Implicit Cooperation: Emotion Detection for Validation and Adaptation of Automated Vehicles’ Driving Behavior

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Abstract
Human emotion detection in automated vehicles helps to improve comfort and safety. Research in the automotive domain focuses a lot on sensing drivers’ drowsiness and aggression. We present a new form of implicit driver-vehicle cooperation, where emotion detection is integrated into an automated vehicle’s decision-making process. Constant evaluation of the driver’s reaction to vehicle behavior allows us to revise decisions and helps to increase the safety of future automated vehicles.

Author Keywords
Automation Behavior; Emotions; Implicit Interaction; Adaptive Automation; Ambient Intelligence; Safety-Critical Interaction; Automated Vehicles; Human-Machine-Cooperation

CCS Concepts
• Human-centered computing → Human computer interaction (HCI); Ubiquitous and mobile computing; Ubiquitous and mobile devices; • Hardware → Sensors and actuators;

Introduction
When driving automated, sensors might work restricted, e.g., due to a car driving in front. In these situations, human intervention is required. Such interventions might be completely manual, or, to maintain comfort, in a coopera-
tive form: The human extends the car's restricted sensor range and resulting insecurities by providing his view and judgment of the situation, e.g., by deciding if overtaking is safe or not [20]. The car leaves the final decision to take action to the human driver/passenger and executes all other driving-related actions, which keeps the driving comfort for the human. In this paper, we want to discuss the idea of a human intervention which requires no explicit interaction, but yet achieves safer behavior of an automated vehicle. In particular, we suggest using implicit emotional states of the driver as an additional input to confirm or cancel the planned vehicle actions.

Cooperative, Implicit Decision Making While Driving

Typically, cooperative driving means that the human intervenes in the decision-making process of an automated vehicle. This kind of cooperation has the potential to combine the strengths of manual driving with automated cars [3]. The driver/passenger is asked for a specific input (option or information), for example, if the car should overtake or not, and then the car executes the actions. These interventions are commonly performed explicitly by giving voice, gesture [2], or touch [15] commands. Implicit interaction modalities have to be interpreted by the system through a set of parameters. So this kind of interaction does not play an important role, as it might not completely match the user's intention. When driving on the highway and the car interprets the driver/passenger's unintended lean to the left as an implicit command to perform a lane change to the left, for example, users will get annoyed and mistrust the system. Hence, implicit interaction seems to be unfeasible for the activation/triggering of driving maneuvers.

In human interaction, when we evaluate ideas together, think about the next meal or speak with another person, the confidence of our thoughts and decisions and our resulting behavior is expressed through multiple, hard to control body parameters. Most of these behavioral/affective parameters are conveyed on implicit interaction channels. If we feel secure, we look confident, our thinking is clear, and we are less aroused. If we feel insecure, we look frightened, we cannot think clearly, and our pulse quickens. Humans can easily interpret these channels and tell such secure or insecure behavior apart. So what if a machine could do, too. Emotion detection can be used to enable a affect-sensitive human-robot cooperation [11].

Even if the driver/passenger does not decide actively to take a particular action during autonomous driving modes, but the car does, he or she is affected by the machine's actions. If (s)he is comfortable with the car's driving, (s)he is relaxed, but an aggressive driving style leads to fearful reactions. So, the passenger's behavioral/affective state reflects the level of driving comfort and safety.

In consequence, if a machine could interpret the affective state of humans, it could also interpret the level of safety and comfort their actions induce. We suggest using this human-confidence-parameters to support the vehicle's decision-making process as well as the decision rollback process. In this paper, we want to analyze the validation and rollback of decisions. That requires a form of human-machine-cooperation, where one can cancel the execution of actions. It requires a continuous decision evaluation process during the execution phase of a maneuver. Further, decisions have to be evaluated with human affects/behavior and measured in real-time. The car could implement a loop which constantly evaluates a maneuver execution with the sensed confidence through its sensors and human reaction against a safe threshold: $\text{Conf}(M)_{SAFE} \geq$
$Conf(M)_{OWN} - Conf(M)_{PASSENGERS}$. Figure 1 summarizes the proposed cooperation process visually.

An Exemplary Scenario: Canceled Overtaking

It is dark and rainy on the highway. You drive home from work with your highly automated car. While driving in the autonomous mode, you are having a warm meal. Your car decides to perform a lane change to overtake a slower car ahead. In some distance behind your car, headlights of another car are approaching. Your car informs you about the planned action on a head-up display and though a special announcement sound. You stay calm because you have experienced this situation many times before. Then, the car performs the lane change. Due to the rain, the radar and ultrasonic sensors of your car get a little bit distorted. Hence, the calculated level of the system’s confidence to perform the lane change is just over the safe threshold. There is some probability that the confidence is unjustified. Unfortunately, it is. The car behind is much faster than expected. You get nervous as the car starts to perform the lane change because you cannot reach the steering wheel timely without spilling your hot coffee. The approaching car in only a few meters away. Luckily, your car’s driver emotion-sensing system has noticed your anxiety. It reevaluates its lane change decision and sets down the calculated confidence level for a few percent. The new confidence value is below the safe threshold, and the car cancels the maneuver just in time.

Further (Non-)Use Cases

For safety-related driving assistants, the inclusion of human reactions can have a negative effect. When the car performs an emergency brake, the action should not be interrupted through humans feeling uncomfortable, or they would not be safe anymore. However, for other use cases, the validation of car actions through human emotions seems useful. Some examples: adjusting speed, adjusting accelerating/breaking behavior, adjusting the distance, changing lanes, turning, automated parking…

Sensing Human Emotions in the Car

For our scenario, two emotions are of special interest: surprise and fear. Both are linked to a rather negative valence and high arousal. However, driver emotion detection applications have focused a lot on drowsiness and high arousal/load detection. In the following, we depict some examples.

Völkel et al. [18] test two app concepts which utilize the driver’s state. First, a dashboard app showing safety-critical states like drowsiness or aggressiveness and second, a warning app that gave feedback to the driver when such an emotion reached a certain threshold. Participants preferred to receive only safety-critical notifications (high threshold). A technical implementation such a system is planned by Vasey, Ko, and Jeon [17]. For a complete review of drowsiness detection, we refer to Sahayadhas, Sundaraj, and Murugappan [14]. Healey, Theocharous and Kveton [6] investigate the reactions of passengers on an aggressive driver’s driving behavior. They found that the fear of passengers correlates highly with galvanic skin response. They formulate the idea to report the passenger’s condition back to the driver, yet they did not test it. In contrast to existing work, we do not confront the driver/passenger with the vehicle behavior after a situation (e.g., [21]), but want to access their passive reactions in real-time and integrate them in the vehicle’s decision evaluation.

Sensing Channels

The body emits emotions on multiple channels. Via affective computing, we can try to approximate human emotion through measurable channels [1]. Not all of these channels
Figure 1: Cooperative Maneuver Execution Process with Constant Evaluation of Vehicle Decisions through Implicit Driver Feedback
Table 1: Body parameters responding to human emotions and how to measure them in the vehicle

| Body Parameter       | Required Technology | Study Example                                                                 |
|----------------------|--------------------|-------------------------------------------------------------------------------|
| Facial expressions   | Video camera       | Facial expressions analysis to detect drowsiness [19]                         |
| Pupil diameter       | Eye-tracking camera / glasses | Automatic stress classification in the car [10]                             |
| Gaze                 | Eye-tracking camera / glasses | Pre-crash gaze behavior to predict crash intensity [16]                      |
| Voice                | Microphone         | Language reliability display to improve UX [4], detecting emotions through voice parameters [8] |
| Gestures             | Video camera       |                                                                               |
| Body position        | Video camera, In-seat force sensors | Postures to detect driver activities [12]                                    |
| Brain activity       | EEG                | Adapt lights in the car to driver arousal [5]                               |
| Heart rate           | Pulse meter, ECG   | Stress correlates with heart rate [7], HRV-analysis [13]                     |
| Electro-dermal activity | EDA-sensor         | Stress correlates with skin conductance [7]                                 |
| Cortisol level       | Magnetic resonance imaging, computerized tomography |                                                                               |
| Thermal response     | Thermal camera     | Driver's emotion recognition through thermal imaging [9]                   |

are suited to sense human emotions in the car. In the following, we will discuss different channels, technologies, and their potential for practical application in automated vehicles in the near future (see Table 1).

A downside of all emotion-sensing approaches is that one cannot link the emotional reactions of humans in the car explicitly to the system's driving behavior. Other environmental factors, like talking to another passenger or watching a horror movie, can lead to arousing emotional states. That is a clear limitation, but we also suggest that future vehicles that already have complex real-time emotion detection, will also have passenger activity detection. Thus, we expect the car to tell these differences apart by using other contextual parameters. Some of the emotion-sensing channels are also well suited to detect driver/passenger activities, which leads to synergistic effects. One should consider such synergies for the rating of future sensing methods in the car.

Discussion of Technologies

Unobtrusive methods like facial expression, gaze, pupil diameter, and thermal imaging seem feasible for the use in automated vehicles in the near future because it is not likely that users put effort into equipping or install a special device before each ride. Further, these channels are constantly available, in contrast to speech, for example. Cameras are already used in vehicles for driver state detection, primary driver drowsiness detection nowadays. There-
fore, camera-based methods are the predestined source for
driver emotion detection. Currently, cameras are commonly
installed in the front only. That makes the detection impos-
sible when the is facing in the “wrong” direction. Neverthe-
less, future vehicles might have more cameras installed in
the cabin to enable complete detection without gaps. Many
drivers/passengers also wear (sun-)glasses, which harden
or hinder the detection, depending on the method. Hence,
further channels might be necessary to ensure steady de-
tection. Additional input sources become available when
drivers/passengers wear devices like smartwatches. HRV-
or skin conductance analysis is possible with pulse sensors.
Car and smartwatch/app companies should work on com-
mon software interfaces to realize this.

Conclusion & Future Work
In the current state, there are major weaknesses in the
practical use of each emotion detection technology. Thus,
emotion detection in the car has to follow a multi-method
paradigm to overcome these weaknesses and dynamically
adapt to a different channel and new technological devel-
oppments (Plug & Play Sensors). In the automotive domain,
emotion-sensing focuses on detecting drowsiness or ag-
gression. The system uses the sensed emotions to reflect
the emotional state to the driver. We present a use case
where implicit driver reactions are integrated into the car’s
decision evaluation process. In our future research, we will
elicit and analyze a data set with human emotional reac-
tions on the near and full failure of automated systems. For
our presented scenario, we will also investigate how emo-
tion detection might help to prevent or weaken the impact of
accidents.

REFERENCES
[1] Rafael A. Calvo and Sidney D’Mello. 2010. Affect
Detection: An Interdisciplinary Review of Models,
Methods, and Their Applications. IEEE Trans. Affect.
Comput. 1, 1 (Jan. 2010), 18–37. DOI:
http://dx.doi.org/10.1109/T-AFFC.2010.1

[2] Henrik Detjen, Sarah Faltaous, Stefan Geisler, and
Stefan Schneegass. 2019a. User-Defined Voice and
Mid-Air Gesture Commands for Maneuver-Based
Interventions in Automated Vehicles. In Proceedings of
Mensch Und Computer 2019 (MuC’19). Association for
Computing Machinery, New York, NY, USA, 341–348.
DOI:http://dx.doi.org/10.1145/3340764.3340798

[3] Henrik Detjen, Stefan Schneegass, and Stefan
Geisler. 2019b. Maneuver-based Driving for
Intervention in Autonomous Cars. In CHI’19 Workshop
on “Looking into the Future: Weaving the Threads of
Vehicle Automation”. ACM.

[4] Anna-Katharina Frison, Philipp Wintersberger, Amelie
Oberhofer, and Andreas Rieder. 2019. ATHENA:
Supporting UX of Conditionally Automated Driving with
Natural Language Reliability Displays. In Proceedings
of the 11th International Conference on Automotive
User Interfaces and Interactive Vehicular Applications:
Adjunct Proceedings (AutomotiveUI ’19). Association
for Computing Machinery, New York, NY, USA,
187–193. DOI:
http://dx.doi.org/10.1145/3349263.3351312

[5] Mariam Hassib, Michael Braun, Bastian Pfleging, and
Florian Alt. 2019. Detecting and influencing driver
emotions using psycho-physiological sensors and
ambient light. In IFIP Conference on Human-Computer
Interaction. Springer, 721–742.
[6] Jennifer Healey, Georgios Theocharous, and Branislav Kveton. 2010. Does My Driving Scare You?. In Adjunct Proceedings of the Second International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’10). Association for Computing Machinery, New York, NY, USA. https://www.auto-ui.org/10/adjunctproceedings/p14.pdf

[7] J. A. Healey and R. W. Picard. 2005. Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on Intelligent Transportation Systems 6, 2 (June 2005), 156–166. DOI: http://dx.doi.org/10.1109/TITS.2005.848368

[8] Christian Martyn Jones and Ing-Marie Jonsson. 2005. Automatic recognition of affective cues in the speech of car drivers to allow appropriate responses. In Proceedings of the 17th Australia conference on Computer-Human Interaction: Citizens Online: Considerations for Today and the Future. 1–10.

[9] A. Kolli, A. Fasih, F. A. Machot, and K. Kyamakya. 2011. Non-intrusive car driver’s emotion recognition using thermal camera. In Proceedings of the Joint IND$^S$’11 ISTET’11. 1–5. DOI: http://dx.doi.org/10.1109/INDS.2011.6024802

[10] Marco Pedrotti, Mohammad Ali Mirzaei, Adrien Tedesco, Jean-Rémy Chardonnet, Frédéric Mérienne, Simone Benedetto, and Thierry Baccino. 2014. Automatic Stress Classification With Pupil Diameter Analysis. International Journal of Human–Computer Interaction 30, 3 (2014), 220–236. DOI: http://dx.doi.org/10.1080/10917318.2013.848320

[11] Pramila Rani, Nilanjan Sarkar, Craig A. Smith, and Leslie D. Kirby. 2004. Anxiety detecting robotic system – towards implicit human-robot collaboration. Robotica 22, 1 (2004), 85–95. DOI: http://dx.doi.org/10.1017/S0263574703005319

[12] Andreas Riener and Alois Ferscha. 2007. Driver Activity Recognition from Sitting Postures. In Mensch & Computer 2007 Workshopband, Thilo Paul-Stueve (Ed.). Verlag der Bauhaus-Universität Weimar, Weimar, 55–62.

[13] Andreas Riener, Alois Ferscha, and Mohamed Aly. 2009. Heart on the Road: HRV Analysis for Monitoring a Driver’s Affective State. In Proceedings of the 1st International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’09). Association for Computing Machinery, New York, NY, USA, 99–106. DOI: http://dx.doi.org/10.1145/1620509.1620529

[14] Arun Sahayadhas, Kenneth Sundaraj, and Murugappan Murugappan. 2012. Detecting Driver Drowsiness Based on Sensors: A Review. Sensors 12, 12 (Dec 2012), 16937–16953. DOI: http://dx.doi.org/10.3390/s121216937

[15] M. Schreiber, M. Kauer, and R. Bruder. 2009. Conduct by wire - maneuver catalog for semi-autonomous vehicle guidance. In 2009 IEEE Intelligent Vehicles Symposium. 1279–1284. DOI: http://dx.doi.org/10.1109/IVS.2009.5164468

[16] Bobbie D. Seppelt, Sean Seaman, Joonbum Lee, Linda S. Angell, Bruce Mehler, and Bryan Reimer. 2017. Glass half-full: On-road glance metrics differentiate crashes from near-crashes in the 100-Car data. Accident Analysis & Prevention 107 (2017), 48 – 62. DOI:http://dx.doi.org/https://doi.org/10.1016/j.aap.2017.07.021
[17] Eric Vasey, Sangjin Ko, and Myounhoon Jeon. 2018. In-Vehicle Affect Detection System: Identification of Emotional Arousal by Monitoring the Driver and Driving Style. In Adjunct Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’18). Association for Computing Machinery, New York, NY, USA, 243–247. DOI: http://dx.doi.org/10.1145/3239092.3267417

[18] Sarah Theres Völkel, Julia Graefe, Ramona Schödel, Renate Häuslschmid, Clemens Stachl, Quay Au, and Heinrich Hussmann. 2018. I Drive My Car and My States Drive Me: Visualizing Driver’s Emotional and Physical States. In Adjunct Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’18). Association for Computing Machinery, New York, NY, USA, 198–203. DOI: http://dx.doi.org/10.1145/3239092.3267102

[19] Esra Vural, Mujdat Cetin, Aytil Ercil, Gwen Littlewort, Marian Bartlett, and Javier Movellan. 2007. Drowsy Driver Detection Through Facial Movement Analysis. In Human–Computer Interaction, Michael Lew, Nicu Sebe, Thomas S. Huang, and Erwin M. Bakker (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 6–18.

[20] Marcel Walch, Marcel Woide, Kristin Mühl, Martin Baumann, and Michael Weber. 2019. Cooperative Overtaking: Overcoming Automated Vehicles’ Obstructed Sensor Range via Driver Help. In Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI ’19). Association for Computing Machinery, New York, NY, USA, 144–155. DOI:http://dx.doi.org/10.1145/3342197.3344531

[21] Peter I.J. Wouters and John M.J. Bos. 2000. Traffic accident reduction by monitoring driver behaviour with in-car data recorders. Accident Analysis & Prevention 32, 5 (2000), 643 – 650. DOI: http://dx.doi.org/https://doi.org/10.1016/S0001-4575(99)00095-0