Machine Learning Agent to Recommend the Best Modality for Takeover during Conditionally Automated Driving

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ABSTRACT

In this study, we investigate how to make takeover in conditionally automated vehicles safer optimizing the takeover request modalities. Using Machine Learning algorithms, we created a smart agent recommending the best modalities combination to use (haptic-visual, auditory-visual and haptic-auditory-visual) to convey a takeover request. This agent considers the driver state before recommending modalities, as well as the weather condition. The proposed agent is able to predict takeover quality better than the baseline by 56.5% (baseline MSE : 0.0600, our agent MSE : 0.0261) and use different recommendations based on the situation. Modality impact on takeover quality was shown to have a mean score of 4.95% (standard deviation: 2.7%). Evaluation of the agent gain on takeover quality compared to standard takeover request design is currently ongoing.

Keywords: Human Factors, Takeover, TOR, Modalities, Machine Learning,

Regression, Smart HMI, Driver State, Physiological Signals

INTRODUCTION

Conditionally autonomous vehicles are getting more and more visibility worldwide, but they bring many challenges. From interacting with the outside world as an actor on the road, to interacting with the driver which shares the control of the vehicle, those challenges must be studied and responded accordingly to reduce the risk of accidents. In particular, the transition of responsibility for the driving task from the vehicle to the driver can be a dangerous situation, especially if the driver is absorbed in a non-driving-related task. In these cases, the vehicle issues a takeover request (TOR). Upon acknowledging the TOR, the driver must take the control back as quickly as possible, but not without understanding correctly the situation and acting accordingly. For example, the correct behavior could be braking, avoiding an obstacle or maintaining the correct trajectory on the road. This whole process is called a takeover, and could lead to accidents if the driver is not able to execute it properly. Moreover, in level 3 automated vehicles, according to the SAE level of automation (SAE, 2021), drivers are not required to monitor the road while they are not driving, meaning they can be out of the driving loop and unaware of their surroundings. Different systems can be used to keep the driver situation awareness as high as possible (Yang, 2018), but ultimately the TOR is the last interaction before a takeover, and as such should be adapted to suit the situation to help improve the chance for a flawless takeover. Study of the literature reveals insights on how TOR can be used to influence takeover quality, as explained in the "Related Work" chapter.

OBJECTIVE

In this study, we propose a smart agent recommending to the vehicle the best choice of modality for a TOR, using Machine Learning algorithms. This agent considers the driver physiological state based on the last 90 seconds prior a TOR, the external environment and three possible multimodal TOR.

RELATED WORK

Study of the literature shows that the driver psychophysiological state, the external environment and the TOR modalities have an impact on takeover quality.

Choice of modalities affects the takeover quality and should be adapted depending on the situation: multimodal TOR are considered to convey a stronger sense of urgency and lead to shorter reaction time than unimodal TOR (Zhang, 2019). Regarding the modality, the most commonly used are visual, haptic and auditory. Visual modality includes peripheral lights (Shah, 2020), icon on the vehicle dashboard or a handheld device (Capallera, December 2019) and so on. Haptic modality refers to shape-changing or vibrating material, such as haptic seat (Grah, 2015) or steering wheel (Borojeni, 2017). The auditory modality consists mainly of different audio chimes (Ko, 2019) or messages (Du, 2021).

Driver state induced by non-driving-related tasks was shown to impact takeover performance (Naujoks, 2018). N-back task is widely used as a non-driving-related task, and its impact on mental workload has been extensively researched.

Regarding the external environment, Capallera et al. (Capallera, September 2019) showed that it is a potential cause of takeover. This category included the weather, the shape of the road, the state of the lane markings, and so on. In addition, Li et al. (Li, 2018) demonstrated the impact of adverse weather (such as rain, fog and snow) on the takeover quality. As such, we decided to focus on the weather condition in our study.

Another main point to consider is that the agent relies on takeover quality prediction to make its recommendation. Research shows that the quality of the takeover can be predicted using Machine Learning. Du et al. got a f1-score of 64% predicting takeover performance in two categories: good or bad (Du, 2020). Pakdamanian et al. predicted with a score of 83% a driver subjective measure of takeover quality (Pakdamanian, 2021). These studies considered classes of quality, where our agent uses a regression to predict directly the takeover quality metrics. Takeover quality can be measured by different metrics, such as the reaction time, which is the time difference between the TOR and the moment the driver takes the control of the vehicle, or the maximum steering wheel angle (MaxSWA).

METHODOLOGY

Data Collection

A 50 minutes driving session took place on a fixed-base driving simulator, where 15 drivers' physiological signals were recorded. The signals were EDA, ECG, and respiration of the drivers. There were 9 takeover situations during the driving session, caused by a fixed obstacle with a time-to-collision of around 7 seconds. The drivers had to perform three different tasks under two different weather conditions (sunny weather and adverse weather).

The tasks were:

1. A visual 2-back task, where the driver has a handheld device showing a series of letters one-by-one, and had to press a button each time the current letter appearing was the same as the one presented 2 trials ago (cf. Figure 1).

2. An auditory 2-back task, which was essentially the same task except the

letters were presented audibly.

3. A monitoring task, where the driver had to monitor the road at all times.

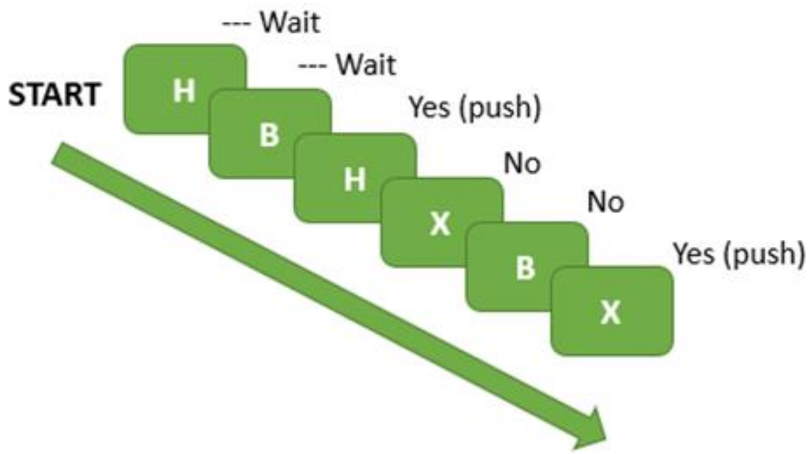

Figure 1. Illustration of the 2-back task, and expected behavior of the participant

If the task score was deemed unsatisfactory, in our case defined as a score equal or below 50%, the current round (until the next takeover) was discarded. This allowed us to discard situations where the participants did not engage properly in the task, which reduces the driver state impact on the takeover quality.
The possible TOR modalities were combinations of haptic (vibrating seat), auditory (short audio chime) and visual (icon on the dashboard). Combinations tested were haptic-visual, auditory-visual, and haptic-auditory-visual. The takeover quality metrics were the reaction time between the TOR and the takeover, and the maximum steering wheel angle attained during the takeover process.

Machine Learning Models

Takeover quality metrics were normalized and aggregated to create a unique label to predict takeover quality. Physiological features were processed from raw physiological signals using Neurokit (Makowski, 2021), and we applied three feature selection techniques to filter the original high number of features (175) to keep only the most relevant ones. First, we filter the trivial redundant features: constant features, duplicate features and features mostly empty. Then, a Pearson correlation analysis allowed us to refine our selection and drop too correlated features. Finally, a Mutual Information analysis further reduces our number of unnecessary features. This gave a final number of 22 usable physiological features.

After outlier suppression and data processing, 80 TOR were kept for the Machine

Learning models (64 for training, 16 for testing). Data Augmentation methods, such as SMOGN (Branco, 2017) and Random Noise were implemented and tested to boost the training dataset.

KNeighbors Regressor, Support Vector Regressor, Random Forest Regressor and Neural Networks were trained using a grid search approach and cross validation. Scores were compared to a baseline defined as the constant prediction of the mean of the takeover quality metrics.

The final Machine Learning model and methodology is detailed in (de Salis, 2022).

TOR Modalities Recommendation

The agent predicts the takeover quality using the ML model, with every possible set of modalities. It then chooses the modalities providing the best theoretical takeover quality. The agent was evaluated to avoid the following trivial situations:

1. The agent always chooses the same modalities, meaning that the training was biased toward one set of modalities.

2. The agent chooses a random modality because the choice has no impact on predicted performance, meaning that the agent was not able to capture the modalities' impact on takeover quality.

A novel metric representing modality impact on takeover quality was defined and used to optimize agent behavior: we defined the takeover modality impact as the difference in percent between the highest takeover quality predicted between the three modalities and the lowest one. The formula can be summarized below:

(Max(takeover_quality_prediction(modality1, …, modalityn) -
Min(takeover_quality_prediction(modality1, …, modalityn)) /
Min(takeover_quality_prediction(modality1, …, modalityn) .

We then analyzed the mean and standard deviation of this metric on the test dataset for our models.

RESULTS

The agent was able to predict takeover quality using a Random Forest Regressor with a MSE of 0.0261, beating the baseline (0.0600) by a ratio of 56.5%. See Table 1. for the results of each model.

Table 1: MSE and MAE scores achieved by each model (best one in bold)

Model Name	MSE
Baseline	0.0600
KNeighbors Regressor	0.0465
Support Vector Regressor	0.0527
Random Forest	**0.0261**
Neural Network	0.0519

The following parameters were selected for the Random Forest using a Grid Search approach: bootstrap: False, maximum depth: 5, maximum features: square root of the number of features, minimum impurity decrease: 0.0, minimum samples leaf: 4, minimum samples split: 5, number of estimators: 30.
The Random Forest Regressor was also able to suggest the 3 different sets of modalities in the final phase, with a distribution of 0.625 for auditory-visual, 0.25 for auditory-haptic-visual and 0.125 for haptic-visual. Modality impact on takeover quality had a mean score of 4.95% (standard deviation: 2.7%).
Regarding the data augmentation techniques implemented and tested, it appeared that both techniques allowed for a slight boost to the final score, but since it is very low its significance and interest is debatable. Random Noise techniques with a maximum noise of 0.1 (each data entry feature is multiplied by a number between 0.9 and 1.1) and an augmentation of the dataset by maximum 40% gave the best results.

CONCLUSIONS

In this paper, we propose an agent able to recommend the best modalities for a TOR in a set of three (haptic-visual, haptic-auditory-visual, and auditory-visual). This agent relies on the prediction of a Random Forest regressor predicting the takeover quality for a given set of modality, the external weather and the driver physiological state in the last 90 seconds prior to the TOR.

The implication of our agent is the possibility for creating a smart HMI designing TOR on the fly, making the transition of control between the car and the driver safer than traditional TOR.

Impacts on using such a HMI on User Experience must be further studied.

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