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Linear and Hammerstein Subspace Identification of a Human Controlling a Ball and Beam using the Quanser Engineering Trainer Haptic Interface

Erin L. Renk, Harish J. Palanthandalam-Madapusi and Dennis S. Bernstein

Abstract— **Identification of human subjects has widespread applications. In this paper we perform system identification of a human controlling a ball and beam setup through a Quanser Engineering Trainer haptic interface. The identification of the human in the loop is performed using subspace-based nonlinear identification algorithms. Several combinations of inputs and nonlinearities in inputs are tested. The identified controllers are implemented through Simulink. Results for two human subjects with and without the haptic feedback and a pre-programmed PID controller are compared.**

I. Introduction

Models of humans operating in a closed-loop are of interest for several applications including cybernetics, airplane control systems, ergonomics, etc. Both analytical and empirical modeling of humans operating in a closed-loop have been considered. Analytical models [13] are difficult to derive and involve assumptions on the behavior of the humans. Empirical models on the other hand are easier to derive since only measured data is required to build such models.

Previous empirical models for human in a loop include parametric models [1], transfer function models [2], autoregressive models [4], [3], describing function models [10] and time-varying models [9]. Human behavior in a closed-loop system is inherently nonlinear and includes non-linear effects such as saturation and dead-band. These aspects of human responses cannot be captured by linear models. Thus by identifying models of humans operating in a closed loop we wish to demonstrate the effectiveness of system identification in constructing models of humans and also compare linear and nonlinear models for the same.

Recent advances in subspace-based nonlinear system identification methods [5], [8], [11] provide numerically robust identification techniques for completely MIMO (multi-input multi-output) systems. Subspace-based linear and nonlinear identification techniques have been successfully applied to a wide variety of applications. Closed-loop identification techniques based on subspace methods have also been developed [12], [7], [6].

The authors are with the department of Aerospace Engineering at the University of Michigan, Ann Arbor, MI 48109-2140. {elrenk,hpalanth,dsbaero}@umich.edu

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In this paper, we present the results of a pilot study in which we apply subspace-based linear and Hammerstein identification techniques to identify the dynamics of a human controlling a ball and beam. In this study we explore the feasibility of system identification for construction of models of humans. Both linear and Hammerstein models for the human are constructed and compared. Finally, we use this application to demonstrate that system identification tools can be used to construct controllers.

The ball and beam setup is controlled through a Quanser Engineering Trainer (QET) interface equipped with haptic feedback capabilities. The measured variables include the angle of the beam, the position and velocity of the ball, the angle of the wheel and the haptic feedback signal. The MIMO capability of the subspace-based methods are vital in this application.

Although, this is a closed-loop identification problem, as a first step we apply open loop identification techniques. An additional goal of the paper is to investigate the advantage of having the haptic feedback signal.

Data are collected for a preprogrammed PID controller as well as for two human subjects operating with and without the haptic feedback signal. These data are then used in linear and nonlinear system identification techniques to identify controllers for the system. The identified models are then implemented through Simulink to control the ball and beam. Several combinations of the input signals are tested, and the effect of adding a nonlinearity to the identified system is examined. The effect of adding haptic feedback is also examined.

II. Ball and Beam Setup

The apparatus for the experiment is a Quanser ball and beam. The beam consists of a metal beam with a built-in potentiometer sensor, while a 1 inch steel ball rolls on the beam. Attached to the metal beam, specifically for this experiment, is a plastic backing containing three evenly spaced LED lights. The beam has its own servo loop and the command to the beam angle is derived from the sensor that

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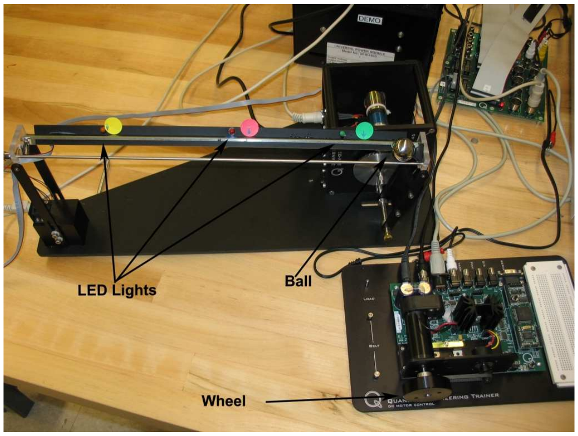

Fig. 1. Quanser Ball and Beam with haptic feedback. The wheel to the lower right of the figure applies a moment to the beam on which the ball rolls. The three lights turn on and off, and the idea is to control the ball so that is settles at the location of the lighted LED.

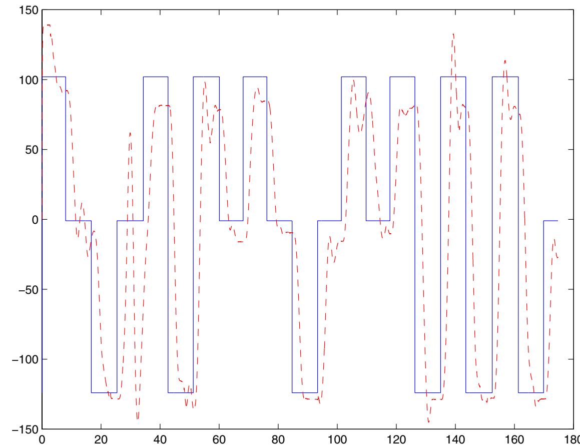

Fig. 2. Actual ball position and commanded ball position for Subject 1 without the haptic feedback signal. The solid line represents the commanded ball position and the dashed line is the actual ball position. The three plateaus represent the three lights. LED lights change every 9-10 seconds. The units for the x-axis is seconds and for the y-axis is mm.

senses the rotation of the knob by a wheel on the Quanser Engineering Trainer (QET) through WinCon (and Simulink). The setup is equipped with a haptic feedback through the wheel of the QET.

The reference command is provided through the LED lights, which blink on and off, one at a time, in regular time intervals. The goal of the controller is to control the angle of the beam so that the ball rolls to the position of the currently lighted LED. A pre-programmed PID computer controller can be used to control the setup or a human can control the system with or without the use of the haptic feedback. When the haptic interface for the wheel is turned on, the position of the ball relative to the light can be felt. That is, the torque felt in the wheel is proportional to the distance of the ball from the lit LED light, with decreased torque on the wheel corresponding to a closer position.

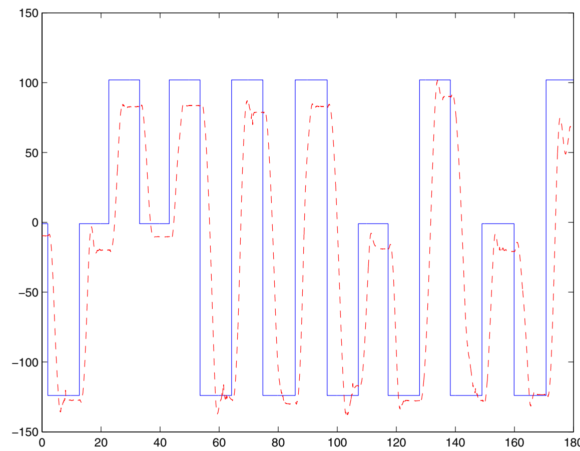

Fig. 3. Actual ball position and commanded ball position for Subject 1 using the haptic feedback signal.

III. Data Collection

For this pilot study, data is collected from two human subjects. Both subjects were given time (a few days) to familiarize themselves with the setup and the control actions. Each subject is then asked to control the ball and beam following the commanded LED light pattern through the QET wheel with and without the haptic interface. Data sets with and without the haptic feedback for Subject 1 are shown in Figures 2 and 3. The lit LED light on the beam changes in intervals of 9-10 seconds for both the haptic and non-haptic case. Data sets are collected for Subject 2 for the non-haptic case and for the case in which haptic feedback is used, see Figures 4 and 5. Data are collected for Subject 2 for LED light time intervals of 9-10.

For the human controlled system, the variables of actual ball position (i.e. controlled ball position), commanded ball position (i.e. lit light position), QET wheel angle and the beam angle are recorded. The additional variable of current command (haptic signal) to the wheel is collected in the haptic case.

In addition, data are collected using the pre-programmed PID controller. The inputs and outputs to the PID controller are recorded in this case. It can be seen from figure 7 that the computer controls the ball closely to the commanded position.

IV. System Identification Techniques

Both linear and nonlinear system identification are used to identify the system controllers. Linear system identification is performed using the `N4SID` command in MATLAB's System Identification Toolbox. Nonlinear system identification is performed using a subspace-based Hammerstein

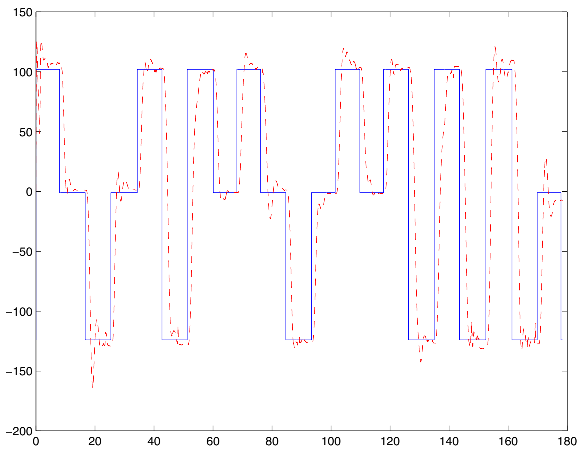

Fig. 4. Actual ball position and commanded ball position for Subject 2 without the haptic feedback. LED lights change every 9-10 seconds.

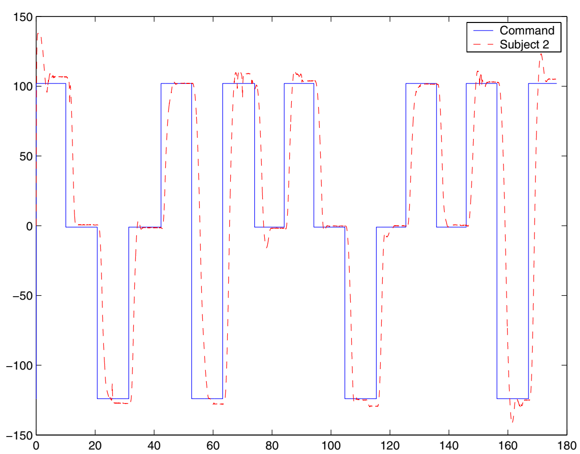

Fig. 5. Actual ball position and commanded ball position for Subject 2 with the haptic feedback.

system identification algorithm developed in [8], [5]. The Hammerstein model (see Figure 8) structure is a static nonlinearity $\mathcal{N}_{\mathrm{H}}$ connected to a dynamic linear model $\mathcal{L}_{\mathrm{H}}$ through a cascade interconnection such that the output of the nonlinearity is the input to the linear subsystem.

V. System Identification Results

Identification is performed for the computer controller, the human controllers without haptic feedback, and the human controllers with haptic feedback. The QET wheel angle is used as the output variable and the remaining variables are used as candidate input variables for the identified models. Different combinations and subsets of the input variables are tested, and details about the inputs are mentioned wherever relevant.

For all data sets, only the first half of the data is used for identification. The identified model is then used to predict the other half of the data. To protect the ball and beam setup

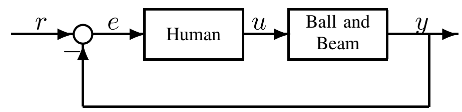

Fig. 6. Ball and Beam Control Setup

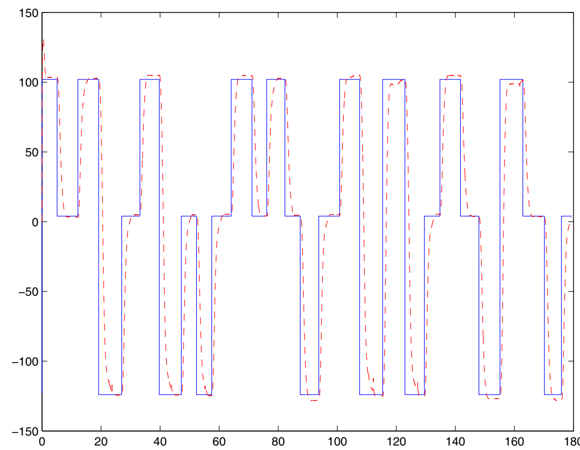

Fig. 7. Actual ball position and commanded ball position for the PID computer controller. LED lights change every 9-10 seconds. The three plateaus represent the three lights.

from damage, only models with good prediction capabilities are implemented on the actual setup.

A. Computer Controller

For the case of the PID controller, linear identification is performed with ball position and ball velocity as input variables, and the PID output signal is taken as the output signal for the model. Linear identification results and prediction are shown in Figure 9, the identified model was a 3^{rd} order model. Also, nonlinear identification is performed with the same output and input variables with a nonlinearity existing in ball position. A second nonlinear identification is performed with a nonlinearity in ball velocity. Each identification produced good fit and prediction.

B. Human Controller without Haptic Feedback

For the case of the human controller without the haptic interface, linear system identification is performed with ball position and ball velocity as input variables and wheel angle as the output variable. Nonlinear system identification is also performed with nonlinear dependence on ball position and then on ball velocity. In all the cases in which nonlinear system identification is performed, the nonlinear dependence is assumed to be on one input variable only.

For Subject 1, the linear model fit the data the worst with poor data prediction. Both models with a nonlinear input in either ball position or ball speed fit the data better with more

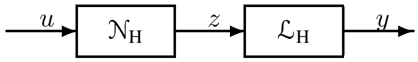

Fig. 8. Hammerstein Model

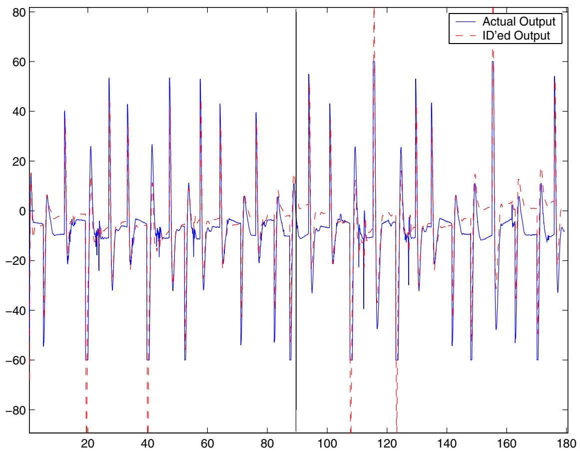

Fig. 9. Linear system identification of the PID controller data set. The input variables are ball position and ball speed. The output variable is wheel angle. The data to the left of the vertical line was used for identification, while the right side of the plot is the prediction region.

precise prediction. The 5^{th} order model with a nonlinearity in the ball speed produced the best fit, see Figure 10.

For subject 2, the linear and both nonlinear system identifications gave poor predictions.

C. Human Controller with Haptic Feedback

For system identification with haptic feedback, the variable capturing the haptic effect is current to QET wheel, which will be referred to simply as current. Both linear and nonlinear system identification are performed with various combinations of the input variables of ball position, ball speed, beam angle, and current. Nonlinearities are examined in ball position and ball velocity. The output variable in each identification is wheel angle.

For subject 1, the best linear fits occurs when at least three variables are used as inputs, with the most accurate being when the beam angle is included as an input. The best nonlinear fit occurs when a nonlinearity in ball position is considered. These are concurrent with the results obtained from Subject 2's data set. Prediction and fit improved for both Subject 1 and Subject 2 when the beam angle is included. Figures 11 and 12 show the results for nonlinear and linear system identification using Subject 2's data set, respectively. The identified models were 4^{th} order models.

VI. Controller Implementation Results

Once the controller for the system is identified, it is implemented through Simulink to control the ball and beam. Input variables are fed to the identified system in the same order as in the system identification code. The identified

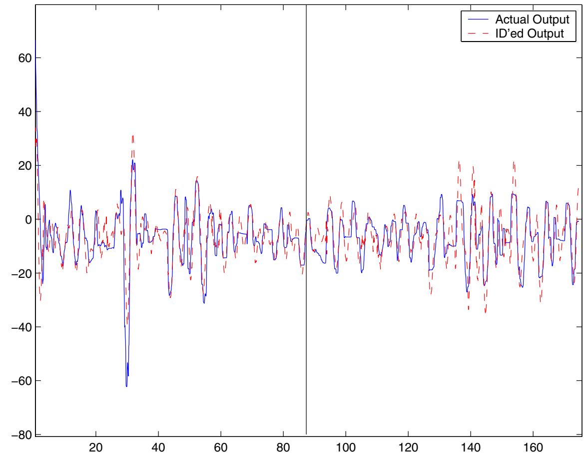

Fig. 10. Nonlinear system identification of Subject 1's non-haptic data set. The input variables are ball position and ball speed. The output variable is wheel angle. Nonlinear dependence on the ball velocity is assumed. The data to the left of the vertical line was used for identification, while the right side of the plot is the prediction region. The units for the x-axis is seconds and for the y-axis is degrees.

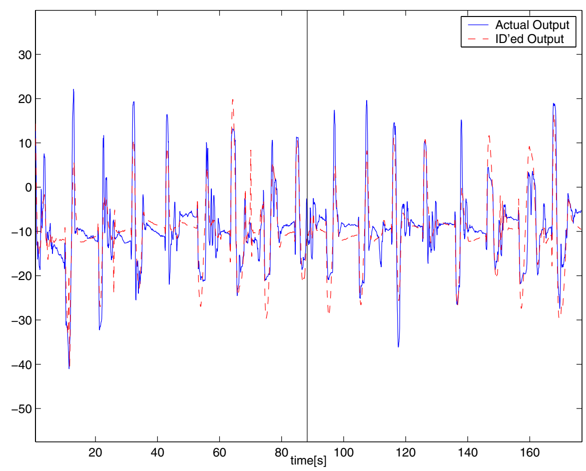

Fig. 11. Nonlinear system identification of Subject 2's haptic data set. The input variables are ball position, ball speed, and current. The output variable is wheel angle. Nonlinear dependence on ball position is assumed. The data to the left of the vertical line was used for identification, while the right side of the plot is the prediction region.

nonlinearities are also implemented. The output from the identified system is then used to control the ball and beam. Both linear and nonlinear identification results are presented in the following subsections.

A. Computer Controller

The identified models of the PID computer controller are implemented. The linear model controls the ball the most accurately out of all of the identified controllers, closely estimating the behavior of the original controller, see Figure 13. The controller with a nonlinearity in ball position tends to move the ball all over the beam, but not towards the lighted

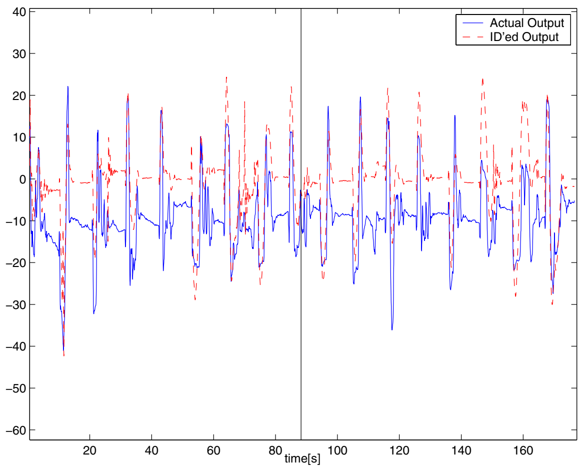

Fig. 12. Linear system identification of Subject 2's haptic data set. The input variables are ball position, ball speed, and current. The output variable is wheel angle.

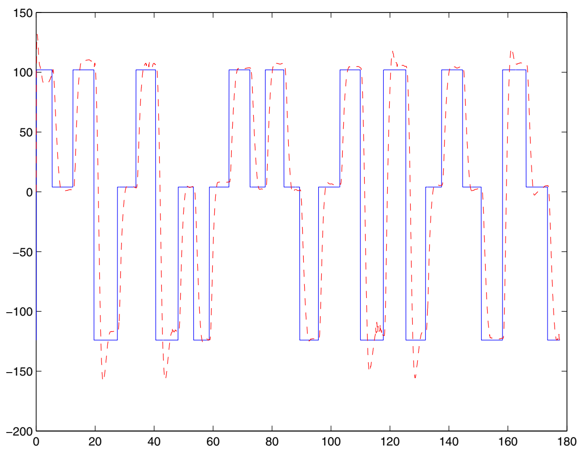

Fig. 13. Performance of the linear controller identified from PID controller data set. The input variables are ball position and ball speed, and current. The output variable is wheel angle.

LED. The controller with a nonlinearity in ball velocity did control the ball towards the lighted LED, but not as accurately as the purely linear controller. It does not stop precisely at the LED, but a slight distance from it, appearing to have a bias.

B. Human Controller without Haptic Feedback

For Subject 1, none of the identified controllers works well. For the purely linear controller, the identified controller moves the ball, but it does not settle on the specified LED. The nonlinear controllers tend to control the ball better but are very oscillatory as seen from Figure 14.

For Subject 2, the linear controller is not able to control the ball and beam. When a nonlinearity in ball position is assumed, the controller works, but with a lot of chatter.

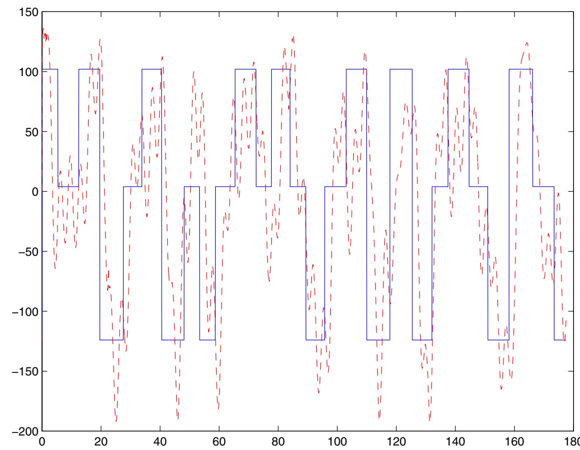

Fig. 14. Performance of the nonlinear controller identified from Subject 1's non-haptic data set. The input variables are ball position and ball speed. The output variable is wheel angle. Nonlinear dependence on ball velocity is assumed.

The controller with a nonlinearity in ball speed also worked better, with less chatter.

C. Human Controller with Haptic Feedback

None of the linear controllers for Subject 1 are able to control the system. They either do nothing to the ball and beam, produce extremely jumpy movements, or move the ball and beam only slightly. For subject 2, the linear controller did control the ball, see Figure 15.

For Subject 1, the only controller that works with any success is that with the input variables of ball position, ball speed, and current, with a nonlinearity occurring in ball position. The ball and beam move as the lights changes, but with a very large bias when the ball settles and stops moving.

Likewise, the controller identified with the input variables of ball position, ball speed, and current, with a nonlinearity in ball position works the best for Subject 2. The commanded and controlled ball positions are displayed in Figure 16. The implemented controller estimates the behavior of the original human controller closely. When there is nonlinear dependence on the ball velocity, the controller works but with a bias in the position of the ball. When ball velocity is eliminated as an input variable, the controller works somewhat, but with significant drift in ball position. In all cases when the beam angle is added as an input variable the controller produces jerky movements.

During identification, the best fits were obtained when all four input signals were used. But when the controllers are implemented, the performance of controllers with all four inputs produce jerky movements and are significantly worse than the ones shown in Figure 16. This could be attributed to overfitting.

The haptic signal made a substantial difference in the

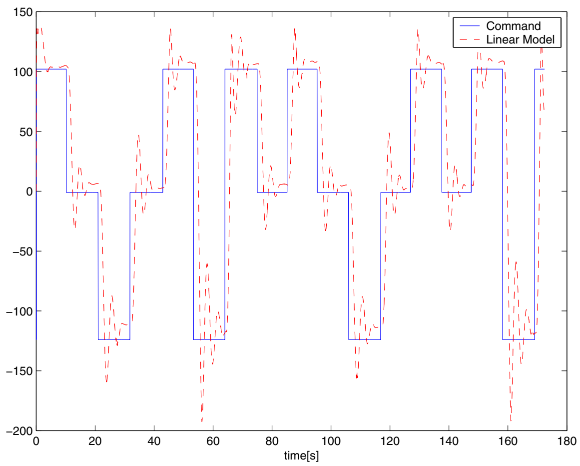

Fig. 15. Performance of the linear controller identified from Subject 2's haptic data set. The input variables are ball position, ball speed, and current. The output variable is wheel angle.

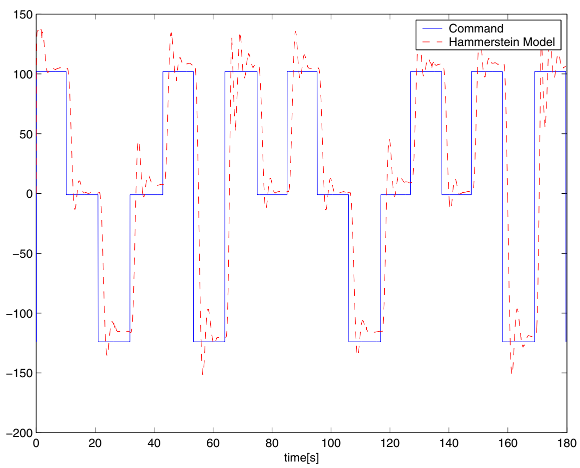

Fig. 16. Performance of nonlinear controller identified from Subject 2's haptic data set. The input variables are ball position, ball speed, and current. Nonlinear dependence is assumed for ball position. The output variable is wheel angle. The nonlinear model decreases overshoot as compared to the linear model.

identified controller's performance as compared to the non-haptic cases, showing that the haptic signal makes the task of controlling the beam significantly easier.

VII. Conclusion

In this paper we presented the results of a pilot study in which subspace identification algorithms were used to identify a human controlling a ball and beam setup. Using both nonlinear and linear open loop identification algorithms were successfully used to construct models, which were then used to control the ball and beam. For controllers constructed using both human subjects, it was seen that Hammerstein models consistently worked better. But we note that this does not imply that humans are Hammerstein, the only conclusion we can draw is that Hammerstein models of humans are better than linear models of humans. This study also demonstrated that subspace identification can be used as a toll to build controllers. Finally, the use of haptic feedback signal increases the accuracy of the controller. This may be due to the fact that the haptic feedback allows for easier control of the apparatus. Future work may include identification of human controllers using other model structures and closed-loop identification techniques. A more in depth comparison of the haptic and the non-haptic will be performed by comparing the least squares error, model orders and structure and the input nonlinearities.

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