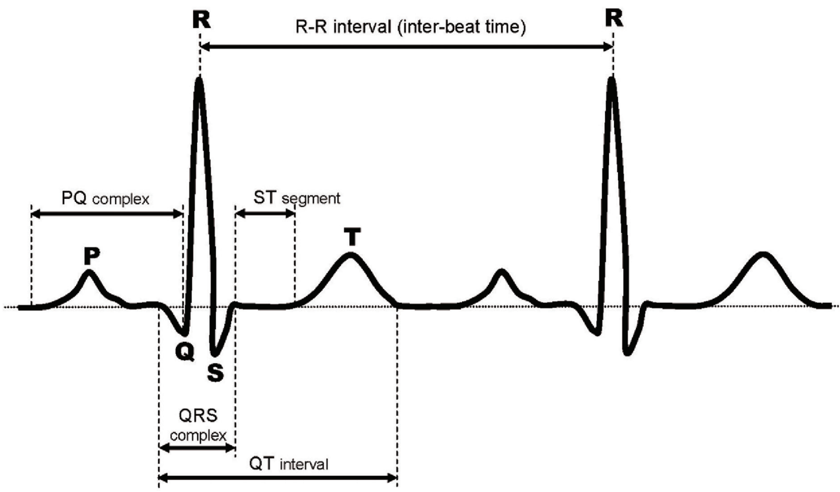
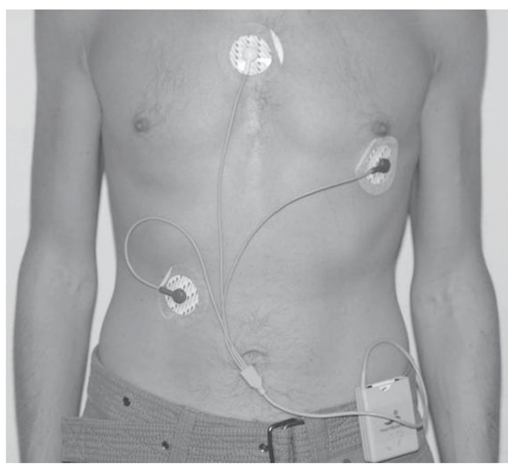


Figure 10. Electrocardiogram of a healthy person (left); 3-lead mobile ECG device type "Heartman 301" attached to a person (test driver)





(according to curve parameters, detected i.e. from the steering wheel angle sensor). Focusing on the low-speed section as shown in Figure 8 we can identify no correlation (at least not for sections driven at a speed around zero) between the vehicle lateral acceleration force and the sitting posture of the driver obtained from the force sensor array (in higher speed segments, an inverse correlation can be deduced from the curve gradients).

In contrast to Figure 8, Figure 9 shows the interrelationship between the vehicle lateral acceleration and body postures in high-speed driving section. Cornering indicates here a significant correlation between vehicles acceleration force and persons sitting attitude – both the shapes and the peaks of the variables acc_y (blue thin, solid line) and $pr_{right—norm}$ (blue thick, solid line) are similar.

Conclusion

We investigated the hypothesis emphasizing a driver's readiness to compensate lateral acceleration when cornering correlates with the driving speed. Preliminary evaluations of conducted driving studies confirmed this hypothesis: Depending on the steering ratio and the cruising speed, we identify that the readiness of a driver to compensate lateral forces exhibits counterintuitive characteristics. Low speed cornering is attempted with moderate readiness to compensate centripetal force (Figure 8), while high speed cornering leads to an increased readiness to compensate lateral forces (Figure 9). This preliminary result motivates to extend the setting towards continuous driver authentication based on a driver's dynamic developing posture gradient.

ECG Analysis for Arousal State Detection

In order to improve driver authentication we added another feature (ECG evaluation) to the sitting posture acquisition system. Unfortunately, the gradient of the electrocardiogram is not a person-specific feature suitable for unique identification; moreover, it is highly susceptible to factors like stress, tiredness, sickness, age, manual work, etc. Electrocardiograms are typically used by medical doctors for early diagnosis of heart disease or for identifying the cause of a heart attack after it occurred.

It is also well known that bio signals are related to the autonomic nervous system (ANS), which controls, amongst others, cardiac muscles. Cardiovascular activity is, according to (Mendes, 2009), one of the most widely used noninvasive methods for measuring ANS activity in emotion research, and electrocardiography (ECG) is one of the most common ways of measurement. Despite the fact that sensors exist for the acquisition of bio signals, 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 established "golden rules" for the usage of bio signals.

For normal cardiac activity, a balance is maintained between the sympathetic and the parasympathetic activities. (The sympathetic system is responsible to prepare the body for a stressful condition; the parasympathetic is responsible to put the body in a calmer state.)

The assumption of the research, followed in the initial experiments, was twofold:

- **Divergence in the arousal state:** Differing affective state values for a person identified during a trip (testing set) in comparison to the training set represents some kind of abnormality and should be immediately forwarded to the driver to avoid danger situations.
- **Person-dependent sympathetic/parasympathetic activity:** Hypothesizing that persons respond with different emotional states for one and the same fixed experimental setting (i.e. driven route), the different behavior, measureable, for instance, as developing over time and/or by applying statistical methods, may be helpful to support or improve driver authentication.

Experimental Setting

In order to study the relationship between a driver's arousal state and a driven route, we conducted initial experiments measuring ECG/GPS pairs, and calculating representations for the two branches of the ANS, the sympathetic (high arousal) and the parasympathetic (low arousal) system. Tests were processed on a specific route and at a fixed daytime on weekdays only to avoid environmental influence, e.g. on traffic jams, as good as possible. A total of 22 trips with more than 500 kilometers driven were logged and analyzed for a single identical person. Based on this data a "personal emotional profile" (for the route and a specific daytime) can be compiled (="training set"), indicating the state of that person for each position on the track.

Signal processing: The ECG signal was preprocessed with a high-pass filter of 1Hz followed by a low-pass filter of 1,000Hz (see Figure 2). 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 Matlab "BioSig" toolkit according to recommendations given by (Nygårds & Sörnmo, 1983). The detector returns the fiducial points of R peaks, which then were used to perform HRV analysis (i.e. calculate LF/HF ratios as an index for autonomic balance).

Generally, the time between consecutive heartbeats, the so-called "inter-beat time" (Figure 10), is irregular (unless the heart is paced by an artificial electrical source such as a pacemaker or due to medical conditions). A widely-used method to measure this irregularity is heart rate variability (HRV). HRV is a promising tool for applications involving medical diagnoses and stress detection. (Blobel et al., 2008; Kim et al., 2008) have reported that HRV statistics is qualified for mental stress estimation. This can be applied to vehicular applications as well, as the estimation of emotional state can gain additional benefit in automation.

Calculation of HRV relies on the analysis of the series of R-R interval differences in the time or frequency domain. Measures of time domain include, for instance, root mean square of differences of consecutive R-R intervals. Frequency domain analysis represents deviations with respect to frequency. For that, several frequency bands, like the very low frequency (VLF) (<0.04Hz), low frequency (LF) (0.04-0.15Hz), and high frequency (HF) (0.15-0.40Hz), should be analyzed independently. VLF measure was indicated as being unreliable for short time intervals; the LF/HF ratio is, however, 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.

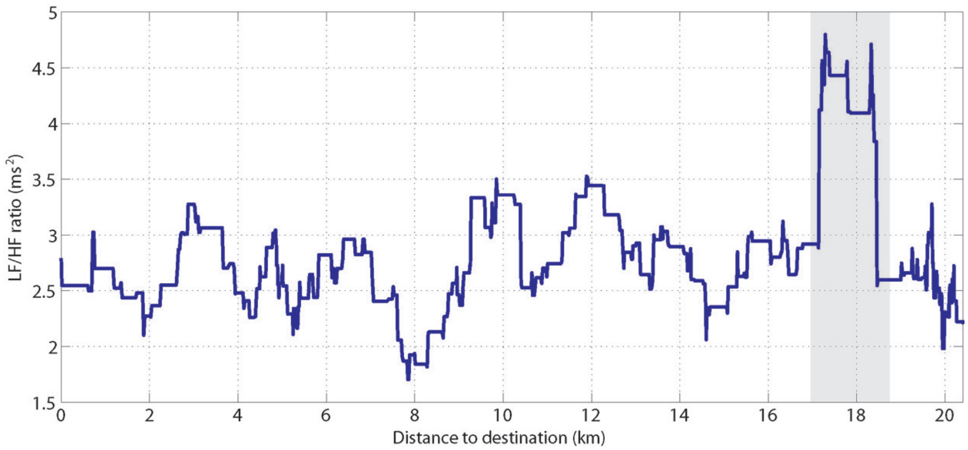
Typically, HRV analysis is done for time windows of 5 minutes or for longer periods like 24 hours (there is no standard mentioned for an ideal time window frame (Clifford et al., 2006) (p.71-83)) and can provide good indication for arousal (but not valence!).

GPS data was converted from the NMEA format to a simplified comma separated values (CSV) file format using (GPSBabel, 2010). Transformed data consisted of the car latitude and longitude, speed, course, and a time stamp. Due to factors like driving speed, road conditions, and traffic congestions the time needed to travel a route varied every day; therefore, an exact synchronization of data based on GPS time was not possible. In order to overcome the synchronization problem, reference routes for the morning and the evening trips were defined. In addition, a time window for segmenting and analyzing the data had to be chosen. 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 1 minute the lowest frequency that can be resolved is $1/60=0.016 Hz$ 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 (Nygårds & Sörnmo, 1983)(p. 79). Applying this formula leads to a lower limit of $N=48 beats$. (As 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).

Discussion: After collecting and processing the datasets, the aggregated LF/HF ratios were visualized along the routes. Figure 11 shows the autonomic balance in relation to the distance to destination (outbound direction only). Higher values are thought to exhibit higher levels of arousal (implied by increased sympathetic activity), lower values are opt to demonstrate lower levels of arousal (as a result of the dominance of parasympathetic activity).

In the following we try to give reasons, based on road characteristics noted throughout the ex-

Figure 11. Distance ranges and aggregated LF/HF ratios of the driver for two weeks. Highest ratio (gray area) occurs in jammed road sections.



periment, that might be likely to exhibit the observed measurements; indeed, we have no means to proof the reasons behind the phenomenon in the data. Looking on Figure 11, the most interesting road segment is that from kilometer 17 to 18.6 (gray area). The state of arousal, varying between 4.2 and 4.8m/s², is here much higher than in any other region of the gradient. The reason for this is probably the incipient traffic congestion (dense traffic, but vehicles are still moving) on the borders of the city. Driving on workdays at around 7.30AM, a traffic jam (standstill) will appear every day between the kilometers 18.5 and 20. The final segment (low to very-low LF/HF ratio) is driven at walking-speed on the parking lot at the destination, with only very little traffic at that time.

One particular issue to cope with is the sensitivity of HRV to parameters like age, gender, activity, medications, and health (Clifford et al., 2006) – it is ambiguous how to differentiate appropriately, e.g. whether a high LF/HF ratio is caused by an increased mental load (attention on the road) or the raised activity of vehicle steering (braking and accelerating, changing gears, steering).

Conclusion

It is undoubted that the cognitive workload of a car driver is increasingly demanded by modern driver assistance systems. The consequence is a possible threat, mainly caused by distraction from 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 post-experiment interview revealed that the subject was not feeling stressed during the experiment, which indicates that LF/HF ratios can be used as an indicator for subconscious stress. Differences in the "personal affective profile" of a driver (curve as indicated in Figure 11) can be used for proactive notifications on possible danger situations (data evaluation has shown, for instance, higher levels of arousal at times of higher volume of traffic) and may also be helpful to improve driver authentication systems, e.g. by analyzing root-mean-square deviation.

It has to be stated once more that we cannot back our observed phenomenon in relation to the road characteristics with a proof; nevertheless, the stated observations are only remarks on what we think is significant.

A lot of issues are still open in this branch of research and will be covered in future. As one focus, we will conduct experiments with different drivers in order to provide evidence for person-related differences.

FUTURE RESEARCH DIRECTIONS

Previous work has already shown that the application of data from bio sensors can be assumed promising; however, contrary to their potential, applications are uncommon today (although a lot of sensors exist for the acquisition of different bio signals of a person). This is most likely caused by the fact that the usage of data from such signals is not an easy task and the application of only a single method is mostly problematic due to measurement errors, noisy data, etc. Moreover, and unlike other approaches, no "golden rules" have been established yet for the usage of bio signals in the field of human-computer interaction.

Our future research approach in this field is aligned on a combination of several sensory channels. For that, we plan to integrate other bio sensors to improve overall data set quality. Table

Table 6. Sensory channels usable for bio signal detection (adapted from (Aly, 2009))

Response System	Technique	Description	Analysis Technique
Central nervous system (CNS)	Electroencephalogram	electrical activity of the brain	time and frequency domain analysis
	Functional magnetic resonance imaging	a form of magnetic resonance imaging of the brain that registers blood flow to functioning areas of the brain	higher blood flow indicates increased brain activity; image analysis techniques
	Positron emission tomography	provides a 3D image of the functional processes in the body by using a radioactive positron emitter	Regions with greater activity in the brain is assumed to have the highest amount of radioactivity; image analysis techniques
Autonomic nervous system (ANS) through electro dermal activity measures	Skin conductance	A small current is passed through the skin and the resistance is measured	time and frequency domain analysis of skin conductance level, skin potential response, skin conductance response, and skin potential level
	Skin potential	skin resistance is measured by unipolar placement of sensors	
ANS through cardiovascular measures	Electrocardiogram (ECG)	Measurement of the electric signal variations of the heart	Heart rate (HR); Heart rate variability (HRV) analysis
	Respiration	measurement of the rate and depth of breaths during inspiration and expiration	time domain analysis
	Impedance cardiography	estimation of blood flow changes in the heart	cardiac output (CO); stroke volume
	Blood pressure	measurement of the pressure on the vessel walls during cardiac cycle	time domain analysis of systolic blood pressure and diastolic blood pressure
ANS through other measures	Pupillary responses	measurement of pupil diameter variation	time domain analysis of size variations and other statistical tools
	Skin temperature	measurement of temperature variation in different skin areas	Time domain analysis
	Skin blood flow	measurement of the volume of blood flowing in skin areas	non-oscillary duration index

6 indicates an overview of the most widely used noninvasive techniques for bio signal acquisition. Any combination of channels from this table can be used for system improvement and extension in future systems and applications. Furthermore, we will put effort in improving the computational models, e.g. for emotion representation and interpretation.

CONCLUSION

The authentication of persons and/or the recognition of activities in the highly dynamic automotive environment based on an evaluation of sitting postures and ECG signals can offer great potential on one hand, however, is subject to several issues on the other. For instance, sudden movements can cause erroneous data collection, resulting in an increased False Accept Rate and/or False Reject Rate, finally leading to an unexpected system behavior. Calculating extended features from the posture patterns, using improved evaluation techniques (such as those established for face recognition in still or moving images), or establishing improved computational models for emotion representation can help to enhance the reliability and stability of the system. Further improvements should be achieved when integrating other biometric measures, such as incorporating the skin conductance of the driver measured with a galvanic skin response (GSR) sensor embedded into the steering wheel or gear shift. Biometric based implicit information processing depending on individual characteristics can enable a new class of vehicular services, such as a safety function that authorizes a person automatically when seated. Only permitted persons would be then allowed to start or drive the car. Posture pattern based identification can furthermore be conceived as an effective car-theft protection system.

On the other hand, notable limitations have to be considered. Suppose that the driver of a car gets injured or incapacitated and someone else is asked to drive him/her to a hospital – would there be any chance to override the authorization process, allowing the helping person to use the vehicle without granted permission (e.g. in a "rescue mode")? Besides these application related issues, the measurement/data acquisition process faces some problems. Sudden movements, as noted above, can cause invalid posture patterns as well as noisy ECG signals. Powerful and effective data cleaning techniques needs to be developed to get this problem under control – as both sensor channels are affected at the same time this is still an open issue maybe requiring the integration of other unaffected sensory channels for compensation.

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KEY TERMS AND DEFINITIONS

Autonomic Nervous System (ANS): A part of a human's peripheral nervous system that controls visceral functions. It is classically divided into the two subsystems parasympathetic (body at rest, state of "calm") and sympathetic (high arousal, "power", active state) nervous system.

Biometrics: Method for uniquely recognizing humans based upon one or more physical or behavioral traits. Biometric characteristics can be divided into an active (explicit) type (e.g. interpretation of retina, voice, or finger print) and a passive (implicit) type, comprising for instance sitting posture pattern or ECG signal evaluation.

Electrocardiography (ECG): Records (and interprets) cardiac electrical potentials of the heart over time. Recording is normally done using skin electrodes connected to an electrocardiographic device. ECG is the best way to measure and diagnose abnormalities in the rhythm of the heart, such as HRV.

Explicit Interaction: This is a type of interaction where the user is in an active and attentive role. Explicit interaction demand active cooperation of the user, which can, in case of cognitive overload, result in unwanted behavior as delivered information or alerts tend to fail to raise the required attention.

Heart Rate Variability (HRV): Is a measure to detect inter-beat time (R-R) irregularities in an ECG. The HRV measure can be used to estimate mental stress (arousal state). Irregularity is the normal condition; a constant R-R time predominates only for artificial pacemaker and in medical conditions.

Implicit Interaction: "Implicit (human computer) interaction is an action, performed by the user that is not primarily aimed to interact with a (computerized) system but which such a system understands as input" (Schmidt, 2000).

NMEA (or NMEA 0183): A specification for communication between electronic devices like GPS defined by the National Marine Electronics Association. NMEA uses a simple, serial ASCII protocol for data communication.

Personal Sitting Profile: A sitting posture pattern is in some respects a feature of an individual, applicable for identifying or authorizing that person in a seat. The calculation of one's profile is based on a weighted combination of several individual parameters extracted from the sitting posture image of that person. Preliminary results have shown that the identification from a sitting posture is not as universal as, for instance, the retina of the eye or the genetic fingerprint.

Pressure Sensing: The utilization of sitting posture patterns to recognize a person's identity is a novel, implicit method compared to other state-of-the-art identification methods. Force-sensitive array mats are used for feature acquisition. These mats satisfies as they are (1) easily integrable into almost any type of seat (sensor arrays are thin and highly flexible), (2) not reliant on the attention of a person/requires no active cooperation of a "user", and (3) continuously in operation while the person is seated.

ENDNOTE

[1] Abbreviations: N...Normal posture, KL... Bunch of keys, left back-pocket, KR...Bunch of keys, right back-pocket, CL...Cell phone, left back-pocket, CR...Cell phone, right back-pocket, DL...Digital camera (Canon IXUS 500), left back-pocket, DR...Digital camera, right back-pocket, DRKL...Digital camera, right back-pocket and bunch of keys, left back-pocket