Human Driving Skill Modeling Using Neural Networks for Haptic Assistance in Realistic Virtual Environments

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Abstract—This work addresses our research on driving skill modeling using artificial neural networks for haptic assistance. In this paper, we present a haptic driving training simulator with performance-based, error-corrective haptic feedback. One key component of our simulator is the ability to learn an optimized driving skill model from the driving data of expert drivers. To this end, we obtain a model utilizing artificial neural networks to extract a desired movement of a steering wheel and an accelerator pedal based on the experts’ prediction. Then, we can deliver haptic assistance based on a driver’s performance error which is a difference between a current and the desired movement. We validate the performance of our framework in two respective user experiments recruiting expert/novice drivers to show the feasibility and applicability of facilitating neural networks for performance-based haptic driving skill transfer.

Index Terms—haptics, motor Learning, performance-based feedback, driving, artificial neural networks, virtual simulation.

I. INTRODUCTION

HAPTIC assistance (HA) provides an amount of assistive feedback in the form of tactile or kinesthetic stimuli. Recently, HA has been popularly facilitated in automobile technologies in addition to visual and auditory assistance [1]. Driving skills require coordinated dynamic controls of limbs via manual interfaces (steering wheel, accelerator/brake pedals, and so on). In particular, the kinesthetic feedback can deliver mechanical momentum and move the limbs of interest, supplying more direct, detailed, and continuous information. Hence, a number of studies have examined the effectiveness of HA (especially, kinesthetic) in virtual driving environments owing to the merits of allowing safe practice in simulated scenarios, especially those including risky driving situations.

Generally, driving with HA can be regarded to a human-machinetask in a cybernetic human-machine shared control (HSC) [2], [3]. In HSC, information flows in both directions between two agents (a human and a machine) via mechanical contact under shared autonomy. First, a user can motorize an action via interfaces and the system reflects the corresponding action. Second, haptic interfaces intelligently delivers assistive information to a user, and then the user perceives the corresponding haptic information and reacts. Thus, most researchers have envisioned that in the simultaneous exchange of useful information, HA can offer two possibilities: task performance enhancement and skill training [4].

For enhancing the task performance, the most representative, effective HA method is haptic guidance (often called haptic HSC) where external haptic stimuli are provided to the user in order to communicate control information on the desired movement. Several studies demonstrated haptic guidance can enhance the task performance of steering [5]–[7] and pedaling skills [8]–[10]. Here a HA system plays a role of a collaborator which encourages humans, mostly by demonstrating appropriate maneuvers and correcting their driving performance. To this end, the human driver and the system share a common goal: a successful driving that both agents perform an effective, safe and robust driving control. Therefore, HSC is considered as a bridge to an autonomous driving with improved performance and reduced effort [11], various car companies keep investigating this semi-autonomous strategy as advanced driver-assistance systems (ADAS) [12], such as a lane-keeping assistance system (LKAS), an intelligent parking assistance system (IPAS), and an adaptive cruise control (ACC).

HA is more widely utilized in motor learning and training, and rehabilitation applications. HA through a number of strategies including haptic guidance and other algorithms were investigated for training efficiency on various tasks [13], [14]. Here a HA system should play a role of a skill trainer; While a driving skill learner tries to drive properly, the system checks the current learner’s performance and provides haptic augmented feedback transferring knowledge of performance (KP [15]). Thus, the feasibility of HA, which the system aware of human performance errors continually to generate KP [15], lies special benefits to driving skill training. The effectiveness of HA under continuous observation of learner’s driving control was shown for several driving tasks, especially for curve-tracing and lane-keeping tasks [17], [18] and a
reverse parking task [19].

Under the HSC manner, both the user and the HA system concurrently intercommunicate in real-time to endeavor an optimized control of the shared goal. The system continuously watches and analyzes a current user’s performance, and then exerts personalized haptic feedback, regarding a certain baseline of task performance, i.e. the ground truth. To this end, to design HA systems, the process of quantifying proper skill performance as a desired reference to a user’s current performance, usually called a modeling process, should be always preveniently required.

However, traditionally, the modeling was so far manually abstracted into deterministic forms without consideration of human agents, and also examined mostly for steering tasks as a sub-skill of driving, irrespective of pedaling tasks. Therefore, the modeling process in previous studies inevitably bears considerable differences from real and complicated driving, which requires simultaneous manipulation of the steering wheel and pedals. We face an immediate demand for reasonable modeling methods of complicated driving skills, which is a prerequisite of competent, intelligent haptic training systems.

In this work, we present a novel data-driven framework of (1) modeling a proper driving skill (steering and pedaling) from expert drivers and (2) utilizing the model for HA, in a freeway driving task (Fig. 1). Our approach is to record how experts execute driving successfully without HA, and then train an adequate continuous model (representing a virtual expert) of associated variables from the collected professional data obtained from virtual environments. Specifically, we propose a useful methodological solution that extracts a behavioral model of expert drivers using artificial neural networks (NNs), and validate the strategy via user experiments. A NN is generally used to find a nonlinear function that explains an input/output relationship and identify a structure beneath a complex dynamic system. Zhang et al. showed that characterization of driving skill levels (expert, typical, and low-skill) are possible, by analyzing individual driving maneuvers using well-trained NNs and other pattern recognition algorithms [20].

Previously, Nechyba and Xu used NNs to model a human driving strategy from driving data collected from a simplified driving simulation using a mouse interface [21], [22]. Their NNs could produce a continuous predictive trajectory based on an individual motor behavior using experimental states and environmental variables as input. However, their studies did not involve realistic driving hardware, so the usability of their behavioral model for practical driving training has not been validated yet. In this study, we complete their NN-based modeling approach in a virtual driving simulator, and validate its practicality for HA.

II. SIMULATOR

This section describes a haptic driving simulator (Fig. 2 and 3) that we have developed for two purposes: (1) Driving Skill Modeling: The simulator records the expert’s driving data. It provides realistic driving experiences to acquire reliable data, including realistic torque feedback to the steering wheel and pedals; and (2) Haptic Assistance: The simulator generates torque feedback in order to assist a current driver’s driving skills with high fidelity. For realistic simulation, the simulator renders virtual driving environments including visual and auditory stimuli based on Vehicle Physics Pro (VPP [23]), a commercial vehicle physics engine running in the Unity 5 game engine (Fig. 2) with an update rate of 50Hz. For the realistic simulation of car dynamics, a particular vehicle (Genesis, Hyundai Motors) was chosen to determine physical parameters of VPP, such as mass, dimension, steering and gear ratios, and engine power curves.

A. Hardware

The simulator consists of a large visual display, a steering wheel, an accelerator pedal, and a brake pedal (Fig. 3). All devices are fastened to an aluminum frame to imitate the real driving seat. We use a 55-inch LCD display (55LW6500, LG Electronics), and the distance from the display to the seat is about 1.2 m for a comfortable field of view of 60°. The simulator also uses a commercial steering wheel (SENSO-Wheel SD-LC, SensoDrive) to provide high-fidelity torque feedback. The maximum instantaneous torque and the maximum continuous torque are 16.58 Nm and 7.5 Nm, respectively.
We have custom-designed and built the accelerator and brake pedals with appropriate torque feedback capability. Two sets of AC servo motor (SGMGV-20A, Yaskawa Electrics) and servo pack (SGDV-18011A, Yaskawa Electrics) are used for independent torque feedback. The communication between the device and PC is done by MechatroLink-II network control board (PCI-R1604-MLII, Ajinextek). The maximum instantaneous torque and the maximum continuous torque of each motor are 27.8 Nm and 10 Nm, respectively.

For compact housing, both motors should be mounted in the same side, maintaining the alignment of the two rotation axes of the pedals. For this reason, while the accelerator pedal is directly connected to the motor with a coupler, the brake pedal is connected to another motor through a four-bar mechanism. The loop formed by the four-bar mechanism is designed to be a parallelogram for a simple kinematic relationship between the pedal and the motor. The steering wheel and the pedals are controlled with a sampling rate of 800 Hz.

**B. Realistic Torque Feedback Control**

In our system, the steering angle $\theta_s$ is between $\theta_{s,min} = -459^\circ$ and $\theta_{s,max} = 459^\circ$, and the steering ratio is 12.0:1. The driver cannot steer outside this range. The simulated steering torque $T_s$ is implemented to be similar to the real torque transmitted from the driving shaft to provide rich information about the road and vehicle status, as follows:

$$T_s = T_{s,align} + T_{s,damping} + T_{friction},$$

(1)

where $T_{s,align}$ is the self-alignment torque, and $T_{s,damping}$ and $T_{friction}$ are the viscous and Coulomb frictions from the car dynamics. In four-wheel drive, the steering reactive torque can be estimated [24] as follow:

$$T_{s,align} \approx G_{shaft} \cdot \frac{1}{2} (F_l + F_r),$$

(2)

where $F_l$ and $F_r$ are the lateral forces applied to the left and right front wheels obtained from VPP. $G_{shaft}$ is the imaginary gain of torque transmission from the shaft. $T_{s,damping} = D_a \dot{\theta}_a$, and $T_{friction}$ is constant, both in the opposite direction of steering wheel rotation. From [2], a user can perceive driving-like sensations on a road with respect to the direction and velocity of the virtual vehicle.

Our haptic pedals are controlled using a spring-damper impedance control scheme. Let the accelerator angle be $\theta_a$. If $\theta_a$ is between $\theta_{a,min} = 0^\circ$ and $\theta_{a,max} = 10^\circ$, it is normalized and sent to the throttle value of the virtual engine in VPP. The simulated torque to the accelerator is computed as follows:

$$T_a = T_{a,spring} + T_{a,max} + T_{a,damping} + g(\theta_a),$$

(3)

where $T_{a,damping} = D_a \dot{\theta}_a$ is a virtual damping torque and $g(\cdot)$ is a gravity compensation term. The spring-like torque $T_{a,spring}$ is determined by

$$T_{a,spring} = K_a (\theta_a - \theta_{a,0}),$$

(4)

where $K_a$ is a virtual spring coefficient, and $\theta_{a,0}(= \theta_{a,min} = 5^\circ = -5^\circ)$ is the initial position of the accelerator pedal. $T_{a,spring}$ pushes the driver’s right foot upward to deliver information about how much s/he is pressing the pedal from $\theta_{a,0}$.

**III. MODELING USING NEURAL NETWORKS**

To provide KP in trajectory learning tasks, e.g., an optimal (desired) trajectory should be given for the computation of task performance errors [13]. We denote the current angle vector by $\theta = [\theta_s \theta_a \theta_b]^T$ and the desired angle vector by $\theta_d = [\theta_{sd} \theta_{ad} \theta_{bd}]^T$. The error vector is $e_\theta = \theta - \theta_d$. The desired current action $\theta_d$ is generally contingent upon the current driving situation and the past values of $\theta$ representing the driving history. For performance-based haptic transfer, we need a model that gives $\theta_d$. We build such a model using NN train it to account for the driving data of experts.

**A. Approach**

In [25], the dynamic nature of human control strategy is abstracted into a static mapping between input and output using NN. In fact, a dynamic system can be approximated using difference equations [26], such that

$$u[k + \tau] = f[u[k], u[k - \tau], \ldots, u[k - (D_u - 1) \tau], x[k], x[k - \tau], \ldots, x[k - (D_x - 1) \tau], z[k], z[k - \tau], \ldots, z[k - (D_z - 1) \tau]],$$

(6)

where $f[\cdot]$ represents a nonlinear map using NN, $u[k]$ is the control vector, $x[k]$ is the state system vector, and $z[k]$ is a vector describing external environmental features at the time step $k$. Then (6) can be rewritten to

$$u[k + \tau] = f[\tilde{u}[k], \tilde{x}[k], \tilde{z}[k]],$$

(7)

where $\tilde{m}[k] = [m[k], m[k - \tau], \ldots, m[k - (D_m - 1) \tau]]^T$ for an arbitrary vector $m$. Using (7), we can predict a future value of $u$ at $\tau$-step later from the current and previous system states and the exogenous environmental variables.

**TABLE I**

| Constant Values for Driving Torque Feedback |
|-------------------------------------------|
| $G_{shaft}$ (m) | 0.75 |
| $D_a$ (m/s/degree) | 0.002 |
| $T_{friction}$ (N) | 0.1 |

$T_{a,max}$ is a unilateral feedback term to provide information as to the maximum angle such that

$$T_{a,max} = \begin{cases} 0 & \text{if } \theta_a < \theta_{a,max} \\ K_a, & \text{if } \theta_a \geq \theta_{a,max} \end{cases}.$$  

(5)

$T_{a,max}$ enables the driver to perceive the virtual endpoint at $\theta_{a,max} = 10^\circ$. We use $K_a = 10K_a$.

We carefully tuned all the other parameters for realistic experiences. Their values are specified in Table I.
B. Neural Network Design

From the expert’s driving data, we observed that the lane-keeping task does not require the manipulation of brake pedal and exclude \( \theta_b \) from the control vector. Also, we do not consider the interdependence between the controls of steering wheel and accelerator pedal and train separate NNs for each. This allows us to use more compact networks still with accurate modeling results. Hence, in the model for the steering wheel, \( u = \theta_s \), and in the model for the accelerator pedal, \( u = \theta_a \). For the vehicle state, we use \( x = [v \ \omega \ r]^T \), where \( v \) is the longitudinal velocity (m/s), \( \omega \) is the angular velocity (degree/s), and \( r \) is the engine’s revolution per minute (RPM) of the virtual car.

To define the environmental features, we rely on the driver’s field of view (FOV), \( \phi \), and the driver’s position to the road boundary of the road in the \( i \)-th direction. The angular values of \( d_i \) were determined considering the driver’s field of view (60°) within the simulated vehicle. The maximum value of \( d_i \) is set to 60 m. Then the environmental feature vector \( z = [z_1 \ z_2 \ z_3 \ z_4 \ z_5]^T \), where

\[
z_i = \frac{1}{1 + d_i}.
\]

\( z_i \) represents the future hazard of collision in the \( i \)-th direction.

Then the two NNs, \( f_s \) and \( f_a \), for the steering wheel and the accelerator pedal, can be written as

\[
\hat{\theta}_s[k] = f_s[\hat{\theta}_s[k], \bar{x}[k], \bar{z}[k]],
\]

\[
\hat{\theta}_a[k] = f_a[\hat{\theta}_a[k], \bar{x}[k], \bar{z}[k]].
\]

\( f_s \) and \( f_a \) are trained using \( \hat{\theta}_s[k + \tau] \) and \( \hat{\theta}_a[k + \tau] \), respectively, in the expert’s driving data as the output. Therefore, the output variables \( \hat{\theta}_s[k] \) and \( \hat{\theta}_a[k] \) should be similar to the expert’s respective \( \theta_s[k + \tau] \) and \( \theta_a[k + \tau] \) used in the training, representing the expert’s predictive driving behavior under the vehicle state \( x \) and the environment state \( z \).

Considering that the human motion bandwidth is less than 5 Hz [27], we use the same constants for all the input vectors: \( \tau = 10 \) and \( D_x = D_k = D_z = 5 \). Then all NNs predict 0.2 s future values of execution from the five current and previous variables in 50-Hz simulations. Before training, all input vectors, \( u, x, \) and \( z \) are normalized.

C. Data Acquisition and Training Results

We designed 25 two-lane paths to collect driving trajectories and other important variables for driving skill modeling. Each path consists of three segments with a total length of 600 m. The first and third are a 200-m straight segment. The second segment is curved with the curvature \( k = \frac{\phi}{L^2} \), where \( R \) is the radius, \( L \) is the arc length, and \( \phi \) is the angle in radian, as shown in Fig. 5a. \( L \) of the second segment is 200 m, but each path has varying \( \phi \) from -180° to 180° with 15° step (Fig. 5b). So \( \phi = 0° \) results in a 600-m-long straight path.

Five driving experts (E1–E5; all males; age 25–51 years, M 37.6, SD 10.8; driving experience 5–30 years, M 15.2, SD 10.3) participated in the data acquisition. In each trial, the expert was instructed to complete driving following a given path, while staying only in the first lane of the path and maintaining 60 km/h velocity on the speedometer. Each trial took about 36–40 s, and every expert completed 6 trials for each path (150 trials per expert).

We trained all networks using MATLAB (R2017a, MathWorks). The training used a network training function of gradient decent backpropagation with an adaptive learning rate and a transfer function of hyperbolic tangent sigmoid. The initial learning rate was 0.5. Every NN consisted of 4 hidden layers with 32, 16, 8, and 4 nodes. We pooled the input-output data of all the expert drivers for NN training. The data were partitioned into training, validation, and test sets in the proportion of 70%, 15%, and 15%, respectively. The training was terminated if the root mean squared error (RMSE) of predicting a test set decreased and was saturated into 1% and 4.5% for \( \theta_s \) and \( \theta_a \), respectively. These values were determined by trials and errors.

IV. EXPERIMENT I: MODELING VALIDITY

We could model the driving behaviors of the expert drivers using NNs. Experiment I was to validate whether our model successfully captured the representative driving skills, with the following research questions: Q1: Can our model work for other general driving environments? Q2: Can our model represent particular driving behaviors different from other drivers’ style? Q3: Can we prove that expert drivers have better driving performance than of novice drivers in an objective manner?
A. Data Acquisition

Our NN models were trained with the expert drivers’ data collected along the 25 simple paths (Section II-C). The first goal of Experiment I was to validate whether the NN models can be applied to general, longer, more complex driving environments. To this end, we designed a long path as a sequence of randomly generated straight and curved segments similarly to [22].

Each straight segment had one parameter, length \(L\). Each curved segment had the radius of curvature \(R\) and its sweep angle \(\phi\) as parameters. The parameters were randomly chosen from 100–150 m (\(L\) and \(R\)) and \(\pm 45^\circ\)–\(\pm 135^\circ\) (negative for right curves) for each segment. A straight segment was followed by a left/right curve with equal probability 0.5. A left (right) curve was followed by a straight segment with probability 0.4 and a right (left) curve with probability 0.6. The total length of the path was 4 km. From many randomly-generated paths, we selected two representative paths respectively consisting of 23 and 22 segments for our experiments (Fig. 6). Compared to the short, simple, predetermined paths used in the NN training (Section II-C), the two paths in Fig. 6 are long, arbitrary and complex, randomized (\(L\), \(R\), and \(\phi\)). Thus, we deem the two paths appropriate for our experiments.

The same five experts (EX: \(E_{1}\)–\(E_{5}\)) and 18 new novice drivers (NO: \(N_{11}\)–\(N_{18}\); all male; 18–28 years old, M 22.8, SD 3.0) participated in collecting new driving data. The latter participants either did not have driving licenses or had licenses but with very little driving experience, e.g., young individuals who had not own and driven a car/motorcycle in the past two years. We controlled the novice drivers’ gender and age since they are important factors for motor learning (the same participants also participated in Experiment II).

As practice, participants drove in three 600-m short paths (\(\phi = -90^\circ\), 0°, and 90°). Then they completed driving in the 4-km long path while staying only in the first lane of the path at 60 km/h. The driving data of each participant was applied to the NN models (\(f_x\) and \(f_a\)) to obtain the trajectories of the predicted device angles (\(\hat{\theta}_s\) and \(\hat{\theta}_a\)).

B. Performance Measures

1) Modeling Performance: For each participant, the NN output \(\hat{\theta}_s\) and \(\hat{\theta}_a\) represent the control action that the experts would do after \(\tau\) steps given the control vectors \(\hat{\theta}_s\) and \(\hat{\theta}_a\), the vehicle state \(\vec{x}\), and the environmental state \(\vec{z}\) of that participant; see (9) and (10). Hence, the following two errors indicate how different the participant’s driving action is from the predicted output of the experts’ action:

\[
\begin{align*}
    e_{s,p}[k] &= \hat{\theta}_s[k] - \theta_s[k + \tau], \\
    e_{a,p}[k] &= \hat{\theta}_a[k] - \theta_a[k + \tau].
\end{align*}
\]

Let \(RMS(\tilde{m})\) be an operator for computing the root mean square of all available samples of \(m[k]\) in the sequence \(\tilde{m}\). Then, the normalized RMSE, \(\tilde{E}_{s,p}\) and \(\tilde{E}_{a,p}\), for each individual driving data are defined by

\[
\begin{align*}
    \tilde{E}_{s,p} &= \frac{E_{s,p}}{\theta_{s,M} - \theta_{s,m}} = \frac{RMS(\tilde{e}_{s,p})}{\theta_{s,M} - \theta_{s,m}}, \\
    \tilde{E}_{a,p} &= \frac{E_{a,p}}{\theta_{a,M} - \theta_{a,m}} = \frac{RMS(\tilde{e}_{a,p})}{\theta_{a,M} - \theta_{a,m}}.
\end{align*}
\]

where \(\theta_{s,M}\), \(\theta_{s,m}\), \(\theta_{a,M}\), and \(\theta_{a,m}\) are the maximum and minimum device angles from the experts’ training data used for NN modeling (also used for the training data normalization (Section III-B)). \(\tilde{E}_{s,p}\) and \(\tilde{E}_{a,p}\) quantify the similarity of the participant’s driving skill to that of the five experts captured in the NN models.

2) Objective Skill Performance: The driving skill of each participant is broken down to steering and pedaling performance. The steering performance is evaluated by a distance error \(e_d\) and an angle error \(e_\phi\) of the virtual vehicle as defined in Fig. 7. The distance error \(e_d\) is the distance between the current car position and the closest point on the (invisible) midline of the first lane. The angular error \(e_\phi\) is the angle between the car heading direction and the road frontal direction at the closest point on the midline of the first lane. Then we use \(E_d = RMS(\tilde{e}_d)\) and \(E_\phi = RMS(\tilde{e}_\phi)\) as measures for the steering performance.

For the pedaling performance, we first define a vehicle velocity error by \(e_v[k] = v[k] - v_d\) where \(v_d = 62.64\) km/h. In our simulator, the target speed 60 km/h imposed on the participants corresponds to the actual vehicle speed of \(v_d\) when the needle of the speedometer reaches 60 km/h from the driver’s perspective. \(E_v = RMS(\tilde{e}_v)\) is used for a measure of the pedaling performance. Since the initial vehicle velocity is 0 km/h, \(E_v\) is computed using only the velocity samples obtained after the vehicle speed first reaches \(v_d\). Additionally, as a measure of pedaling efficiency, we compute \(\Omega_a = RMS(\tilde{\omega}_a)\), where \(\omega_a[k] = |\tilde{\theta}_a[k]|\), focusing on the pedaling speed. \(\Omega_a\) increases if the participant operates the pedal more abruptly.

C. Results and Discussion

Fig. 3 shows examples of an expert (\(E_2\)) and a novice (\(N_{11}\)) who achieved a median performance of \(\tilde{E}_{s,p}\) and \(\tilde{E}_{a,p}\) among the respective groups. The expert’s driving trajectories seem to be in better agreement with the desired trajectories.

The means of the six performance measures are shown in Fig. 9 and 10. We applied Welch’s t-test (unequal sample sizes and unequal variances) to assess the effect of participant group (EX and NO) on each measure. Results are: \(\tilde{E}_{s,p}: \) EX (1.55\%) < NO (2.55\%), \(t(17.99) = -4.08, p < 0.001\); \(\tilde{E}_{a,p}: \) EX (2.18\%) < NO (5.78\%), \(t(18.40) = -2.48, p = 0.023\); \(\tilde{E}_d: \) EX (0.34 m) < NO (0.46 m), \(t(5.67) = -2.20, p = 0.072\); \(\tilde{E}_v: \) EX (1.01\%) < NO (1.45\%), \(t(9.62) = -4.11, p = \)
The followings are research questions: Q1: Can haptic guidance be implemented with NN?; Q2: Can haptic guidance implemented with our NN transfer experts’ driving behavior?; and Q3: Can haptic guidance implemented with our NN provide the competitive performance to conventional haptic guidance?

A. Methods

We report three different methods tested in the experiment. 
1) N: No Haptic Guidance: A driver completes driving, receiving only realistic driving feedback (Section II-B). 
2) G: Haptic Guidance with Neural Networks: A driver completes driving, receiving assistive haptic feedback using NN. First, \( \hat{\theta}_a[k] \) and \( \hat{\theta}_a[k] \) (50 Hz) have been smoothened to \( \hat{\theta}_a(t) \) and \( \hat{\theta}_a(t) \) by moving average filters to command semi-continuous feedback (800 Hz). Let the desired device angles be predicted experts’ behavior, i.e. \( \theta_d = \hat{\theta} \). Then, PID-based steering feedback \( T_s,\text{assist} \) to deliver \( \hat{\theta}_s \) can be computed as follows:

\[
T_s,\text{assist} (t) = K_{\text{pid}}e_s(t) + I_{\text{pid}}\int_{t_0}^{t} e_s(t') dt' + D_{\text{pid}}\dot{e}_s
\]  \( (15) \)

where \( t_0 \) is the recent time when \( e_s \) becomes zero. Whole steering feedback is replaced by,

\[
T_s = T_s,\text{assist} + T_s,\text{stable},
\]  \( (17) \)

where \( T_s,\text{stable} = D_{\text{stable}}\hat{\theta}_s \) provides stable feedback with increased viscosity and without the Coulomb friction. \( K_{\text{pid}} = 0.60 \text{ Nm/degree}, I_{\text{pid}} = 0.12 \text{ Nm-s/degree}, \) and \( D_{\text{pid}} = 0.06 \text{ Nm-s/degree} \). By trials and errors, the gains have been appropriately tuned for two purposes; (1) to exert the steering wheel feedback strongly so that the virtual vehicle can complete driving only with pedal manipulations (similarly to autonomous steering), but also (2) to enable a driver to overcome the feedback to adjust device angles.

Since the driver’s foot and the accelerator pedal are not in full contact in any time, for assistive pedaling feedback, an unidirectional torque rather than PID-based feedback is utilized. \( T_{a,\text{assist}} \) to deliver \( \hat{\theta}_a \) is as follows:

\[
T_{a,\text{assist}} (t) = \begin{cases} 
0, & \text{if } \theta_a(t) < \hat{\theta}_a(t), \\
K_{a,\text{max}} \cdot e_a(t), & \text{if } \theta_a(t) \geq \hat{\theta}_a(t), 
\end{cases}
\]  \( (18) \)

which replaces \( \theta_{a,\text{max}} \) in \( T_{a,\text{max}} \) to \( \hat{\theta}_a \). From \( (18) \), the accelerator pushes the driver’s foot upwards when a driver pushes it more than \( \hat{\theta}_a \). Then, whole pedaling feedback is altered to:

\[
T_a = T_{a,\text{assist}} + T_{a,\text{spring}} + T_{a,\text{damping}} + g(\theta_a).
\]  \( (20) \)

3) C: Conventional Haptic Guidance: A driver completes driving, receiving conventionally-designed assistive haptic feedback. In comparison to G, C determines \( \theta_d \) by external environments. The same torque control equations \( (13) \) and \( (18) \) are adopted. For steering feedback, predictive haptic guidance \( (17), (18) \) was adopted. The predictive haptic guidance is based on the observation that a driver determines his/her
driving based on a prediction. This method considers two error terms, a look-ahead direction error \( e_p \) and the distance error \( e_d \) (Figure 7), and determines a desired angle \( \theta_{s,d} \), as follows:

\[
\theta_{s,d} = K_p e_p + K_d e_d.
\]  

Using \( K_p = 7.65 \) and \( K_d = 1.00 \) degree/m and the same torque gains of \( G \), this method can also support the vehicle to complete driving only with pedal manipulations.

For the accelerator, there exist several applicable algorithms [9], [10], but none of them guarantees effectiveness of training. Hence, we implemented a simpler, deterministic feedback which only provides overspeed cues. Let \( v_M = 66.0 \) km/h be a criterion of overspeed. We computes \( \theta_{a,d} \) as follows:

\[
\theta_{a,d} = \begin{cases} 
\theta_{a,max}, & \text{if } v < v_M, \\
\theta_{a,min}, & \text{if } v \geq v_M,
\end{cases}
\]  

From (22), the drivers perceives a impulse-like feedback from the right foot when the vehicle velocity exceeds \( v_M \).

**B. Experimental Protocol**

Every participant (the same in Experiment I) completed three different driving trials in a complicated path different from the path in Experiment I (Fig. 6), by receiving corresponding assistive feedbacks. Since there are total \( 3! = 6 \) possible permutations from three conditions, novices of three each was assigned to the same presentation order.

After each trial, the participant was asked to answer the following questions for both steering and pedaling feedbacks, respectively, on a 7-point Likert scale: (1) Was the training effective for driving? (Effectiveness); (2) Was the training comfortable/uncomfortable? (Comfort); (3) Was the training fun? (Fun); (4) Do you think a longer training under the corresponding feedback can help to improve your skill (Helpfulness). Thus, there were total 24 questions (4 questions \( \times \) 2 devices \( \times \) 3 conditions) for each participant. Every participant was paid KRW15,000 (\( \approx \) USD13) after the experiment.

**C. Results and Discussion**

This section reports the quantitative (the same metrics in Experiment I) and qualitative results of Experiment II. For a statistical analysis, we applied a repeated measures ANOVA with methods as a within-subject factor. Tukey’s multiple testing was conducted as a post-hoc test for significant effects.
Pedaling speed

0.0 0.4 0.6 0.8 1.5 2.0

1.4 1.6

1 3 6

0.0 0.2 0.3 0.4 0.5 0.6 0.7 Distance Error (m)

N G C*

Fig. 11. Mean \( \bar{E}_{s,p} \) (left) and \( \bar{E}_{a,p} \) (right) for each method. Error bars represent standard errors. Asterisks indicate statistically significant differences.

(a) Distance error \( E_d \)

(b) Angular error \( E_\theta \)

(c) Vehicle velocity error \( E_v \)

(d) Pedaling speed \( \Omega_d \)

Fig. 12. Mean objective skill measure for the steering wheel and (a and b) and the accelerator pedal (c and d). Error bars represent standard errors. Asterisks mean significant differences.

1) Behavioral Similarity: We computed the predictive errors \( \bar{E}_{s,p} \) and \( E_{\theta,p} \) for each resulted trajectory (Fig. 11). If a driving behavior is similar to experts' behavior, then the errors decrease. The ranking of \( \bar{E}_s \) is G (1.10%) < C (1.42%) < N (2.36%). Since the assumption of sphericity had been violated from the Mauchly's test \( (\chi^2(2) = 29.04, p < 0.001) \), the Greenhouse-Geisser estimate of sphericity \( (\epsilon = 0.54) \) was used for re-computation of statistics. In results, there exists a significant difference \( (F(1.09, 18.51) = 34.27, p < 0.001) \), and in the post-hoc test, G < N \( (t(34) = 11.27, p < 0.001) \) and C < N \( (t(34) = 8.39, p < 0.001) \). The ranking of \( \bar{E}_\theta \) is N (4.63%) < C (6.32%) < G (6.38%), and the assumption of sphericity was not violated \( (\chi^2(2) = 5.92, p = 0.052) \). There exists a significant difference \( (F(2, 34) = 5.55, p = 0.008) \), and in the post-hoc test, N < G \( (t(34) = 4.15, p = 0.016) \) and N < C \( (t(34) = 4.01, p = 0.020) \). Two haptic guidance methods showed significant differences from N.

2) Objective Skill Performance: We computed the objective skill measures \( E_d \), \( E_\theta \), \( E_v \), and \( \Omega_d \) for each resulted trajectory (Fig. 12). The ranking of \( E_d \) is N (0.46 m) < G (0.50 m) < C (0.56 m), and the assumption of sphericity was not violated \( (\chi^2(2) = 1.74, p = 0.418) \). There exists a significant difference \( (F(2, 34) = 4.73, p = 0.015) \), and in the post-hoc test, N < C \( (t(34) = 4.35, p = 0.011) \). The ranking of \( E_\theta \) is C (0.94°) < G (1.12°) < N (1.35°), since the assumption of sphericity had been violated \( (\chi^2(2) = 25.68, p < 0.001) \), the Greenhouse-Geisser estimate of sphericity \( (\epsilon = 0.56) \) was used for re-computation. In results, there exists a significant difference \( (F(1.11, 18.90) = 30.60, p < 0.001) \), and in the post-hoc test, G < N \( (t(34) = 6.37, p < 0.001) \), C < N \( (t(34) = 11.02, p < 0.001) \), and C < G \( (t(34) = 4.65, p = 0.007) \).

The ranking of \( E_v \) is C (1.62 km/h) < G (1.91 km/h) < N (2.25 km/h), and the assumption of sphericity was not violated \( (\chi^2(2) = 1.24, p = 0.538) \). There exists a significant difference \( (F(2, 34) = 5.74, p = 0.0071) \), and in the post-hoc test, C < N \( (t(34) = 4.79, p = 0.005) \). The ranking of \( \Omega_v \) is N (3.33 degree/s) < G (4.47 degree/s) < C (4.98 degree/s), and the assumption of sphericity was not violated \( (\chi^2(2) = 3.15, p = 0.207) \). There exists a significant difference \( (F(2, 34) = 8.08, p = 0.001) \), and in the post-hoc test, N < G \( (t(34) = 3.82, p = 0.028) \), and N < C \( (t(34) = 5.56, p = 0.001) \). In summary, G showed better performance of \( E_\theta \) but worse performance of \( \Omega_\theta \) than N. C showed better performances of \( E_\delta \) and \( E_v \), but worse performance of \( E_d \) and \( \Omega_\delta \) than N. In comparison between two haptic guidance methods, C achieved better performance than G in \( E_\delta \). However, they have no difference in other measures.

3) Qualitative Results: We computed the mean scores for each subjective question (Fig. 13). For a statistical analysis, we applied Kruskal-Wallis test. Dunn's post-hoc nonparametric test was conducted as a post-hoc test for significant effects. For the steering wheel, the rankings of the effectiveness, comfort, fun, helpfulness scores are: N < G < C \( (\chi^2(2) = 22.24, p < 0.001) \), N < C < G \( (\chi^2(2) = 7.08, p = 0.029) \), C < G < N \( (\chi^2(2) = 5.04, p = 0.001) \), and C < G < N \( (\chi^2(2) = 6.56, p = 0.038) \), respectively. For the accelerator pedal, the ranks of the subjective scores are: N < G < C \( (\chi^2(2) = 5.77, p = 0.056) \), C < N < G \( (\chi^2(2) = 2.19, p = 0.335) \), C < G < N \( (\chi^2(2) = 0.65, p = 0.722) \), and C < G < N \( (\chi^2(2) = 0.05, p = 0.975) \), respectively. The significant differences are observed in the effectiveness/comfort/helpfulness scores of steering feedback. In the post-hoc test, the subjects reported that both haptic guidance methods are felt more effective than N. However, they reported that only G is felt more comfortable, and C is felt less helpful than N.

These results provide answers to our research questions.

1) Q1: We successfully implemented haptic guidance which involves performance error vector \( e_\theta = \bar{\theta} - \theta_d \), utilizing \( \theta_d = \bar{\theta} \) which is a predicted outcome from NNs.

2) Q2: Receiving the steering feedback based on the NNs, the novices could steer the vehicle with decreased predictive errors \( \bar{E}_{s,p} \), which indicates that the novices had similar steering behavior to experts. However, receiving the pedaling feedback, the novices moved the accelerator with increased predictive errors \( \bar{E}_{a,p} \), which indicates that the novices had awkward pedaling behavior distinct from experts. Therefore,
the steering feedback could, but the pedaling feedback could not effectively transfer experts’ behavior.

3) Q3: Both haptic guidance methods helped the novices to achieve better steering performance of $E_d$ than driving without guidance, which implies that the guidance methods can be adequately applied to the skill transfer. The predictive haptic guidance improved performance of $E_d$ but vitiated performance of $E_d$, compared to haptic guidance with NN. Hence, it is inconclusive to assert which method is the better. The qualitative results also support that two guidance methods have competitive effectiveness. The effectiveness of the two methods can be vary depending on implementation details, e.g., tuning the parameters.

In contrast, our implementation of pedaling guidance using NN was inappropriate for the skill transfer. Only the pedaling feedback providing overspeed cues achieved better pedaling performance of $E_d$, whereas haptic guidance with NN failed to show an improvement. Both haptic guidance methods increased $\Omega_n$, which indicates that the novices abruptly moved the accelerator pedal when the assistance feedback was given.

VI. GENERAL DISCUSSION

1) Driving Skill Characteristics: Point-to-point human movements consist of a gross, less accurate transfer motion with slower responses and fine, more accurate corrective movements with faster responses [30], [31], in a speed-accuracy tradeoff. We used four measures for analysis of driving performance, and each measure is closely related to an ability to corresponding subskills: $E_d$ for motion-initiating, $E_d$ for fine-tuning (both for steering), and $E_d$ for motion-initiating, $\Omega_n$ for a fine-tuning (both for pedaling). A driving skill is a vague mixture of the subskills.

$f_s$ captured experts’ subskill of gross steering more effectively (Experiment I). Usually, haptic guidance is effective in transferring gross skills by providing kinetic references with specific timing and force [18], [32]. Hence, haptic guidance could successfully transfer experts’ steering behavior of gross motions (Experiment II). In contrast, $f_s$ captured experts’ subskill of fine pedaling more effectively (Experiment I). Haptic guidance may not be effective in transferring experts’ pedaling behavior of fine motions, which leads a failure of pedaling skill transfer (Experimet II).

We used the same configuration of $\tau = 0.2$ s for both NNs, which provides desired information in 5 Hz updating frequency. However, the sensing accuracy and dexterity of lower limbs are often regarded as lower than those of hands [33]. Moreover, the simultaneous nature of driving which requires manipulation of both steering and pedaling which impose learners a selection of learning either one of them. Therefore, compared to $f_s$, $f_a$ may have too frequent assistive feedback, which resulted in ineffective skill transfer. Thus, we suggest that a NN with $\tau > 0.2$ leading less frequent feedback may mediate better facilitation of haptic guidance for pedaling.

2) Application to Various Haptic Assistance: In this study, we selected haptic guidance among the variety of performance-based HA. However, haptic guidance has a demerit named the guidance hypothesis: excessive concurrent augmented feedback may make learners dependent on the feedback and reduce their focus during the training, rather interfering with retention of the learned skill [34]. In Experiment II, the novices reported that even they think the concurrent haptic feedback might not be helpful to a longer training, which is an attribution to the guidance hypothesis.

The human performance error vector $e_\theta$ formulated by NNs is adaptable to other HA. For example, error amplification providing the haptic stimuli that increase trajectoryal errors [35], or haptic disturbance (an extension to error amplification) providing random, unpredictable force fields [36] can employ the same performance errors. Hence, they are possible candidates for our approach based on modeling of experts’ skill using NNs, which can induce more effectiveness of driving skill training.

VII. CONCLUSIONS

We developed a haptic driving training simulator providing realistic experiences, to accomplish modeling and transferring a driving skill. In our simulator, performance-based haptic feedback can be delivered to a learner to assist the training of simultaneous manipulation of both a steering wheel and an accelerator pedal. To design proper haptic feedback, an adequate optimized model of the skill is necessary, and we used NNs to extract a driving expert’s motor behavior for modeling of the skill. To this end, we validated our model with predictive errors and proved objective performance of haptic guidance using the model via human experiments. In results, our approach showed a potential to transferring experts’ skill. We are planning to conduct a user study to figure out the educational effectiveness of our approach in a longer training.
We note that still opportunities of other famous approaches, such as Learning from Demonstration (LfD) [37], remain for efficient reference modeling for the driving skill. Moreover, several machine learning techniques based on a human decision behavior, such as Hidden Markov Model (HMM) [21] would be a novel addition for our modeling approach for more difficult, decision-based driving tasks. The area of these studies is the direction our research should proceed in future.

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