Detecting Driver Normal and Emergency Lane-Changing Intentions With Queuing Network-Based Driver Models

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Detecting Driver Normal and Emergency Lane-Changing Intentions With Queuing Network-Based Driver Models

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Driver intention detection is an important component in human-centric driver assistance systems. This article proposes a novel method for detecting driver normal and emergency left- or right-lane-changing intentions by using driver models based on the queuing network cognitive architecture. Driver lane-changing and lane-keeping models are developed and used to simulate driver behavior data associated with 5 kinds of intentions (i.e., normal and emergency left- or right-lane-changing and lane-keeping intentions). The differences between 5 sets of simulated behavior data and the collected actual behavior data are computed, and the intention associated with the smallest difference is determined as the detection outcome. The experimental results from 14 drivers in a driving simulator show that the method can detect normal and emergency lane-changing intentions within 0.325 s and 0.268 s of the steering maneuver onset, respectively, with high accuracy (98.27% for normal lane changes and 90.98% for emergency lane changes) and low false alarm rate (0.294%).

1. INTRODUCTION

Intelligent driver assistance systems have been developed to improve driving performance and safety (Chang, Hwang, & Ji, 2011). As better driver assistants, these systems need to know driver intentions. Because driver intentions cannot be observed directly, they have to be inferred from observable data from drivers (e.g., head motion and eye gaze), vehicle states (e.g., steering wheel angle, pedal position, and vehicle speed), and environment information (e.g., lane position and road geometry).

Various methods have been proposed to infer driver intentions. Pentland and Liu (1999) first proposed to infer driver intentions by using hidden Markov models (HMMs) to map steering and acceleration data into one of a set of possible intentions. Their experimental results obtained with a driving simulator showed that the method was feasible. Oliver and Pentland (2000) further extended the work of Pentland and Liu. They used HMMs and coupled HMMs to detect seven driver intentions (e.g., right and left lane changes, passing, and stopping) from lane position, head pose, and vehicle states. Furthermore, their experimental results were promising, although they did not consider the lane-keeping intention and thus did not report the false alarm rate of their system, which is rather critical for practical applications. Several researchers (Doshi, Morris, & Trivedi, 2011; Doshi & Trivedi, 2009; McCall & Trivedi, 2007; McCall, Wipf, Trivedi, & Rao, 2007) have applied sparse Bayesian network to infer lane-changing intentions from head motion, vehicle parameters, and environments. Their experimental results obtained with real vehicles showed that their systems could detect intentions 1 s before the maneuver onset with high accuracy and relatively low false alarm rate, and the use of head motion data improved driver intention detection. Their studies represent a major step forward in bringing the intention inference system from laboratories to roads, although their systems may be perceived as intrusive to some drivers (Berndt, Emmert, & Dietmayer, 2008).

Recently, some driver models have been developed (Bi, Gan, & Liu, 2014; Bi, Gan, Shang, & Liu, 2012; Cacciabue & Vollrath, 2011; Hjälm Dahl Shinar, Carsten, & Peters, 2011; Salvucci, 2006; Ungoren & Peng, 2005) and have started to be applied to detect driver intentions. Salvucci, Mandalia, Kuge, and Yamamura (2007) developed a method to detect driver lane-changing intentions by comparing the actual collected steering angle and pedal position data with the simulated data generated by driver models they developed with the Adaptive Control of Thought-Rational (ACT-R) cognitive architecture. Furthermore, they analyzed the recognition accuracy as a function of time or vehicle position during the process of lane change in a driving simulator. However, Salvucci’s study, like most of the existing studies, focused on the normal lane-changing intention inference. Kuge, Yamamura, Shimoyama, and Liu (2000) applied HMMs to detect driver emergency lane-changing intentions from steering wheel angle and steering wheel angle velocity. Although their method showed high accuracy on the detection of emergency lane change in a driving simulator, they evaluated only their model under a constant speed of driving.
To the best of our knowledge, no existing studies explore how to detect drivers’ normal and emergency lane-changing intentions (like sudden evasive maneuvers). If a driver intention inference method could not only detect driver lane-changing intentions but also classify the intentions into normal and emergency lane-changing ones, it would better help develop driver-centric assistance systems.

In this article, we propose a novel method for detecting drivers’ normal left and right lane-changing (LCNL and LCNR) intentions and emergency left and right lane-changing (LCEL and LCER) intentions by using driver models based on the queuing network cognitive architecture (Bi et al., 2012). More details about the queuing network cognitive architecture can be found in Feyen (2002); Liu (2009); Liu, Feyen, and Tsimhoni (2006); and Wu and Liu (2008). Furthermore, we evaluate our system at a speed that is desired by participants rather than a constant speed.

The remainder of this article is organized as follows. In section 2, we describe the Queuing Network–based driver lane-changing models. In section 3, the inference method of driver intentions is introduced. Model validation is presented in section 4. Finally, we conclude this article and describe our future work.

2. QUEUING NETWORK-BASED DRIVER LANE-CHANGING MODELS

2.1. Driver Lateral Control Model Based on the Queuing Network

The queuing network cognitive architecture represents human information processing as a queuing network system on the basis of neuroscience and psychological findings (Liu, 1996; Liu et al., 2006). It includes three major components: servers, entities, and routes. Various servers stand for different functional units in the human brain that can process entities, which represent pieces of information to be processed. An entity travels on routes that link related servers and represent the flow of information in the brain and cognitive system.

In our previous work (Bi et al., 2012), we have modeled driver lateral control with the queuing network (QN) architecture, as shown in Figure 1, which describes eight effective servers and their functions. Entities with the visual information first enter the visual perceptual subnetwork (Servers 1 (visual input) → 2/3 (visual recognition/visual location) → 4 (perceptual integrator)). Via Server 4 (Perceptual-Integrator server), the entities are transmitted to the cognitive subnetwork, including Servers A (visuospatial sketchpad), C (central executor), and F (complex cognitive function), in which the decision is obtained. Then entities with the decision results travel to the motor subnetwork and initiate the motor response to steer the wheel. More details of the structure, assumptions, and implementation of the QN architecture can be found in Liu et al. (2006) and Liu (2009).

The driver lateral control function has been implemented at Server F of the QN architecture with three main modules: (a) preview module, which previews the desired path for a preview time to obtain the information of the desired path (note that the desired path needs to be determined for specific driving tasks); (b) prediction module, which predicts the vehicle response within the preview time by using an internal model (i.e., 3 degree-of-freedom vehicle dynamics model, including longitudinal, lateral, and yaw movement); and (c) control module, which computes the desired control input (steering angle) based on the lateral position error between the desired and predicted paths to make a vehicle track the desired path.

The control module computes the desired control input (i.e., the increment of steering angle \( \Delta \theta \)) to make a vehicle track the desired path. The calculation proceeds as follows (Bi et al., 2012). The desired acceleration \( a_y \) (assuming it is a constant in the preview time) is first calculated

\[
a_y = \frac{2 \times (\Delta E - v \times t_p)}{t_p^2},
\]

where \( \Delta E \) is the error between the desired lateral position obtained with the desired path and predictive lateral position computed with the internal vehicle dynamics model, \( v \) is the current velocity, and \( t_p \) is the preview time.

The changed steering angle \( \Delta \theta \) is then calculated with a proportional derivative controller of acceleration, as follows:

\[
\Delta \theta = k_p \times a_y + k_d \times a_y',
\]

where \( k_p \) and \( k_d \) are the coefficients of the proportional derivative controller, and \( a_y' \) is the first derivative of the acceleration.

Finally, a new steering angle \( \theta \) is computed

\[
\theta = \Delta \theta + \theta',
\]

where \( \theta' \) is the steering angle of the last cycle.
The parameters used in the proposed model can be classified into two sets. One set consists of the standard and basic parameters of the QN architecture. It includes server processing time and server capacity, which were set to values from Liu et al. (2006). The second set of parameters is specifically related to driving, including parameters of the preview, prediction, and control modules (i.e., \( f_p, k_p, k_d \)). These parameters were taken values from Bi et al. (2012). More details on QN-based driver lateral control model can be found in Bi et al. (2012).

### 2.2. Driver Lane-Changing Models

Lane change is a typical lateral control. When the QN-based driver lateral control model is extended to develop these driver lane-changing models, what needs to be done is to determine the desired paths. The driver lateral control model (described in section 2.1) can be extended to the corresponding lane-changing models by substituting corresponding desired paths into (1).

We take the desired trajectory of a normal left lane change as an example to describe how to determine the desired trajectory as follows. Each of \( P \) participants first performs \( M \) left lane changes at a certain speed with the lateral displacement being collected. The desired trajectory at this speed is then obtained by averaging \( M \times P \) LCNL trajectories, and a straight line is fit against lateral and longitudinal displacements to represent the desired trajectory at this speed. In this way, a set of straight lines associated with the desired trajectories at a set of speeds can be obtained. Finally, we fit a curved line to the set of the slope values of these straight lines representing these desired paths. With the fitted curve line, we can approximate the slope of the straight line associated with the desired trajectory at the current velocity in real time. In other words, we can obtain the LCNL models under any speed by substituting corresponding desired trajectories into the driver lateral model previously validated as mentioned above in section 2.1.

Likewise, we can obtain the LCNR model and LCEL and LCER models under any speed. For lane keeping, the desired path can be taken as the centerline of the lane where the vehicle is traveling. Thus, we can easily obtain the driver lane-keeping model.

### 3. DRIVER LANE-CHANGING INTENTION INFERENCE

The basic idea of the method for inferring driver lane-changing intentions developed in this paper is to compare the actual collected behavior data (i.e., steering angle sequence) of a driver with a set of simulated steering angle sequences associated with a set of possible driver intentions generated by using the corresponding driver models, respectively.

The procedure of inferring a driver’s lane-changing intention by using the QN-based driver models can be described as the following three steps: (a) model simulation, (b) actual data collection, and (c) intention inference. The following sections describe the three steps in detail.

#### 3.1. Simulated Behavior Data With Driver Models

The first step of the inference is to produce the simulated behavior data (i.e., five sets of steering angle sequences) associated with the five intentions by using the corresponding QN-based driver models as matching templates.

When the intention inference system works, for a given speed at each recognition period \( D \), five driver models associated with five driver intentions are built in real time as described in section 2. To be able to infer the lane changing intention at an early stage of the lane-changing maneuver, we used only the first \( T \) seconds of the simulated data sampled at a rate of \( S \) Hz to form templates. Five templates are expressed as

\[
X_{i=1 \sim 5} = [x_i(1), x_i(2), x_i(n), \ldots, x_i(N)]
\]

where \( x_{i=1 \sim 5} \) represent the templates of LCNL, LCNR, LCEL, LCER, and lane keeping, respectively, \( x_i(n) \) is the \( n \)th simulated data of the \( i \)th template, and \( N = T \times S \).

#### 3.2. Actual Driver Behavior Data

The second step of the procedure is to collect the actual behavior data. The steering angle of the driving simulator can be easily collected and sampled at the same rate as that of the simulated data and expressed as

\[
X' = [x'(1), x'(2), x'(n), \ldots, x'(N)],
\]

where \( x'(n) \) is the \( n \)th sampling data. In addition, the lateral velocity is collected for further analysis.

#### 3.3. Intention Inference

The third step of the procedure is the intention inference. The root-mean-square error (RMSE) values between the actual steering angle sequence and the five simulated templates are calculated and used as a metric to infer the driver lane-changing intention. To infer the intention of drivers, the intention associated with the smallest RMSE value is determined as inference outcome

\[
Y = \arg \min_{i=1 \sim 5}(RMSE_i),
\]

where \( RMSE_i \) represents the RMSE between the actual steering angle sequence and the \( i \)th template. Once the system detects the lane change, the system pauses to infer driver intentions until the vehicle reaches the target lane, which can be determined according to whether the average of the absolute value of the lateral velocity in one window length \( N \) of data is less than a threshold (set to be 0.03 km/h in the driving simulator experiment).
4. VALIDATION

4.1. Experiments

The validation experiments consisted of two subexperiments. The first was to determine the desired paths of lane changes and thus build the driver lane-changing models. The second was to evaluate the proposed lane-changing intention inference system under the normal and emergency situations.

Considering the potential dangers of the emergency lane-changing experiment in a real vehicle, we conducted the experiments in a driving simulator with a 14 degree-of-freedom vehicle dynamics model. Fourteen male drivers (ages 22–26) with 1 to 3 years of driving experience were randomly divided into two groups. One group with six participants attended the first subexperiment for building the driver models, whereas the other group with eight participants attended the second subexperiment for testing the intention inference system. Participants were required to drive naturally as they would drive in a real vehicle in the right lane of a two-lane road.

The first subexperiment consisted of two phases. One was for training the normal lane-changing (LCN) models and the second was for training the emergency lane-changing (LCE) models. Each phase began with several minutes of practice, and participants were given a 10-min break between the two phases. For a normal lane change situation, a leading car moving slower than the driver’s car occurred at designated positions, and drivers were required to change to the left lane in the same way as in ordinary driving when they felt appropriate and then keep in the left lane and change to the right lane when a leading car moving slower occurred. For an emergency lane change situation, a pedestrian suddenly appeared as an obstacle within the safe distance in front of drivers without any prior warning. The subjects were required to execute an evasive steering maneuver immediately upon seeing the pedestrian. Participants did not know in advance when pedestrians may appear.

In the phase of training the LCN models, participants completed nine sessions of LCN. In each session, drivers were asked to perform three trials at a constant speed selected randomly from the set of [30 40 50 60 70 80 90 100 110] km/h, and each speed was selected once. In each trial, participants executed six LCN including three LCNL and three LCNR. Thus, we collected nine samples of LCNL and nine samples of LCNR at each selected speed per driver, and a total of 54 samples of LCNL and 54 samples of LCNR across drivers. In the phase of training the LCE models, in the same way, we collected 54 samples of LCEL and 54 samples of LCER across drivers.

Compared to the first subexperiment, the experiment of testing the inference system has three differences. First, participants were required to drive at their desired speed. Second, the normal and emergency lane-changing scenarios were randomly presented in each trial. Third, each subject was required to complete 12 trials. We collected 18 samples for each type of lane change per subject and a total of 144 samples for each kind of lane change across all subjects.

4.2. Results

To evaluate and test the inference system, we need to give a definition of a lane change. In this article, we adopted the definition of a lane change from Salvucci et al. (2007, p. 537): “the vehicle starts moving toward another lane and continues, without a reversal, through to that lane.” We also used a minimum threshold (set to be 0.03 km/h in the driving simulator experiment) on the absolute value of the lateral velocity to determine slow, likely unintended drifts as lane keeping maneuvers to concentrate on typical intended lane change maneuvers according to Salvucci et al. (2007).

**Desired trajectories.** According to the method described in section 2.2, we first averaged a total of 54 samples across six subjects (i.e., $L = 6, M = 54$) at one certain speed to obtain the desired trajectory of each kind of lane change at this speed, and then used a straight line to approximate each desired trajectory. Figure 2a and 2b show the desired trajectories and approximated straight lines of the LCNL and LCEL under the speed of 50 km/h, respectively. As shown in Figure 2, the straight lines have a good fit against the data of the desired trajectories (i.e., $R^2 = 0.98$, and the RMSE = 0.11 for the LCNL; $R^2 = 0.99$, RMSE = 0.11 for the LCEL). The results of LCNL and LCEL for other speeds and results of LCNR and LCER for the set of speeds were similar to Figure 2.

Further, we fitted an exponential function, shown in Equation 7, to the slopes of the desired paths under each kind of lane change. Figure 3a and 3b show the slopes of the associated with the LCNL and LCEL compared to the speed of the vehicle, respectively. The curves are the models of prediction lines.

$$K = a \times e^{bv},$$  
(7)

where $K$ is the slope of the desired trajectory, $v$ is the speed of the vehicle, and $a$ and $b$ are constant. The values of $a$ and $b$ for the LCNL were 0.227 and –0.010, respectively. The model showed a good fit with the experiment data ($R^2 = 0.99$ and RMSE = 0.002). The values of $a$ and $b$ for the LCEL were 0.052 and –0.012, respectively. In addition, the model showed a good fit with the experiment data (i.e., $R^2 = 0.99$ and RMSE = 0.001). Likewise, the values of $a$ and $b$ for the LCNR were –0.223 and –0.009, respectively, whereas the values of $a$ and $b$ for the LCER –0.049 were and –0.010, respectively. Also, they have a good fit with experimental data (i.e., $R^2 = 0.98$, RMSE = 0.003 for LCNR; $R^2 = 0.98$, RMSE = 0.002 for LCER).

**Inference system evaluation.** To evaluate the lane-changing intention inference system, we applied accuracy, false alarm rate, and response time as the evaluation metrics. Accuracy was defined as the ratio of the number of each kind of lane change detected successfully to the number of this kind of lane change required to finish. False alarm rate was calculated by the number of recognition results, which are lane changes, over the total number of detection results during the whole process of lane keeping. Response time, RT1, was defined as the time length
DETECTING DRIVER LANE-CHANGE INTENTIONS

FIG. 2. The desired trajectories and corresponding approximated straight lines of (a) the normal left lane-changing intentions and (b) the emergency left lane-changing intentions at 50km/h. Note. RMSE = root-mean-square error.

from the start of the lane-changing steering maneuver to the time when the system detects the lane change correctly. Figure 4 shows two examples to illustrate how we calculate the response time. Time point A is the start of lane-changing steering maneuver and time point B is the time when the system detects the lane change.

In addition, we define another response time RT2 for the LCE, which was calculated as the time when the system correctly detects the LCE intention minus the time when a pedestrian suddenly appears. This response time RT2 can be objectively computed compared with the response time RT1.

In this article, the sampling rate \( S \) of the driving simulator was 100 Hz. The window length \( T \) was set to 0.3 s. That is, the length \( N \) of templates used by the inference system was 30 (\( N = T \times S = 100 \times 0.3 = 30 \)). The recognition period \( D \) was set to 0.1 s. In other words, the step size of our system was 10 (\( D \times S = 0.1 \times 100 = 10 \)). The window length and step size were set by the trial-and-error method according to the experimental results.

Table 1 shows the evaluation results of the inference system across all subjects. We can see that the average response time RT1 of our system for the LCN and LCE are 0.325 s and 0.268 s. The average response time RT2 for LCE is 0.626 s, which is consistent with the general reaction time for the onset of evasive steering maneuver (Kuge et al., 2000). The average accuracies for the LCN and LCE are 98.27% and 90.98%, respectively, and the average false alarm rate is 0.294%. The accuracy for the LCE is not as high as that for the LCN, and our experimental results show that all false recognition results
for the LCE were detected as the LCN intentions. This is likely because participants sometimes had slow response and thus the steering maneuver did not show the pattern associated with the emergency situations.

5. DISCUSSION AND CONCLUSION

In this article, we proposed a novel method for inferring driver lane-changing intentions under normal and emergency situations by comparing the collected with the simulated steering angle sequences, which were generated with the corresponding driver models based on the QN cognitive architecture. The experimental results from fourteen participants in a driving simulator showed that the proposed method can detect a driver’s normal and emergency lane-changing intentions within 0.325 s for LCN and 0.268 s for LCE of the steering maneuver onset, respectively, with high accuracy (98.27% for LCN and 90.98% for LCE) and low false alarm rate (0.294%). Furthermore, the proposed system is not intrusive to the drivers, in comparison to those systems based on head motion and eye gaze, which generally need to be collected with cameras. In practice, this method can be applied to help better develop human-centric intelligent driver assistance systems. For example, the proposed method can first be used to infer the normal and emergency lane-changing intentions of drivers, and then the assistance system can issue a warning command to drivers or take over the vehicle according to the inferred intention.

Our current system has two limitations. One is that we evaluated our system in a driving simulator, which does not simulate all possible conditions experienced in the real world, and thus the robustness of the system needs to be further examined. The other is that although our method has achieved rather low false alarm rate, it is still not sufficient for the real-world application.

### TABLE 1

<table>
<thead>
<tr>
<th>Evaluation Results of the Inference System</th>
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<tbody>
<tr>
<td>LCNL Accuracy (%)</td>
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<td>Sub. 8</td>
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<td>M with SE</td>
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Note. LCNL = normal left lane-changing intentions; LCNR = normal right lane-changing intentions; LCEL = emergency left lane-changing intentions; LCER = emergency right lane-changing intentions; Sub. = subject.
because false alarms distract and annoy drivers and reduce their acceptance of the inference system. Our reported lab work lays the foundation for and represents an important step toward applying the inference system to the real world.

Our future work focuses on addressing the issues just listed, including evaluating our system in a real vehicle on road conditions and traffic situations and further improving the performance of the system by combining our current method with some methods based on other signals.

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**REFERENCES**


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