Identification of manual control employed during bicycling

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Introduction

When balancing and directing a bicycle the human rider senses his or her motion and the environment and then actuates the body to cause the bicycle to travel in the desired direction. This requires both stabilization, as the bicycle-rider system is, in general, an unstable system, and path following. The most effective control input for controlling a bicycle under typical operation is to apply forces to cause the front frame to rotate about the steering axis. But riders are also capable of using other body motions to enable control of a bicycle. It is possible to predict the control actions of the rider using manual control theory but there have been few attempts to do so while controlling bicycles or motorcycles.

We have collected a large set of time history data from an instrumented bicycle which includes the most important kinematic and kinetic variables to describe the bicycle-rider motion from three different riders on the same bicycle for a variety of speeds. Furthermore, the instrumented bicycle was designed so that the riders were not able to move their legs or torso relative to the rear frame of the bicycle, to ensure that the assumption of rider rigidity of the Whipple bicycle model was as close to valid as possible and to enforce a single control input from the rider. In the experiments we perturbed the bicycle-rider system with an externally applied lateral force and measured the rider's response.

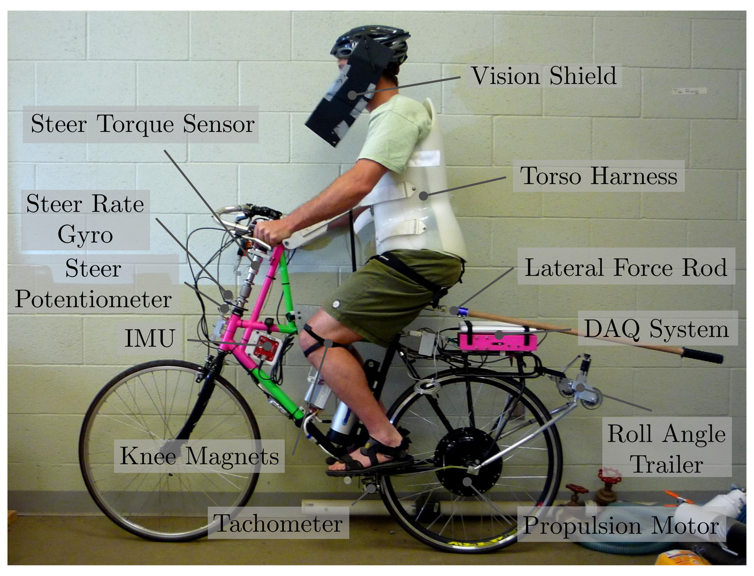

Figure : (3) Instrumented bicycle.

With the single-input multi-output data set in mind we formulate an 8th order grey box state space model [1] in the directly parameterized innovations form. The model is made up of the plant and the controller. Due to the poor predictive ability of the Whipple bicycle model we make use of a bicycle-rider system model identified from a larger superset of the data used here [2]. We combine this model with a 2nd order model of the rider's neuromuscular system to form the plant. The controller structure is taken from [3] which uses five gains nested in sequential feedback loops each simulating realistic sensory cues used by the rider.

We then identify the unknown controller gains for each of the runs using the prediction error method, giving system models that predict the state trajectories with an average of 62 ± 12 percent of the variance accounted (VAF) for over all the identified runs. The resulting models are then analyzed and shown to hold well to the manual control theory presented in [3].

Continuous Control Model

We bounded our controller identification to the controller design hypothesized in [3]. The control structure was designed to meet these requirements:

- Roll stabilization is the primary task, with path following in the outer loops. The system should be stable in roll before closing the path following loops.
- The input to the bicycle and rider biomechanic model is steer torque. The neuromuscular mode of the closed system should have a natural frequency around 10 rad/s to match laboratory tracking tasks of a human operator.
- The system should be simple. In our case, only simple gains are needed to stabilize the system and close all the loops.
- We should see evidence of the crossover model in the open loop roll, heading, and lateral deviation loops.

The multi-loop model we use is constructed with a sequential loop closure technique that sets the model up to follow the dictates of the crossover model [4]. The three inner loops, 2a, manage the roll stabilization task with steer angle δ, roll rate $\dot{\phi}$, and roll angle ϕ feedback. The outer two loops, 2b, manage the path following with heading and lateral deviation feedback. We include a simple second order model of the human's open-loop neuromuscular dynamics, $G_{nm}(s) = \frac{\omega^2}{s^2+2\zeta\omega s+\omega^2}$, which produces a steer torque T_δ from the steer angle error. This model provides a parametric framework for the grey box identification of the controller gains and neuromuscular parameters.

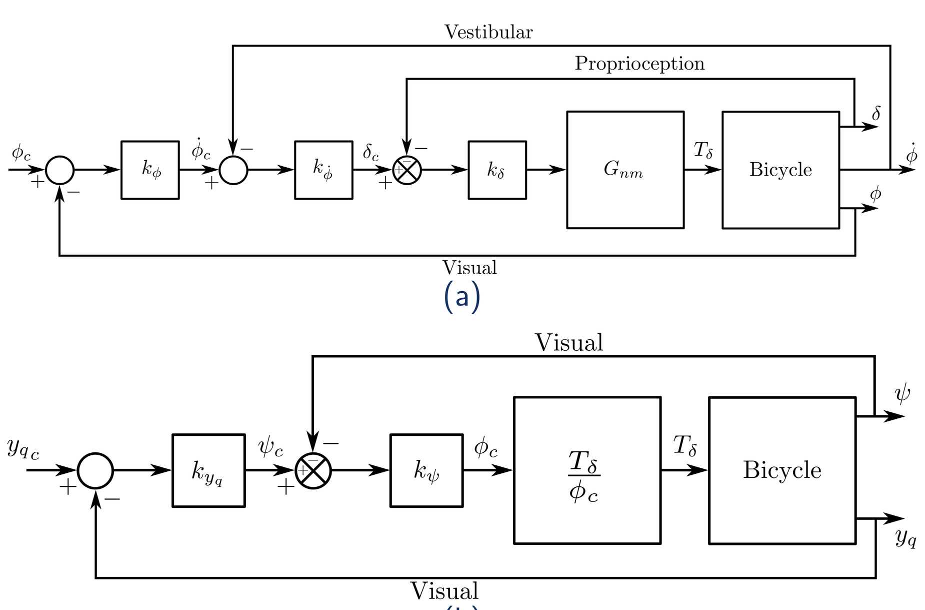

Figure : (4) (a) Schematic of inner "balance" control loops. (b) Complete rider/vehicle feedback model.

Experiments

The analysis herein focuses on two maneuvers we call *Heading Tracking* and *Lateral Deviation Tracking*. During heading tracking the rider was instructed simply to balance the bicycle and keep a relatively constant heading while focusing their vision at a point in the distance. During lateral deviation tracking the rider focused on a straight line marked on the ground and attempted to keep the front wheel on this line. Both tasks were performed with random manually applied lateral perturbation forces, F, just below the seat, random in direction and time during the trials. Each maneuver was performed on both a 1 meter wide treadmill and an open gymnasium floor [2]. We collected data from these two maneuvers for three subjects at speeds from 1.5 m/s to 9.5 m/s for a total of 262 runs.

Identification

We formulated two continuous grey box models, one for each maneuver. The heading tracking model did not include the lateral deviation feedback loop and the lateral deviation tracking model did. The bicycle model was found from a separate identification procedure [2] which identified a fourth order model from a larger subset of the collected data. This identified portion of the plant ensured a realistic relationship between the steer torque input and the system outputs, as the first principles Whipple model was not sufficiently predictive.

The state and input matrices of the closed loop system take this form:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ a_{b\ddot{\phi}\phi} & a_{b\ddot{\phi}\delta} & a_{b\ddot{\phi}\dot{\phi}} & a_{b\ddot{\phi}\dot{\delta}} & 0 & 0 & 0 & 0 \\ a_{b\ddot{\delta}\phi} & a_{b\ddot{\delta}\delta} & a_{b\ddot{\delta}\dot{\phi}} & a_{b\ddot{\delta}\dot{\delta}} & 0 & 0 & 0 & 0 \\ 0 & a_{b\dot{\psi}\delta} & 0 & a_{b\dot{\psi}\dot{\delta}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_{b\dot{y}_p\psi} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ -\omega^2 k_\delta k_{\dot{\phi}} k_\phi & -\omega^2 k_\delta (1+c_{by_q\delta} k_{\dot{\phi}} k_\phi k_\psi k_{y_q}) & -\omega^2 k_\delta k_{\dot{\phi}} & 0 & -\omega^2 k_\delta k_{\dot{\phi}} k_\phi k_\psi (1+c_{by_q\psi} k_{y_q}) & -\omega^2 k_\delta k_{\dot{\phi}} k_\phi k_\psi k_{y_q} & -\omega^2 & -2\omega\zeta \end{bmatrix} \quad (1)$$

$$\mathbf{B} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ b_{b\ddot{\phi}F} & 0 \\ b_{b\ddot{\delta}F} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \omega^2 k_\delta k_{\dot{\phi}} k_\phi k_\psi k_{y_q} \end{bmatrix} \quad (2)$$

Where the states are

$$x = \begin{bmatrix} \phi & \delta & \dot{\phi} & \dot{\delta} & \psi & y_p & T_\delta & \dot{T}_\delta \end{bmatrix}^T \quad (3)$$

and the inputs are

$$u = \begin{bmatrix} F & y_{qc} \end{bmatrix}^T \quad (4)$$

The only unknowns in the system are the controller gains and the neuromuscular model's natural frequency and damping terms, ω, ζ. The a and b entries are associated with the bicycle model and are pre-identified. We then discretized this continuous system with a zero order hold and formulate the directly parameterized innovations form [1] of the discrete linear system. The one step ahead prediction of the system outputs can be used to define a regressive cost function in which the error in the measured outputs and the model's outputs can be minimized with respect to the unknown parameters. Given a set of data the unknown parameters are identified using the prediction error method. We identify the unknown parameters for each of the 262 runs.

Results

We identified the gains and neuromuscular frequency for each run with a 62% average self-validated VAF for all runs and outputs. The identified models predict the outputs around the input response very well and less so when there is no external perturbation due to the output error formulation of the model. Thus the models capture the linear portion of the human's control scheme, and leaves the remnant to output error.

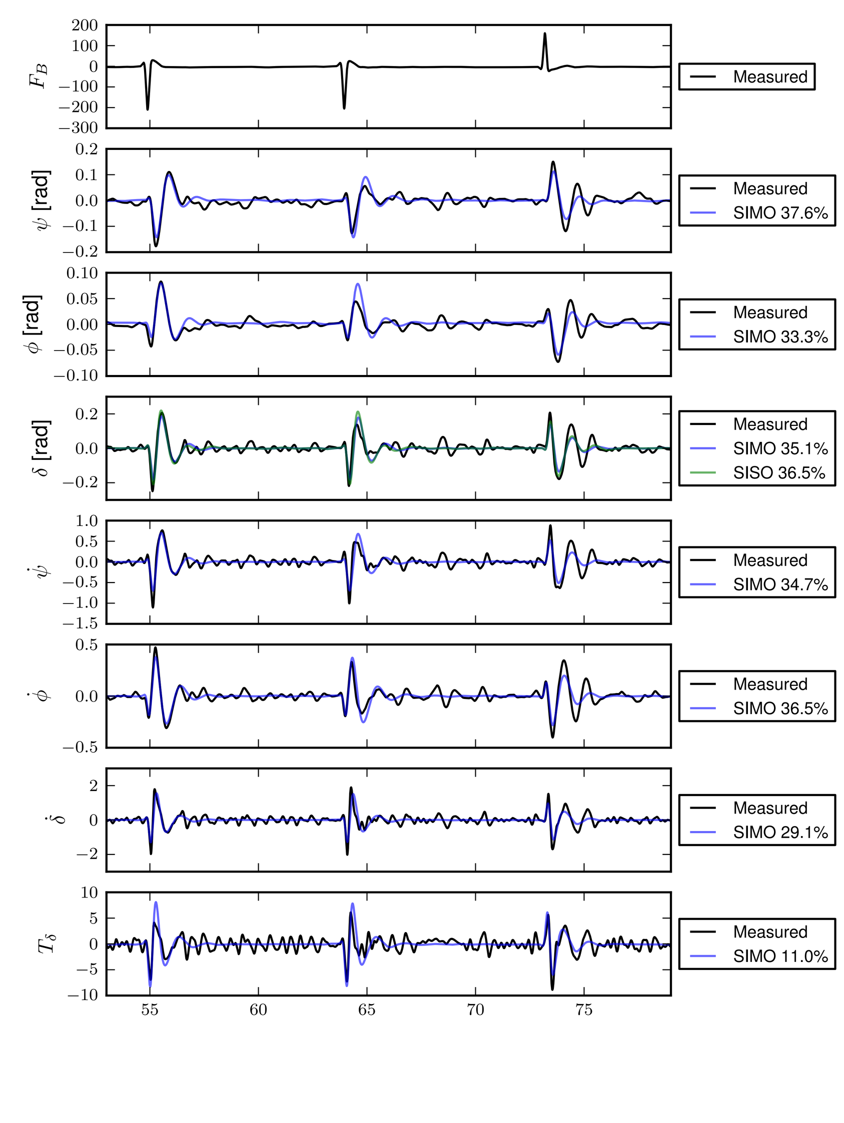

Figure : Simulation of an identified model derived from the inputs and outputs (SIMO) of one of rider C's treadmill runs #288 (4.23 m/s) validated against the data from run #289 (4.22 m/s). The black line is the processed and filtered (low pass 15 Hz) measured data, the blue line is the simulation from the identified SIMO model and the green line is the identified SISO model.

Results

The identified gains for each run, Fig. 4, have a large spread, which is to be expected in a output error model and with three different human subjects. But there are some trends:

- The gains increase with speed with $k_\phi$and k_{yq} having small slopes.
- The low speed runs have much more spread. This is probably due to the fact that the human remnant is relatively large at these speeds and the model attempts to fit the noise.
- The 9 m/s runs have poorer data quality due to the treadmill interference in the measurement electronics, thus the spread is large.
- The neuromuscular frequency stays relatively constant just below 30 rad/s, barring the higher variability in the low speed runs.
- The gains may be reasonably characterized with simple linear relationships.

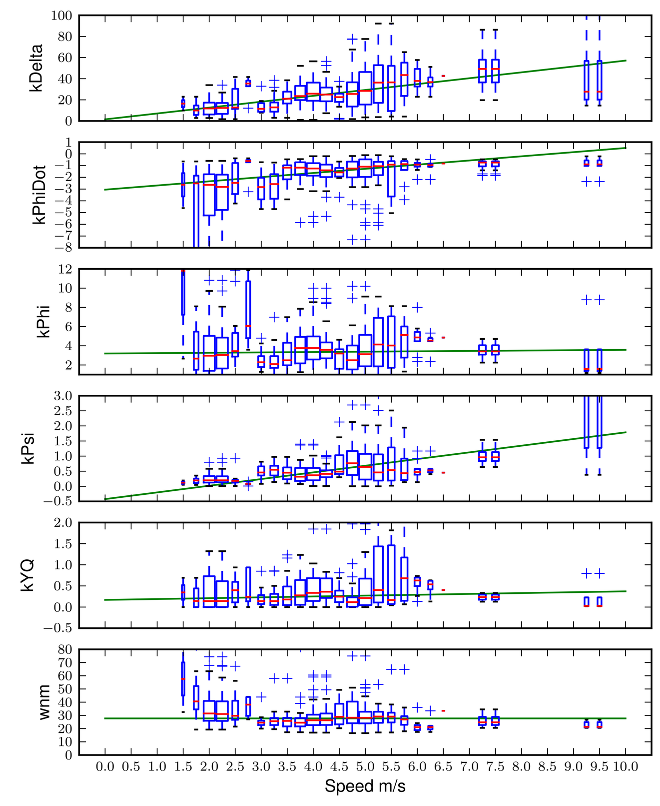

Figure : Each of the five identified parameters as a function of speed. The parameter values are grouped into 0.5 m/s speed bins and box plots showing their distributions are given for each speed bin. The red line gives the median of the speed bin, the box bounds the quartiles, and the whisker is 1.5 times the inner quartile range. The width of the boxes are proportional to the square root of the number of runs in the bin. The green line gives the linear fit to the median values which are weighted with respect to the inverse of the standard deviation of each speed bin. The neuromuscular frequency is the best constant that fits the data.

The identified models also exhibited similar frequency domain characteristics to the hypothesized models in [3]. We see the typical human neuromuscular pole in the roll rate closed loop around 10 rad/s in both the identified data and the first principles models from [3], Fig. 5.

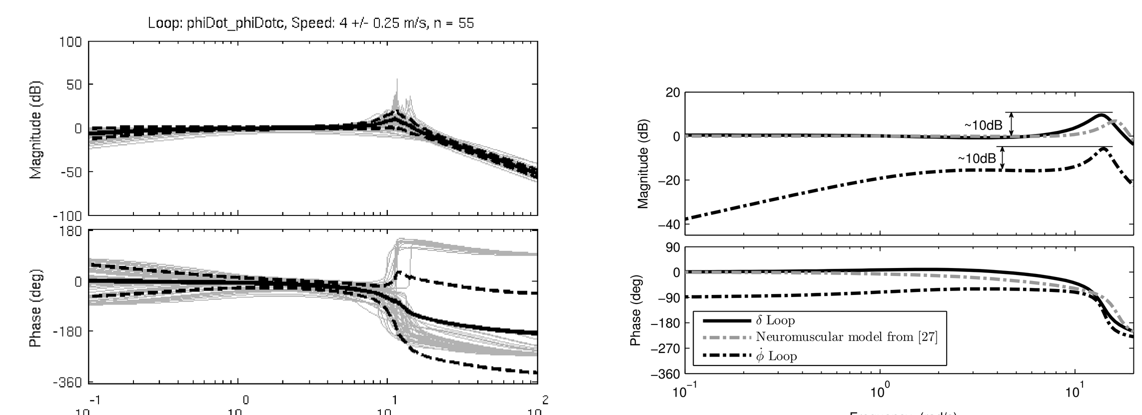

Figure : (a) Frequency responses of the identified closed roll rate loop around 4 m/s. The grey lines plot the response of each individual run in the speed bin while the solid black line give the mean gain and phase bounded by the dotted black lines which indicate the one sigma standard deviation. (b) Frequency response of the first principle derived closed loop roll rate loop for the benchmark bicycle [5] at 5 m/s.

The outer three loops crossover in sequence as predicted [3] but at frequencies that suggest slightly more aggressive control. The crossover frequencies are also relatively constant with respect to speed, as expected, Fig. 6a. Finally, the closed loop tracking response, Fig. 6b shows a stable system for all runs and the tracking performance is 1 to 1 out to for a bandwidth of 10 rad/s and the phase is low out to a bandwidth of 1 rad/s.

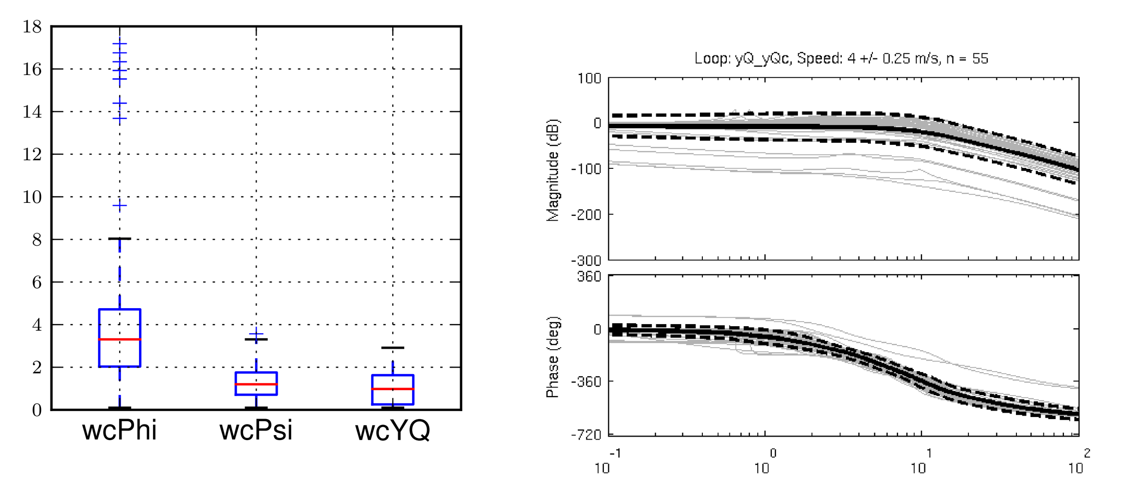

Figure : (a) Median crossover frequencies in rad/s for the open outer loops for all runs at all speeds. (b) Frequency responses of the closed loop system lateral deviation tracking response around 4 m/s. The grey lines plot the response of each individual run in the speed bin while the solid black lines give the mean gain and phase bounded by the dotted black lines which indicate one standard deviation.

References

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