Predicting Takeover Quality in Conditionally Automated Vehicles Using Machine Learning and Genetic Algorithms

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Abstract. Takeover requests in conditionally automated vehicles are a critical point in time that can lead to accidents, and as such should be transmitted with care. Currently, several studies have shown the impact of using different modalities for different psychophysiological states, but no model exists to predict the takeover quality depending on the psychophysiological state of the driver and takeover request modalities. In this paper, we propose a machine learning model able to predict the maximum steering wheel angle and the reaction time of the driver, two takeover quality metrics. Our model is able to achieve a gain of 42.26% on the reaction time and 8.92% on the maximum steering wheel angle compared to our baseline. This was achieved using up to 150 seconds of psychophysiological data prior to the takeover. Impacts of using such a model to choose takeover modalities instead of using standard takeover requests should be investigated.

Keywords: Human Machine Interaction · Machine Learning · Conditionally Automated Vehicles · Genetic Algorithms · Artificial Intelligence · Takeover Request

1 Introduction

Nowadays, much progress is being made to create fully automated vehicles, but we are not there yet. If we can maybe see fully autonomous cars working in research labs as early as this year (2020) [1], we will probably see in the meantime conditionally automated vehicles populating our roads, corresponding to level 3 of the SAE taxonomy [2]. At this level of automation, it is not mandatory for the driver to monitor the

environment while the car is driving, but they must be able to regain control of the car if the vehicle issues a takeover request (TOR). This transfer of control from the car to the driver is a critical moment that can lead to accidents if not executed correctly. Therefore, the Human-Machine Interface (HMI) used to convey the TOR (called the TOR modalities from now on) must be chosen carefully.

Currently, TOR are standardized in modern cars, meaning they depend on the model of the car and do not change depending on the situation, despite research having highlighted that some TOR modalities are better suited for different situations (cf. Related Work). However, there are currently no models able to foresee takeover quality based on inputs known to influence takeover quality, such as the driver psychophysiological state. In this paper, we aim at creating a Machine Learning solution able to predict takeover quality based on driver psychophysiological state and TOR modalities, thus allowing us to refine the TOR modalities if needed to ensure the best takeover possible. This will also provide a tool able to estimate takeover quality to researchers and car manufacturers, hopefully useful in later research.

2 Objective

This study aims to investigate if Machine Learning (ML) can be used to predict the takeover quality before a TOR is issued, using the driver's physiological data and the TOR modalities. This would allow a smart HMI to select the TOR modalities providing the best takeover quality, thus reducing the risk of accident. In particular, we aim at predicting two widely used metrics: Reaction Time (RT) [3] and Maximum Steering Wheel Angle (MaxSWA) [4]. RT is the time between the TOR and the effective takeover of the driver, either by braking or steering the wheel upon a certain threshold. MaxSWA is the maximum angle reached by the steering wheel during the takeover procedure, until control is given back to the car. Both RT and MaxSWA should be minimized to ensure the best takeover quality.

3 Related Work

The driver state has an impact on takeover quality, as shown in various study. For example, drivers are slower to disengage the autopilot when performing a visual-manual texting task with high cognitive load [5]. In addition, drowsiness leads to slower first braking reaction [6].

TOR modalities also impact takeover quality, with multimodal TOR perceived as more urgent and leading to shorter RT but more stress on the driver [7]. Visual modalities were shown to be less effective than auditory or haptic modality [7] when used as unique modality.

At the extent of our knowledge, no research studied the possibility of using ML to predict takeover quality for MaxSWA. RT was studied by Gold [8] (called Take-Over Time in the cited research) as well as lateral acceleration, longitudinal acceleration, and Time-to-Collision. Gold showed that computing the regression of RT was possible, opening the way to more complex models.

4 Methodology

4.1 Experiment

80 participants (54 females) were recruited for this study. Participants' age ranged from 19 to 66 years old (M = 23.94 years old; SD = 8.25 years old). Having a valid driving license was mandatory to participate in this study. They reported on average driving 6312 km per year (SD = 14 415 km) and have held a driving license for about 5 years and a half (SD = 8.10 years). The written informed consent of all participants was obtained.

The experiment consisted in a driving session on a fixed-base driving simulator. The driving scenario consisted in an hour-long driving session in a rural environment without traffic, with five takeover situations. Each takeover was caused by a different limitation of automation, depicting five of the six categories of the taxonomy proposed by Capallera et al. [9]. The causes of each takeover and their associated category are: a steep slope limiting visibility (Road category), fading lane markings (Lanes category), massive rock obstructing the right lane (Obstacle category), heavy rain (Environment category) and a deer crossing the road from the right side (External Human Factor category).

The participants were asked to participate in cognitive non-driving secondary tasks (NDST), in the form of N-Back tasks, to ensure a wide variety of driver psychophysiological states. NDST and causes of takeovers were randomized throughout the study in order to minimize bias.

The TOR was conveyed using audiovisual modalities through a handheld device for half the participants and through a dashboard located behind the steering wheel for the others. The participants' physiological data (respiration, electrodermal activity and electrocardiogram) were recorded during the experiment.

4.2 Machine Learning

Driver physiological data were processed using Neurokit [10] to be used as features, based on five periods of different lengths, from 0 to 30 seconds (Dataset30), 0 to 60 seconds (Dataset60), 0 to 90 seconds (Dataset90), 0 to 120 seconds (Dataset120) and 0 to 150 seconds (Dataset150) before the TOR. This allowed us to refine what is the relevant time window needed prior to the TOR to predict its quality. The TOR modality, either through a handheld device or through the dashboard, was also used as input. Missing values were dropped and not interpolated, since every instance of takeover was independent. Datasets size were 307 takeovers for Dataset30, 332 takeovers for Dataset60, 338 takeovers for Dataset90, 339 takeovers for Dataset120 and 341 takeovers for Dataset150.

Various regression models were then trained using a grid search with a genetic algorithm approach for the selection of the models and their parameters. This was achieved using TPOT [11], which was shown to work well with biomedical data [12]. Population of models were trained and tested on every dataset independently, in a 5–fold cross validation manner on 75% of the data, and validated after the genetic process on the remaining data. Population size was 50 and trained during 5 generations.

The validation score was then used to compare models across datasets. The metrics used to compare scores is the Mean Square Error (MSE).

5 Results

The regression models were compared to a constant prediction of the mean of the metrics (baseline). Improvements is calculated as described in the following equation (Equation 1):

$$\text{Improvement} = (\text{ New score - baseline }) / \text{baseline} . \quad (1)$$

The best model for every dataset and their score can be seen in Table 1 for RT, and Table 2 for MaxSWA.

Table 1. Datasets and their corresponding best model for RT, along with their score. Improvements over baseline is indicated in parenthesis if there is any

Dataset	Model	Score (improvement)
Dataset30	Random Forest Regressor (RFR) applied on a selection of features by Variance Threshold and Principal Component Analysis.	2.4120 (17.61%)
Dataset60	Combination of RFR and ElasticNet.	2.4200 (17.35%)
Dataset90	Combination of RFR, ElasticNet and Gradient Boosting.	3.2113 (-)
Dataset120	Combination of RFR, Linear SVR and Lasso.	3.4150 (-)
Dataset150	**Extra Trees Regressor**	**1.6906 (42.26%)**

Table 2. Datasets and their corresponding best model for MaxSWA, along with their score. Improvements over baseline is indicated in parenthesis if there is any

Dataset	Model	Score (improvement)
Dataset30	**K-Nearest Neighbors (k = 86)**	**161.93 (8.92%)**
Dataset60	Combination of ElasticNet, RBFSampler [13] and Independent Component Analysis	189.32 (-)
Dataset90	K-Nearest Neighbors (k = 67)	175.20 (1.45%)
Dataset120	Combination of RFR and ElasticNet	182.83 (-)
Dataset150	Gradient Boosting	186.65 (-)

We can see that overall, an Extra Trees Regressor achieved an MSE of 1.6906 for the RT, (baseline = 2.9279), an improvement of 42.26%. For the MaxSWA, a K-Nearest Neighbors regressor achieved an MSE of 161.93 (baseline = 177.79), an improvement of 8.92%. RT seems easier to predict than MaxSWA, with multiple models achieving more than 17% improvement over the baseline, while MaxSWA did not get higher than an 8.92% improvement. We can also see that Dataset150 was more suited

for RT prediction, in contrast with MaxSWA which got better results for Dataset30. This leads to think that using multiple time windows for prediction of TOR quality is advisable, instead of choosing only one.

6 Conclusion

This study showed promising results of using ML to predict TOR quality, with models able to predict the RT and MaxSWA. Further research is necessary to evaluate the total gain of takeover quality achievable using this model instead of standard HMI of car models available on the market. Comparing the impact on the user experience of using a dynamic TOR, which modalities will change depending on the situation, instead of a fixed one is also an interesting possible research.

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