

# Using Multilevel Hidden Markov Models to Understand Driver Hazard Avoidance during the Takeover Process in Conditionally Automated Vehicles

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Ensuring a safe transition between the automation system and human operators is critical in conditionally automated vehicles. During the automation-to-human transition process, hazard avoidance plays an important role after human drivers regain vehicle control. This study applies the multilevel Hidden Markov Model to understand the hazard avoidance processes in response to static road hazards as continuous processes. The three-state model—Approaching, Negotiating, and Recovering—had the best model fitness, compared to the four-state and five-state models. The trained model reaches an average of 66% accuracy rate in predicting hazard avoidance states on the testing data. The prediction performance reveals the possibility of using the hazard avoidance pattern to recognize driving behaviors. We further propose several improvements at the end to generalize our models into other scenarios, including the potential to model hazard avoidance as a basic driving skill across different levels of automation conditions.

## INTRODUCTION

Automated vehicles (AVs) have developed rapidly in recent years, with the advantages of reducing human drivers' responsibilities and shifting them to automation systems. However, given the current limitations in technology, AVs are not capable of handling all traffic situations or are confined by ethical or legislation requirements, which necessitates the intervention of human operators and sets a shared control situation in the human-automation collaborative system (Janssen et al., 2019). Thus, how to ensure a safe transition from the automation system to the human driver, also known as the takeover process (McDonald et al., 2019), is critical in conditionally automated vehicles and has received considerable attention. The takeover process involves physical, visual, and cognitive components (Figure 1). Upon the takeover request to a precipitating event, drivers exert extensive efforts to ensure the physical, visual, and cognitive readiness to assess and process the hazardous stimuli. Such readiness prior to regaining vehicle control and executing the evasive action can be affected by a variety of factors, which further influence the action execution (McDonald et al., 2019).

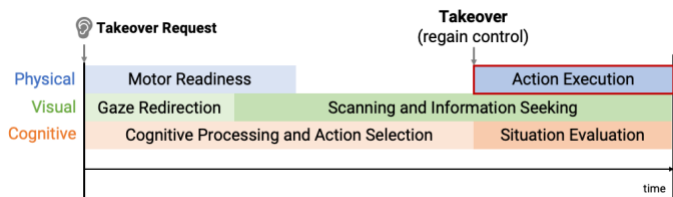


Figure 1. A conceptual takeover process model [modified from McDonald et al. (2019)]

Empirical human-subject studies have been carried out to understand the effectiveness of different displays on driver performance during takeover processes in conditionally automated vehicles. In these studies, drivers typically received a takeover request through visual, auditory, and/or haptic displays (e.g., Huang & Pitts, 2022; Roche & Brandenburg, 2020; Wang et al., 2022) and regained vehicle control to negotiate hazardous events that the system cannot handle. Their

takeover performance was measured in terms of takeover timeliness and vehicle control stability. However, such empirical studies are effortful and resource-demanding, and often require additional adjustment to be able to apply to novel contexts.

In lieu of empirical studies, computational simulation models can quantitatively model human physical and cognitive performance and provide realistic predictions of human behaviors. These computational simulations can integrate complex factors that influence driver behaviors and allow quick adjustment to model parameters to accommodate different situations. Well-built models can provide accurate and precise results. For example, Deng et al. (2018) used an improved Hidden Markov Model and reached 91.9% accuracy when predicting human lane-changing behaviors. Existing modeling attempts have covered driver reactions to auditory displays (Jeon et al., 2021; Ko et al., 2022; Y. Zhang et al., 2016), driver braking and steering behaviors, and braking/steering decision-making (McDonald et al., 2019). Nevertheless, most of these modeling attempts either focus only on drivers' reactions prior to the actual action execution (e.g., response time), or can only explain discrete driving responses (e.g., brake or steer decisions) while overlooking the continuity and spatiotemporal features of driving behaviors.

The primary objective of this study is to apply the Hidden Markov Model (HMM) to model continuous driver hazard avoidance maneuvers after the human driver regains vehicle control. The Hidden Markov Model (HMM) is a type of time-series statistical model with the advantages of analyzing dynamic data and the temporal evolution of states (Deng & Soffker, 2022; X. Zhang et al., 2014). HMM, and its variations have been successfully used to identify driving styles, fatigued driving, drunk driving, driving skills, and traffic environments (Deng & Soffker, 2022). We believe that HMM will be able to uncover the dynamic and chronological characteristics of driver behaviors in response to hazardous events in our study.

Hazardous events that require human intervention in conditionally automated driving can be split into three primary categories: (1) static hazards (e.g., construction site), (2) dynamic hazards (e.g., pedestrians), and (3) weather conditions

(e.g., low visibility due to fog). With this first attempt to model continuous post-takeover behaviors, we mainly focused on static hazards that pose a relatively low risk for attentive drivers who received speech takeover requests. We aim to identify the number of hidden driving states of static hazard avoidance during the action execution in the takeover process (Figure 1) and establish an HMM model that can predict the driving states based on the driver input data.

Hazard avoidance is an overarching term that describes the whole process from hazard detection, hazard processing, hazard appraisal, and hazard response for collision avoidance (Pradhan & Crundall, 2016). There are several subprocesses that lie within hazard avoidance. A different combination of these processes can be used to describe a variety of scenarios. Based on the hazard avoidance theory (Pradhan & Crundall, 2016), a typical hazard avoidance process for a static hazard can be explained as hazard precursor > hazard onset > hazard processing and appraisal > hazard reaction/response. Hazard precursor refers to the clues indicating an upcoming hazard; it can be evidence from the hazard itself (e.g., a pedestrian is looking around next to the road), or from in-vehicle displays. Once the hazard is onset, hazard processing refers to the time taken to identify the hazardous object, and hazard appraisal refers to the hazard risk level assessment (Pradhan & Crundall, 2016) prior to any actions. Hazard reaction differs from hazard response because reactions are unplanned behaviors that can have both negative and positive outcomes, while responses are deliberate strategic actions that always have positive outcomes (Pradhan & Crundall, 2016). We introduce a new subprocess—recovery—to describe the process after the operator successfully avoids the collision but is still in the vicinity of the static hazard and ready to exit the hazardous zone. We believe that adding a recovery subprocess will complete the hazard avoidance process, which is helpful to differentiate novice drivers and experienced drivers.

With the computational modeling attempts on hazard avoidance, the unique contributions of the current study include: (1) identifying three driving states of hazard avoidance in takeover events; (2) providing both a group-level and an individual-level sets of HMM parameters to predict hazard avoidance driving states based on drivers’ manual control input. Our model also has the potential to be generalized into hazard avoidance under different driving automation conditions. We also suggest the possibility of using hazard avoidance patterns to recognize different driving styles.

## METHOD

### Participants

We recruited 24 participants (7 females) aged between 19 and 33 years old ( $Mean = 23.12$ ,  $SD = 4.49$ ) with normal or corrected-to-normal vision. All participants held valid driver’s licenses, with an average driving experience of 5.93 years ( $SD = 3.37$ ) and an average driving frequency of 4.67 days per week ( $SD = 2.22$ ). Prior to the study, participants signed the informed consent approved by the Institutional Review Board.

### Experimental Apparatus and Procedure

NervTech™ (Ljubljana, Slovenia) driving simulator was used in this study. The simulator setup consists of three 48"

displays, a surrounding sound chamber, an adjustable seat, a steering wheel, and a pedal set with gas, brake, and clutch. A conditionally automated vehicle with automatic transmission was simulated in this study. Thus, participants only used gas and brake inputs. Simulated driving scenarios were programmed in the SCANeR studio and designed to simulate SAE Level 3 Conditional Driving Automation (SAE International, 2021). Most of the time, the simulated subject vehicle drove itself along a pre-defined route that consisted of highways and urban areas. When the system reached its limit, it issued a speech takeover request (TOR) (e.g., “Please take over. Construction ahead.”) prior to the potential collisions, and participants were mandated to take over control by either applying the brake or using a toggle to deactivate the auto-drive. Then, they operated the vehicle and navigated through the hazardous events, before exiting the takeover zone and handing the control back to the vehicle. There were four takeover events in the scenario: construction site, jaywalker, tunnel, and fog. The focus of the present study was the construction site as a static road hazard.

### Data Collection and Pre-Processing

The driving simulator automatically logged vehicle kinematics and control input data (e.g., gas, brake, and steer). Only control input data during the manual control period were used to build the model later. The data were logged with a sampling rate of 100 Hz. Participants’ manual control period ranged from 9 seconds to 15 seconds, resulting in 900 ~ 1500 data records for each participant. We further aggregated the data into a sampling rate of 10 Hz, resulting in each data point representing the observational sequence across a 0.1-second period. After examining the raw observational data, we further classified them into different categorical levels (Table 1). The number of levels for each observational type was set based on trial and error, which allowed us to capture sufficient differences across levels but not over-complexify the levels.

Table 1. Observational data range and levels

Obs. Type	Data Range	Unit	Levels	Attribute Use
Gas	0 <sup>1</sup> – 1	-	6	Level 1 – No gas Level 6 – Full gas
Brake	0 – 400	N	6	Level 1 – No brake Level 6 – Full brake
Steer	[-90, 90] <sup>2</sup>	Degree <sup>3</sup>	7	Level 1-3: Steer right Level 4 – No steer Level 5-7: Steer left

<sup>1</sup>0 is depressed; <sup>2</sup>Negative indicates steering right; <sup>3</sup>The raw data are in rad.

### HMM Introduction and Structure

A Hidden Markov Model (HMM) describes a doubly stochastic process with a hidden stochastic process that is not observable but can only be derived from another observable stochastic process that generates observed data (Rabiner & Juang, 1986). In the current study, the observed data are drivers’ manual control input (i.e., gas, brake, and steer) that generated a series of observational sequences, while the hidden process is the hazard avoidance process that contains the unknown number of states and their sequences.

An example structure of the HMM with three hidden states used in this study is presented in Figure 2.

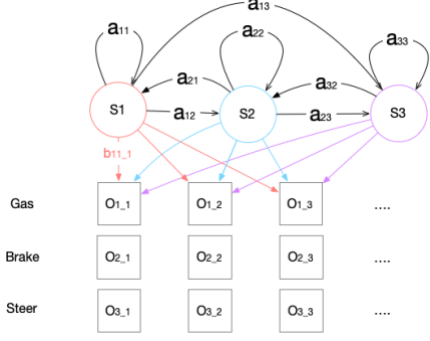


Figure 2. Example Structure of HMM (simplified for readability).

Each  $a_{ij}$  represents the transition probability from  $S_i$  to  $S_j$ . The full combination of  $a_{ij}$  forms the transition probability matrix  $\mathbf{A}$ . The transition matrix for this study is represented as:

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \quad (1)$$

Given each state  $S_i$ , the probability of generating observation  $o_{m,n}$  is denoted as  $b_{im,n}$ , where  $n$  refers to the level of observation, and  $m$  refers to the observation type. For example,  $b_{11,1}$  refers to the probability of observing  $o_{1,1}$  (i.e., gas input as “no gas”) when in state 1 ( $i = 1$ ). A full combability of all  $b_{im,n}$  forms the emission probability matrix  $\mathbf{B}$  for each category of observational sequences. The emission matrix of gas input is represented as:

$$\mathbf{B}_{gas} = \begin{pmatrix} b_{11,1} & b_{11,2} & b_{11,3} & b_{11,4} & b_{11,5} & b_{11,6} \\ b_{21,1} & b_{21,2} & b_{21,3} & b_{21,4} & b_{21,5} & b_{21,6} \\ b_{31,1} & b_{31,2} & b_{31,3} & b_{31,4} & b_{31,5} & b_{31,6} \end{pmatrix} \quad (2)$$

## Multilevel HMM

Multilevel hidden Markov models (MHMMs) allow fitting the same HMM based on multiple categorical observational sequences (i.e., gas, brake, and steering input in this study) of multiple subjects but also accommodate for the heterogeneity between subjects. In MHMMs, model parameters are estimated on different levels of the data: subject-specific level and group level. The subject-specific-level parameters are trained based on the data of a certain subject and are unique to them, which also follows a given group-level distribution. The group-level parameters are estimated based on the subject-level parameters. Thus, the mean and the variance of a group-level parameter represent the overall mean parameter of a given group of subjects and the variability among subjects in the group. Using MHMM allows us to acquire more generalizable parameters and utilize them for decoding hidden driving states.

In the current study, we adopted the MHMM in a Bayesian context with a shorter time to reach model convergence (Y. Zhang & Berhane, 2014). The “mHMMbayes” R package was used to train, validate, and apply the model (Aarts, 2022). This package requires an initial emission matrix for each observation type to start with. Our initial matrixes were set in a way that higher gas inputs were less likely in earlier stages right after regaining control and were more likely towards the end of action execution. The matrix for the brake input was set to match with gas input. The matrix for steering was set to reflect different motor control corresponding to hazard avoidance states described in the next section.

## Hazard Avoidance States

The main purpose of the present study is to use participants’ manual control data to uncover the hidden states during hazard avoidance. After reviewing the raw data and the driving clips produced from participants’ data, we have proposed three possibilities for the hidden driving status during the process of static hazard avoidance (Figure 3).

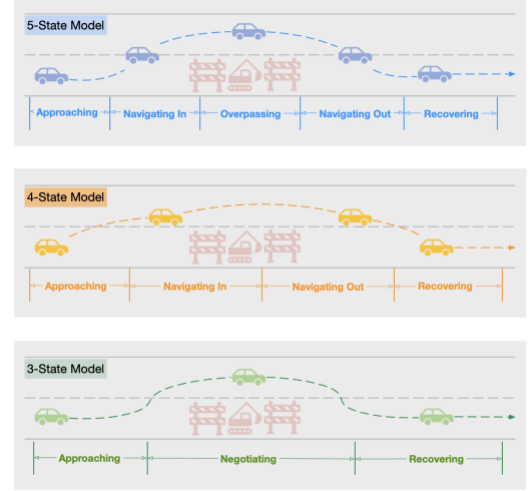


Figure 3. Three possibilities of driving status.

**Five hidden driving states.** The five-state hazard avoidance model divided the hazard avoidance based on the temporal process when participants navigated through the construction site: approaching, navigating in the zone, overtaking the hazard, navigating out of the zone, and recovering from the hazard (Figure 3, top).

**Four hidden driving states.** Considering the potential overfitting issue with the five-state model, we further proposed a four-state model (Figure 3, center). The four-state model integrates the states of navigating through the construction site into two states: navigating in the zone and navigating out of the zone, given that the construction site only took place in a more condensed area.

**Three hidden driving states.** Finally, we further simplified hazard avoidance into three states: Approaching, Negotiating, and Recovering by integrating the states between starting and ending into one state (Figure 3, bottom).

## RESULTS

### Model Training

Data from 24 participants were split into the training sets (80%) with 19 participants’ data, and the testing set (20%) with the remaining 5 participants’ data. Three possible models were first trained using the training set. The Akaike Information Criterion (AIC), a frequently used measure to indicate the goodness of fit for a model (Bozdogan, 1987), was used to help us determine the number of hidden states. The three-state model resulted in the smallest AIC (504.16), compared to the four-state (532.70) and five-state (587.76) models, and thus, became our best model.

The group-level state transition probability matrix ( $\mathbf{A}$ ) is presented below. All states are stable as the probability of remaining in the same state is higher than 0.6, as shown by the

diagonal values in the matrix  $A$ . The model also produced individual-level parameters for each subject. We mainly focused on the group-level parameters in the current paper.

$$A = \begin{pmatrix} \mathbf{0.822} & 0.106 & 0.072 \\ 0.048 & \mathbf{0.904} & 0.048 \\ 0.039 & 0.040 & \mathbf{0.921} \end{pmatrix}$$

### Model Convergence and Label Switching

We further investigated the model convergence and label switching. With a different but conceptually similar set of initial

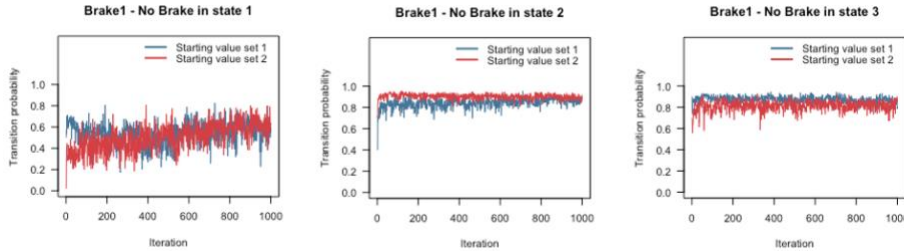


Figure 4. Model Convergence Check (example Brake input).

### Model Performance

The group-level parameters were used to obtain the most likely state sequence for each participant in the testing set using the “vit\_mHMM” function (Aarts, 2022) that uses the Viterbi algorithm (Forney, 1973; Viterbi, 1967). The actual states were determined from the raw data with the assistance of other vehicle kinematics data and vehicle position data. The model verification details for each participant are listed in Table 2.

Table 2. Model performance on the testing set.

	Correct/Total Count	Accuracy
Test P1	50/101	49.5%
Test P2	59/97	60.8%
Test P3	81/100	81.0%
Test P4	42/93	45.2%
Test P5	103/111	92.8%
<b>Average Accuracy:</b>		<b>65.7%</b>

The model reaches an average accuracy of 65.7%, with the highest prediction accuracy reaching 92.8% and the lowest prediction accuracy at 45.2%. We revisited the observational sequences for Test P4 and found that this participant drove more aggressively by speeding right after taking over the control and only releasing the accelerator in the Negotiating state. This participant did not apply the brake to reduce their speed at any point during the manual control period (Figure 5). The prediction recognized Recovering at the start of action execution due to speeding and transitioned to Negotiating before transitioning back to Recovering (Figure 5, “state” bar).

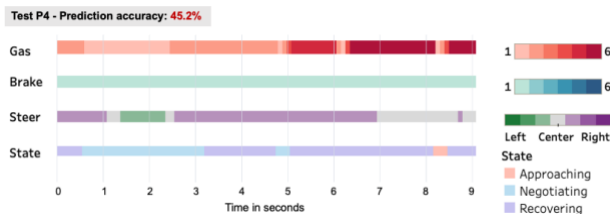


Figure 5. Observational sequences and predicted states for Test P4.

We also revisited the observational sequences for Test P5, which represented a typical hazard avoidance pattern as we

emission distributions, we fitted the three-state model again. Trace plots were used to visually check model convergence. Figure 4 shows that the parameter estimates for brake input data from the starting value set 1 (the original values used to fit the model) and starting value set 2 converge to the same parameter space and mix well (Figure 4).

We then switched the label and trained the three-state model again. The trace plots indicated that there was no evidence of label switching either.

expected (Figure 6). P5 slightly applied the brake and reduced their speed right after taking over and approaching the construction site. The Negotiating state covered a period when P5 switched lanes to avoid the construction site and then switched back to their original traveling lane (Figure 6, “steer” bar). P5 only speeded up when necessary: at the beginning of Negotiating state to maintain speed, and during the Recovering state to exit the construction site sooner as the hazardous event was cleared (Figure 6, “gas” bar).

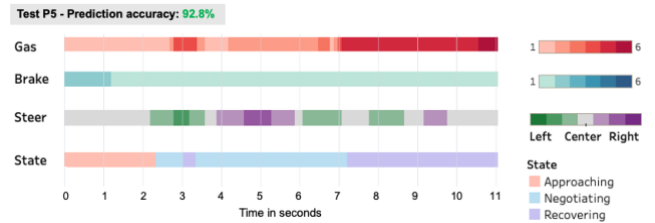


Figure 6. Observational sequences and predicted states for Test P5.

## DISCUSSION

This study makes the first attempt to use multilevel Hidden Markov Models to uncover the hazard avoidance process after the takeover in conditionally automated vehicles. The model fitness examination indicates that physical components of hazard avoidance in a takeover process have three subprocesses: Approaching, Negotiating, and Recovering. After receiving the hazard precursor, drivers start to process and appraise the hazard before strategizing hazard response and preparing for the Negotiating state. Based on the gas, brake, and steering inputs, our model can accurately predict the Negotiating and Recovering states; such prediction is robust across participants. However, the prediction of the Approaching state remains unstable, which might be incorrectly predicted as the Recovering state. A potential explanation derives from different driving styles; while the observations remained similar in the Recovering state across drivers with different styles, those values differ in the Approaching state, especially for speed selection. The model prediction indicates the potential to train a separate set of parameters for aggressive driving styles, whose performance deviates from the majority of drivers. In the

future, the Support Vector Machine, a supervised machine learning method as a two-class classifier (Deng & Soffker, 2022), can be used to classify aggressive and safe drive styles before training HMM for each style.

Although our model is able to predict driving states at a certain level, it can still be improved in several aspects in the future. First, our model only takes drivers' motor control as input but overlooks the vehicle kinematics information. Such information can increase the precision in understanding the vehicle status (e.g., accelerating, decelerating, maintaining current speed) compared to using only motor control input, especially in the real world where the terrain features are various and result in different motor control requirements. Second, the model does not take environmental features into consideration. The road curvature will affect model performance when using steering input as observations. The construction sites in this study were all positioned on straight roads. Thus, the data collected were not subject to curvature impacts, but the generalization of our model is compromised. In the future, the model can include vehicle kinematics and environmental features to reach higher robustness and external validity. These data can be acquired from the vehicle directly or from the equipped sensors and used to train models lively. Finally, although the model indicates lower possibilities of transiting back to a previous state (e.g., from Negotiating to Approaching), a left-to-right HMM is more appropriate to depict such sequential events.

In addition, although our model is trained and verified using data collected in a conditionally automated driving condition, we believe that the model parameters can be adjusted to generalize to different levels of automation, considering that hazard avoidance is a basic driving skill until the realization of fully autonomous driving.

Finally, the hazard precursor used in this study is monotonous: we only used a speech warning with limited information. Alerts from different types of displays in terms of communication modality can have different influences on drivers' hazard searching and response (Bakhtiari et al., 2019; Scott & Gray, 2008), depending on the alert salience and effectiveness. Even within the same modality, the impacts can differ due to the alert design. In the future, our model needs to be validated and generalized under other circumstances with various types of displays and alerts.

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