Human Model-based Active Driving System in Vehicular Dynamic Simulation

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Abstract—This study proposes a new system framework for simulating human driver-vehicle interactions, which integrate the vehicle controller, dynamics vehicle model, and biomechanical human model. The framework is proposed for investigating the interactive effects of active human maneuvering motions and vehicle dynamics, and the control of vehicles on the physical sensations and safety of the human driver. To this end, we develop a driver-vehicle interaction controller for rendering stable contacts between vehicle structures and whole-body human model simulated using OpenSim. We also develop closed-loop controllers to regulate the human model dynamics, such that the human model can track the planned vehicle maneuver motions. The usability of the proposed human-vehicle interaction framework is demonstrated through the simulation of coordinated gas/brake pedal operation and wheel-steering in highway driving tasks. The proposed controllers successfully maintain contact stability of human-vehicle interaction, and balanced human model that performs vehicle maneuvers. The simulated vehicle dynamics and vehicle maneuvers (steering angle and gas/brake pedal angles) are also compared to previously published experimental data of car-following driving.

Index Terms—Human-vehicle systems, Motion control, Motion planning, Systems modeling, Vehicle dynamics

I. INTRODUCTION

Driver-assistance or autonomous driving technologies have the potential to change the human-vehicle systems in driving tasks [1]-[4]. For example, intelligent driving systems may assist human drivers in vehicle maneuver actions to improve their safety and comfort, e.g., adaptive cruise control, automatic braking, lane departure warning, and lane-keeping assist [5]. In order to implement these complementary actions, these systems may need to actuate the vehicle controls causing the human driver to experience some mechanical forces or torque sensations from driving interfaces. Conversely, human drivers may need to regain control from the intelligent driving systems in order to maneuver in various driving situations. Therefore, vehicular driving behavior and resulting responses may be determined by interactive maneuvers from active actuation of both the human driver and intelligent driving systems [1]. Previous studies revealed human factors during transitions of driving authority from autonomous to manual driving modes may affect human’s response times and driving performance [6]-[9]. However, conventional human-vehicle simulations mostly reflect the unidirectional interactions of vehicle dynamics on the human body, ignoring the effects of human dynamics on the vehicle. Therefore, a new bi-directional simulation framework for human-vehicle systems would be important for general transportation environments and developing intelligent driving systems.

This research focuses on rendering the whole-body coordination in vehicle maneuvers in response to the vehicle dynamics. For many driving tasks, a driver needs to coordinate the motion for gas and brake pedals with steering control, which results in complex motion responses ranging from passively maintaining body posture to actively maneuvering the vehicle according to traffic and road conditions. So far, there have been limited investigations of whole-body coordination that involves both passive and active motion reflex/control. Khatib et al. [10] studied whole-body motion coordination for complex balancing tasks [11], yet it is still unclear how to render active maneuver motion control in response to the dynamic environment. Previous research on mathematical modeling of the human driver has investigated motion coordination of the upper and lower extremities in driving tasks [12]-[15]. The lower extremities control vehicular longitudinal dynamics through coordination of leg and foot. The joint angles and torques of the hip, knee, and ankle control the angles and torques of the brake and gas pedals. Mulder et al. [12] studied the timing and control forces of vehicle pedal pressing motions and demonstrated that haptic gas pedal feedback improves driver vigilance in car-following tasks, which requires accurate real-time control of pedal position for maintaining inter-vehicle distance. To study human-vehicle interactions in simulation, it is important to equip the computational human model with low-level motion planning and controllers that can render stable contacts and track desired human motion trajectories during vehicle maneuvers. In addition to motion planning and control, the framework for simulating human-vehicle interaction should also integrate a high-level decision-making module that accounts for the driver's cognitive behavior and performance according to theoretical driving models [14]-[17]. For instance, Salvucci proposed a hierarchical framework as a cognitive...
architecture that incorporates a driver model with components for vision-based vehicle control, environment monitoring, and vehicle maneuver decision-making [14]. However, since these studies usually represent human drivers as linear or non-linear time-delay functions, the desired maneuvers are guaranteed with the assumptions that no failures or errors in human behavior occur. On the other hand, motion measurement studies using human volunteer subjects reported accuracy and performance of pedal tasks depend on foot position and status at the beginning of maneuvers in real field driving environments [18]. In addition, further investigation using human volunteer subjects shows that human drivers’ age, vehicle seat position, traffic signal phases, and driving sequences can alter the driver foot trajectory and time durations in either a laboratory testbed or out-of-laboratory with real running vehicles [19],[20]. Therefore, variability in human performance due to biomechanical or behavioral variability with disturbances in dynamics needs to be considered in human-vehicle systems [21].

In this paper, we propose a framework for an integrated human model-based active driving system (HuMADS) for rendering whole-body coordination in physical interaction between a human driver and a vehicle in typical driving scenarios. The main contributions of this paper are:

1) Implementation of robotics algorithms to connect theoretical driving models, biomechanical human models, and vehicle physics models.

2) Consideration of the effects of physical interactions due to inertial or contact forces and force equilibria on resulting maneuver performance and vehicle dynamics.

3) Coupled analysis among driving scenario, vehicle dynamics, human driver performance, and biomechanical estimation that may contribute to further studies for automotive safety and ergonomics.

In order to achieve the aforementioned points, we employ a human body model platform and motion control algorithms based on robotics engineering enabling gas/brake pedals and steering maneuvers. Validating velocity and lateral positioning controls against previously published highway driving data [17],[22], we investigate driving performance, human motion control, and the resulting trajectories between static setups such as static driving simulators and dynamic setups as found in real moving vehicles. Other potential applications are for human-vehicle interfaces and applications for driver ergonomics and safety as well as for system information processing studies in vehicular dynamic simulations.

The structure of this article is as follows: Section II presents the model and system structure of HuMADS. Section III describes the vehicle test data and simulation condition parameters. Results and conclusions are presented in Sections IV and V, respectively.

II. HUMAN-VEHICLE DRIVING FRAMEWORK OF HuMADS

A. Simulation Platform

Various simulations of the human body have been proposed for automotive ergonomics or safety purposes. Chaffin and his group developed a digital human model for digital mock-up methods; however, their platforms were limited to static kinematic analyses [23]. The AnyBody simulation system was employed in biomechanical musculoskeletal analyses in the automotive research domain [24]. However, since that system was developed based on inverse dynamics theory, it is impossible to utilize it in a feedback control system. Finite element (FE) simulation and human body modeling were also used for automotive safety studies in [25]. Although FE human body models are good at soft contact and flexible body properties as well as forward dynamics simulations, they are inferior in computational speed. In addition, FE models generally require a remeshing process for any repositioning or re-posturing of the human body. On the other hand, multibody models allow one to easily change model positions using state variables. In particular, OpenSim has capabilities of forward dynamics (FD) analysis as well as inverse kinematics (IK) and inverse dynamics (ID) analyses [26]-[28]. The Application Programming Interfaces (APIs) defined in OpenSim and SimBody allow programs to access parameters of the models and dynamics to calculate the equation of motions at runtime. Therefore, this study selected OpenSim as the simulation platform for the human-vehicle driving simulation system.

Because the targeted tasks of the driving system follow typical driving scenarios, the HuMADS in this study is assumed to represent a mid-sized human driving a regular passenger car on the highway traffic. Fig. 1 shows the mechanical models of the HuMADS in OpenSim, consisting of a human body with height of 1.8 m and weight of 77.4 kg, and 2012 Toyota Camry. The human body part has 37 coordinate joints for the neck, lumbar, upper and lower extremities. Muscle elements of OpenSim human body models are replaced with ideal torque actuators at the joints for simplicity. The vehicle model, with three coordinate joints of pedals and steering wheel, is linked to the ground with three degrees of freedom of longitudinal (x) and lateral (y) translations and yaw rotation. Vehicle geometry and inertial properties come from a FE model of a Toyota Camry [29]-[30]. This model includes...
major components of the vehicle exterior and interior, such as driver seat, pedals, and steering wheel. The joint center, mass center, and inertial properties for all components are estimated from material properties of the FE models. The joint stiffness characteristics of the gas and brake pedals are computed according to a non-linear viscoelastic with friction torque model. Pedal force characteristics against the displacement for gas and brake pedals agree with literature data [31]-[32].

Our simulation defines the contact interfaces between the human body parts and vehicular interior instruments and components, including the gas and brake pedals. In particular, the contact geometries of the human body come from skin mesh models of the Hybrid III 50th percentile male dummy [33]. The contact forces are computed using the ElasticFoundationForce model [27], while the contact parameters are determined according to the data of the pendulum foot impact in [34].

Given the above setup, our simulation generates impact reaction forces consistent with the test results of a dummy foot with two loading speeds. Although the literature data compares dynamic responses of human bare feet and dummy bare feet, we assumed that the dummy bare feet data may be reasonable for general drivers’ feet wearing shoes. The half-space contact geometry defined by OpenSim is used to represent soft contact interfaces on the seat cushion and back [35]. Although the human pelvis is mounted on the seat cushion with constraints on its rotational motion, pelvis translational motions are determined by equilibrium of contact, seatbelt, and inertial forces. Because this study employs driving on a highway as the human motion task scenario, we assume that the human driver holds the steering wheel with both hands. Therefore, nonlinear spring force models are used to constrain hand positions on the steering wheel.

The aforementioned contact and constraint forces are defined by virtual bodies for the human body regions. Since the point contact forces are not clearly expressed by the current OpenSim, external force vectors \( F_{ext} \) are calculated by the 6-DOF joint reaction force outputs on the weld joint between the inertial and zero-mass virtual bodies.

**B. Hierarchical Controller Structure**

This study designed a high-fidelity model for the human driver’s motions in normal driving scenarios as a vehicle-following task model with two vehicles as in Fig. 2.

The preceding vehicle moves at velocity \( V_p \), then the host vehicle follows the preceding vehicle with velocity \( V_h \) and headway distance \( D_{hw} \). The interactions between human and vehicle models are built upon two controllers: the vehicle controller controls the longitudinal and lateral motions of the vehicle (i.e., accelerating, braking, lane following, etc.), while the human motion controller as an inner-loop of the whole system controls the dynamic human driving motions accordingly. The vehicle controller is designed based on a linear feedback system with the driving task reasoning and vehicle dynamics models proposed by Saigo [17]. The human motion controller consists of a human motion planner, human motion controller, and human-vehicle forward dynamics analysis.

**C. Driving Task Reasoning**

The Driving Task Reasoning layer, which is part of the vehicle controller, computes the reference pedal \( \delta_{pd} \) and steering angles \( \delta_{wr} \) for longitudinal and lateral motion control individually.

For longitudinal motion, the host vehicle sets its reference velocity \( V_h^r \) to follow the preceding vehicle that moves at velocity \( V_p \). \( D_{hw} \) and \( D_{hdw} \) are the actual and desired headway distances between the preceding vehicle and host vehicle. The desired headway distance, \( D_{hdw} \), is determined based on the assumption that human drivers try to maintain a constant separation in time between their vehicle and the preceding one.

![Vehicle position and objective pathway](image)

Fig. 3. Vehicle position and objective pathway.
This time separation is $T_{hw}^d$, typically 1.5 sec. The driver sets the desired headway distance $D_{hw}^d$ based on own vehicle velocity $V_h$ and time separation $T_{hw}^d$. The actual headway distance is related to the vehicle velocities as follows:

$$D_{hw} = V_p - V_h.$$  

(1)

The reference pedal angles $\delta_{pa}^r$ can be described by the following control equation:

$$\delta_{pa}^r = H_P[D_{hw} - D_{hw}^d] + H_V[V_p - V_h].$$  

(2)

where $H_D$ and $H_V$ are the gain constants for headway distance and vehicle velocity, respectively.

The lateral motion controller is a forward-gaze model on the highway (Fig. 3) based on the theory of vehicle dynamics described by Abe [36], which determines the yaw angle $\psi_m$ and yaw rate (angular velocity) $\gamma_m(=\dot{\psi}_m)$ of the vehicle around the vertical axis to follow the objective trajectory $P_m^d$ in an X-Y coordinate system. The X-Y axes show the fixed plane centered at the vehicular center of gravity (CG), vehicle directions, respectively. The origin of the local frame is at the vehicular center of gravity (CG), $P_{cm}$: Defining $f_F$ and $f_F$ as unit vectors in ground coordinates, the lateral deflection of the vehicle current position $P_{cm}$ from the objective pathway in the vehicle coordinate system is expressed as $y_{crm}$, using the minimum distance between $P_{cm}$ and $P_m^d$, and the rotational transformation of yaw angle $\psi_m$ as follows,

$$y_{crm} = \min\left\{(P_m^d - P_{cm}) \cdot i_L \sin(-\psi_m) + (P_m^d - P_{cm}) \cdot j_L \cos(-\psi_m)\right\}.$$  

(3)

In addition, the expected vehicle position $P_{sm} = (P_{sm,x}, P_{sm,y})$ is expressed in terms of the forward-gaze time duration $T_p$ as:

$$P_{sm,x} = P_{cm,x} + T_p V \cos \psi_m$$

$$P_{sm,y} = P_{cm,y} + T_p V \sin \psi_m.$$  

(4)

The lateral deflection of the expected position $P_{sm}$ from the objective pathway in the vehicle coordinate system is expressed as $y_{srm}$ in the same manner as equation (3),

$$y_{srm} = \min\left\{(P_m^d - P_{sm}) \cdot i_L \sin(-\psi_m + T_p \gamma_m) + (P_m^d - P_{sm}) \cdot j_L \cos(-\psi_m + T_p \gamma_m)\right\}.$$  

(5)

Then the driver is assumed to set steering angle $\delta_{sw}^r$ proportional to the lateral deflection $y_{srm}$.

$$\delta_{sw}^r(t) = h \cdot y_{srm},$$  

(6)

where $h$ is a gain for the driver corrective steering angle.

The reference pedal angles $\delta_{pa}^r$ and steering angle $\delta_{sw}^r$ are achieved by the inner-loop motion planner and controller, described in the following subsection.

D. Human Motion Planner

The Human Motion Planner computes the desired joint angles $\theta^d$, angular velocities $\dot{\theta}^d$, and angular accelerations $\ddot{\theta}^d$ given the reference pedal angles $\delta_{pa}^r$ and steering angle $\delta_{sw}^r$ that control the longitudinal and lateral motions of a vehicle. To obtain these joint space variables, we first plan feasible 3D Cartesian trajectories of the hands and feet. Then we utilize inverse kinematics (IK) to determine desired joint angles from the planned trajectories.

First, we plan feasible trajectories for the coordinated lower extremity joints that implement the motion for pedal pressing. In regular passenger vehicles, no obstacles exist around the driver’s feet workspace other than the gas and brake pedals. However, the driver’s right foot must approach pedal surfaces in consideration of each pedal’s movable directions. Wu et al. reported that the foot-to-pedal trajectory describes a rounded curve that approaches the pedals from normal directions to the pedal surfaces [19]. Therefore, we assume that a typical task space trajectory of the foot during pedal switching is a continuous curve that connects the initial and end pose of the foot as shown in Fig. 4. The motion planner needs to convert the desired trajectory to a sequence of desired joint angles and angular velocities. Shown in Fig. 5, our motion planner uses 3D potential and force fields to generate the desired task space trajectory, which will be further converted to a joint space trajectory through inverse kinematics (IK).

We define a force field $F(p)$ as the sum of an attractive force $F_{att}$ centered at the goal and a set of repulsive forces $F_{rep,j}$ centered at regions of space to avoid, such as behind the pedals:

$$F(p) = F_{att} + \sum_{j} F_{rep,j}.$$

![Image](image.png)

Fig. 4. Brake and gas pedal locations and ideal trajectory.

![Image](image.png)

Fig. 5. Arrangements of current point with attractor and repulsions.
\[ F(p) = F_{\text{att}}(p) + \sum_j F_{\text{rep},j}(p). \]  

(7)

In Fig. 5(a), we denote the current target position and center of attractor as \( p \) and \( C_{\text{att}} \), respectively. The relative position of these points is denoted as \( \frac{p - C_{\text{att}}}{|p - C_{\text{att}}|} \). Thus, the attractive force \( F_{\text{att}}(p) \) can be computed as:

\[ F_{\text{att}}(p) = \zeta \frac{p - C_{\text{att}}}{|p - C_{\text{att}}|}. \]  

(8)

where \( \zeta \) is a coefficient that indicates the strength of the attractive force, which always points away from the center in the goal direction.

In Fig. 5(b), the current target position and the \( j \)-th center of repulsion are denoted by \( p \) and \( C_{\text{rep},j} \), respectively. The relative positions of these points are denoted as \( \frac{p - C_{\text{rep},j}}{|p - C_{\text{rep},j}|} \). Thus, the \( j \)-th repulsive force \( F_{\text{rep},j}(p) \) can be computed as:

\[ F_{\text{rep},j}(p) = -\eta_j \frac{p - C_{\text{rep},j}}{|p - C_{\text{rep},j}|}. \]  

(9)

where \( \eta_j \) is a term that indicates the strength of the repulsive force, which always points away from the center of repulsion.

Term \( \eta_j \) comprises two components. One decreases linearly from 0 to distance \( R_{2j} \), the other follows an inverse square law from 0 to distance \( R_{1j} \). Combining these components based on the distance from each center of repulsion \( |p - C_{\text{rep},j}| \) gives:

\[
\eta_j = \begin{cases} 
\lambda_1 \frac{R_{1j}^2}{|p - C_{\text{rep},j}|^2} + \lambda_2 \frac{(R_{2j} - |p - C_{\text{rep},j}|)}{R_{2j} - R_{1j}} : |p - C_{\text{rep},j}| < R_{1j} \\
\lambda_2 \frac{|p - C_{\text{rep},j}|}{R_{2j} - R_{1j}} : R_{1j} \leq |p - C_{\text{rep},j}| < R_{2j} \\
0 : R_{2j} \leq |p - C_{\text{rep},j}| 
\end{cases}
\]  

(10)

Since the human driver is assumed to hold the steering wheel with both hands during driving on a highway, the hand positions are determined from transferred positions on the steering wheel. Therefore, desired hand positions are planned by required reference steering angle \( \delta_{\text{sw}}^R \) during the driving.

In the regular highway driving task, the human driver can be assumed to maintain their initial posture, therefore the desired position and orientations of the head and torso bodies will also maintain their initial posture.

As the latter part of the motion planner, we employed OpenSim’s IK analysis to obtain desired joint angles from planned trajectories. The OpenSim’s IK analysis computes the joint angles \( q^d \) using the weighted least squares method, in order to fit the desired marker positions.

Fig. 6 shows the virtual markers for positioning a human body with indicated weights. Since the pelvis is a base for the hierarchal human body model, three virtual markers of Hip and Belt positions for right and left have greater weights. We consider the top tip position (i.e., the Toe and Hand_1 in Fig. 6) as the end effector position of the lower and upper extremities and compute the desired trajectories. Ferber et al. [37] reported that the peak velocity of the ankle joint was 291 [degrees/s] in dorsiflexion. Since the distance between toe and ankle joint is 0.18 [m] in this model, this creates a foot velocity around 0.9 [m/s]. Therefore, discrete desired points of end \( p^d_j \) at time \( t \) are determined with intervals of time step and foot velocity. Given the desired discrete positions of the top tip, we further compute the desired discrete joint angles \( q^d \) through the inverse kinematics (IK) analysis. To calculate desired joint angular velocities \( \dot{q}^d \) and angular accelerations \( \ddot{q}^d \), we compute the polynomial curve function fitting with discrete joint angles and obtained differential variables. The other virtual markers such as Hand_2/3, Elbow, Heel, Tibia, Femur_bottom, Head top, and Gaze_R/L are placed in initial positions to keep the human body driving positioning.

E. Human Motion Controller

The human motion controller layer computes the desired joint torques \( \tau \) given the desired joint angles \( q^d \), angular velocities \( \dot{q}^d \), and angular accelerations \( \ddot{q}^d \) of the vehicle maneuver motion. Through inverse dynamics, we compute the desired joint torque for the whole-body human driver model to maintain its body posture while tracking the desired trajectory for pedal pressing or switching. Inverse dynamics is one method of feedback linearization [38]. The inverse dynamics requires the mass, Coriolis forces, and gravity of a dynamic system. Specifically, the dynamics of an \( n \)-link rigid robot can be expressed as:

\[
M(q)\ddot{q} + C(q, \dot{q}) + N(q) + J^T F_{\text{ext}} = \tau.
\]  

(11)
represents the system Jacobian matrix, $F_{\text{ext}}$ captures the external forces, and $\tau$ is the joint torques.

The idea of inverse dynamics introduced by Spong et al. [38] is to express $\tau$ as the function $f(q, \dot{q}, t)$. Therefore, the dynamics equation (11) can be modified by substituting $\ddot{q}$ for a new input $a_q$ as follows:

$$
\tau = M(q)a_q + C(q, \dot{q}) + N(q) + f^T F_{\text{ext}}. 
$$

(12)

Given the desired joint positions, velocities, and accelerations, our motion controller guarantees that:

$$
\ddot{q} = \ddot{q}^d - K_p(q - q^d) - K_d(\dot{q} - \dot{q}^d) - K_F f^T F_{\text{ext}} = 0, 
$$

(13)

where $q^d$ is the vector of desired state variables, $\ddot{q}$ represents the error of state variables ($\ddot{q} = q - q^d$), $\ddot{q}^d$ is the desired acceleration, $F_{\text{ext}}$ is the error of the external forces ($F_{\text{ext}} = F_{\text{ext}} - F_{\text{ext}}^d$), $K_p$, $K_d$, and $K_F$ are diagonal matrices of position, velocity, and force gains, respectively. To control a linear second-order system, we need to regulate $a_q$:

$$
a_q = \ddot{q}^d - K_p(q - q^d) - K_d(\dot{q} - \dot{q}^d) - K_F f^T (F_{\text{ext}} - F_{\text{ext}}^d). 
$$

(14)

We assume that the human driver determines pedal positions based on force feedback and remembers – and therefore compensates for – the expected reaction forces from the pedals based on the pedal positions. Therefore, we designed the desired pedal force as a non-linear function of pedal positions $F_P(\delta_{pd})$. In addition, the human driver may adjust the pedal position at the request of pedal position $\delta_{pd}$ from the driving task reasoning layer, therefore, the desired force is expressed as follows:

$$
F_{\text{ext}}^d = F_P(\delta_{pd}) - K_{dp}(\delta_{pd} - \delta_{pd}^r), 
$$

(15)

where the function $F_P$ represents a function of pedal angle and contact force relationship and $K_{dp}$ is a pedal position gain.

The vehicle motions given from the vehicle dynamics in Fig. 2 are produced by the coordinated actuation forces $F_h$ in the longitudinal, lateral, and yaw directions. The required actuation forces are calculated as follows:

$$
F_h = M_h[A_h^r - K_{hp}(P_h - P_h^r) - K_{hd}(V_h - V_h^r)]. 
$$

(16)

where $M_h$ is the inertia matrix of the vehicle body, $A_h^r$, $V_h^r$, and $P_h^r$ are the reference variables of vehicle acceleration, velocity, and displacement from the vehicle dynamics layer.

F. Vehicle Dynamics

The human-vehicle forward dynamics layer uses the whole-body human model to simulate the human driver’s forward kinematics and dynamics in order to predict the actual control angles of the pedal $\delta_p$. Next, the vehicle dynamics layer, which is another part of the vehicle controller, converts the driver’s commanded pedal angles $\delta_p$ and steering wheel angle $\delta_{sw}$ to vehicle dynamics. The host vehicular acceleration $A_h^r$ can be expressed as follows:

$$
A_h^r + T_g A_h^r = K_g \delta_p, 
$$

(17)

where $K_g$ and $T_g$ are the gain and time constants of the pedal function, respectively. When air resistance $C_{air}$ is considered, the host vehicle velocity $V_h^r$ can be expressed as:

$$
c_{air} V_h^r + V_h^r = A_h^r. 
$$

(18)

Vehicular lateral motions are expressed based on the equivalent bicycle model in Fig. 7. The actual front tire angle $\delta_m$ is determined by the actual steering wheel angle $\delta_{sw}$ and gear ratio $n$:

$$
\delta_m = \delta_{sw}/n. 
$$

(19)

The angle $\beta$ between velocity vector $V$ and longitudinal direction $x$ in Fig. 7 is called the side slip angle. Considering the component of acceleration in the lateral direction, the lateral dynamics are expressed as:

$$
mV(\dot{\beta} + \gamma_m) = 2F_f + 2F_r, 
$$

(20)

where $m$ is vehicle mass, $F_f$ and $F_r$ are the lateral forces on front and rear tires, and $\gamma_m$ is the yaw rate.

The lateral forces also result in a moment in the yaw direction around the vehicle CG, given by:

$$
l\dot{\gamma}_m = 2F_f \beta_f - 2F_r \beta_r, 
$$

(21)

where $l$ is moment of inertia, $\beta_f$ and $\beta_r$ are distances from vehicle CG to front and rear wheel axes, respectively.

The lateral forces $F_f$ and $F_r$ on each tire are proportional to the side slip angles on the front $\beta_f$ and rear $\beta_r$ tires; the proportionality constants are denoted as the cornering stiffness $K_f$ and $K_r$. Since rotational directions of all angles are expressed as positive in the anticlockwise direction in the vehicle coordinate system (Fig. 7), side slip angles and lateral forces can be expressed as positive and negative, respectively. Therefore, the lateral forces are described as:

![Fig. 7. Equivalent bicycle model for vehicular lateral motion.](image-url)
Given $F_t = -K_f \beta_f = -K_f (\beta + l_f \gamma_m / V - \delta_m)$ and $F_r = -K_r \beta_r = -K_r (\beta - l_r \gamma_m / V)$, the equations of dynamics in (20) and (21) can be expanded as:

$$mV \ddot{\gamma}_m + 2(K_f + K_r) \beta + \left\{ mV + \frac{2}{V} (l_f K_f - l_r K_r) \right\} \gamma_m = 2K_f \dot{\delta}_m$$

$$2(l_f K_f - l_r K_r) \beta + l_r \ddot{\gamma}_m + \frac{2(l_r^2 K_f + l_l^2 K_r)}{V} \gamma_m = 2l_f K_f \dot{\delta}_m$$

Equation (23) can also be expressed by a Laplace transformation, where $\beta(s)$, $\gamma(s)$, and $\delta(s)$ are the Laplace transforms for $\beta$, $\gamma_m$, and $\delta_m$:

$$\{mV s + 2(K_f + K_r)\} \beta(s) + \left\{ mV s + \frac{2}{V} (l_f K_f - l_r K_r) \right\} \gamma(s) = 2K_f \delta(s)$$

$$2(l_f K_f - l_r K_r) \beta(s) + \left\{ l_s + 2\left( \frac{l_r^2 K_f + l_l^2 K_r}{V} \right) \right\} \gamma(s) = 2l_f K_f \delta(s)$$

The side slip angle transfer function $G_\phi(s)$ is:

$$G_\phi(s) = \frac{\beta(s)}{\delta(s)} = G_\phi(0) \frac{1 + T_p s}{1 + \frac{2\xi}{\omega_n} s + \frac{s^2}{{\omega_n}^2}}$$

$$G_\phi(0) = \frac{1 + \frac{l_f}{2l_t K_r} V^2}{1 + K V^2}$$

where $\omega_n$ and $\xi$ are expressed as follows:

$$\omega_n = 2l \sqrt{\frac{K_f K_r(1 + K V^2)}{m l}}$$

$$\xi = \frac{m(l_r^2 K_f + l_l^2 K_r) + l(K_f + K_r)}{2l \sqrt{m l K_f K_r(1 + K V^2)}}$$

The yaw rate transfer function $G_\psi(s)$ is:

$$G_\psi(s) = \frac{\gamma(s)}{\delta(s)} = G_\psi(0) \frac{1 + T_p s}{1 + \frac{2\xi}{\omega_n} s + \frac{s^2}{{\omega_n}^2}}$$

$$G_\psi(0) = \frac{1}{1 + K V^2 T_r}$$

When the current vehicle position is described as $P_{cm}(t) = (P_{cm,x}(t), P_{cm,y}(t))$, the vehicle velocity in ground coordinates can be described with vehicle speed $V$ and yaw angle and side slip angle as follows:

$$\dot{P}_{cm,x}(t) = V \cos(\beta(t) + \psi_m(t))$$

$$\dot{P}_{cm,y}(t) = V \sin(\beta(t) + \psi_m(t))$$

The resulting vehicle motions are fed back to the driving task reasoning layer.

### III. Simulation Setup

In [17], Saigo validated the driver-vehicle model based on a linear feedback system against the experimental data obtained from human subjects driving on expressways. Our study follows that simulation setup for vehicle dynamics and therefore compares the simulation result to the dataset used in the previous study. Saigo et al. [17], [22] obtained vehicle dynamics and driver operation data such as host vehicle longitudinal and lateral accelerations, vehicle velocity, yaw rate, headway distance, gas pedal position, brake pedal pressure, and steering angle directly from the controller area network (CAN), which is a robust data bus in the vehicle. The preceding vehicle velocity was calculated from adding host vehicle velocity to the differential headway distance value. The road pathway was obtained from front facing camera images. Tables I and II show the parameters used for the driver-vehicle model. In our simulation, the brake pedal gain $K_b$ is set the same as the gas pedal gain $K_g$ in order to compare vehicle performance with that reported in [17]. One significant difference in parameters between [17] and this simulation concerns the time constants for the human driver in the pedal and steering tasks. In [17] these were set to $\tau_p = 1.0$ and $\tau_{sw} = 0.4$, respectively, to account for the time delay in force transmission. However, that model did not include human body dynamics, which our model explicitly includes. Our more realistic model effectively introduces time delays in the human body dynamics; thus, we assume smaller delay time constants in TABLE I. The pedal position gain $K_{GP}$ for equation (15) is determined as 16000 N/rad.

An instance of an OpenSim class to manage the execution of a simulation is declared with the Runge-Kutta-Merson integrator through the SimBody API. We choose a range of integration time steps from 0.5 [$\mu$s] to 0.5 [ms].

The update frequency for reference variables between the outer and inner loops is 50 Hz, while the human motion controller inner loop updates the desired (reference) joint variables and contact forces at 1 kHz.

Our simulation renders the motion of the human driver upper and lower extremities with two different setups for vehicle motion (dynamic and static). The dynamic motion setup represents driving a real car on the road, while the static motion setup represents a laboratory environment with driving simulators.
PARAMETERS FOR THE DRIVING TASK REASONING LAYER

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desired headway distance behind preceding vehicle</td>
<td>$T_{bw}$</td>
<td>1.4</td>
</tr>
<tr>
<td>Gain for distance difference [%/m]</td>
<td>$H_D$</td>
<td>2.0</td>
</tr>
<tr>
<td>Gain for velocity difference [%/(m/s)]</td>
<td>$H_V$</td>
<td>6.0</td>
</tr>
<tr>
<td>Time delay for human driver in pedal task [s]</td>
<td>$\tau_p$</td>
<td>0.4</td>
</tr>
<tr>
<td>Steering compensation gain [rad/m]</td>
<td>$h$</td>
<td>0.05</td>
</tr>
<tr>
<td>Forward-gaze time duration for steering task [s]</td>
<td>$T_p$</td>
<td>2.0</td>
</tr>
<tr>
<td>Time delay for human driver in steering task [s]</td>
<td>$\tau_{sw}$</td>
<td>0.1</td>
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</table>

PARAMETERS FOR THE VEHICLE DYNAMICS LAYER

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<tr>
<th>Parameter</th>
<th>Symbol</th>
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<tr>
<td>Time constant for gas pedal function [s]</td>
<td>$T_p$</td>
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<tr>
<td>Gain of gas and brake pedal function $K_g$, $K_b$</td>
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<td>Distance from vehicle C.G. to front tire [m]</td>
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<tr>
<td>Distance from vehicle C.G. to rear tire [m]</td>
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<td>1.52</td>
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<tr>
<td>Cornering force on front tire [N/rad]</td>
<td>$C_r$</td>
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<td>Cornering force on rear tire [N/rad]</td>
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<td>61999</td>
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<tr>
<td>Moment of inertia [kg m^2]</td>
<td>$I$</td>
<td>72.7</td>
</tr>
</tbody>
</table>

IV. RESULTS AND DISCUSSION

A. Overall kinematics and dynamics

TABLE III shows the results of applying the Student t-test between the vehicle kinematics of the OpenSim model and reference variables from the vehicle dynamics layer. These matches between physical vehicle model and vehicle dynamics layer is favorable for human-vehicle interaction studies.

Fig. 8 shows simulated driver motions and driving maneuvers. The motion planner and motion controller successfully generated a typical trajectory for the foot tip to travel between the gas and brake pedals while turning the steering wheel and balancing the whole human body.

B. Resulting vehicle maneuvers and performances

Fig. 9 compares human driving maneuvers and resulting vehicle kinematics in terms of pedal position, vehicle velocity, steering angle, and vehicle lateral displacement error against desired pathway among current simulation models and previous model of Saigo [17] and human subject (driver# R3) data from an experimental test [17]. This driving scenario contains decelerating from 110 km/h to 70 km/h within a 60 s time segment. Driving task reasoning may contain several functions of sensing, cognition, and high-level task planning. This study employed a linear model for providing reference variables of pedal positions and steering angle, as was done in the previous study [17]. Therefore, pedal position changes during continuous gas pedal operation are comparable between the current HuMADS model and Saigo’s model.

Although brake pedal position of the test data indicates only

![Image](https://via.placeholder.com/150)

(a) Pressing brake pedal with 10 deg turning steering wheel to the left. (b) Pressing gas pedal with 5.6 deg turning steering wheel to the right.

Fig. 8. Human body model posture while driving a vehicle model.

![Image](https://via.placeholder.com/150)

(a) Dynamic Gas (b) Static Gas (c) Test data Gas (d) Saigo model

Fig. 9. Comparison of driving performance and resulting vehicle performance among the HuMADS model in dynamic and static setups, the previous model from Saigo [17], and experimental data.
record of braking switch in Fig. 9(a), brake pedal operations are observed around 1, 40, and 75 [s]. Simulation results from HuMADS expressed brake pedal performances with peaks of striking pedals at the similar timings as the test data in dynamic and static vehicle setups. There exists a time delay when switching the foot position to another pedal, which is caused by the motion planner and parameters of the motion control layer. In contrast, the previous model exhibited smoother pedal position changes because there is no foot transfer from gas pedal to brake pedal.

Overall steering angle curves expressed by simulation models run along the line of test data (Fig. 9c). However, simulation results from HuMADS shows oscillations on the steering angles. This may be because of constraint definitions between the hands and steering wheel with the current model. Since each hand of HuMADS connects to the steering wheel by point-to-point spring forces as simplified grasping constraints without any contact definitions, there is no constraint in rotational degrees of freedoms for the hands. In addition, it is difficult to add damping to reduce the 3D translational oscillations. Future versions of HuMADS need a soft contact definition with friction similar to the feet-pedals contact model.

The resulting lateral displacement errors in vehicle position in HuMADS with dynamic setup reaches 3 m. By contrast, HuMADS with static setup and the previous model keep magnitudes of displacement error under 1 m.

C. Force feedback control in driving task

Fig. 10 shows comparisons of pedal positions and steering angles between resulting model performed and desired variables. Pedal position gain $K_{GP}$ shows an important role in maintaining desired pedal positions. When smaller position gain $K_{GP}$ is used, gas or brake pedal positions cannot reach the desired values. On the other hand, since upper arm control does not employ desired steering forces around hands, steering angles cannot track the desired steering angles (Fig. 10b).

Because of unstable conditions between hands and steering wheel, the hand controller is designed based on position feedback. Therefore, we believe that force feedback control and gain variables with contact definitions between hands and steering wheel would be essential to perform steering maneuvers properly.

D. Motion plan and Time delay of human driver

The time constants for time delay models of human driver are assumed 0.4 s and 0.1 s for pedal and steering task, respectively. However, Scott et al. reported that response time delays due to sensory feedback such as passive joint movements or skin contacts are generally quicker than those requiring visual feedback based on neuroscience experiments [39],[40]. Since this proposed model can divide cognition processes from vision and force feedback into driving task reasoning and internal force feedback of human body control, the time constants from [17] may be dispersed among the feedback sources with appropriate factors. In addition, time delays due to dynamics may be estimated based on forward analysis. Further validation studies may provide better understanding about the effects of biological time delays on driving performance and interaction with vehicle dynamics.

On the other hand, preceding velocity curves used for this study were almost comparable with host vehicle velocity curves because the preceding vehicle velocity was estimated as a summation of host vehicle velocity and difference values of headway distance changes. Therefore, the vehicle velocity calculated by the models are always delayed with respect to test results.
In addition, further motion analysis from learning algorithms and the design of high-level motion planners are necessary for reproducing more human-like driver behaviors. Even with the force feedback controller as currently implemented, the generated motions are still smoother than real human motions. A human motion study of vehicle pedal maneuvers revealed that complex foot motions can be decomposed into motion primitives and that it is possible to reproduce complex motions from learned motion libraries [41].

E. Vehicle dynamics and biomechanics of the human driver
This section introduces an example estimation of internal forces and reactions around a driver’s pelvis region. Fig. 11 shows simulation results around a driver’s lumbar joint. External forces $F_{ext}$ around the pelvis consist of contact forces against seat cushion and seat back, seat belt constraint forces, and constraint forces in rotations. Significant force changes are observed at around 40 and 70 s. Comparing to Fig. 9, those timings correspond to when the brake pedal was pressed. However, these deceleration timings may not relate to the changes of pelvis position, actuated joint torques by controller, and joint reaction forces on the lumbar joint in the lateral direction. The outlines of pelvis positions, actuated torques, and joint reaction forces and torques alter at 40, 50, and 75 s. These synchronizations may indicate some relationships between these parameters. When the actuated joint torques are compared between dynamic and static setups, required joint torques differ even though the pedals and steering task performances are comparable. For further investigation for human safety and ergonomics, overall behavior and kinematics should be validated with human subject experimental data.

In general, human motions can be expressed as outputs from a closed-loop motor control system of humans with vision and sensory prediction feedbacks. Physiological sensors such as joint receptors, muscle spindle organs, Golgi tendon, and Renshaw cells may have analogs in robotics sensory systems of joint angle, velocity, actuator effort, and reaction forces [42], [43]. Because OpenSim includes biomechanical analysis feature such as adaptive scaling methods for individual subjects and musculoskeletal analysis, it may be possible to use biomechanical variables such as electromyogram (EMG) measurement for better understanding of human-vehicle dynamics.

VI. CONCLUSIONS
This paper proposed a new framework of the Human model-based active driving system (HuMADS) for human driver-vehicle interactions including driving task reasoning, human driver motion, and resulting vehicle dynamics. We described how to connect theoretical driving vehicle models with biomechanical human and vehicle models based on force equilibria and dynamics. In the highway driving scenario, the HuMADS generated driving maneuvers and vehicle performance comparable to those of human subject test data. While the HuMADS behaves similarly to the real world driving data, further refinements of our framework are needed to improve overall fidelity to human-like motions. We are convinced that the HuMADS has potential as a future tool for development of intelligent transportation systems and investigation of integrated safety, and we hope to make it accessible to a wide audience of researchers in the future.

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