One of the challenging problems with bicycle simulators is to deal with the virtual bicycle dynamics that is coupled with rider’s motion. For the virtual bicycle dynamics calculation and the real time simulation, it is necessary to identify the control inputs from the rider as well as the virtual environments. The steering, pedaling, and braking torques can be easily measured by using torque sensors and the virtual environments can be generated and provided by a visual system. However, direct measurement of the rider’s net moment that significantly affects the bicycle motion is not practical. In this work, it is shown that six control forces of the Stewart platform-based motion system can be used for effective estimation of the rider’s net moment, incorporated with the sliding mode controller with perturbation estimation.

1. INTRODUCTION

A variety of vehicle simulators such as the automobile, flight, tank, motorcycle, and ship simulators are nowadays becoming widely used for testing of design, evaluation of environments, training for driving, entertainment, and so on. Among many kinds of riding simulators, the bicycle simulator has not yet been tackled in depth, primarily because of the difficulty in simulating the complex interactive mechanism between bicycle and human rider. Since the bicycle is simply a daily commuting vehicle that is directly human-controlled and powered, the feeling of steering, balancing, pedaling, and riding a bicycle is familiar to most people. That familiarity, however, makes the high fidelity simulation more difficult to achieve. So far, there have been only a few works on bicycle simulators available in the literature. Brogan has developed a bicycle simulator with a single degree-of-freedom (DOF) motion platform, which is essentially a visual simulator developed for the Olympic bicycle race environments. Recently, a bi-
cycle simulator with a 6-DOF Stewart platform and a force feedback system, and an interactive racing bicycle simulator were developed. A challenging problem is to deal with the virtual bicycle dynamics that is coupled with human rider’s motion for a bicycle simulator. For the virtual bicycle dynamics calculation and real time simulation, it is necessary to identify the control inputs from the rider as well as the virtual environments. The virtual environments include terrain, ground condition, scenery, and so on. Since they are automatically generated according to the bicycle position by a visual system, the necessary information such as the normal vector and condition of the ground is easily provided for the virtual bicycle dynamics calculation. Unlike the virtual environments, some of the rider’s control inputs are difficult to identify. We assume that the rider’s control inputs to the bicycle are composed of the steering, pedaling, and braking torques and the rider’s net moment, and the rider is regarded as the combination of the rider’s net moment source and a dead weight, in addition to the power source for steering, pedaling, and braking. The rider’s net moment is exerted from the rider to the bicycle frame through the handlebars, pedal, and saddle. Among those rider’s inputs, the steering, pedaling, and braking torques can be measured directly by using torque sensors attached to the corresponding components. However, direct measurement of the rider’s net moment that has a significant effect on the bicycle motion is not practical. Through accurate identification of the rider’s net moment, a bicycle simulator would be much more realistic, although a bicycle simulator is essentially different from a real bicycle in the sense that the real bicycle is fixed on a moving platform that provides a washout-filtered bicycle motion. To this end, an indirect and accurate method for the rider’s net moment estimation is developed using the six control forces to the 6-DOF Stewart motion platform of the KAIST bicycle simulator. Even though Stewart platform-based force/torque sensors were presented by Kerr, Nguyen, and Ferraresi, they were not yet used with motion systems for simulators.

In order to enhance the control performance of the Stewart motion platform for realistic motion feeling, a model-based controller with perturbation estimation can be applied to the motion system, in addition to the rider’s net moment estimation. The net moment from the rider and model uncertainty is then regarded as an external perturbation to the Stewart motion platform model. Kim et al. proposed the sliding mode controller with perturbation estimator, which is a well-known model-based controller, for reduction of the low frequency tracking error associated with the perturbation dynamics. In this work, a similar sliding mode controller is adopted not only to enhance the robustness of the controlled system to external disturbances, but also to effectively estimate the perturbations. The rider’s net moment is estimated from each actuator control force and then transformed to the three moments, which can then be applied to the virtual bicycle dynamics and used for real time simulation. Unlike the net moments, however, accurate estimation, by using the proposed method, of the rider’s net linear forces to the bicycle frame is found to be difficult due to the high sensitivity in estimation to the model uncertainties. It has been well known, though, that the rider’s net linear forces, which normally do not play a significant role in virtual bicycle dynamics, are often ignored, implying that accurate estimation of the rider’s net forces becomes unimportant. This work thus focuses on the rider’s net moment estimation during normal cycling, of which frequency range is limited below 1.5 Hz. For the motion-based controller, the dynamic model of the Stewart platform including actuator dynamics is derived incorporated with both analytical and experimental methods. The experimental results show that the simulator rider’s net moments can be well estimated from the control forces of the motion system in the low frequency range and that the motion system gives a good tracking performance irrespective of the perturbation from the simulator rider.

2. BICYCLE SIMULATOR

2.1. Overview of KAIST Bicycle Simulator

The KAIST interactive bicycle simulator consists of a spring supported 6-DOF Stewart platform for motion feeling, haptic systems for reaction feeling through the handlebars and pedal, a visual system for dynamic images, and an audio system for three-dimensional sound realization. Figure 1 shows the bicycle, motion, and haptic systems and the coordinates system fixed on the moving platform of the Stewart platform such that the x-axis is aligned with the fore-going direction of the bicycle system, the z-axis is pointing upward, and the y-axis is defined according to the right-hand rule. The rider, while he is riding on the bicycle simulator, may attempt to control the Stewart motion platform on which the bicycle system is installed. He tilts his body to balance the bicycle and control its moving direction, while he is engaged with handling, pedaling, and braking, as if he were...
riding a real bicycle. Therefore, the rider’s net force/moment due to his body posture and movements has significant influence on the control forces of the Stewart platform.

Figure 2 shows the signal flow of the bicycle simulator. The rider gives the input force to the bicycle in response to the view generated by the visual system, and the handlebar and pedal reaction systems measure the handlebar angle, pedaling torque, and braking torque, while the motion platform estimates the rider’s net moment. Then, the acquired data are transferred to the virtual bicycle dynamics module, which calculates the location, speed, and reactions of the bicycle. The visual and motion cues and the reactive forces are then fed back to the rider. Especially, the motion cues are generated through a washout filter to overcome a limited motion range of the motion system.

2.2. Hardware and Software of the Motion System

The hardware of the motion system consists of a Stewart platform and its motion control system. The Stewart platform is made of moving and base platforms, six linear motion actuators, and a spring support system. In each actuator, an ac servomotor (maximum power: 200 W) equipped with a 3000-pulse encoder generates torque and rotational motion, and a linear ball-screw system (lead: 25 mm) converts the torque and rotational motion into the linear force (maximum rated force: 240 N; peak force: 720 N) and linear motion. To increase the static load capacity of the Stewart platform enough for the bicycle simulator, the spring support system is attached between the lower and upper platforms by a universal joint and a spherical joint, respectively. The linear coil spring with the spring constant of 690 N/m led to an increase of 410 N in the static load capacity.

The motion control system of the Stewart platform includes a personal computer (PC) with CPU of 750 MHz, a 12-bit D/A board, two 24-bit up–down counter boards with four channels and a 16-bit extension slot system for connecting a computer with add-on boards. The control commands, which are the desired torques, are calculated by the PC according to the control law that will be shown in Section 4.1, and then the D/A board converts the command signals to the control currents to drive the six ac servomotors. Each up–down counter functions to measure the instantaneous actuator length of each actuator using the encoder signal synchronized to the motor. The actuator velocities are calculated by the direct backward difference method, from the measured actuator lengths.

A model-based control strategy generally needs calculation of system dynamics at every sampling time. Since parallel manipulators such as Stewart platform have a very complex system dynamics that needs numerical forward kinematics, a multiprocessor has been used for a model-based control system design. Recently, the rapid development of computer systems, however, allows the whole control process, including the command generation, the data input/output and transfer, and the kinematics and dynamics calculation, to take place within the sampling time, say, 1 ms. In this work, a single PC unit with a real-time QNX O/S was found enough to form the control system, performing all required control routines within the sampling time of 1 ms. The QNX O/S provided periodic and one-shot timers, so that the feedback loop time can be precisely set.
3. MOTION SYSTEM MODELING

While the kinematics of parallel manipulators has been studied extensively during the last two decades, fewer works on the dynamics of parallel manipulators are available in the literature, since the associated dynamic equations are quite complicated due to the closed-loop structure and kinematic constraints and, moreover, its dynamic effect remains often insignificant. In recent years, the dynamics of parallel manipulators has attracted many researchers’ attention as the demand arises for the high speed, high frequency, and high precision motions. Several approaches have adopted the Newton–Euler and Lagrangian formulations, the principle of virtual work, and Kane’s equation.\(^{10-13}\) The principle of virtual work appears to be the most efficient analysis method, even though the concept of virtual work is not straightforward for the forward dynamics because of the complicated velocity transform between the joint and task spaces.

In order to design a model-based controller, the dynamic model of the spring-supported Stewart platform including actuator dynamics is derived incorporated with both analytical and experimental methods. The principle of virtual work is used to analytically formulate the dynamic equations of motion in order to increase the computational efficiency. The moments of inertia of the bicycle system and the dynamic parameters of the actuator such as the Coulomb friction and damping are experimentally obtained.

3.1. Dynamic Modeling of the Actuator System

The dynamic characteristics of the actuator system are very complex since the friction and damping forces vary depending upon the operating circumstance such as load condition. However, neglecting the electrical dynamics of the ac motor, its driver dynamics, and the flexibility of the actuator components, and leaving only the main effects in the actuator, the equivalent actuator inner dynamics can be modeled as

\[
\tau_a = m_{eq} \ddot{l} + c_{a,1} \dot{l} + c_{a,2} \text{sgn}(l) + \tau_e. \tag{1}
\]

Here, \(l\) is the actuator length and \(\tau_e\) is the actuating torque to drive the actuator system. The first term on the right-hand side denotes the inertia force, and the second and third terms represent the proportional damping and Coulomb friction forces, respectively. The last term corresponds to the remaining unmodeled force, which includes the torque ripple of the ac motor, plus the model uncertainties. The equivalent mass \(m_{eq}\) of the inner moving part in the actuator is estimated to be 10.8 kg. To experimentally obtain the values of \(c_{a,1}\) and \(c_{a,2}\), triangular wave motion with the time period of 5 s was commanded simultaneously to all actuators of the Stewart platform, when it is loaded with the 85 kg dead weight, representing the total mass of the bicycle system and rider, and then the control forces were observed. During the experiments with the triangular wave command, its amplitude was varied, which is equivalent to changing the up and down velocity of the actuator. The actuator systems tracked the command signal fairly well with the negligibly small actuator errors. Note that, during the piecewise constant speed test, the Stewart platform moves up and down at a constant absolute speed, trying to track the command signal. The inertia effect of the Stewart platform system including actuator systems can be neglected since the amplitudes of the given waves are kept small and the acceleration of the waves, except at the turning points, is nearly zero.

Figure 3 shows the typical measured actuator control forces, where the actuators extend (contract) during the time interval from 0 to 2.5 s (2.5 to 5 s) when the Stewart platform moves upward (downward). Note that the measured control forces in each time interval are characterized by a large mean value contaminated by fluctuating random errors with relatively small amplitude, irrespective of actuators. Figure 4 indicates the linear relation between the mean control force and the actuator speed with its moving direction. Since the difference between the mean control forces associated with the up and down motions

\[\text{control force N} \pm 0.006 \text{ m/s}.\]
of actuators at zero speed is due to the Coulomb friction, the coefficient $c_{s,1}$ is found to be 43.5 N. On the other hand, the slope indicates the proportional damping coefficient $c_{s,2}$, which is 1685 and 1603 Ns/m for the up and down motions, respectively.

### 3.2. Dynamic Modeling of a Spring-Supported Stewart Platform

If the virtual motion is admissible in the Stewart platform, i.e., it does not violate the kinematic constraints of the system, we can derive the equations given by

\[ l^* = J_p \dot{X}^*, \quad \omega^* = G_p \dot{X}^*, \quad v^*_s = H_j \dot{X}^* \]

for $ith$ actuator system,

\[ l_s^* = J_x \dot{X}^*, \quad \omega^*_s = G_s \dot{X}^*, \quad v^*_s = H_{ij} \dot{X}^* \]

for the spring support system,

\[ \omega^*_p = G_p \dot{X}^*, \quad v^*_p = H_p \dot{X}^* \]

for the moving platform,

where $i=1,2,...,6$, and $j=1,2$,

\[ l = [l_1 \quad l_2 \quad \cdots \quad l_6]^T, \]

\[ \dot{X}^T = [v_p^T \quad \omega_p^T] = [v_x \quad v_y \quad v_z \quad \omega_x \quad \omega_y \quad \omega_z]. \]

Here, the superscript $^*$ means the virtual motion; the subscripts $p$ and $s$ mean the moving platform and spring, respectively, and the subscript $j$ means the cylinder part ($j=1$) or piston part ($j=2$) of the actuator and spring support system; $l$ and $l_s$ are the actuator and spring velocity vectors; $X$ is the velocity vector of the Stewart platform centroid relative to the base platform, consisting of three linear velocity components, $v_x$, $v_y$, $v_z$, and three rotational velocity components, $\omega_x$, $\omega_y$, $\omega_z$, defined in the base platform fixed coordinates; and $J_p \in \mathbb{R}^{6 \times 6}$ and $J_s \in \mathbb{R}^{3 \times 3}$ are the Jacobian matrices of the Stewart platform and the spring system, respectively. We can derive the partial derivative matrices, $G_i$ and $H_{ij}$, of the actuator angular velocity, $\omega_i$, and linear velocity $v_{ij}$ vectors with respect to the velocity vector of the moving platform centroid, as

\[ G_i = \left[ \frac{\partial \omega_i}{\partial v_x} \quad \frac{\partial \omega_i}{\partial v_y} \quad \cdots \quad \frac{\partial \omega_i}{\partial \omega_z} \right], \quad i=1,2,...,6, \quad (3) \]

\[ H_{ij} = \left[ \frac{\partial v_{ij}}{\partial v_x} \quad \frac{\partial v_{ij}}{\partial v_y} \quad \cdots \quad \frac{\partial v_{ij}}{\partial \omega_z} \right], \quad i=1,2,...,6, \quad j=1,2. \quad (4) \]

Note that $\omega_i$ and $v_{ij}$ are defined in the actuator fixed coordinates. Similarly, the partial derivative matrices, $G_s$ and $H_{s,j}$, of the angular velocity, $\omega_s$, and linear velocity, $v_{sj}$, vectors of the spring support system with respect to the velocity vector of the moving platform centroid can be derived. Note that $\omega_i$ and $v_{sj}$ are defined in the spring support system fixed coordinates.

The moving platform, $G_p$ and $H_p$ can easily be derived from Eq. (2c), that is, $G_p = [0_{3 \times 3} \quad I_{3 \times 3}]^T$ and $H_p = [I_{3 \times 3} \quad 0_{3 \times 3}]^T$.

According to the virtual work principle, the sum of the virtual work done by all forces and moments should be zero in the virtual time interval $\delta t$ for the Stewart platform. Thus we have

\[
\{[f_s^*]^T \tau_p + [f_j^*]^T f_s\} \delta t + \sum_{i=1}^{6} \sum_{j=1}^{2} \left( [v_{ij}^*]^T R_{ij} \right) \delta t + \left( [\omega_i^*]^T T_p \right) \delta t + \sum_{j=1}^{2} \left( [v_{ij}^*]^T R_{ij} \right) + [\omega_i^*]^T T_s \\
+ [v_p^*]^T R_p + [\omega_p^*]^T T_p \delta t = 0, \quad (5)
\]
where $\mathbf{r}_p$ is the actuator force vector; $\mathbf{R}_{ij}$ and $\mathbf{T}_i$ are the resultant force and moment vectors exerted to the $i$th actuator including the inertia force and torque, respectively; $(\mathbf{R}_p, \mathbf{T}_p)$ are the resultant force and moment vector pairs that are exerted to the spring support system and the moving platform, respectively; and $f_s$ is the spring force. Substituting Eqs. (2)–(4) into Eq. (5), we can derive the actuator force vector as

$$
\mathbf{r}_p = -[\mathbf{J}_p^T]^{-1} \left[ J_p f_s + \sum_{i=1}^{6} \left\{ \sum_{j=1}^{2} (\mathbf{H}_{ij})^T \mathbf{R}_{ij} + [\mathbf{G}_j]^T \mathbf{T}_i \right\} + \sum_{j=1}^{2} ((\mathbf{H}_{ij})^T \mathbf{R}_{ij}) + [\mathbf{G}_j]^T \mathbf{T}_s + (\mathbf{H}_{ij})^T \mathbf{R}_p + [\mathbf{G}_p]^T \mathbf{T}_p \right].
$$

(6)

The above dynamics can be transformed through the complex manipulation to

$$
\mathbf{r}_p = \mathbf{M}_p(X) \dot{\mathbf{l}} + \mathbf{V}_p(X, \dot{X}) + \mathbf{G}_p(X) + \mathbf{F}_p(X),
$$

(7)

where $\mathbf{l} \in \mathbb{R}^{6 \times 1}$ is the actuator length vector; $\mathbf{M}_p \in \mathbb{R}^{6 \times 6}$ is the symmetric and nonsingular inertia matrix of the Stewart platform defined with respect to the actuator length coordinates; $\mathbf{V}_p \in \mathbb{R}^{6 \times 1}$ corresponds to the centrifugal and Coriolis force vector of the Stewart platform; $\mathbf{G}_p \in \mathbb{R}^{6 \times 1}$ is the gravity force vector of the Stewart platform; and $\mathbf{F}_p \in \mathbb{R}^{6 \times 1}$ denotes the spring force vector. The system properties of the Stewart platform with respect to its neutral position, when it is equipped with the bicycle and haptic systems, are given in the Appendix.

4. MOTION PLATFORM CONTROL AND ESTIMATION OF RIDER’S ACTION FORCE/MOMENT

4.1. Sliding Mode Controller with Perturbation Estimation

The derived total Stewart platform dynamics becomes, from Eqs. (1) and (7),

$$
\ddot{\mathbf{l}}(t) = \mathbf{f}(\mathbf{l}(t), \dot{\mathbf{l}}(t)) + \Delta \mathbf{f}(\mathbf{l}(t), \dot{\mathbf{l}}(t)) + [\mathbf{b}(l(t)) + \Delta \mathbf{b}(l(t))] \tau + \mathbf{d}(t),
$$

(8)

where $\mathbf{r} = \mathbf{r}_s + \mathbf{r}_p$, $\mathbf{f}$ is the nonlinear dynamic function vector, $\mathbf{b}$ is the control gain matrix (the inverse of the mass matrix), $\Delta \mathbf{f}$ and $\Delta \mathbf{b}$ are the perturbations of $\mathbf{f}$ and $\mathbf{b}$, respectively, and $\mathbf{d}$ denotes the external disturbance vector from the simulator rider. Equation (8) can be rewritten as

$$
\ddot{\mathbf{l}}(t) = \mathbf{f}(\mathbf{l}, \dot{\mathbf{l}}) + \mathbf{b}(\mathbf{l}) \tau + \mathbf{P}_E(\mathbf{l}, \dot{\mathbf{l}}),
$$

(9)

where the unknown actual perturbation vector, $\mathbf{P}_E$, becomes

$$
\mathbf{P}_E(\mathbf{l}, \dot{\mathbf{l}}) = \Delta \mathbf{f}(\mathbf{l}, \dot{\mathbf{l}}) + \Delta \mathbf{b}(\mathbf{l}) \tau + \mathbf{d}(t).
$$

(10)

The dynamic Eq. (9) may be divided into two parts: the modeled and perturbation parts, i.e.,

$$
\ddot{\mathbf{l}}_m(t) = \mathbf{b}(\mathbf{l}(t)) \tau_m(t) + \mathbf{f}(\mathbf{l}(t), \dot{\mathbf{l}}(t))
$$

(11)

$$
\ddot{\mathbf{l}}_p(t) = \mathbf{b}(\mathbf{l}(t)) \tau_p(t) + \mathbf{P}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t)).
$$

(12)

Here, $\mathbf{l} = \mathbf{l}_m + \mathbf{l}_p$, $\mathbf{l}_m = [l_{m1}, l_{m2}, \ldots, l_{m6}]^T$ and $\mathbf{l}_p = [l_{p1}, l_{p2}, \ldots, l_{p6}]^T$ are the actuator coordinate vectors associated with the modeled and perturbation dynamics, respectively, and $\tau_m$ and $\tau_p$ are the corresponding control force vectors.

If we let $\Phi(t) = -\mathbf{b}(l(t)) \tau_p(t)$, Eq. (12) becomes

$$
\ddot{\mathbf{l}}_p(t) = \mathbf{P}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t)) - \Phi(t).
$$

(13)

Provided that $\mathbf{P}_E$ can be estimated, the estimated part may be separated from the remaining part, i.e.,

$$
\mathbf{P}_E = \tilde{\mathbf{P}}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t)) + \Delta \mathbf{P}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t)),
$$

(14)

where $\tilde{\mathbf{P}}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t))$ is the estimated perturbation part and $\Delta \mathbf{P}_E(\mathbf{l}(t), \dot{\mathbf{l}}(t))$ is the residual part. Using Eq. (14), we can rewrite Eq. (9) as
\[ \bar{h}(t) = f(l(t), \dot{l}(t)) + b(l(t)) \tau + \bar{P}_E(l(t), \dot{l}(t), t) + \Delta P_E(l(t), \dot{l}(t), t). \]  
\[ (15) \]

For the system dynamics (15), a sliding mode controller with boundary layer can be derived as

\[ \tau = b^{-1}[I_d - \lambda \dot{e} - f - \bar{P}_E - K_s sat(s, s_0)], \]
\[ (16) \]

where \( I_d \) is the desired actuator length vector; \( \lambda \) represents the slope vector of sliding surface in the phase plane; \( e = I - I_d \) means the error vector; \( s = \dot{e} + \lambda \dot{e} \) denotes the sliding function; \( s_0 \) is the boundary layer thickness vector; \( K_s = \text{diag}(k_{r,1} \ldots k_{r,6}) \) where \( k_{r,j} \geq \max|\Delta P_{E,j}| \); \( sat \) is defined as

\[ sat(s, s_0) = \begin{cases} \text{sgn}(s) & \text{for } |s| \geq s_0, \\ s/s_0 & \text{for } |s| < s_0. \end{cases} \]
\[ (17) \]

The error dynamics of the system with the above controller can be derived as

\[ \dot{s}_j + \frac{k_{r,j}}{s_{0,j}} s_j = \Delta P_{E,j}. \]
\[ (18) \]

The error dynamics can also be transformed as

\[ \dot{l}_{r,j}(t) + a_{j1} l_{r,j}(t) + a_{j2} l_{r,j}(t) = \Delta P_{E,j}(t), \]
\[ (19) \]

where \( a_{j1} = \lambda_j + k_{r,j} / s_{0,j} \) and \( a_{j2} = \lambda_j k_{r,j} / s_{0,j} \).

Equation (13) implies that, as far as the designed controller works well, \( \Phi(t) \) can be an appropriate candidate for perturbation estimator. \( \Phi(t) \) and \( P_E \) contain high as well as low frequency components. But it becomes extremely difficult, if not impossible, to estimate the high frequency components of \( P_E \) by using \( \Phi(t) \). It suggests then use of a low pass filter. That is, if we use \( \Phi(t) \) as an estimator of \( P_E \), we can establish the relationship given by

\[ \bar{P}_E(l(t), \dot{l}(t), t) = \Phi(t). \]
\[ (20) \]

By using Eqs. (13), (19), and (20), we obtain

\[ \Phi_j(t) - \Phi_j(t) + a_{j1} \dot{l}_{r,j}(t) + a_{j2} \dot{l}_{r,j}(t) = 0. \]
\[ (21) \]

Since a first-order low-pass filter holds,

\[ \Phi_j(t) + \omega_{n,j} \Phi_j(t) = \omega_{n,j} \Phi_j(t), \]
\[ (22) \]

we obtain

\[ \Phi_j(t) = \omega_{n,j} \Phi_j(t). \]
\[ \Phi_j(t) = \omega_{n,j} \Phi_j(t). \]

Figure 5. Structure of the proposed controller with perturbation estimation.

\[ \dot{\Phi}_j = k_{p,j} \dot{\lambda} e_j + k_{p,j} h_j \int_{t_0}^{t} s_j \, dt. \]
\[ (23) \]

Here, \( k_{p,j} \) is the cutoff frequency, \( \omega_{n,j} \), of the low pass filter, and \( h_j = k_{r,j} / s_{0,j} \).

4.2. Estimation of Rider's Net Force/Moment

If the modeling errors, \( \Delta f \) and \( \Delta b \), are negligibly small compared with the disturbance induced by the rider, the rider’s net force/moment, \( F_R \), can be well estimated from the estimated perturbation in the \( j \)th actuator, \( \dot{\Phi}_j \), i.e.,

\[ \dot{F}_R = J^T b^{-1} \dot{\Phi}, \]
\[ (24) \]

where the estimated rider’s net force/moment vector \( \dot{F}_R = [\dot{F}_x \dot{F}_y \dot{F}_z \dot{M}_x \dot{M}_y \dot{M}_z]^T \). Here, \( \dot{M}_z \) is the rolling moment to the bicycle simulator, which plays the most important role, among six rider’s force/moment components, in the virtual bicycle dynamics. Figure 5 shows the structure of the proposed controller with perturbation estimation.

5. EXPERIMENT

Figure 6 shows the control flow of the Stewart platform. The command signal \((X_c)\) given in the operation coordinates is converted into the actuator length signal \((l_c)\) through the inverse kinematics. The forward kinematics and dynamics are calculated with the actuator lengths obtained from the six-channel counters. The mass matrix \((M)\), the centrifugal and Coriolis force vector \((V)\), and the gravity vector \((G)\) through the dynamics and the error signal as well as the established control gains are used for the sliding
mode controller. The calculated control signals drive
the motor driver through the D/A board. In the
course of control, the controller not only controls the
Stewart platform, but also estimates the external dis-
uturbance.

In the experiments for estimation of rider’s net
force/moment, the parameters of the controller (12)
were tuned based on the tracking performance and
the estimation range in frequency and estimation er-
ror of the perturbation as

\[
\lambda_i = 60 \text{ rad/s}, \quad s_{0,k} = 0.075 \text{ m/s},
\]

\[
k_{r,j} = 1.0 \text{ N/kg}, \quad k_{p,j} = 34.6 \text{ N}.
\]

First, in order to investigate the effect of the mod-
eling error of the Stewart platform on estimation of
the rider’s net forces and moments, the command sig-
na was given such that the motion system was ex-
pected to undergo a pure harmonic yaw motion of
0.02 \sin(2\pi t) rad with no external disturbances ex-
pressing the rider’s net force/moment. Figure 7
shows that the tracking errors associated with the lin-
ear and rotational motions are kept less than 0.1 mm
and 0.0004 rad, respectively. It suggests that the cur-
tent motion control system, capable of good tracking
performance, is adequate for bicycle simulator. Fig-
ure 8 indicates that, for no external disturbances, the
force estimation errors are less than about 10, 20,
and 30 N in the x, y and z directions, respectively, and
the estimated moment errors are less than about
7, 7, and 20 Nm in the roll, pitch, and yaw direc-
tions, respectively. Note that the estimation errors of
the forces and moments are strongly dependent upon
the nature of the commanded motion to the Stewart
platform. The estimation error of the yaw moment
disturbance becomes the largest when the yaw mo-
tion is commanded to the Stewart platform. It may be
concluded here that the proposed perturbation esti-
mator and the established model are acceptable for
the indirect measurement of the applied moments by
a bicycle simulator rider, since even the largest mo-
ment estimation error is considered to be far less in
magnitude than the actual moments, typically about
100 Nm, exerted by a simulator rider during normal
wheeling. The force estimation errors, although not
negligibly small, are not taken into consideration in
this work, because the linear forces normally do not
come into play in calculation of the virtual bicycle dy-
namics.

To simulate the typical tilt action from a rider, the
virtual roll moment disturbance, \(D_{M_z} = 100 \sin (1.0 \pi t) \text{ Nm}\), was given with the same yaw
command as before. In this way, the simulator was

expected to generate a harmonic yaw motion of 1 Hz, while it is disturbed by a harmonic roll moment of 0.5 Hz, which is most likely to be generated by a rider’s alternating tilt motion. Comparison of the tracking errors with and without harmonic roll moment disturbance, shown in Figures 9 and 6, respectively, indicates that all tracking errors remain almost unchanged, except the error associated with the roll motion, which becomes larger due to the nature of the disturbance. The roll error, however, is still kept less than 0.0004 rad so that the tracking performance is adequate even for the bicycle simulator subjected to disturbances generated by a rider. Figure 10 shows the estimated forces/moments under the given harmonic roll moment disturbance. The estimated forces/moments except the estimated roll moment are also similar to those in Figure 8, since the estimation errors are mainly due to the modeling errors. Figure 11 compares the actual and estimated roll moment disturbances, indicating that the latter lags the former by a time delay of about 50 ms. Such a small amount of time delay may be lead-compensated for more accurate estimation of disturbances in advanced simulators.14

In order to investigate the performance of the disturbance moment estimator, pitch and yaw moment disturbances were also given to the simulator while the harmonic yaw motion of 1 Hz was commanded as before, although they are less important in the virtual bicycle dynamics than the roll moment disturbance. Figure 12 (13) shows the estimated pitch (yaw) moment disturbance with the actual pitch (yaw) moment of 0.5 Hz with amplitude of 100 Nm. Note that the results in Figure 12 are similar in essence to those

Figure 9. Tracking errors: harmonic roll moment disturbance of 0.5 Hz.

Figure 10. Estimated forces/moments: harmonic roll moment disturbance of 0.5 Hz.

Figure 11. Actual and estimated roll moments: harmonic roll moment disturbance of 0.5 Hz.

Figure 12. Actual and estimated pitch moments: harmonic pitch moment disturbance of 0.5 Hz.
shown in Figure 11. On the other hand, the estimation error associated with the yaw moment, as shown in Figure 13, is significantly increased, due to the direct dynamic coupling between the yaw motion and the yaw moment disturbance.

And, in order to investigate the frequency response characteristics of the perturbation estimation, the harmonic yaw motion of 1 Hz was given as before, while the frequency of the harmonic roll moment disturbance with the amplitude of 100 Nm was varied from 0.1 to 3 Hz, simulating the rider’s tilt moment. Figure 14 shows the frequency response of the estimated roll moment, indicating that the phase attenuation is less than $20^\circ$ with insignificant magnitude attenuation in the frequency range below 1 Hz. The phase attenuation mainly comes from the lag characteristics of the perturbation estimator. It has been reported that simulator riders hardly tell the phase attenuation up to $20^\circ$. Therefore, the proposed estimator can be successfully applied to estimate the rider’s net moment of up to 1.0 Hz in a bicycle simulator.

Finally, Figure 15 shows a typical example of the roll moment estimated from the KAIST bicycle simulator. A simulator rider generated the roll moment during normal cycling while the Stewart platform was undergoing the harmonic yaw motion as before. The roll moment estimated through the proposed estimator can be used for improving calculation of virtual bicycle dynamics in order to make the bicycle simulator more realistic. Note that the estimated roll moment is up to about 200 Nm in magnitude and it is dominated by frequency components of less than 1 Hz.

6. CONCLUSION

In a bicycle simulator, a rider’s net moment significantly influences the bicycle motion, and thus the net moment should be accurately identified for realistic simulator operation. In this work, the control forces of the Stewart platform in the laboratory were used for the rider’s net moment identification. The dynamic model of the spring-supported Stewart platform including actuator dynamics was derived incorporated with both analytical and experimental methods. The sliding mode controller was used for tracking control of the motion system and disturbance estimation in the real time QNX O/S. It was shown that the simulator rider’s net moments can be well estimated from the control forces of motion system without any direct measurement and that the motion system gives a good tracking performance irrespective of the perturbation from the simulator rider.
7. APPENDIX

The calculated system properties in Eq. (7) of the Stewart platform with respect to its neutral position are as follows:

\[
\mathbf{M}_p = \begin{bmatrix}
120.9 & -75.8 & -17.9 & 16.6 & -17.7 & -3.3 \\
-75.8 & 120.8 & -3.4 & -17.8 & 16.7 & -17.7 \\
-17.9 & -3.4 & 120.9 & -75.8 & -17.8 & 16.6 \\
16.6 & -17.8 & -75.8 & 121.0 & -3.4 & -17.8 \\
-17.7 & 16.7 & -17.8 & -3.4 & 120.8 & -75.9 \\
-3.3 & -17.7 & 16.6 & -17.8 & -75.9 & 120.8
\end{bmatrix} \text{ kg,}
\]

\[
\mathbf{V}_p = \begin{bmatrix}
0.0 \\
0.0 \\
0.0 \\
0.0 \\
0.0 \\
0.0
\end{bmatrix} \text{ N,}
\]

\[
\mathbf{G}_p = \begin{bmatrix}
109.9 \\
109.9 \\
109.9 \\
109.9 \\
109.9 \\
109.9
\end{bmatrix} \text{ N,}
\]

and

\[
\mathbf{F}_s = \begin{bmatrix}
-74.5 \\
-74.5 \\
-74.5 \\
-74.5 \\
-74.5 \\
-74.5
\end{bmatrix} \text{ N.}
\]

REFERENCES