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A Novel Control Framework of Haptic Take-Over System for Automated Vehicles

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***Abstract*— Autonomous driving presents an exciting new development in vehicle technology. It poses a new challenge in driver-automation collaboration particularly during handover transitions between human and machine. In order to deal with this problem, this paper proposes a novel control framework for the haptic take-over system. The high-level framework of the haptic take-over control system, which takes driver cognitive workload, neuromuscular dynamics and optimal trajectory planning into consideration, is developed. Under the proposed framework, the determination approach of the optimal input sequence is introduced. The model of the allowed driver take-over authority, which is associated with driver's cognitive workload, as well as muscle readiness during take-over, is investigated and developed. The haptic feedback torque controller is then designed so as to minimize the deviation between the allowed control authority and driver's current degree of participation. A handover process, along with the proposed take-over control method, is also simulated. The simulation results validate the feasibility and effectiveness of the proposed approach.**

I. INTRODUCTION

Automated vehicles have been gaining increasing attention from both academia and industry [1-4]. Before realizing fully autonomous driving, highly automated vehicles will play a significant role in the development of vehicle intelligence technologies. Level 3 vehicle automation or highly automated driving presents an exciting new development in vehicle technology. They allows the driver to freely engage in non-driving tasks, but the driver is required to disengage from their non-driving tasks to regain manual control whenever requested by the system. This poses a new challenge, namely how to enable the human to switch back from non-driving tasks with different psychological and physiological states to driving, ensuring a safe and smooth take-over transition [5-9].

This challenge requires new cross-disciplinary research and design approaches, demanding on a novel design of driver-automation collaboration that considers the driver's take-over capability in real time. Driver's take-over capability can be assessed through his or her cognitive attention and workload, neuromuscular condition, as well as the required driving trajectory. The existing conception of driver workload has mostly been based on driving-related tasks, while the limited work on driver neuromuscular dynamics has mostly focused on conventional manual driving. Due to the large differences in the task, these bodies of research cannot inform our understanding of driver states during the handover process in highly automated driving.

In order to deal with the above driver-automation collaboration problem in automated vehicles, this paper proposes a novel control haptic take-over system, along with a detailed methodology. The rest of the paper is organized as follows. Section II presents the high-level framework of the haptic take-over control system. Under the proposed framework, the optimal input sequence of the system is described in Section III. The take-over authority model, which takes driver's cognitive workload into consideration, is developed in Section IV. Section V describes the evaluation method to measure driver muscle readiness for the take-over control authority determination. Section VI highlights the haptic feedback torque control synthesis. Simulation results of the proposed method are reported in VII, and Section VIII concludes the paper.

II. HAPTIC TAKE-OVER CONTROL FRAMEWORK

Once the driver perceives a take-over request signal and shifts his or her attention back to the driving task, haptic feedback torque is expected to be generated in accordance with the driver's cognition condition, the neuromuscular dynamic state, and the vehicle's optimal trajectory, guiding the human driver to take back control of the vehicle safely and smoothly.

In this paper, we propose a novel haptic take-over control framework, as shown in Figure 1. During the take-over process, an optimal sequence of control input will firstly be derived from the planned trajectory of the vehicle. In the meantime, the human and the machine dynamically share the vehicle's control authority, jointly completing the required optimal control task. Driver's actual input $\boldsymbol{u}_D$, which is generated by the neuromuscular system (NMS), takes up α percent of the overall input applied to the vehicle. And the

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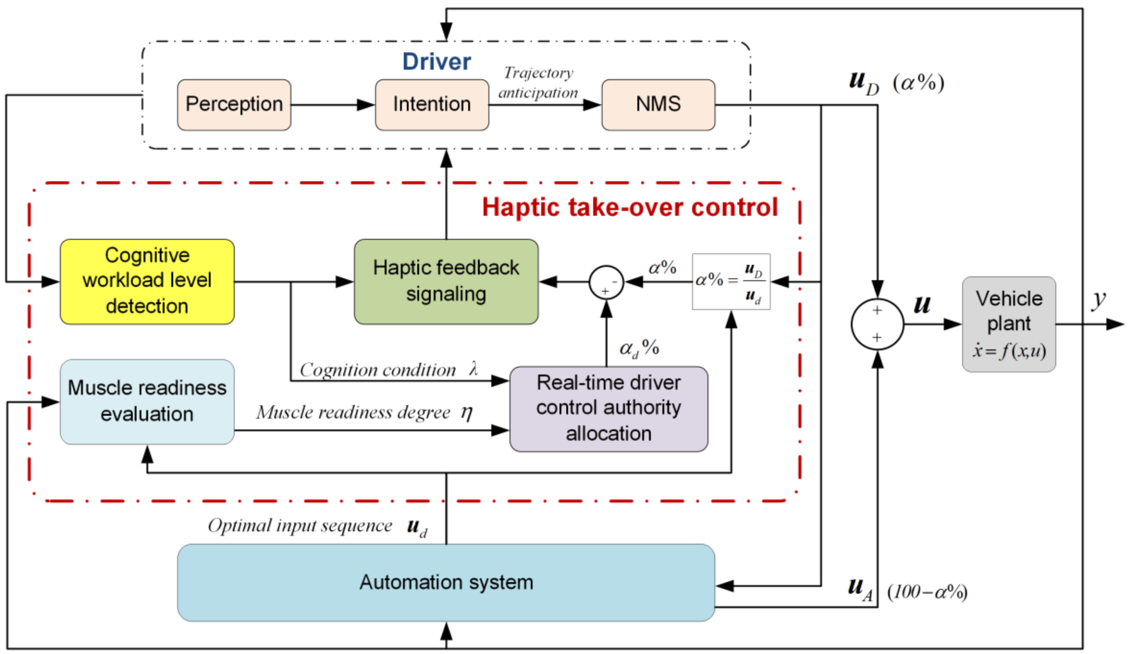

Figure 1. The proposed novel haptic take-over control framework for Level 3 automated driving.

input contributed by automation u_A, always compensates for the driver's input, occupying the remaining proportion of the optimal control input. Once the α increases to 100%, then it indicates the take-over process has been completed.

Since the take-over transition is expected to be completed in a safe and smooth manner, it is not possible to simply cease automation and handover the control to the human driver. Instead, it is necessary to assess the driver's take-over capability, in real time, and then decide how much control authority should be allocated, gradually increasing this until the driver is fully in control. With this concept in mind, a control authority allocation module was designed to calculate the optimal human control authority α_d in real time, based upon the driver's cognitive workload, neuromuscular state and the vehicle's optimal trajectory. The real value of the driver's current degree of participation α will then be compared to the allowed one α_d. The haptic feedback signal will then be generated in order to minimize any deviation between the two. The haptic feedback is used in order to guide driver to use appropriate degree of steering torque in an appropriate manner so as to gradually complete the overall handover process.

In order to realize the proposed haptic take-over, there are a number of key technologies that needed to be developed, including trajectory planning with optimal input sequence determination, driver workload estimation, muscle readiness evaluation, a control authority determination algorithm, and haptic feedback torque controller synthesis. In the following sections, these key components will be investigated.

III. Optimal Input Sequence of the System

A. Driver-Vehicle System Modelling

In order to determine the optimal input sequence, the driver-automation collaboration system, along with vehicle dynamics, needs to be modeled. As this paper focuses on take-over control during the vehicle steering process, the 2-DOF linearized bicycle model was adopted to approximate the vehicle's dynamic behaviour [10]. Assuming that the longitudinal velocity is constant at V_x, then the power steering system of the vehicle can be described by the following state space:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ z(t) &= Cx(t) \end{aligned} \qquad (1)$$

where the state $x(t) = \left[v_y(t) \quad \omega(t) \quad y(t) \quad \psi(t) \quad \theta_{sw} \quad \dot{\theta}_{sw} \right]^T$, $v_y(t)$ is the lateral velocity, $\omega(t)$ is the yaw rate, $y(t)$ is the lateral displacement, $\psi(t)$ is the yaw angle, and θ_{sw} is the angular position of the steering wheel. The steering torque $T(t) = T_D(t) + T_A(t)$ is the system input, $T_D(t)$ is the torque applied by the human driver, and $T_D(t)$ is the torque contributed by automation system. $z(t) = y(t)$ is the output of the system. A, B and C are constant continuous-time matrices, which can be represented by:

$$A = \begin{bmatrix} \frac{-(C_f + C_r)}{mV_x} & \frac{-(aC_f - bC_r)}{mV_x} - V_x & 0 & 0 & \frac{C_f}{i_s m} & 0 \\ \frac{-(aC_f - bC_r)}{I_z V_x} & \frac{-(a^2 C_f + b^2 C_r)}{I_z V_x} & 0 & 0 & \frac{aC_f}{i_s I_z} & 0 \\ 1 & 0 & 0 & u & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & \frac{-K}{J} & \frac{-B}{J} \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & \frac{1}{J} \end{bmatrix}^T, \; C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}.$$

where m is the total mass of the vehicle, C_f is the front cornering stiffness, C_r is the rear cornering stiffness, m is the vehicle mass, a is the distance from the center of mass to the front axle, b is the distance from the center of mass to the rear axle, I_z is the polar moment of inertia, and i_s is the transmission ratio of the steering system. V_x is the longitudinal velocity with a constant value.

By further discretizing Eq. (1) with a sampling time of Γ_s through the zero-order hold method, then the discrete-time representation of the system model can be shown by:

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d u(k) \\ z(k) &= C_d x(k) \end{aligned} \tag{2}$$

where $A_d = e^{A\Gamma_s}$, $B_d = \int_0^{\Gamma_s} e^{A\tau} d\tau \cdot B$, and $C_d = C$ are the discrete matrices.

B. Optimal Input Sequence of Steering Torque

The car is assumed to track the lane centerline. Then the optimal input sequence can be derived through a trade-off between path-tracking error and control effort. The determination of the optimal input for the system can be first formulated as an optimization problem:

$$\begin{aligned} & u(k) = \mathbf{u}_{d,(1)}(k) \\ & \mathbf{u}_d(k) = \underset{\{u_d(k), u_d(k+1), \ldots, u_d(k+N_c-1)\}}{\arg\min} J(k) \\ \text{s.t.}\ & x(k+1) = A_d x(k) + B_d u(k) \\ & z(k) = C_d x(k) \end{aligned} \tag{3}$$

where N_c is the control horizon, $\mathbf{u}_d$ is the optimal input sequence over the control horizon, and $\mathbf{u}_{d,(1)}$ denotes the first element of $\mathbf{u}_d$. J is the cost function, which can be designed to penalize path-tracking error and control effort as:

$$J(k) \equiv \omega_1 \sum_{i=1}^{N_p} \| z(k+i) - r_d(k+i) \|^2 + \omega_2 \sum_{i=0}^{N_c-1} \| u(k+i) \|^2 \tag{4}$$

where r_d is the reference path at each step, N_p is the predictive horizon, ω_1 and ω_2 are the weighting factors.

Then the optimal input sequence $\boldsymbol{u}_d$ can be obtained by employing existing solutions for unconstrained model predictive control.

IV. Cognitive-Workload-Aware Take-over Authority Determination

According to existing studies on the relationship between cognitive workload and human task performance, both underload and overload result in a deterioration in task performance, but a sweet spot exists where both workload and performance are within an acceptable range [11].

For the human driving task, the above logic also applies. The research on driver assistance systems indicates the level of assistance that the vehicle automation function should be designed to assist the driver in underload and overload conditions [12-14], see Figure 2.

During the take-over transition process, a driver's driving performance will also be affected by his or her cognitive workload. Thus, in the proposed high-level control framework, shown in Figure 1, when evaluating a driver's take-over capability and determining the control authority to be allocated to the human, the cognitive workload condition must be taken into account.

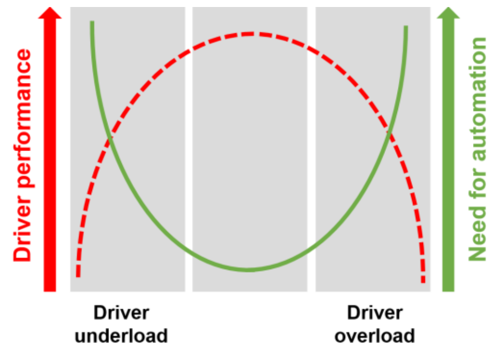

Figure 2. The relation between driver performance and automation assistance demand in underload and overload conditions [13].

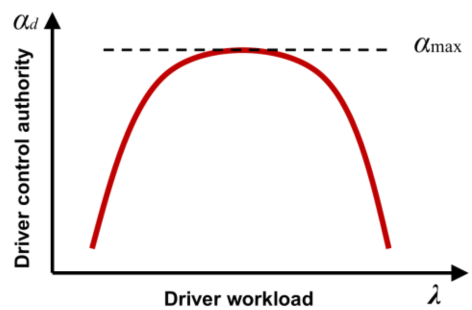

Figure 3. The relation between control authority and driver workload.

In order to realize the above design logic, we propose to modulate the desired control authority α_d that is allocated to the driver in accordance with the real-time cognitive workload of the driver, as shown in Figure 3. The yield driver control authority α_d should also allow the automation system to provide continuous assistance to the driver, according to his or her real-time cognitive workload. Thus, in this work we model the referenced control authority α_d as a time-varying function of the workload level λ, corresponding to the U-shape function characterizing the need for automation assistance for the driver, as shown in Figure 2.

$$\alpha_d(\lambda) = \alpha_{\max} - \varphi_1 (\lambda - \varphi_2)^2 \tag{5}$$

where $\alpha_d \in [0,1]$ is the current desired value of driver control authority, φ_1 and φ_2 are designed parameters, α_{max} is the maximal value for driver control authority, and λ represents the driver's cognitive workload.

In recent years, a number of studies have been conducted in relation to the measurement and estimation of driver workload using different signal processing and machine learning methods. In order to extract features that are highly correlated to workload variation, multi-source data, including driver's physiological states (e.g. skin conductance response, body temperature, heart rate and electrocardiogram signals) and vehicle states (e.g. vehicle position, longitudinal velocity and acceleration, lateral velocity and acceleration), are important signals to analyze [15, 16].

V. Muscle-Readiness-Aware Take-over Authority Determination

Apart from the cognitive state, the driver's biomechanical state also impacts their manual driving performance. Thus, to assess driver's take-over capability and determine the allowed control authority, muscle readiness must also be evaluated in real time.

Muscle readiness state, which can be represented by the neuromuscular dynamics of the driver's arms during the steering operations, is considered to be nonlinear in nature. During the take-over process, large steering torque may be required to avoid obstacles or to keep the car within the lane. If the driver's arm muscles are completely relaxed, then the driver's readiness for the driving task can be considered to be low. Possible reasons that could lead to the driver being distracted by non-driving tasks and a lack of awareness regarding the surrounding environment or effort required. However, since humans have the ability to learn and adapt, muscle readiness could increase exponentially with time as the driver refocuses on the driving tasks and completely resumes control. Thus, the control authority α_d can be modelled as a function of the degree of muscle readiness (see Figure 4).

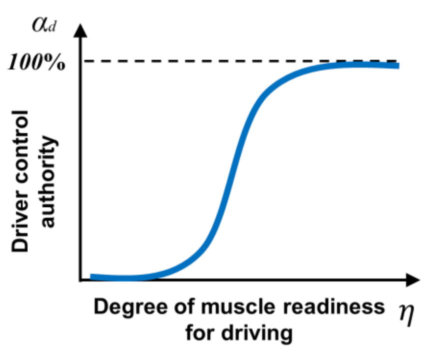

Figure 4. The relation between the modelled control authority and driver muscle readiness.

To quantitatively assess the degree of muscle readiness, characterization and parameterization of the dynamic neuromuscular system are carried out, and feature parameters and evaluation indices are investigated. We abstract the driver-steering-wheel coupled system from its physical structure into a simplified inertia model. The dynamic equation for the driver-machine interacting system can be represented as [17]:

$$T_D - T_{dis} = J\ddot{\theta}_{sw} + B\dot{\theta}_{sw} + K\theta_{sw} \tag{6}$$

$$J = J_{dr} + J_{sw} \tag{7}$$

$$B = B_{dr} + B_{sw} \tag{8}$$

where T_D is the driver's steering torque, T_{dis} is the disturbance torque. K is the stiffness coefficient of the interacting system, and θ_{sw} is the steering angle. J is the lumped inertia, J_{dr} is the driver arm's inertia, J_{sw} is the inertia of the steering wheel, B_{dr} and B_{sw} are the viscous damping terms of the driver's neuromuscular system and steering wheel bearings, respectively, and B is the lumped viscous coefficient.

According to the above established dynamic model, the transfer function of the driver-vehicle interacting system can be developed, as shown in the Eq. (4).

$$\frac{\theta_{sw}}{T_D} = \frac{1}{Js^2 + Bs + K} \tag{9}$$

In order to characterize the interactions between the driver and steering wheel, key parameters of the transfer function need to be identified. We formulate this system identification as a nonlinear least squares problem, and adopt the Gauss-Newton method as the search algorithm to solve it [18].

Based on the above methodology, steering experiments were carried out using different steering tasks, distinct driver postures and hand griping positions in the driving simulator. Correlations were then used to investigate the relationships between neuromuscular state and the key parameters of the estimated transfer function model in multiple driving activities. The results showed that the parameter of stiffness coefficient K was highly correlated with muscle activity during driving. Thus, the stiffness coefficient K is selected as the best indicator of neuromuscular state, and the real-time degree of muscle readiness can be expressed as:

$$\eta = K_{actual} / K_{ref} \tag{10}$$

where K_{ref} and K_{actual} are the reference and actual values of the stiffness coefficient, respectively. The reference value of the muscle stiffness coefficient required for driving can be derived using experimental data, and the actual coefficient can be estimated in real time using driver steering torque and steering angle.

Therefore, to represent the curve-shape function characterizing the allowed take-over control authority, taking into consideration muscle readiness η, the desired value of α_d can be modelled as:

$$\alpha_d(\eta) = 1 - \mu_1 e^{-\mu_2 \eta} \tag{11}$$

where μ_1 and μ_2 are two designed parameters.

VI. Haptic Feedback Torque Controller Design

In a Level 3 automated vehicle, once the automation system can no longer handle the vehicle, the automated driving mode will disengage in a few seconds and control authority will be given back to the human driver. Under the proposed haptic feedback control framework, a desirable multimodal take-over request signal (visual, auditory, tactile, combined) would be generated, based on the identified attention level of the driver.

Once the driver perceives a take-over request and shifts their attention to the driving task, the haptic take-over system will be activated, which will apply haptic feedback torque on the steering wheel. The direction, as well as the intensity of the haptic feedback torque will be determined by the control authority allocated and driver's current degree of participation, guiding the driver to complete the transition safely and smoothly.

The determination of the desired control authority $\alpha_d\%$ allocated to the driver mainly considers the three factors introduced above, namely the optimal input sequence, cognitive workload, and the neuromuscular dynamic state. The driver's current degree of participation can be assessed using the current and required steering torque:

$$\alpha\% = \frac{u_D}{u_d} \tag{12}$$

Following this, the haptic feedback torque is generated and applied on the steering wheel in order to minimize the deviation between $\alpha\%$ and the desired control authority $\alpha_d\%$, which will help the driver to complete the take-over transition. According to the above description, the synthesis of the haptic feedback torque controller can be formulated as a tracking control problem, and a combined feed-forward and feed-back structure is adopted, as:

$$T_{hpt} = T_{ff} + T_{fb} \tag{13}$$

where T_{hpt} is the value of the haptic feedback torque, T_{ff} and T_{fb} are the feed-forward and feed-back components, respectively. These functions can be expressed as:

$$T_{ff} = u_d - u_D = u_A \tag{14}$$

$$T_{fb} = -K_P e_c - K_I \int e_c dt \tag{15}$$

$$e_c = \alpha_d\% - \alpha\% \tag{16}$$

where K_P and K_I are the gains of the feedback term in the controller, and e_c is the control error.

VII. Simulation and Results

In order to validate the feasibility and effectiveness of the proposed haptic take-over control algorithm for highly automated vehicles, simulations were conducted. The vehicle models and the proposed methodologies were integrated in the MATLAB/Simulink environment [19]. In the simulations, the longitudinal speed of the vehicle was set to a constant 30 *km/h*. Some key parameters adopted in the simulations are listed in Table I, and the main results are described below.

TABLE I. Key Parameters of the Simulation Model

Parameter	Value	Unit
Vehicle mass	1360	kg
Wheel base	2.33	m
Frontal area of the vehicle	2.142	m²
Coefficient of air resistance	0.32	-
Front wheel cornering stiffness	0.275	N/rad
Rear wheel cornering stiffness	3.79	-
Polar moment of inertia	1750	kg·m²
Steering ratio	15	-
Longitudinal velocity	30	km/h

After receiving the take-over request, the driver shifts their attention back to the driving task, and the cognitive workload and muscle readiness are assumed to rapidly recover to their desirable level, as shown in Figure 5. Thus, the allowed take-over control authority for the driver increases from 0 to 100% within 3 seconds, as illustrated in Figure 6.

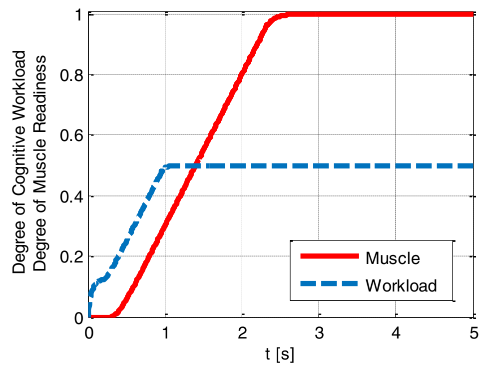

Figure 5. Simulation results of driver workload and muscle readiness.

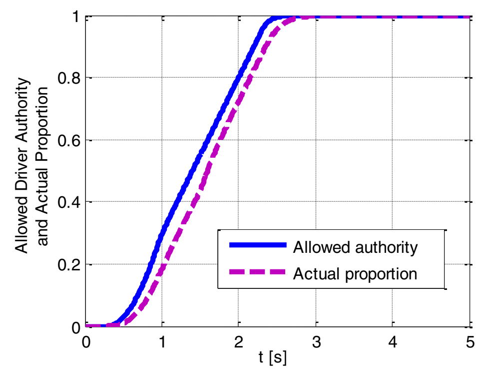

Figure 6. Simulation results of driver authority and the actual proportion.

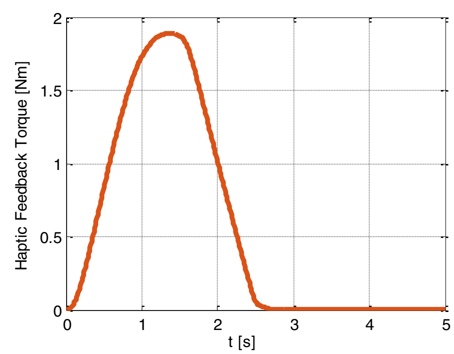

Figure 7. Simulation results of the haptic feedback torque.

During the take-over transition process, the haptic feedback torque is generated on the steering wheel and dynamically adjusted (see Figure 7) so as to minimize the deviation between the actual proportion of driver input and the desired control authority. This results in a smooth transition from automatic control to manual driving. Figure 8 shows that during the first 1.5s the driver is not well prepared for the take-over process, due to the workload and the neuromuscular state, and so the automation system dominates the overall steering torque input. After this time period the driver gradually applies more torque, under the assistance of the generated haptic feedback, and the contribution of the system decreases accordingly. Figure 8 also shows that the handover transition process is completed at around 3s. During the whole take-over control procedure, the actual value of the total torque contributed by human and automation fits the required control input sequence very well (see Figure 9), indicating the feasibility and effectiveness of the proposed haptic take-over control framework.

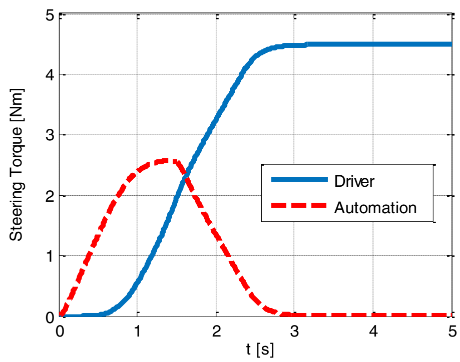

Figure 8. Simulation results of the applied steering torque.

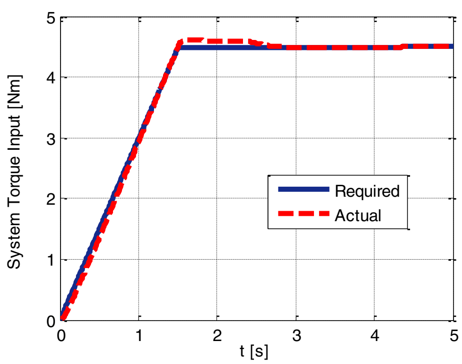

Figure 9. Simulation results of the overall input torque.

VIII. CONCLUSION

In this paper, a novel control framework of the haptic take-over system was proposed, which takes driver cognitive workload, neuromuscular dynamics state and optimal trajectory planning into consideration. Under the proposed framework, the determination approach of the optimal system input sequence is introduced. The model of the allowed driver take-over authority, which associates with driver's cognitive workload as well as muscle readiness during take-over, is investigated and developed. Then, the haptic feedback torque controller is designed so as to minimize the deviation between the allowed control authority and the driver's current degree of participation. A handover process, along with the proposed take-over control method was simulated. The simulation results showed that the haptic take-over controller developed was able to guide the driver to collaborate with the automation system and resume manual control safely and smoothly, validating the feasibility and effectiveness of the proposed approach.

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