Identification of the open loop dynamics of a bicycle-rider system under manual control

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Traditionally, dynamicists develop models of the bicycle-rider system from first principles, i.e. Newton's laws and various other atomic fundamental models of nature. The first principle approach has guided much of engineering throughout its history but today's experiments are capable of delivering a staggering amount of both kinematic and kinetic data leading to data driven modeling approaches.

The Whipple bicycle model is often regarded as a highly predictive model of the bicycle-rider system and is constructed from first principles, yet very little experimental data proves that the Whipple model is in fact a robust model for the open loop dynamics of the bicycle-rider system. Two remedy this, we have collected a large set of time history data from an instrumented bicycle which includes the most important kinematic and kinetic variables describing the bicycle-rider motion from three different riders on the same bicycle for a variety of maneuvers and speeds. These experiments generated about 1.7 million time samples from each of about 30 sensors collected at 200 hertz (representing about 2.4 hours of real time).

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.

We start by simulating the Whipple model given carefully measured physical parameters and the measured steer torque for each of the 374 runs and show that the trajectories of the kinematic variables in the simulation are a factor of magnitude larger than the measurements of those same variables. We conclude that the Whipple model requires much less steer torque to drive it through the same trajectory than our real bicycle-rider system.

To rule out the possible invalidations of rigid rider assumptions from allowing the rider to move his arms while controlling the bicycle we then simulate a bicycle-rider model with the inertial effects of the rider's arms in the same fashion as previously described. In general, the model with the arms shows better agreement to the measured data than does the Whipple model.

Finally, we make use of two structured black box system identification techniques to identify the coefficients of the Whipple model in both state space form and mass-spring-damper form. These identification methods result in various 4th order models that predict the measured data more accurately than the Whipple model.

In this paper we will show that a fourth order structured state space model is both adequate for describing the motion of the bicycle under manual control in a speed range from approximately 1.5 m/s to 9 m/s. The fact that higher order models may not be necessary for bicycle dynamic description is an important finding. More robust models of single track vehicles are typically higher than 4th order, with degrees of freedom associated with tire slip, frame flexibilities, and rider biomechanics. These findings suggest that the more complex models may be overkill for many modeling purposes.

The data subsequently also reveals that fourth order archetypal first principles models, such as the Whipple model, are not robust enough to fully describe the dynamics. The inability to identify realistically valued parameters and model coefficients points to model deficiencies. The deficiencies are likely due to un-modeled effects, with the knife-edge, no side-slip wheel contact assumptions being the most probable candidate. Un-modeled rider biomechanics such as passive arm stiffness and damping and head motion may also play a role.

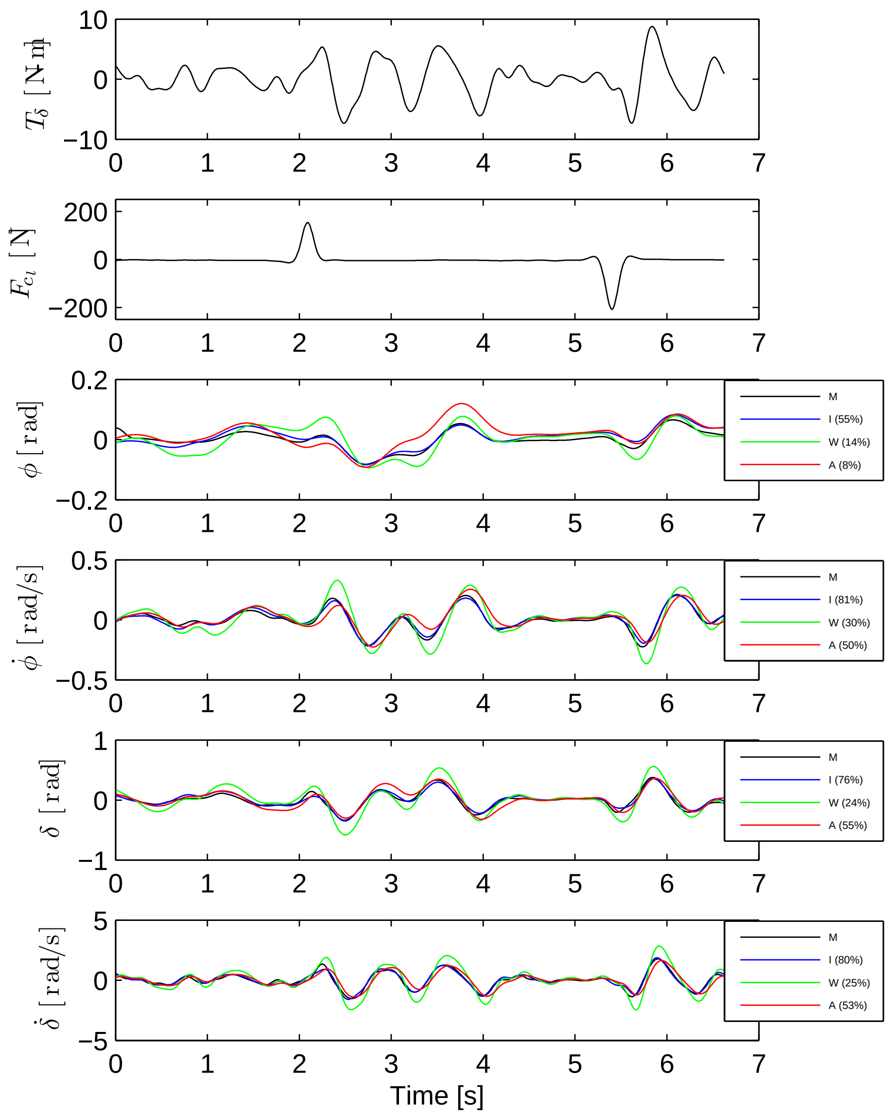

Figure 1: Example results for the identification of a single run (#596). Experimentally measured steer torque and lateral force are shown in the top two graphs. The remaining four graphs show the simulation results for the Whipple model (W), Whipple model with the arm inertia (A), and the identified model for that run (I) plotted with the measured data (M). The percentages give the percent of variance explained by each model.

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