

# Human Modeling in a driver analyzing context: challenge and benefit

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## Abstract

In the past years, driver analyzing has become a field of increasing interest. Within this topic, camera based as well as camera free systems are in the scope of researchers all over the world with the overall goal to detect, for example, critical driver states like drowsiness or distraction. Unfortunately, there are yet no comprehensive models for understanding the driver and his states in the automotive context. Therefore, we present a user model tailored to automotive needs. This model allows us to understand the driver in the automotive environment and to set up a general architecture from which we can decide on necessary input information for detecting a certain driver state.

**General Terms** Driver Analyzer, Driver Monitoring, Vehicle Context Information, Context Recognition, Driver Model

## 1. Introduction

In this research field *driver analyzing*, *driver monitoring* or *driver distraction analysis* refer to overlapping areas of study. In general, it can be said that different strategies of data acquisition (cameras, biometric data) go along with a plenitude of data analysis algorithms taken from AI, data mining or image analysis, to name just a few (e.g.: [3, 16, 31]). Real-time analysis of driver behavior being a relatively young field, it is no surprise that no common approach for data source selection and analysis exists so far.

A related topic is *driver modeling*. Researchers try to model the behavior of the driver in certain situations, for example in collisions or other accidents (e.g. [19, 20]). Although of special importance, this is a very restricted perspective, because it only allows a view on the driver during a tiny time interval like 30 to 60 seconds. Therefore, it is not possible to make a general statement about the driver's state or behavior or monitor changes.

When talking about the automotive context, we also have to refer to Rasmussen's general model of human performance and related models designed for the driving task [10, 23]. Although these models are already over 25 years old, they are still state of the art

concerning the psychological description of the driving task. But these models and the approaches based on them are not operational models in the sense of real-time driver state analysis used as input for intelligent in-car applications. Summing up, there is a broad basis of research in the driver analyzing field, but no comprehensive model exists which helps to describe and analyze human behavior in the automotive context based on continuous real-time data acquisition. Due to this, we have designed a model which shall fill in this gap and provide a general architecture which describes what input signals are needed to detect a certain state.

## 2. User Modeling and the General User Model Ontology (GUMO)

Wahlster and Kobsa define a user model as follows: "A user model is a knowledge source in a system which contains explicit assumptions on all aspects of the user that may be relevant to the behavior of the system. [...]" [17, p. 6]. In his PhD Thesis, Heckmann develops the general user model ontology - GUMO<sup>1</sup> based on this well-established definition [12, 13]. Here, different categories for describing the human considering different areas like facial expressions, emotional or mental states as well as physiological conditions are given. Due to its comprehensiveness and integrity, this ontology may be used for deriving a driver model.

## 3. Towards an automotive human model

For our automotive model, we decided to use Contact Information, Demographics, Personality (respective: the Five Factor Model), Emotional State, Physiological and Mental State, Facial Expression and last (Personal) Interest. Due to the fact that we design the system for an automotive environment, all categories which are not useful for an automotive human model were eliminated. These dimensions were: *Contact*, *Demographic Information* and the *Five Factor Model*. In the following subchapters we give arguments for these cuts and show how the remaining categories can be used for generating a generic architecture which allows for a holistic view on driver analyzing.

### 3.1 Matching Basic User Dimensions and Automotive Requirements

We focus on driver analyzing by using CAN data only [15]. Therefore, for each possible driver state ways of measuring this state based on CAN data have to be identified. In order to obtain a

<sup>1</sup> GUMO can be found here: <http://ubisworld.ai.cs.uni-sb.de/ontology/>

generic and general model, we focus on technologies already in use in automotive contexts, e. g. camera and CAN data. Speech will be considered sparsely, electrocardiograms and other biometrical measurements not at all (yet). From this generic model, we can derive the states which can be detected by only using selected CAN data. Our model was developed top-down starting with the GUMO ontology which means that we first modeled the driver from a birds-eye-view and then specialized the model with respect to the automotive environment.

Contact and demographic data like age, name, address, nationality, gender, or native language have to be entered by the user himself. Indeed we might initiate automated routines for this request when the driver first enters his car, but we cannot measure one of these values by sensors or cameras directly. Thus, contact and demographic data do not play a role for our model for the time being.

The *five factor model* postulates that there are five basic dimensions of personality: Agreeableness, Conscientiousness, Extraversion, Neuroticism, Openness. Within these dimensions, other personal characteristics can be described. But these values can only be collected statistically, like Haller et al. [11] state. Therefore, we can also eliminate personality from our model.

Before discussing further physiological or psychological states, we focus on facial expressions. Facial expressions are a good indicator for a certain state of mind, because feelings appear (often) with facial expressions. In this field, two models are very influential: (i) Paul Ekman’s *six basic emotions* [4, 5] and (ii) the *eight basic emotions* of Robert Plutchik [21]. Both contain anger, disgust, fear, joy, sadness and surprise. Plutchik extends these basics with acceptance and expectation. For our research, we will use the model of Ekman, because it is not only well discussed [4, 5, 29], but Ekman’s results are still in use in recent projects [9]. *Disgust* will not be discussed any longer as disgust does not play a role in our automotive context. As we will see when talking about emotional and mental state, facial expressions are very helpful, because they enable state detection with camera based systems.

For obtaining synergy effects, we have merged *emotional* and *mental* states into one group called *psychological state* by only taking suitable<sup>2</sup> information for automotive contexts from both groups. Next, we analyzed the respective values concerning their automotive ability by answering the following questions:

- What are the physical characteristics of this potential state?
- What are the measurable values?
- Are there possibilities to measure these values / states in a car?

It is obvious that for emotional and mental states, physiological forms of measurement are available but impractical for current in-car usage. Therefore we show which data- and data analysis-based alternatives for state detection exist.

For many categories, different approaches for measurement exist: Being *happy* can be observed and measured in different ways, as [1] states. Besides the possibility of analyzing the facial expression, happiness is also measured. As we do not take bio-sensors into account yet, and as individual ratings are not obtainable in real-time, the only remaining way to detect the state *happy* in the car is to use a camera for face detection.

Besides the fact that the facial expression can be used to detect *sadness*, typical physical properties for sadness are anorexia, gas-

<sup>2</sup>As an example: *Pride* or *hope* from Emotional State or *hypnosis* from Mental State are non suitable information in an automotive context. Whereas *nervousness* or *anxiety* can influence the way of steering the car and should therefore be included in the model (e.g. If a driver is nervous while driving through construction zones, pre-activated safety features are helpful.).

Psych. State	Characteristics	Measurable Values	Automotive Measurability
Happiness	tiny raise of blood pressure	Blood pressure	Camera (Fac. Expr.)
	Less stress hormones	Blood levels	
	More Immunoglobulin	Fac. Expr.	
	Facial Expression (Fac. Expr.)		
Nervousness	Wavering hands	Blood pressure	Microphone (Voice)
	Attacks of sweating	Puls	
	Raised articulation	Voice	
	Racing heart	Fac. Expr.	
	Harsh / loud voice	Fac. Expr.	
Attentiveness	Less perception of environment	Eye movement / tracking	Camera
	Focus lies on actual activity	Use of Multimedia (and / or other) systems	CAN
	Decreases with secondary task activities		
Drowsiness	Decreasing eyesight and reaction time	Eye movement and blinking	Camera
	Freezing	Use of fresh air supplying buttons	CAN
	Yawn	Reaction / Operation rate	
	Fresh air supply		

**Table 1.** Some exemplary psychological states in the context of their automotive appropriability

trointensional disorder, a drop in the blood pressure, or circulatory disorders [25].

The physiological effects of *anger* are, for example, raising heart level, low breathing or stomach trouble [2, 22, 26]. Besides these rather medical effects, anger can be detected by analyzing the facial expression with a camera.

*Anxiety* is responsible for various symptoms, meaning that mind, body and personality functions might change in different ways. For measuring anxiety, especially body functions are needed [6]. Obviously, we have the same situation again: we would need medical equipment for detecting anxiety, or we use Ekman’s results and detect the state with a camera.

For *nervousness* a corresponding facial expression exists as well. Other physiological characteristics are wavering hands, attacks of sweating, raised articulation, racing heart, or a harsh and / or loud voice [18]. In the car, we could use a camera to detect the facial expression, or we could install a microphone to analyze the driver’s voice and detect whether he is nervous or not [24].

Being *relaxed* can relate to different situations: being in the flow, having fun, etc. The most easiest way to prove whether a driver is relaxed or not is to analyze the facial expression with a camera [7].

According to [7], being *stressed* means that the breathing begins to rise; so does also the heart beat. Furthermore, the body starts to produce more adrenaline. Besides these biological effects, the body also starts to increase the size of the airways for being able to get more oxygen. In the car, this effect can be recognized when the driver opens the window or starts to change the climate settings. Another result is that we begin to be in a state of agitation, which reflects in an uneasy driving, measurable form CAN data.

Being *inattentive* (in the literature, *distraction* is often used as a synonym) implicates reduced perception of the environment. Due to the fact that a person’s main focus always lies on the actual task activity, attentiveness decreases when doing secondary tasks like e.g. using the navigation system. For detecting inattentiveness, two different approaches have been established. One approach is to supervise the driver with a camera, the other one is to analyze CAN messages, generated from multimedia, radio, or navigation systems, or the car itself [7, 14, 30].

Physiological indicators for *drowsiness* are, for example, decreasing eyesight and reaction time, freezing and yawning, demand for fresh air, or eye rubbing. What’s also an impact on drowsiness is the so called circadian rhythm [7, 28].

Physiological states as indicators for mental and emotional states can hardly be measured without medical equipment. Hunger and thirst are a prominent exception, as they may be measured indirectly using simple heuristics: We may assume that someone is hungry or thirsty, when it is, for example, lunch time or when the trip duration exceeds 3 hours [8], acknowledging the risk of false positives for drivers who are drinking and eating while they drive.

### 3.2 Discussion of the Resulting Automotive Human Model

Summarized, we get the following driver model:

*Physiological States:* {Hunger, Thirst}

*Psychological States:* {Happiness, Sadness, Anger, Anxiety, Nervousness, Relaxed, Bored, Stress, Attentiveness, Drowsiness}

This results from picking up Ekman's results and not those of Plutchik on the one hand, and cutting any categories not derivable from digital data available in the car on the other hand.

For obvious reasons *drowsiness* and *inattentiveness* are - at the moment - among the most discussed topics in driver analyzing. Thus, one might ask why we also analyze states like *happy* or *sad* or *hungry*. Often, not the driver himself is modeled, but rather the actual situation he is in. That means, when we are focusing on *drowsiness*, we can detect whether the driver is drowsy or not, but we don't know whether at the same time he is *stressed* or *inattentive*. The accident risk will not decline, if we focus on "not letting the driver fall into sleep", but do nothing against his inattentiveness. Hence, it is useful to build a more comprehensive model which allows for taking into account the interactions and relations between various emotional and mental states.

## 4. Using the model to create a generic architecture

Based on the reduced driver description ontology above, we have created a general architecture for driver monitoring and driver state analysis which we will discuss now. The structure of our architecture is built upon a simple processing model which can be applied to different data sources as well like this:

*Input => Classification Algorithm => Driver State => Use Case*

On the input side, data are divided in four areas: *Driving Environment, Interior, Motor Data* and *Meta Data*. For classification algorithms, we consider rule based systems as well as various types of classification algorithm. This means that we analyze pre-processed vehicle data in order to classify the driver's state. Due to the fact that our work is not restricted on one or two states only, we have to merge the different states with their appropriate classification algorithm. An example shall illustrate this: The different facial expressions and their meanings can be described with pre-defined rules, i.e. image processing results are mapped to a fixed set of facial expressions representing specific emotional states. For other data, approaches like neural networks or support vector machines are needed to correctly classify, e.g. steering wheel angle, pedal movement and lane departure with respect to the question whether the driver is drowsy or not.

Assuming that our approach lets us identify the driver's state for the reduced ontology sketched above, this information can be used for modeling situation-based use cases. For example, if we know that the driver is drowsy, we can warn him by steering wheel vibration, or - as *Mercedes* driver assistance systems currently do - advise the driver to make a break by displaying a coffee cup. Figure 1 illustrates the general architecture: It is clear that numerous combinations of classification algorithms for input data as well as relationships of states with respect to possible use cases may be studied. The architecture is deliberately not restricted to a problem-specific software design which works for a single use

case only like, e. g. in [27]. The general framework is modular and extendable for additional input types, classification algorithms as well as use cases.

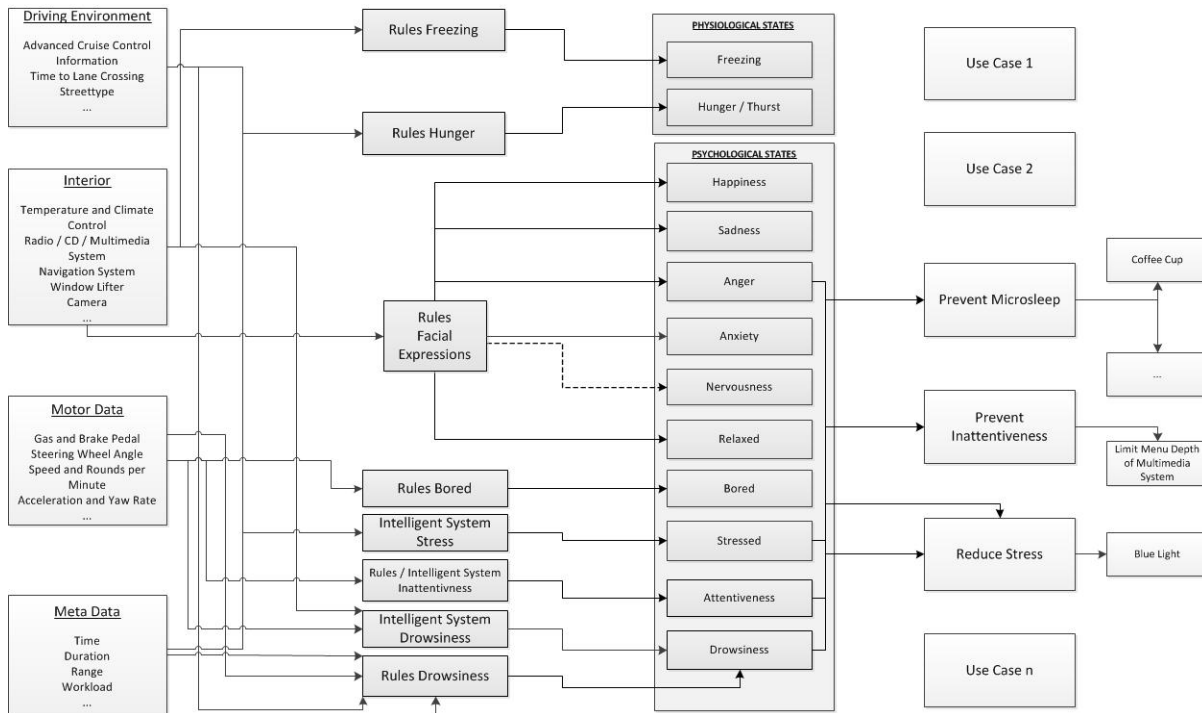
## 5. Discussion and future work

In this paper, we have introduced and discussed a human model for the automotive environment. We stress the importance of driver modeling and argue why a use case-specific view on driver analysis is not always useful. Next, we have created a generic software architecture for driver state detection. This architecture is based on the driver model and allows us to consider several conceivable driver states. The benefit is a non restricted, generic architecture for driver analyzing. Though we have not implemented graphical user interfaces yet, we created the requirements for them by developing this architecture.

Our future work will include analysis of actual driver data from simulation experiments that can be used as training material for the classifiers. Regarding use cases, we will focus on driver inattentiveness and measures to avoid it or to bring the driver back to his primary task: driving.

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**Figure 1.** A schematic and simplified diagram of our architecture. On the left side, we can see the different input data. Next, we can find the classification tier, which includes rule based systems as well as artificial systems. The driver state tier is in column three, in which we can find the states described in ch. 3. Last, the picture shows the way the use cases are implemented in the architecture. The different tiers are generic and can be improved or edited separately.

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