Abstract—Pose estimation of human motor skills such as bicycling in natural environments is challenging because of highly-dimensional human motion. In this paper, we present a dynamic rider/bicycle pose estimation scheme that can be used in outdoor environments. The proposed estimation scheme is based on the integration of the rider/bicycle dynamic model with the measurements from the force sensor and inertial measurement units (IMU). We take advantages of the attractive properties of both the force and IMU sensors in the design, that is, the force measurements do not suffer drifting while the IMU measurements generate real-time attitude and acceleration information. The rider/bicycle dynamic model provides an underlying relationship between the force and the IMU measurements. We demonstrate the effectiveness and performance of the pose estimation design through extensive bicycle riding experiments.

I. INTRODUCTION

Pose and gait estimation in personal activities benefit not only clinical analysis and diagnosis [1], but also provide tools to understand human sensorimotor mechanisms and their interactions with machines and environment. Pose estimation of human motor skills in physical human/machine interactions such as bicycling in natural environments is challenging because of the highly-dimensional and redundant musculoskeletal structures and complexity of human/machine interactions. The goal of this paper is to present a real-time estimation scheme to simultaneously predict rider trunk and bicycle poses in outdoor environments.

We choose rider/bicycle interactions as a human motor skill example for several reasons. An everyday transportation means and recreational sport, bicycles offer an excellent platform to study physical human/machine interactions. Unlike commonly studied biped walking and quiet stance, rider/bicycle interactions are through multiple contacts at the handlebar, the seat and the pedals. The multi-contact interactions result in challenges but also provide new features in pose estimation. Sitting on the unstable platform, riders have to actively react to the sensory feedback through body movement for balancing and navigation. Therefore, bicycles also provide a superior platform for studying coupled human sensorimotor functions with machines than quiet stance.

Recently, many studies are reported for human/bicycle interactions. In [2], a rider/bicycle simulation model is presented and compared with experiments. The human trunk is considered as a point mass connected to the bicycle. In [3], [4], rider’s trunk movement is modeled as an inverted pendulum mounted at the bicycle seat. Similar treatments are used in biomechanics for studying quiet stance (e.g., [5]–[8]). The human steering models are also discussed in [9], [10]. Although all the models try to simulate and explain human riding behaviors, no theoretical work could directly reveal how a rider actually controls the bicycle through steering and trunk movement [10].

To fully understand the human motion in natural environment, an accurate motion sensing system is critical. The optical-, acoustic-, or magnetic-based tracking systems are either limited to indoor usage within a confined space or easily interfered by environment. Wearable sensors have been extensively used for human pose estimation for movement sciences, biomechanics and clinical applications [11]–[15]. However, all of the work mainly deal with human walking or standing studies. In this paper, we use force measurements in physical human/machine interactions and integrate with inertial sensors for bicycle riding motion estimation.

We use extended Kalman filter (EKF) design to integrate the force sensors with the inertial measurement units (IMU) to estimate rider/bicycle poses. The multiple rider/bicycle contact forces provide information about human motion and these force measurements do not suffer significant drifting that IMUs have. On the other hand, IMU measurements provide direct information about human motion. We take advantages of the attractive properties of both the force and IMU sensors and use the rider/bicycle dynamic model to build the underlying relationships between the forces and the inertial measurements. Compared with our previous work in [4] in which only stationary case is considered, we here consider general bicycle riding motions and dynamic effects.

The main contributions of this work are twofolds. First, we build the IMU kinematic model and the force measurement model to describe the physical multi-contact features in rider/bicycle interactions. We also present a new model that captures the rider/bicycle dynamic interactions. Such developments provide a new modeling framework to study other highly dynamic physical human/machine systems that involve forceful and energetic interactions. Second, the new human pose estimation scheme relies only on the human wearable sensors and onboard bicycle sensors and therefore, it can be potentially used for human gait study in other daily activities or surroundings.

The rest of the paper is organized as follows. We first present the instrumented bicycle system, the IMU model and the rider/bicycle dynamic model in Section II. The force sensor model and the EKF design are presented in Section III. Experimental results are demonstrated in Section IV before...
we conclude the paper in Section V.

II. RIDER/BICYCLE INTERACTION AND DYNAMICS

A. Instrumented bicycle system

Fig. 1(a) shows the instrumented bicycle system. The platform is modified from a commercial mountain bike. The bicycle is instrumented by various sensors. The rider’s movement is captured by the camera-based motion sensing systems (8 Bonica cameras from Vicon Inc.) One IMU sensor (from Motion Sense Inc.) is placed at the back of the human rider and another IMU is attached to the bicycle’s main frame. The IMU sensors have tri-axis gyroscopes and tri-axis accelerometers. A 6-DoF seat force/torque sensor (from JR3 Inc.) is mounted along the seat supporting rod. Moreover, three load cells are installed inside the customly-built bicycle seat to measure the sitting force distribution. An optical encoder is mounted on the rear wheel to measure the bicycle speed. Stain gauges are installed on the bicycle handlebar to measure the handling forces. A real-time CompactRIO system (from National Instruments Inc.) collects all sensor measurements at the sampling rate of 50 Hz.

B. IMU model

Fig. 1(b) shows the schematic of the rider/bicycle system. The rider’s trunk is modeled as an inverted pendulum. A ground-fixed inertial frame \( \mathcal{I} (X, Y, Z) \) is defined with the \( Z \)-axis downwards. A moving frame \( \mathcal{R} (x, y, z) \) is defined with the \( x \)-axis along wheel-ground contact points \( C_1 \) and \( C_2 \), the \( z \)-axis along the \( Z \)-axis, and the origin at \( C_2 \). The bicycle roll and yaw angles are denoted as \( \varphi_b \) and \( \psi \), respectively. A bicycle-fixed frame \( \mathcal{B} (x_b, y_b, z_b) \) is defined by rotating frame \( \mathcal{R} \) with \( \varphi_b \) about the \( x \)-axis; see Fig. 1(b). The IMU on the bicycle frame is tilted by angle \( \alpha \) with respect to the \( x_b \)-axis. Let \( \mathcal{I}_h \) and \( \mathcal{I}_b \) denote the rider and bicycle IMU frames, respectively. The orientation of the trunk is defined by three Euler angles with the \( X-Y-X \) ordered rotation from frames \( \mathcal{R} \) to \( \mathcal{I}_h \): roll angle \( \varphi_h \) around the \( x \)-axis, angle \( \theta \) around the \( y \)-axis, and finally self-spinning angle \( \phi \) around the \( x \)-axis. The generalized coordinates for the trunk and the bicycle are denoted as \( \mathbf{q}_h = [\varphi_h, \theta, \phi]^T \) and \( \mathbf{q}_b = [\varphi_b, \psi]^T \), respectively. We also define \( \mathbf{q} = [\mathbf{q}_h^T, \mathbf{q}_b^T]^T \).

1) Gyroscope model: The bicycle IMU gyro measurements are obtained as

\[
\dot{\mathbf{q}}_b = \mathbf{f} (\mathbf{q}_b; \mathbf{\omega}_b) = \begin{bmatrix} \dot{\varphi}_b \\ \dot{\theta} \\ \dot{\phi} \end{bmatrix} = R_y^T (\alpha) R_x^T (\varphi_b) \begin{bmatrix} 0 \\ \dot{\varphi}_b \\ \dot{\psi} \end{bmatrix} \]

where \( R_i (\beta) \) represents rotational matrix around \( i \)-axis for angle \( \beta, i = x, y, z \). Similarly, it is straightforward to obtain the rider IMU gyro measurements \( \mathbf{\omega}_h = [\omega_{hx}, \omega_{hy}, \omega_{hz}]^T \) as

\[
\dot{\mathbf{q}}_h = \mathbf{f} (\mathbf{q}_h; \mathbf{\omega}_h) = \begin{bmatrix} \dot{\varphi}_h \\ \dot{\theta} \\ \dot{\phi} \end{bmatrix} = R_x^T (\phi) R_y^T (\theta) R_z^T (\varphi_h) \begin{bmatrix} 0 \\ \dot{\psi} \end{bmatrix} \]

Combining (1) and (2), we obtain rider and bicycle attitude kinematic equations, respectively, as follows.

\[
\dot{\mathbf{q}}_h = \mathbf{e} (\mathbf{q}_h; \mathbf{\omega}_h) = \begin{bmatrix} c_{\varphi_h} s_{\varphi_h} \\ c_{\varphi_h} c_{\varphi_h} \\ \frac{c_{\varphi_b} c_{\varphi_b} + s_{\varphi_h} s_{\varphi_b}}{c_{\varphi_h}} \end{bmatrix} \begin{bmatrix} \frac{s_{\varphi_h}}{c_{\varphi_h}} \\ \frac{c_{\varphi_h}}{c_{\varphi_h}} \\ 1 \end{bmatrix} \mathbf{\omega}_h
\]

\[
\dot{\mathbf{q}}_b = \mathbf{e} (\mathbf{q}_b; \mathbf{\omega}_b) = \begin{bmatrix} 0 \\ 0 \\ c_{\varphi_b} s_{\varphi_b} \end{bmatrix} \begin{bmatrix} c_{\varphi_b} & 0 & -s_{\varphi_b} \\ 0 & \frac{s_{\varphi_b}}{c_{\varphi_b}} & \frac{c_{\varphi_b}}{c_{\varphi_b}} \\ -\frac{s_{\varphi_b}}{c_{\varphi_b}} & \frac{c_{\varphi_b}}{c_{\varphi_b}} & \frac{s_{\varphi_b}}{c_{\varphi_b}} \end{bmatrix} \mathbf{\omega}_b
\]
2) Accelerometer model: In frame $B$, we denote the position vector of the bicycle IMU as $r_{bI} = [p_x \ 0 \ -p_z]^T$, where $p_x$ and $p_z$ are the horizontal and vertical distances from the bicycle IMU location to point $C_2$, respectively. The angular velocity of bike in $R$ is $\omega = [\psi]^T$. Considering the nonholonomic constraint at $C_2$, i.e., $\dot{v}_{ry} = a_{ry} = 0$, the acceleration vector of $C_2$ in $R$ is then $\ddot{r}_{bC_2} = [\dot{v}_{rx} \ 0 \ \dot{v}_{rz}]^T$, where $q$ is the gravitational constant and $\dot{v}_{rx}$ is the longitudinal acceleration of $C_2$. The bicycle IMU accelerometer measurements $a_b = [a_{bx} \ a_{by} \ a_{bz}]^T$ in $I_b$ are then calculated as
\begin{equation}
\ddot{r}_b = \frac{d}{d^n} R_T \left[ \frac{\ddot{r}_{bC_2} + \omega \times \omega b \times B \ R_{bI} + \omega b \times B \ R_{tI}}{\omega b \times B \ R_{tI}} \right],
\end{equation}
where $\frac{d}{d^n} R = R_x(\varphi_b)$ and $\frac{d}{d^n} R_T = R_y(\alpha) R_x(\varphi_b)$ are the rotational matrices from $R$ to $B$ and $I_b$, respectively. The final calculation results of $a_b$ are shown in (6) on the top of the next page.

It is clear to see that in the $a_{by}$ and $a_{bz}$ formulations in (6), the coefficients of $\dot{v}$ are approaching to zero when $\varphi_b$ is near zero. Therefore, the accelerometer in bicycle IMU is not able to be used to differentiate $\dot{v}$ and $\dot{\varphi}_b$ simultaneously when the roll angle is around zero. In this work, we take the fact that the mean of $\dot{\varphi}_b$ must be around zero during normal bicycle riding. Thus, we approximate $\dot{\varphi}_b \approx 0$. From the $a_{by}$ component in (6), we obtain $\dot{v}$ in $I_b$ by the accelerometer measurements as follows.
\begin{equation}
\dot{v} = g_1(a_b) = \frac{a_{by} - s_{\varphi_b} p_x}{p_x c_{\varphi_b}} \dot{\psi} - \frac{s_{\varphi_b}}{p_x c_{\varphi_b}} \dot{\varphi}_b - \frac{s_{\varphi_b} \dot{\varphi}_b}{c_{\varphi_b} p_x},
\end{equation}
The seat position vector in $B$ is $r_{s} = [l_s \ 0 \ -h_s]^T$. Similar to (5) for obtaining the IMU acceleration, it is straightforward to calculate the seat acceleration $\omega_s$. To make calculation tractable, the angular velocity of human trunk in $R$ is approximated as $\omega_s = [\dot{\varphi}_h \ c_{\varphi_h} \ 0]^T$. We denote the position vector of rider IMU in $I_b$ as $r_{bI} = [h_0 \ 0 \ 0]^T$ with respect to seat, where $h$ is the distance from rider IMU to the seat. Then, the rider IMU accelerometer measurements $a_{h} = [a_{hx} \ a_{hy} \ a_{hz}]^T$ is calculated similar to (5). After re-organizing the calculation of $a_{hy}$ and $a_{hz}$, we obtain the formulation for obtaining the rider attitude acceleration in terms of IMU acceleration measurements as shown in (8) on the top of the next page.

With (7) and (8), it is straightforward to see that the accelerometer measurements $a_{hx}$ and $a_{hy}$ can provide the attitude accelerations $\dot{\varphi}_h$, $\dot{\theta}$ and $\dot{\psi}$.

C. Rider-bicycle dynamic model
We consider the rider/bicycle system as three parts: the bicycle rear frame, the human trunk with mass $m_h$, and the steering part. The distance between the human trunk mass center $H$ and the seat is $h_s$, see Fig. 1(b). We denote the position of bicycle mass center $G$ as $r_{bG} = [l_b \ 0 \ -h_b]^T$ in $B$, where $l_b$ and $h_b$ are the horizontal and vertical distances from $C_2$ to $G$, respectively. Comparing with other modeling developments in [16], we here do not consider the steering effect since it is negligible for pose estimation. Using the Lagrange’s equation, we obtain the equations of motion for the rider as
\begin{equation}
M_h(q) \ddot{q}_h + C_h(q, \dot{q}_h, \ddot{q}_h, v_r, \dot{v}_r) + G_h(q) = \tau_h,
\end{equation}
where matrices $M_h$, $C_h$ and $G_h$ are given in (10) on the top of the next page. The input $\tau_h = [r_{\tau_h}, \tau_0]^T$ represents the torques to drive human trunk. For the purposes of pose estimation, we here do not consider the bicycle moving dynamics that govern the translational motion in the horizontal plane. The bicycle’s forward velocity will be measured by the wheel encoders and therefore, we assume that $v_{rx}$ and $\dot{v}_{rx}$ are known. A detailed discussion of bicycle dynamics can be found in [17].

III. Pose estimation
A. Force/torque sensor model
The rider/bicycle force and torque interactions are complicated due to multiple contacts at the seat, the handlebar, and the pedals. The pedaling movement is relatively separated with the trunk and upper-limb motion and the pedaling forces are also reflected on the bicycle seat force measurements. We thus only consider the forces acting on the bicycle seat and the handlebar.

The interaction between the hip and the bicycle seat is a surface contact. We use the center of pressure (CoP) on the seat to capture the contact. We design and fabricate a special seat as shown in Fig. 2. We install three load cells right underneath the seat cover to measure the CoP location. In addition, we also install a 6-DoF force/torque sensor on the seat supporting rod to obtain the resultant total forces and torques.

Let $R_h = [R_x \ R_y \ R_z]^T$ and $M_h = [M_x \ M_y \ M_z]^T$ denote the forces (acting at the CoP) and torques between the rider and the seat in frame $S_t$, respectively. Frame $S_t$ has same orientation as $R$ with the origin at the intersection of seat rod and the seat surface; see Fig. 2(a). Let $F_s = [F_x \ F_y \ F_z]^T$ and $T_s = [T_x \ T_y \ T_z]^T$ denote the sensed forces and torques by the seat force sensor (in sensor frame $S_t$), respectively. We obtain the following relationship between $S_t$ and $S_r$
\begin{equation}
\begin{bmatrix}
R_h \\
M_h
\end{bmatrix} = \begin{bmatrix}
S_{rI} R & \mathbf{0} \\
S_{rI} R & \mathbf{0}
\end{bmatrix} \begin{bmatrix}
F_s \\
T_s
\end{bmatrix},
\end{equation}
where $S_{rI} = R_y(\gamma)$ is rotational matrix from frames $S_t$ to $S_r$. The skew-symmetric matrix $S(r_c)$ is given as
\begin{equation}
S(r_c) = \begin{bmatrix}
0 & -r_z & r_y \\
-r_z & 0 & r_x \\
r_y & -r_x & 0
\end{bmatrix},
\end{equation}
where $S(r_c) = [r_x \ r_y \ r_z]^T$ is the position vector of the force sensor in $S_t$ with respect to the CoP.
From Fig. 2(a), we obtain $r_s = L_1 c_{\gamma}$, where $L_1$ is the length of rod between sensor frame and seat. Since the CoP location varies, $r_x$ and $r_y$ are not fixed. The force measurements from the three load cells provide the estimate.
Therefore, we obtain \( \tau \) \( \text{force/torque transformation.} \)

\[
\begin{align*}
\alpha_b &= \left[ c_\alpha \, \dot{v}_x + \left( c_\alpha \, c_{\phi_b} \, p_z - s_\alpha \, c_{\phi_b} \, p_x \right) \dot{v}_y \dot{\phi}_b + \left( s_\alpha \, s_x^2 \, p_z - c_\alpha \, p_x \right) \dot{v}_x^2 + s_\alpha \, p_x^2 \dot{\phi}_b^2 + \left( c_\alpha \, s_{\phi_b} \, p_z + s_\alpha \, s_{\phi_b} \, p_x \right) \dot{v}_y - s_\alpha \, c_{\phi_b} \, g \right] \\
&\quad \mp c_{\phi_b} \, s_{\phi_b} \, \psi \, \dot{\phi}_b + c_{\phi_b} \, p_x \, \dot{v}_y - p_x^2 \, \dot{\phi}_b + s_{\phi_b} \, g \\
&\quad s_\alpha \, \dot{v}_x + \left( s_\alpha \, c_{\phi_b} \, p_z + c_\alpha \, c_{\phi_b} \, p_x \right) \dot{\phi}_b - \left( s_\alpha \, s_x^2 \, p_z - c_\alpha \, p_x \right) \dot{v}_x^2 - s_\alpha \, p_x^2 \dot{\phi}_b^2 + \left( s_\alpha \, s_{\phi_b} \, p_z - c_\alpha \, s_{\phi_b} \, p_x \right) \dot{v}_y + s_\alpha \, c_{\phi_b} \, g
\end{align*}
\]

(6)

\[
\begin{bmatrix}
\dot{\phi}_b \\
\dot{\theta}
\end{bmatrix} = 
\begin{bmatrix}
\frac{1}{h} \, \frac{a_h \, s_h + s_{\phi_b} \, c_{\phi_b} \, \psi \, \dot{v}_y}{c_{\phi_b} \, \dot{\phi}_b^2} - \frac{s_{\phi_b} \, \dot{v}_y}{c_{\phi_b} \, \dot{\phi}_b} - \frac{c_{\phi_b} \, \dot{\phi}_b}{c_{\phi_b} \, \dot{\phi}_b} + \frac{c_{\phi_b} \, \dot{\phi}_b}{c_{\phi_b} \, \dot{\phi}_b} - \frac{c_{\phi_b} \, \dot{\phi}_b}{c_{\phi_b} \, \dot{\phi}_b} - \frac{c_{\phi_b} \, \dot{\phi}_b}{c_{\phi_b} \, \dot{\phi}_b}
\end{bmatrix}
\begin{bmatrix}
\omega_a \\
\omega_b
\end{bmatrix} - \frac{s_{\phi_b} \, \dot{v}_y}{c_{\phi_b} \, \dot{\phi}_b} + \frac{s_{\phi_b} \, \dot{v}_y}{c_{\phi_b} \, \dot{\phi}_b}
\]

(8)

of CoP locations; see Fig. 2(b). We denote the measurements of the three load cells as \( P_1, P_2, P_3 \), respectively. Then, the location \((x_C, y_C)\) of the CoP in \( S_i \) is estimated by

\[
x_C = \frac{P_1}{P_1 + P_2 + P_3} \, L_x - L_m, \quad y_C = \frac{P_2 - P_3}{2(P_1 + P_2 + P_3)} \, L_y,
\]

where \( L_x \) and \( L_y \) are the \( x \)- and \( y \)-axis directional distances between the front and rear load cells, respectively, and \( L_m \) is the \( x \)-axis distance between \( B \) and rear two load cells. Therefore, we obtain \( \{x_C, L_1, s_y, -y_C, L_1, c_y\}^T \).

Fig. 2. Force/torque sensor model. (a) A schematic of bicycle seat force/torque transformation. (b) The CoP calculations through three load cell-measured forces.

We now consider to estimate the rider applied torques \( \tau_{\phi_b} \) and \( \tau_\theta \) from the force sensor measurements. To capture the sitting position variations among different riders, we define the CoP location \( \mathbf{r}_V = [x_V, y_V]^T \) in \( S_i \) when the truck is upright. As shown in Fig. 3(a), along \( \psi_b \) direction, \( \tau_{\phi_b} \) is estimated by the force sensor measurements as

\[
\dot{\tau}_{\phi_b} = -M_x - R_z (y_C - y_V).
\]

(12)

Along the \( \theta \) direction, the handlebar forces also contribute the torque that drives the trunk motion. If neglecting the arm dynamics and steering effect, we can treat the arms like rigid links between the handlebar and the rider’s trunk. With this treatment, the estimated torque \( \dot{\tau}_\theta \) is approximated as

\[
\dot{\tau}_\theta = -M_g + F_{hx} \, D_z + F_{hz} \, D_x - R_z (x_C - x_V),
\]

where \( F_{hx} \) and \( F_{hz} \) are the resultant reaction forces on two sides of the handlebar along the \( x_b \)- and \( z_b \)-axis directions, respectively, and \( D_x \) and \( D_z \) are the horizontal and vertical distances from the handlebar to seat, respectively. Finally, we use the force sensor measurements to estimate bike roll angle by the following equation [4]

\[
\dot{\phi}_b = \tan^{-1} \left( \frac{R_y}{R_z} \right).
\]

(14)

B. Extended Kalman filter design

Fig. 4 shows the EKF design structure. The EKF system dynamics are built on the IMU kinematic model. The rider-bicycle dynamic model is used as output equations to bridge
the EKF state variables with the force sensor model. The IMU accelerometer model provides the attitude acceleration calculations to the rider-bicycle dynamic model.

![Diagram](image)

Fig. 4. The structural and information flow diagram of the EKF design.

We define the state variable for EKF as

$$X(t) := [\varphi_h, \theta, \phi, \varphi_b]^T \in \mathbb{R}^4.$$  

Bicycle yaw angle $\psi$ is not considered as a part of the state variables because the bicycle yaw motion is not a relative motion between the rider and the bicycle. We define a kinematic function vector $f_x(X; \omega_h, \omega_b) := [f(q_h; \omega_h, \omega_b)]^T$, where $f(q_h; \omega_h, \omega_b)$ is obtained from (3) and $e_1(X; \omega_h)$ is the first element of $e(q_h; \omega_h)$ in (4). We rewrite the kinematics $f_x$ in a discrete-time form as

$$X(k) = X(k-1) + \Delta T f_x(X(k-1), u(k-1)),  \quad (15)$$

where $u(k) := [\omega_h^T(k), \omega_b^T(k)]^T$ is the IMU gyro measurements at the kth step, $\Delta T$ is the data sampling period.

To obtain the output equation and for presentation clarity, a group of auxiliary variables are introduced

$$W_v(k) = \begin{bmatrix} \dot{\varphi}_h(k) \\ \dot{\psi}(k) \\ \dot{\varphi}_h(k) \\ \dot{\theta}(k) \\ \dot{\phi}(k) \\ \dot{\varphi}_b(k) \\ v_{rx}(k) \\ v_{rz}(k) \end{bmatrix}^T \in \mathbb{R}^9.$$  

$W_v(k)$ is obtained through the relationships given by (3), (4), (7), (8) and measurements by IMUs and wheel encoders for $v_{rx}(k)$ and $v_{rz}(k)$.

For EKF outputs, the estimates $\hat{\tau}_{\varphi_b}$ and $\hat{\tau}_h$ are obtained from the force sensors as described in (12) and (13). Furthermore, we use (9) to capture the output equation of $\tau_{\varphi_b}$ and $\tau_h$. The estimated $\hat{\varphi}_b$ is obtained by (14) as another measurement. Finally, we take the fact that the rider always tries to keep his/her head upright when riding bicycle, and a virtual constraint is then obtained among the trunk orientation angles, namely,

$$s_c = s_{\varphi_h} c_\phi + c_{\varphi_h} s_\phi s_\psi = 0.  \quad (16)$$

Thus, the EKF output equation is

$$y(k) = h(X(k), W_v(k)) + n_y(k) = \begin{bmatrix} \tau_{\varphi_b}(k) \\ \tau_h(k) \\ s_c(k) \\ \varphi_b(k) \end{bmatrix} + n_y(k)  \quad (17)$$

where the first two elements of $h(X(k), W_v(k))$ are given by (9) and $n_y(k) \sim N(0, \sigma_y) \in \mathbb{R}^4$ is the white noise vector with variance matrix $\sigma_y$. An EKF design is applied to the system (15) and (17). A similar design is given in [18] and we omit the details here.

**IV. EXPERIMENTS**

Five healthy and experienced bicycle riders (four male and one female with age: 27 ± 3 years, height: 176 ± 4 cm, and weight: 70 ± 7 kg) were recruited to conduct the experiments. When they ride the bicycle, the subjects were asked to move their upper bodies arbitrarily in experiments. The duration for each riding experiment was around 2 minutes. All the subjects gave their informed consent before being tested using a protocol approved by the Institutional Review Board (IRB) at Rutgers University. The values of the rider-bicycle systems are listed in Table I.

![Graph](image)

Fig. 5. Comparison result of $\varphi_b$ by the vision capturing systems, the EKF estimates, and the integrations of IMU measurements for Subject #1.

Due to the page limit, only the trunk pose estimation for Subject #1 is shown in Fig. 5. For comparison purposes, we also plot the pose estimate of $\varphi_b$ by integrating the IMU gyro measurements by (3) and (4). The motion capturing data is considered the ground truth. It is clearly seen that this subject tried to move his trunk aggressively in the experiment. The EKF-based estimation result clearly demonstrates a better tracking performance than that by the IMU integration. The estimate by direct IMU integration diverges quickly after 50 s as shown in Fig. 5, while the EKF-based posture estimate consistently matches the ground truth.

To further demonstrate the performance of the EKF-based design, we compute the statistics of the posture estimation errors for all subjects. Table II shows the accuracy performance in terms of the mean and standard deviation (SD) of root mean square (RMS) errors for all subjects. Fig. 6 shows the calculated errors over time for all subjects. The
For example, the calculated torques ̂τ from imperfect models for IMU measurement noises, the interactions between the legs and the trunk. Measurement error by the Vicon motion capturing system is another error source.

The EKF pose estimation errors are mainly due to the imperfect models for IMU measurement noises, the interaction forces, and the complicated rider-bicycle interactions. For example, the calculated torques ̂τ}_h and ̂τ}_θ in (12) and (13) do not consider the articulated arm dynamics and the interactions between the legs and the trunk. Measurement error by the Vicon motion capturing system is another error source.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a rider/bicycle dynamic modeling and the pose estimation scheme by using wearable sensor measurements. The proposed scheme was built on the dynamic model and the integrated force/IMU measurements. An EKF-based estimation approach was used to fuse the two IMU measurements with the force/torque sensor measurements. We demonstrated and validated the performance of the proposed pose estimation scheme through extensive bicycle riding experiments.

We are currently working on improving and extending the estimation by consideration of upper-limb and lower-limb movements in bicycling. Outdoor experiments and experiments by various subjects are also among ongoing research.

TABLE I
THE RIDER-BICYCLE MODEL PARAMETERS

<table>
<thead>
<tr>
<th>(\alpha) (deg)</th>
<th>(\gamma) (deg)</th>
<th>(g) (m/s^2)</th>
<th>(l_x) (m)</th>
<th>(l_y) (m)</th>
<th>(l_z) (m)</th>
<th>(L_1) (m)</th>
<th>(L_2) (m)</th>
<th>(L_3) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>20</td>
<td>9.8</td>
<td>0.26</td>
<td>0.38</td>
<td>0.06</td>
<td>0.37</td>
<td>0.71</td>
<td>0.13</td>
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</table>

TABLE II
THE MEAN AND STANDARD DEVIATION (SD) (IN DEGS) OF ROOT-MEAN-SQUARE (RMS) ERRORS FOR ALL SUBJECTS

<table>
<thead>
<tr>
<th>(\varphi_h)</th>
<th>(\theta)</th>
<th>(\phi)</th>
<th>(\varphi_b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.73 ± 1.46</td>
<td>1.84 ± 1.09</td>
<td>5.81 ± 1.42</td>
<td>0.84 ± 0.35</td>
</tr>
</tbody>
</table>

Fig. 6. Posture estimation errors from the EKF-based design. The solid lines indicate the mean values of the errors of all subjects and the dashed lines are one-standard deviation (SD) bounds.

estimation errors are all around zero and do not grow over time. The results shown in Table II and Fig. 6 demonstrate the consistently robust performance of the estimated trunk and bicycle postures by the EKF-based sensing fusion.

The EKF pose estimation errors are mainly due to the imperfect models for IMU measurement noises, the interaction forces, and the complicated rider-bicycle interactions. For example, the calculated torques ̂τ}_h and ̂τ}_θ in (12) and (13) do not consider the articulated arm dynamics and the interactions between the legs and the trunk. Measurement error by the Vicon motion capturing system is another error source.

REFERENCES