Identification of manual control employed during bicycling

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September 30, 2013

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 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 body motion 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.

With the single-input multi-output data set in mind we formulate an 8th order grey box state space model [**?**] 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. 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 [1] 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 for over all the identified runs, Figure 1. The resulting models are then analyzed and shown to hold well to the manual control theory presented in [1].

We show that a simple rider controller can be identified from the collected data given that the plant model of the bicycle/rider system is properly chosen. In addition, these basic conclusions arise: (1) The fundamental, remnant-free, control response of the rider under lateral perturbations can be described reasonably well by the simple five gain sequential loop closure and an eighth order closed loop system. (2) No time delays are needed and the continuous formulation is adequate for good prediction, (3) The identified gains seem to exhibit linear trends with respect to speed as predicted by theory and the identified neuromuscular frequency seems to be constant with a median around the theoretical prediction of 30 rad/s, (4) The identified parameters show resemblance to the patterns in the theoretical loop closure techniques, especially in that the riders select their gains such that the closed roll rate loop exhibits a 10 dB peak around 10-11 rad/s and the riders cross over the outer three loops in the predicted order, (5) the crossover frequencies of the three outer loops are relatively constant with respect to speed and point to a speed independence of system response bandwidth selection among riders in this task.

This paper is based on work supported by the National Science Foundation under Grant No 0928339.

References

[1] Ronald Hess, Jason K. Moore, and Mont Hubbard. Modeling the manually controlled bicycle. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 42(3):545–557, 2012.

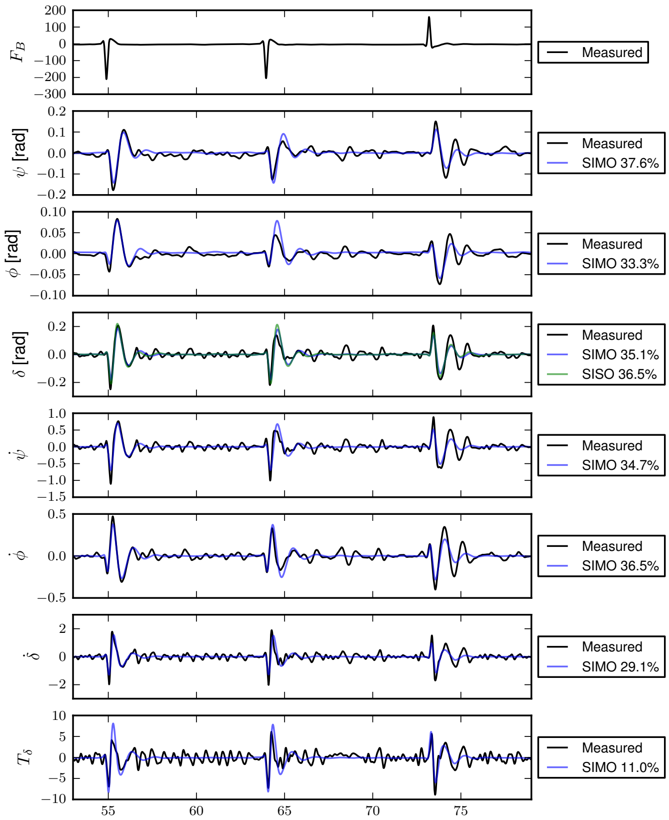

Figure 1: Simulation of an identified model derived from the inputs and outputs (SIMO) of one of Charlie's treadmill runs #288 (4.23 m/s) validated against the data from run #289 (4.22 m/s). The black line is the processed and filtered (low pass 15 Hz) measured data, the blue line is the simulation from the identified SIMO model and the green line is the identified SISO model.