After Vehicle Automation Fails: Analysis of Driver Steering Behavior after a Sudden Deactivation of Control

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ABSTRACT: Vehicles with SAE Level 2 or 3 automation rely on the driver to intervene and resume control when failures occur. In cases which the driver must steer upon regaining control, the initial conditions of the vehicle’s state variables can affect the success of the drivers' recovery. Hence, a model to determine the consequences of these initial states could help identify the requirements of shared control to guarantee a smooth recovery after an automation failure. Such a modeling tool should be simple, such as a two-point visual continuous control model of steering. Data to validate such a model were collected from participants driving in the NADS-1 simulator who were placed in a situation similar to an extreme case of automation failure by drifting their vehicle to a target heading angle and lane deviation. This was done while the drivers were distracted with a secondary task that kept their eyes off the road. The maximum lane deviation reached during recovery shows that the initial heading angle and steering wheel angle strongly affected the maximum lane deviation. Moreover, a slightly modified version of the two-point visual control model was used to simulate the drivers' steering profiles. The model was successful at recreating the participants heading angle and lane deviation profiles but failed to replicate the drivers' steering profile. This simple model of steering control could be used to assess the consequences of a vehicle ceding control at various initial conditions, but is not able to reproduce all aspects of steering control.

KEY WORDS: Safety, Automation Failure, Modeling Steering Control, Perceptual Cues, Recovery [C1]

1. Introduction

Increasingly capable automation is changing the role of the driver. The Society of Automotive Engineers (SAE) has defined levels of driving automation systems ranging from Level 0 to Level 5, with an aim to define drivers' roles with different vehicle technology. According to the SAE standard J3016 (1), a Level 2 (partial automation) system requires the driver to monitor the driving environment and intervene immediately. Level 3 automation, in contrast, requires the driver (also called user) to intervene when requested. Even though the driver remains primarily responsible for vehicle control, such automated systems (2) will likely increase drivers' desire to engage in secondary tasks (3, 4, 5), leaving them less prepared to take back control.

An evident consequence of such distraction and disengagement is diminished situation awareness and the driver being out of the loop, resulting in degraded responses to sudden automation failures (5, 6). Among other factors that can influence the quality of a drivers' take-over response is the intensity of the take-over request and its modality (7), the time budget provided to the driver (8), and the severity and complexity of the driving situation (9, 10). Given enough time to establish sufficient situation awareness to guide an appropriate action, a driver might brake, accelerate, steer, or perform some combination. The smoothness and safety of the drivers' response also depends on the vehicle state at the time that the automation fails, such as heading, lane position, and angle of the steering wheel. Modeling drivers' steering behaviors in these sudden interventions and transitions of control can indicate how the vehicle state at failure will affect drivers' emergency steering performance and subsequent safety outcomes.

Lateral control or steering models have a long history, with the earliest mathematical model of human steering control dating back 50 years (11). This early model described the drivers' steering profile as a jerky curve with flat segments that can be partially approximated using a linear transfer function. However, that model failed to account for non-linear behavior, which has increasingly become the focus of much research (12). Among the many proposed driver lateral control models, such as the cross-over model (13) and the two-level model of steering control (14), one of the most prominent and promising models is the two-point visual control model by Salvucci and Gray (15). The two-point visual control model is a linear transfer function—a Proportional-Integral controller—that uses psychologically plausible perceptual cues as the input to a continuous output steering control model (16). Although recent research is shifting towards the notion that human drivers' steering response is mainly the sum of instances of intermittent control (17) and not continuous control like the two-point visual control model, this model might be useful in estimating drivers' steering performance after a sudden transfer of control.
In this paper, we apply a slightly modified version of the two-point visual control steering model to data describing drivers' steering profile after an event similar to automation failure: drivers were distracted by a secondary task, during which time the vehicle was forcibly drifted, and the drivers had to suddenly apply corrective lateral control when they returned their attention to the road. No prior instructions or safety warnings were given to the drivers. The study considers how well a continuous steering control model can estimate the consequences of vehicle state (i.e., heading, lane position, and steering wheel angle) at the time the automation fails on drivers' emergency steering performance and subsequent safety outcomes.

2. Methods

2.1. Simulator-Based Data Collection

The dataset for this study was obtained from an experiment conducted using the National Advanced Driving Simulator (NADS-1) at the University of Iowa. A Chevy Malibu sedan retrofitted with a Toyota steering wheel was used. Data were sampled at 240 Hz. The driving scenario consisted of a single drive through a rural environment in dry daytime conditions. The speed limit was set at 55 mph for the events under study.

The scenario events allowed the investigation of the diver's steering recovery responses that began with varying lane positions and heading angles. The drivers were distracted with a secondary task to take their eyes off the road, and while they were engaged in the task, the vehicle heading was manipulated to drift the vehicle to the desired state. No warning was provided to the drivers.

A number recall task was used as throughout the drive. This task was designed to reliably draw drivers' focal and peripheral visual attention away from the forward roadway to allow for the lane-departure event to unfold. The display for the number recall task was designed to reliably draw drivers' focal and peripheral visual attention away from the forward roadway to allow for the lane-departure event to unfold. The display for the number recall task was located at least 90 degrees to the right of the participants' forward-facing position, behind the passenger headrest (Fig. 1).

One second after receiving an auditory instruction to begin the task, five random, single-digit numbers were presented for 472 ms each. The participants were asked to repeat them aloud in the forward-facing position, behind the passenger headrest (Fig. 1). One second after receiving an auditory instruction to begin the task, five random, single-digit numbers were presented for 472 ms each. The participants were asked to repeat them aloud in the correct order. The duration of the task was kept constant at 2.36 seconds to ensure that the drivers' attention was on the task and away from the forward roadway when the event began.

Forty-eight participants, 12 from each of four age groups (18-25, 26-40, 41-60, and 61-80) enrolled in the single-session study. One participant, a female in the 61-80 age group, chose to stop driving early because she found the combination of the number recall task and driving particularly stressful. Three other participants' data, a male and a female in the 41-60 age group and a male in the 26-40 age group had to be excluded due to errors in their recorded data. Hence, 44 participants were used in the data analysis. Participants were recruited from the NADS participant registry and screened by phone for eligibility. Participants had to be licensed without restriction (other than corrective lenses), drive at least 2,000 miles per year, and be able to drive without the aid of special equipment. Additionally, participants were screened for possible health conditions that could interfere with driving. These included serious illness, heart conditions, neurological problems, untreated psychological conditions, motion sickness, and sedating medications. The testing session lasted approximately 1.25 hours and participants were reimbursed for their time. The University of Iowa Institutional Review Board approved all procedures.

2.2. Steering Control Model

The two-point visual control model of steering developed by Salvucci and Gray (2004) predicts steering control based on drivers' perceptual orientation with respect to two salient visual reference points on the roadway: a near point and a far point. The near point is used to monitor the position of the vehicle within the lane boundaries, and to maintain lateral position and stability. On the other hand, the far point term adds stability to the model by adding a predictive steering element to compensate for the roadway ahead.

The near point angle is defined using a fixed distance ahead and the visual angle from the driver to this point indicates distance of the vehicle from the center of the lane. The far point is defined by one of three options: 1) a vanishing point on a straight road, usually calculated based on a time headway, 2) the tangent point of an approaching curve and 3) a lead vehicle or a specific target on the roadway.

This model uses the rate of change of the steering angle, instead of the steering angle itself, with Equation 1 being the final discrete form of the two-point visual control model.

\[
\Delta \varphi = k_f \Delta \theta_f + k_n \Delta \theta_n + k_\theta \Delta \theta_n \Delta t
\] (1)

In Equation 1, \( \Delta \varphi \) is the change in steering wheel angle, \( \theta_f \), the far point angle, \( \theta_n \), the near point angle, with \( k_f \) and \( k_n \) being the proportional gains while \( k_\theta \) is the integral gain of the near point angle. Moreover, \( \Delta t \), can either be a constant for periodic updates of the steering output, or it could be varying to account for intermittent updates to the steering wheel angle output.

In this study, Equation 1 has been adjusted to include an additional parameter \( \alpha \), as reflected in Equation 2. This parameter reflects the neuromuscular lag and the physics of the human arm movement, which limits the frequency of steering corrections: the current steering wheel position depends on its previous value.

\[
\varphi_{t_i} = -(k_f \Delta \theta_{f_{t_i}} + k_n \Delta \theta_{n_{t_i}} + k_\theta \theta_{n_{t_i}} \Delta t) + \alpha \varphi_{(t_{i-1})}
\] (2)
According to Equation 2, drivers’ steering behavior is a weighted combination of the near and far point angles along with the previous steering wheel angle. \( \varphi_n \) is the current steering input, \( \Delta \theta_f \) and \( \Delta \theta_n \) are the change in the far and near point angles. \( \theta_{ni} \), is the current near point and \( \varphi_i((t,(i − 1))) \) is the steering wheel angle of the previous time step. \( k_f, k_n, k_f \) and \( \alpha \) are the weights that need to be adjusted to replicate the human drivers’ steering behavior.

\[ \varphi = k_f \Delta \theta_f + k_n \Delta \theta_n + \alpha (t, (i − 1)) \]

In this modified model, as seen in Fig. 2, the near point angle is the angle between the vehicles’ lane deviation from the center of the roadway and an offset six meters ahead of the vehicle on the centerline. The far point angle, is the angle between the vehicles’ heading and the center of the roadway.

Nevertheless, not all drivers choose the center of the lane as their target line for adjusting their vehicle’s position and stabilization. In such cases, a line reflecting their behavior could be used for calculations.

### 3. Results

This analysis focusses on one of the more extreme lane drift events in the simulator experiment. In this event the vehicle was drifted to a lane deviation of about 1.4 m from the center of the lane. For this event we focus solely on drivers’ steering behaviors because the responses show no braking and negligible deceleration. Hence the drivers' speeds during recovery remained fairly constant, meaning that steering was the main recovery response behavior.

Analysis of the recovery steering profiles of drivers (upon regaining control of the vehicle after automation failure) showed that one of the most important factors to consider was the maximum lane deviation that the vehicle reaches during recovery. Maximum lane deviation is an important indicator of a smooth take-over from automation, because higher values of lane deviation can indicate either a lapse of steering control or over-steering. A large deviation might result in a collision with oncoming traffic or a run-off-road crash. Therefore, a regression model was fit to assess how the vehicle state at the time that the driver regained control affected the maximum lane deviation. These initial conditions included: lane deviation initial condition (LDIC), heading angle initial condition (HIC), and steering wheel angle initial condition (SIC) at the moment of the intervention. A set of linear regression models were developed to assess how these variables influenced the maximum lane deviation during recovery.

Table 1 shows that the maximum lane deviation is affected by all three initial conditions and the interaction of the initial steering wheel position and initial heading angle. At the instant of take-over, especially in extreme cases, such as in this experiment, we expected the initial lane deviation would affect the maximum lane deviation during recovery, but had no strong expectations regarding the initial steering and heading angles.

|         | df | Sum of Square | Mean Square | F value | Pr(>F) |
|---------|----|---------------|-------------|---------|--------|
| SIC     | 1  | 7.77          | 7.77        | 153.69  | < .001 |
| HIC     | 1  | 19.64         | 19.64       | 388.49  | < .001 |
| LDIC    | 1  | 20.21         | 20.21       | 399.84  | < .001 |
| SIC:HIC | 1  | 0.37          | 0.37        | 7.24    | 0.01   |
| SIC:LDIC| 1  | 0.0           | 0.0         | 0.0     | 0.95   |
| HIC:LDIC| 1  | 0.09          | 0.09        | 1.81    | 0.19   |
| SIC:HIC:LDIC | 1 | 0.0          | 0.0         | 0.13    | 0.71   |
| Residuals| 36 | 1.82          | 0.05        |         |        |

Further analyzing the relationship between the maximum lane deviation and the SIC and HIC revealed a relatively linear relationship between each pair as shown in Fig. 3 and Fig. 4. The solid black lines in Fig. 3 and Fig. 4 depict the linear regression model whereas the dashed line is the corresponding LOESS fit to the data points.

![Fig. 3 Relationship between maximum lane deviation and initial heading angle.](image-url)
Fig. 4 Relationship between maximum lane deviation and initial steering wheel angle during recovery.

To further investigate the effect of the HIC and SIC, and also examine whether the two-point steering model can replicate these steering behaviors, three participants representing the three conditions (Table 2) were chosen from the original 44 participants. These participants are denoted by the triangles in Fig. 5.

The LDIC for all three selected participants was close to the median of the initial lane deviations from the center at the point of intervention shown by the blue dashed line. The far right vertical dashed lane is the 90th percentile of initial heading points at the instant of recovery. These three points were selected because they are representative of the population of initial lane deviation and different initial steering and heading angles. Condition 1 and Condition 2, share the same HIC, explaining the overlap of the two triangles in Fig. 5, while having different SICs. On the other hand, the SICs for Conditions 1 and 3 were similar, but their HICs were different.

Fig. 6, shows the recovery behavior of the three chosen participants. The light gray lines in the background are the other 41 participants from this event. The dotted line displays the Steer Constant - Heading Value Small condition, the dashed line is the Heading Constant - Steer Value Large condition and the solid line depicts the Heading Constant - Steer Value Small condition.

Fig. 6 shows all three conditions beginning from a similar starting point with regard to lane deviation. However, following the lane deviation profiles over the recovery period, the difference between the maximum lane deviations of each condition can be clearly seen.

For instance, the Steer Constant - Heading Value Large condition and the Heading Constant - Steer Value Small condition, which are depicted by dotted and solid lines, exceed their initial condition of 1.37 m increasing the risk of a collision and lane departure. The cause of these differences can be traced back to Fig. 3 and Fig. 4 and the variation in the initial steering wheel angle and heading angle at the take-over point.

Assuming that human action operates on a discrete rhythmic clock (19), the $\Delta t$ in Equation 2 can range from a constant value to a varying value to represent intermittent or occasional updates. The delay in human response can be considered as the sum of delays due to perception, decision and motor action stages (17). This delay was set at a constant 200 ms. Hence, the three representative driver steering responses, along with their corresponding steering rate profiles were studied in 200 ms increments. In Fig. 7, the solid black line is steering wheel angle over time and the dashed line is the steering wheel angle rate.

A corrective steering action begins when a driver reverses the steering wheel either to the right or left. Such corrective actions result in peaks and valleys in the steering wheel angle profile. To locate these instances of corrective steering being initiated, the points of the first derivative of the steering angle (i.e., steering wheel angle rate that were equal to zero) were found. These instances embody a local minima or maxima in steering wheel angle with the rate being zero. Fig. 7 shows these points as red dots on the steering profile.

| Condition | Label                          | LDIC (m) | HIC (Degree) | SIC (Degree) |
|-----------|--------------------------------|----------|--------------|--------------|
| 1         | Heading Constant - Steer Value Small | 1.38     | 0.50         | -2.15        |
| 2         | Heading Constant - Steer Value Large | 1.37     | 0.50         | -12.25       |
| 3         | Steer Constant - Heading Value Large | 1.40     | 0.93         | -1.93        |
Fig. 6  Steering, lane deviation and heading profile of three representative participants during recovery, and the light grey lines indicate those of the other drivers.

Fig. 7 demonstrates that corrective steering actions did not occur at consistent times throughout the recovery period and that each driver initiated corrective actions at different times. Therefore locating these corrective instances could be useful in assessing the ability of the driver model to recreate a human-like steering pattern.

To validate the model, we developed a computer simulation using the NADS MiniSim™ as the vehicle dynamics engine and Equation 2 as the driver model to generate the recovery steering behaviors. The computer simulation places the vehicle at the same lane deviation, heading angle, and steering wheel position from Table 2. Upon the vehicle reaching the desired initial condition, the driver model was activated to generate a recovery steering profile.

Fig. 8 shows the steering profiles generated by the human drivers as dashed lines, and the solid lines show the steering behavior produced by the driver model. In this model the parameters $k_c$, $k_n$, $k_i$ and alpha were 25.0, 6.0, 6.0, and 0.7 respectively. Fig. 8, shows that even though the model failed to replicate the details of the steering profile (i.e., the red dots being instances of correction initiation), the heading angle and lane deviation profiles look very similar especially in the Steer Constant - Heading Value Large condition (Condition 3).

4. Conclusion

When vehicle automation fails, aiding the driver to have a smooth and safe recovery is of crucial importance. In this study, the effect of the drivers' sudden take-over of control of the vehicle at different heading and steering angles was evaluated. Both these variables can strongly affect the maximum lane deviation that a driver experiences during recovery. Therefore, providing the driver with a suitable set of initial conditions at the instant of take-over can reduce the risk of an unsuccessful recovery.

The three examples presented in this study had relatively similar initial conditions to keep the focus on assessing the model. We modified the parameter values from Salvucci and Gray (2004) to fit each example, using a grid search method to estimate the parameters. In future research we plan to apply the Approximate Bayesian Computation (ABC) to estimate parameters. By estimating the parameters with the ABC technique we will be able to evaluate the between subject variation along with the within subject variation across different events (i.e., different initial conditions at point of takeover) to gain further insight into different steering avoidance behaviors and their outcomes.

The modified two-point steering model successfully replicated several aspects of driver response. This model was not successful in recreating the detailed fluctuations in the drivers' steering profile. However, the model was able to reasonably recreate the heading and lane deviation trajectories making this comparatively simple model a useful design tool to simulate the consequences of drivers' emergency steering intervention at relatively extreme initial conditions.

Although the proposed steering model recreated trajectories for relatively extreme take-over conditions, detailed models of human drivers' steering control, such as the model introduced by Markkula et al. (18), might provide more precise trajectories. More generally, the effectiveness of this linear continuous model for a wider range of severe initial conditions should be further assessed in future studies. Because more extreme initial conditions might
lead drivers to respond in a way that is not proportional to the perceptual cues, the resulting control behavior could be non-linear and require a different type of model (22).

Choosing between these models depends on the application. Extreme recovery strategies might require a non-linear model that accounts for the full range of driver control strategies. While extending the model might improve its accuracy, this continuous control model can be considered as an acceptable candidate for assessing how drivers’ lane deviation and heading trajectories depend on the initial conditions in cases of relatively extreme takeovers. Combining the model with the understanding of the impact of initial conditions on the recovery process, designers can better evaluate opportunities to improve sudden transitions of control.

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