Abnormal Driver Behavior Detection for Automated Emotion Recognition

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Problem Definition

The goal of this project is to investigate the effect of emotion on the driving style. We aim to develop *behavior profiles* which represent patterns of driving style influenced by certain emotions. These patterns are then used to classify the emotional state based on the driver behavior. For instance, stressed drivers tend to pay less attention to the traffic and environment [1, 2]. However, in the field of emotion recognition, using the modality of behavior is a relatively neglected research field compared to the modality of facial expression. Therefore, we started this project in the hopes that there are such patterns, which methods based on machine learning will be able to detect. As the result of our survey show, there are various commonly agreed behavior profiles.

Objective	Investigate the effects of emotion on driver behavior and develop driver behavior profiles for automated emotion classification

Definition of in-cabin Behavior

We define Behavior as the **typical range of actions** by occupants in conjunction with themselves or with the vehicle, which includes the environment around that vehicle too. It is the response to various stimuli, whether internal or external, conscious or subconscious, overt or covert, and voluntary or involuntary. Our research aims to understand what the effect of emotions on the in-cabin response is.

Actor ID	Tracked Object	Point in time	Variable
1	Left_Hand	t	on_steering_wheel
1	Left_Hand	t+2	not_on_steering_wheel
1	Left_Hand	t+3	not_on_steering_wheel

Figure 1. Visualizing Behavioral Actions

Input Data – Behavioral Actions

We limit the input stream to five variables of which we assume that they provide the most relevant information to model behavior [1, 4]. These variables are **acceleration**, **steering wheel usage, hand movements** and **placements**, **head movements** and **directions**, and **eye movements.** Figure 1 visualizes how behavioral information is collected. We track the in-cabin actions of occupants. Every behavioral action is represented by a feature vector which is split into three parts: actor, operation, and interaction with car component. Subjects are monitored over a time frame (t defines a point in time) to measure the typical velocity of movements or interactions with the car. As depicted in Figure 1, this data is collected as vectors for each input variable which can be used to detect behavioral profiles in order to classify the emotional state of subjects.

Output Classes – Emotions

The modality of driver behavior can indicate specific emotions with certainty [2,3]. Hence, the target emotions in this modality are **anger, fatigue, stress, confusion, sadness** as main negative emotions and **happy**, and **neutral** as positive factors. Furthermore, the final method that we use is a multimodal approach. This means that each emotion is classified with a score. Those scores are merged into a combination of valence and arousal. This is a common output format in the field of automated emotion recognition [3, 4, 5].

A Survey On Driver Behavior

The goal of this online survey is to analyze commonly agreed assumptions of the impact of emotions on the driver behavior. To access the results of this survey, please send an e-mail to mesut.kuscu@tum.de.

Content of Survey

Our survey consists of three parts:

1. The first section contains general questions to identify the country in which the subject drives, the age, and the gender.
2. Section 2 contains five different scenarios which imply specific emotions on the subjects. Based on these emotions, we analyze the impact on the driver behavior. This is the main part of our survey.
3. In the third section, we ask two general questions. First, we analyze the general typical comfort level of drivers, and second, if participants believe that their driver behavior is impacted by their emotional state.

Result of Survey

In Figure 2-6 we depict the results of our survey. Each graph represents one scenario and visualizes the impact of the associated emotion on the five input variables. We define 5 levels of impact which are based on the relative behavior of the subject. The subject might behave *slower* than usual, *normally* (no impact of the emotion), and relatively *faster.* Those levels are numbered from 1 to 5, in which 1 is *slower than usual* and 5 is *faster than usual*.

We emphasize the level of agreement in our survey by four different colors for each bar. Green represents an agreement over 70%, blue represents an agreement over 60%, and orange represents an agreement over 50%. If there is no agreement (below 50%) the bar is colored gray.

Participants

103 people in total participated in this survey. 95 of 103 participants are between 20 to 30 years old and 8 people are older than 30. 67% of all participants are male and 33% are female. 85 of 103 who participated are drivers in Germany, 11 people are from Spain and the 7 remaining participants are from Azerbaijan, Turkey, UK, Poland and South Korea.

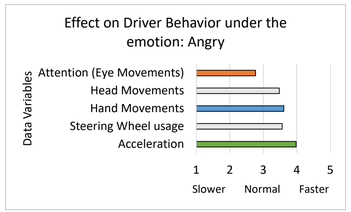

Figure 2. Survey result on the emotion angriness.

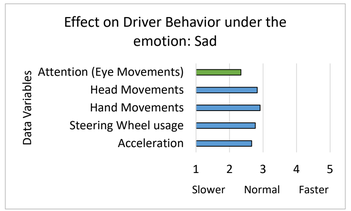

Figure 3. Survey result on the emotion sadness.

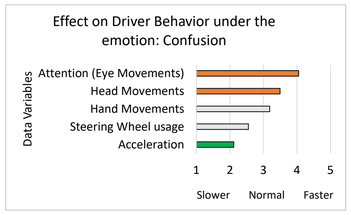

Figure 4. Survey result on the emotion confusion.

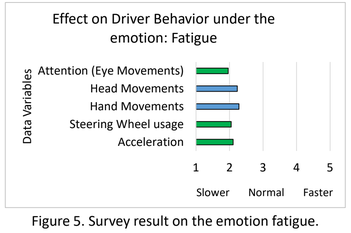

Figure 5. Survey result on the emotion fatigue.

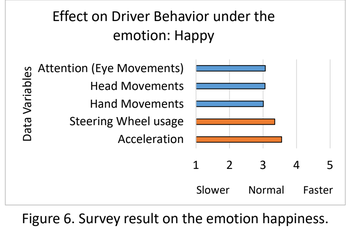

Figure 6. Survey result on the emotion happiness.

Driver Behavior Profiles

Table 1 shows our final driver behavior profiles based on the presented results of the survey. We can see that fatigue is the most represented emotion, and therefore, easier to detect. Additionally, some emotions do not impact specific variables, as being sad has no clear effect on hand movements, head movements or usage of the steering wheel. These driver behavior profiles represent common patterns of which we believe can be observed under certain emotions.

Tracked Object	Faster	Normal	Slower
Acceleration	Angry, Happy	Neutral	Tired, Confused, Sad
Steering Wheel Usage	-	Happy, Neutral, Sad	Tired
Head Movements	Confused	Happy, Neutral, Sad	Tired
Hand Movements	Angry	Happy, Neutral, Sad	Tired
Attention (Eye Movement)	Confused	Happy, Neutral	Tired, Angry, Sad

Table 1. Final Driver Behavior Profiles

Do Emotions impact Driver Behavior?

The last question of our survey analyzes if the participants believe that their driving style is impacted by their emotional states. The outcome is depicted in Figure 7. 87% answered with “yes” and 13% answered with “no”. The participants who answered with "no" have also indicated a higher level of comfort while driving in general. Therefore, we assume that those people are less stressed and feel generally happier while driving.

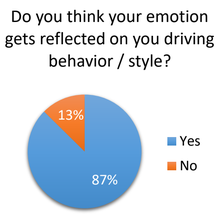

Figure 7. Result of last question of our survey to analyze the impact of emotions.

Perspective and Future Work

- The majority of the participants are between 20 to 30 years old. Hence, our extracted profiles might be biased towards young adults. We will further search for elderly participants for our survey to reduce this bias.
- We will develop a method to automatically classify the emotional state based on the introduced behavior profiles, and test it in real cars. These experiments will evaluate the accuracy, robustness and the confidence of our method. Based on these tests, we will further investigate to develop more accurate driver behavior profiles.

References

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