# A physics-based model for predicting user intent in shared-control pedestrian mobility aids

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*International Conference on Intelligent RObots and Systems - IROS*

# A Physics-Based Model for Predicting User Intent in Shared-Control Pedestrian Mobility Aids

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*Abstract*— **This paper presents a physics-based model approach to infer navigational intent of the user of a walker, based on measuring forces and moments applied to the walker's handles. Our experiments use two 6-DOF force/moment sensors on the walker's handles, a 2-D kinematic-dynamic model of the walker and a digital motion capture system to trace the path of the walker. The motion capture system records the path the walker follows while the 6 DOF sensors record the handle forces used to guide the walker along that path. A dynamic model of the walker that determines user navigational intent from force/moment data was developed and validated against the motion capture data streams. This paper describes the development and validation of the model as well as plans for using the model as a path predictor. The inferred user intent will be incorporated into a passive shared steering control system for the walker.**

***Keywords-Assistive and Healthcare Robotics, Personal Robots, Man-Machine Systems***

## I. INTRODUCTION

One of the most important factors in quality of life for the older adults is their ability to move about independently. Not only is mobility crucial for performing the activities of daily living (ADLs), but for maintaining fitness and vitality. Lack of independence and exercise can lead to a vicious cycle. Decreased mobility due to a perceived lack of safety can cause muscular atrophy and a loss of the feeling of empowerment (both of which contribute to further decreased mobility).

We are developing a pedestrian mobility aid for elderly users. The primary goal of this work is to augment a user's ability to walk, not replace it. In this sense, we are seeking to help those who *can* and *want to* walk perform this task more safely and easily. As the world's elderly population rises (doubling in the US alone in the next 30 years [1]) and the cost of healthcare skyrockets (to $4 trillion over the same period [2]), robotic mobility aids increase in importance.

The long-term goal of this work is to develop a shared control framework for a wheeled walker that provides situation-dependent synthesis of control signals from both human and machine. As a part of the shared control, the User's navigational goals based on forces and moments exerted on the walker's handles are ascertained. Based on this goal and relevant safety concerns as determined from the perception of the environment, the Walker controller attempts to influence the motion of the Walker-Human system. This paper presents our work in developing a physics-based model of the walker that can be used to predict a user's navigational intent from the force/moment data read from 6-DOF sensors on the walker's handles [3].

In the shared control paradigm, *User intent* is distinctly different from *path prediction* (although predicted path is a key component for assessing User intent). Path prediction from time integration of differential equations typically produces prediction over short time horizons after which the driving forces and moments must be refreshed. The overall User intent has a longer time horizon. Any User intent assessment model therefore must take into consideration how far to project the path prediction from the present time, and how much error (or conversely confidence) to expect as the time horizon gets longer. Accordingly, the assessment of User Intent involves multiple levels of quantitative estimates—both deterministic as well as probabilistic. The physics-based approach presented in this paper yields the quantitative assessment at the lowest level. A probabilistic, Bayesian or possibility-based process involving predicted paths, perception of the environment as well as other information (such as wheel encoders) will be added to build up a higher level model of User Intent model over time

In this paper, the focus is on the dynamic model of the Walker, with the key features of this model embodied by the fact that the Walker wheels can slip, slide, and roll as the human User and the Walker controller cooperate or "fight". Correlations with experimental data are shown to be excellent. The model, therefore, provides a solid predictive ability, and the role of the model in the overall User intent assessment is further discussed.

## II. A PHYSICS-BASED APPROACH TO USER INTENT

The shared control system architecture presented in [3] and depicted in Fig. 1 integrates information from different sources including environment perception system, forces and moments measured at the handles, and the walker's state to identify and predict User Intent and consequently take the appropriate control actions. In this paper we will focus on exploiting a physics-based model of the walker system, together with force and moments measured at the walker's handles, to identify the current User Intent. With assumption on the force and moments applied, the model can be used to predict a set of possible paths that the user may take. The predicted paths can take into account errors resulting from the approximations of the walker's kinematic and dynamic model, as well as quantifiable errors due to noise in force-moment measurements, and the probability distribution along the predicted paths exponentially decays with the increasing time horizon; the constant governing the rate of decay significantly varies according to the turn being made, the sharper the turn, the less likely it will continue for a long time.

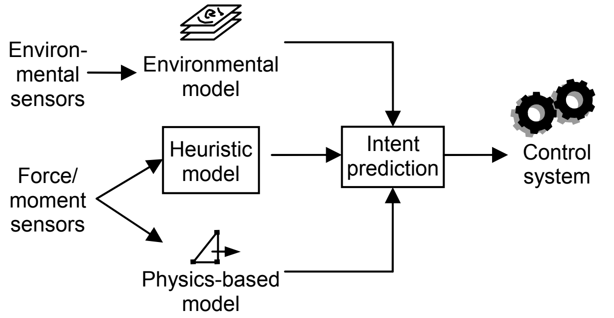


Figure 1. Walker Architecture

Referring to Fig. 2, The forces and the moments exerted by the Subject (User) on the left and the right handles constitute time-series of twelve data channels—three (3) forces and three (3) moments for each of the two handles.

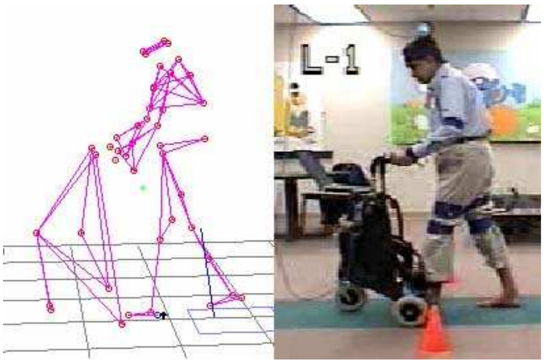


Figure 2. The Walker/User kinematic model (left) represented by Vicon Motion Capture System and the corresponding video (right)

The twelve (12) channels of data can be utilized to isolate the walker from the Subject (User) for the modeling and simulation of the Walker. Fig. 3 is a representation of the walker itself, with handle axes indicated.

Now referring to Fig. 4, which is a 2-Dimensional model of the Walker, it should be noted that the motion dynamics of the Walker are modeled to occur in the XY plane, but the forces/moments on this Walker are *3-Dimensional*, because the effects of these forces/moments normal to the plane of the motion must be accounted for in the computation of friction between the walker's wheels and the ground.

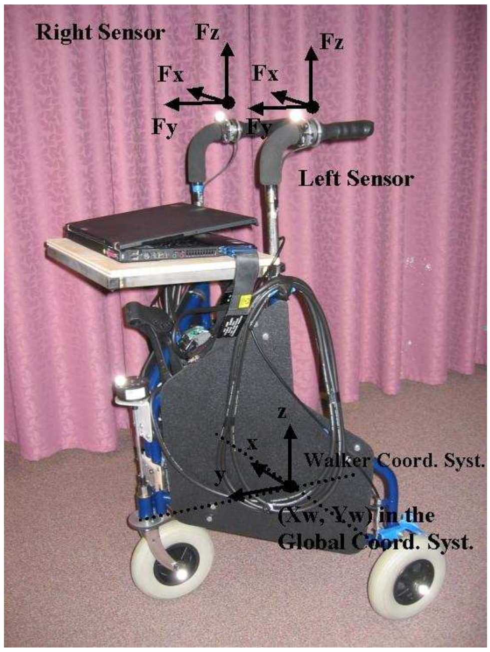


Figure 3. Walker with Handle Axes for Force and Moment Components

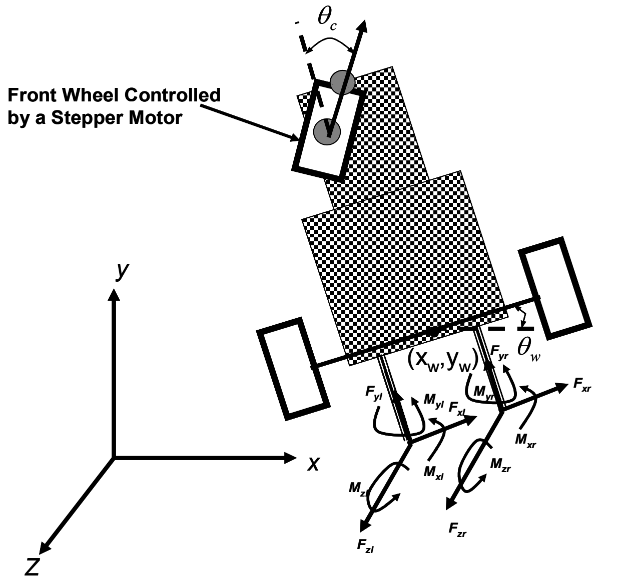


Figure 4. 2-Dimensional Motion Dynamics Model of the Walker with 3-Dimensional forces/moments

The configuration space of the Walker is represented by four variables $\left[x_W, y_W, \theta_W, \theta_C\right]^T$. A careful consideration for modeling the behavior of the three wheels is necessary. The propulsive effort to the Walker is being imparted by the human Subject, with the points of application of this effort at the handles, which are located at some height above the wheels. Therefore, it is reasonable to assume rolling without slipping in the direction of motion of the wheels; however, with reference to Fig. 5, it is possible for each of the wheels to slide sideways normal to the plane of the wheel.

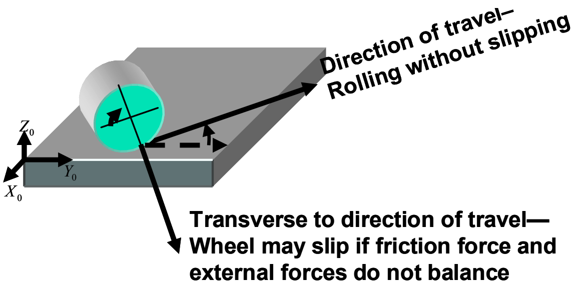


Figure 5. Modeling of Wheel Motions involves Rolling Without Slipping Condition in the Direction of Travel with the possibility of Sliding in Transverse Direction

The issue of rolling without slipping versus sliding is a key modeling issue for the passive shared control of the Walker wherein the front wheel may have an active steering input that can indeed conflict with the inputs at the handles from the User of the Walker. As will be seen, this can possibly lead to a sliding behavior. From modeling of the dynamics, therefore, the wheels are not always subjected to the nonholonomic constraints, but rather one may think of the nonholonomic constraints on the front or the two rear wheels being broken if the friction forces are not sufficient at their respective ground contacts to enforce these constraints. The friction forces, of course, depend upon the coefficient of friction between the wheels and the ground, as well as on the dynamically changing normal forces as exerted by the User through the handle. The complete dynamic model is a nonlinear, coupled set of differential equations developed from the Lagrangian and the Lagrange multipliers for the system. The complete derivation is available in [12].

## III. Experiments and Setup

The walker is a standard three-wheel commercial walker augmented with a stepper motor, to control the steering direction of the front wheel, and two 6-DoF load cells from *ATI Industrial Automation* (US120-160). These sensors provide the load/moment transfers between the walker and the user. Experiments were conducted in the University of Virginia gait lab using a total of eight participants, three of whom were older adults (above 65). Each user performed a total of 49 experiments emulating 16 navigational scenarios designed to determine navigational intent from measured forces and moments recorded at the handles of the walker using the developed physics-based model described in section 2; the first experiment is aimed at calibrating the data capture systems. The navigational scenarios covered walking straight, turning right and left at two different angles on each side, and docking to a chair on both sides. The experiments were performed under two conditions: when the walker is passive, and when the steering front wheel is controlled by a stepper motor; the controlled front wheel experiments covered agreement between the User's and motor's control actions as well as attempts to resist the motor's control action. Each navigational scenario was performed 3 times. The motion model (Walker+User) is computed from the test data by using reflective markers and the Vicon system 612 connected to six 120Hz video cameras [4]. The Vicon system creates a 3-D motion model by using the positions in the (x-y-z) space of particular real points (markers) placed on the human and the walker frame. In this model, seven markers represent the walker and thirty-eight are used for the human body. A capture from the video of a trial and its corresponding kinematic model (skeleton form) are shown in Fig. 2.

## IV. Model Validation Results

All cases when the walker is in passive mode, i.e. allowing the front wheel to turn solely based on the user's control input, are simulated using load cell inputs to get the response of the dynamic model of the walker. These trials include "go straight", "light" and "sharp" left and right turns as well as "docking" with an object. Three cases representing the go straight, light left turn and sharp right turn trials were randomly selected to present graphical comparisons between the path trace obtained from the model simulation data and the experimental data obtained from VICON. These are shown in figures 6, 7 and 8. Additionally, we compare simulation result against VICON data when the Walker is active, i.e., the stepper motor controls the front wheel. Fig. 9 shows the case when User "follows" the direction guided by the motor. Fig. 10 shows this case when User tries to go straight while the Walker attempts to turn, resulting in a "fighting" situation between the User and the Walker control and some sliding with broken nonholonomic constraints.

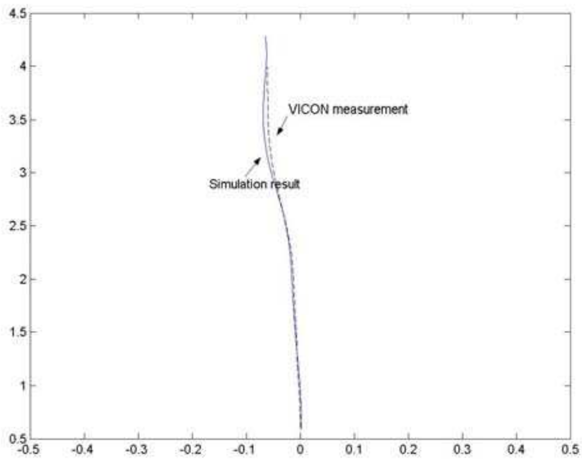


Figure 6. Measured vs. Simulated Walker Trajectory for the "Go Straight" Case

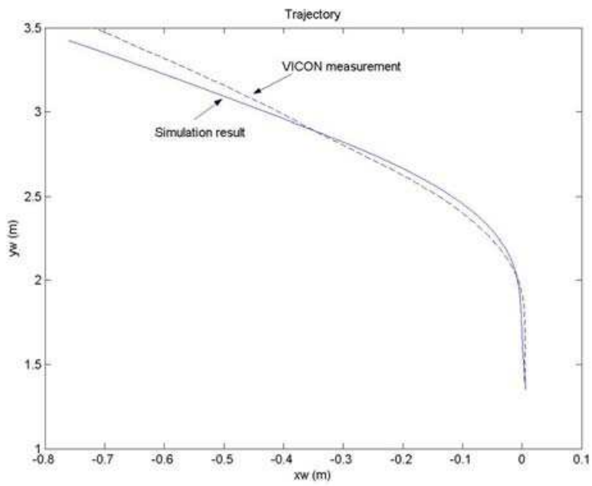


Figure 7. Measured vs. Simulated Walker Trajectory for “Light Left Turn” Case

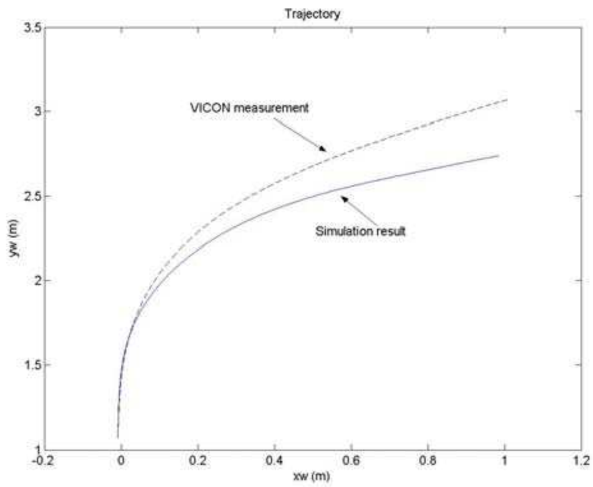


Figure 8. Measured vs. Simulated Walker Trajectory for “Sharp Right Turn” Case

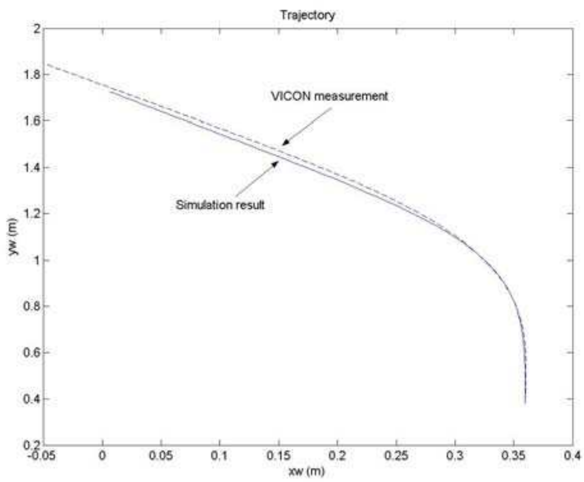


Figure 9. Measured vs. Simulated Walker Trajectory for “Light Left Turn” Case when User Follows Active Motor

In the experiment shown in fig. 10, the Walker slid sideways as the User was "fighting" the motor controlled steering action. The start and end points of sliding were detected by the model as the earliest and latest time that the constraint force required to enforce the nonholonomic condition exceeded the maximal friction force the ground could provide, which was also confirmed from the video of the test. These points are indicated in fig. 11. There is a 0.2s delay between the simulation result vs. the VICON test data; this may be due to the phase shift of the digital filter (3rd order Butterworth low pass filter, cutoff frequency is 30HZ applied to force / moment data, which is the input to the simulation). The difference in the velocity between the VICON data and the model simulation can be attributed to error in estimating the front wheel’s initial orientation as well as the estimated model’s friction parameters. Also, the dynamics of the stepper motor are ignored in the simulation and only the velocity profile from the stepper controller code is utilized as an idealized motion constraint on the front wheel.

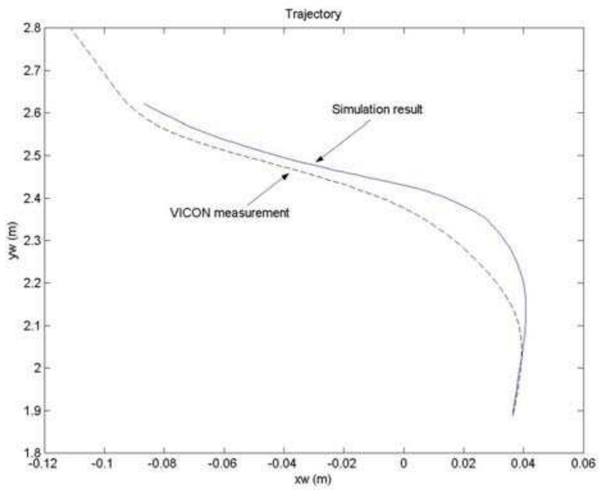


Figure 10. Measured vs. Simulated Walker Trajectory for “Light Left Turn” Case when User Fights Active Motor

The correlation coefficients of the simulation results with the measured data in the above cases are shown in table 1. It can be observed that the simulation results correlate well with the measurement. It should also be noted that the parameters of the Walker (mass, inertia, geometry) and the coefficient of friction between the wheels and the floor at the Gait lab were very carefully measured for these experiments and simulations. Of course, in real applications, the coefficient of friction information is not expected to be readily available or even remain constant during a given path. However, the main objective of the physics based approach (Fig. 1) is to provide *one* component of an overall information system for assessing User Intent, and the expected errors in predictions from parameter variations, modeling assumptions, noise in the signals, etc. must be factored into an overall User Intent assessment model.

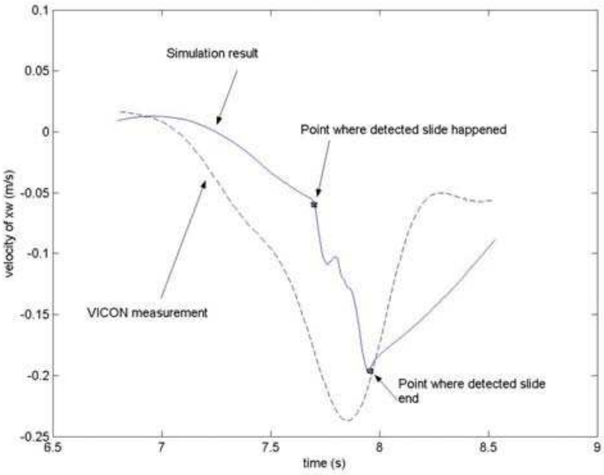


Figure 11. Measured vs. Simulated Walker sideway velocity of the "fighting" case showing Walker slide during "fighting"

TABLE I. CORRELATION COEFFICIENT OF THE SIMULATION RESULTS OF THE TEST CASES PRESENTED VS. TEST DATA

| | $x_w$ (m) | $y_w$ (m) |
|---|---|---|
| Go straight | 0.9742 | 0.9994 |
| Left light turn | 0.9996 | 0.9991 |
| Right sharp turn | 0.9976 | 0.9956 |
| Following Walker | 0.9999 | 0.9999 |
| Fighting with Walker | 0.9510 | 0.9973 |

After the model was validated, it was simulated with the forces and moments fixed. A point in time was chosen and the values of the corresponding forces and moments were kept constant; this point was chosen in the middle of a turn. The aim is to evaluate the model's prediction capability and to select the appropriate *look-ahead* prediction span. The absolute error between the actual path traced by VICON and the predicted path was computed. Fig. 12 shows the absolute prediction error, in meters, with time for the different cases presented above.

It is clear from the graph that for a prediction span of 0.5 second or less, the prediction error is small for the straight path, and that it increases with the increase of the sharpness of the turn. However, the prediction error may significantly change if a different point was chosen for fixing the forces and moments. The graph shows that a look-ahead prediction time horizon span may be selected with a decreasing confidence factor as the time span increases. This would become an input to User Intent assessment scheme for the controller.

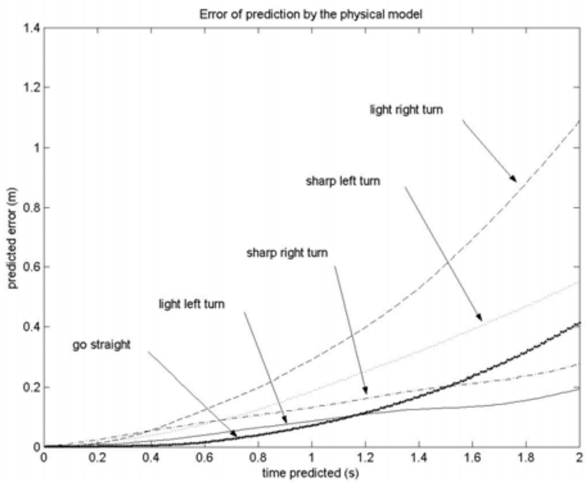


Figure 12. Absolute error of prediction by the model with Time

## V. RELATED WORK

The "user's intent" concept, required for the shared control design paradigm discussed here, was introduced in [5] and expanded upon in [3]. Similar concepts have also been encountered in the literature employing various sensing techniques. However, the scope of this review is focused on research work where the measurement of forces and/ or moments is exploited to infer user's intent, and the use of vehicle dynamics for path prediction. A Walker that provides guidance implemented on top of a commercial omni directional mobile robot platform equipped with two force-sensing handlebars that play the role of a haptic interface to the system is described in [6]. Each handle bar is equipped with two independent force sensing resistors, one before and one after the gripper handle, and measure the force only along the handle bar's axis. The force readings are then transformed to planar translational and rotational velocities of the platform. The intent is intuitively translated as follows: a forward push on handles results in forward motion, a differential push-pull combination results in rotary motion, and a pull on both handlebars stalls the robot. User-intended motion is determined through a user-specific motion model that represents a mapping of force sensor readings recorded to trajectory commands. The model is used to compute the user's desired translational and rotational velocities from force input data to drive and steer the platform. PAMM is another mobility aid based on a cane supported by a mobile platform with nonholonomic drive capabilities that is designed to support and guide a person using ceiling signposts distributed in the environment [7]. The cane moves in response to the forces and torques applied to a force/torque sensor. The inference of the user's intent requires distinguishing forces and torques applied to the handle for support from those applied by the user to indicate directional intent to control both the steering and propulsion of the cane. On the other hand, the use of system's dynamics to predict a path of vehicles into the future is not new. Researchers at the University of Michigan have used Kalman filters to simultaneously estimate a motor vehicle's lateral velocity and external disturbances for the purpose of path prediction. The prediction is used to compute Time of Lane Crossing (TLC) for automated driver assistance on highways; the system employed a camera to sense roadway in front of the vehicle, measured front wheel steering angle and employed a gyroscope to measure the yaw rate [8]. In this work, path prediction is achieved by numerically integrating a simplified linear "bicycle" model of the vehicle's lateral motion using state estimates from the near-range Kalman filter, as well as the vehicle's initial conditions [9], rather than the vehicle's kinemtic-dynamic model. The prediction errors were statistically characterized in [10]. Similarly, the RoboCup team at the Freie Universitat Berlin, have used an ANN-based linear prediction model using a fixed camera to track and control a fast moving mobile robot. The prediction model, which has 42 constants, uses the current position and orientation of the robot as well as the current control command to predict the robot's path. The predicted path is fed to the controller, as feedback, to compensate for and minimize the effect of delays resulting from the vision system and the wireless communication with the robot on the path. The values of the model's constant were obtained from training the neural network with data recorded from real robot [11]. The prediction model, in this case, approximates the physics based model of the mobile robot.

## VI. Conclusions

A physics based model of the Walker showed excellent correlation with the experimental data, with the model constructed to allow friction limiting sliding dynamics and the cooperative or uncooperative ("fighting") actions between the human User and the Walker's control within a shared control framework. While the correlation is highly encouraging, it is expected that in real applications for assessing User Intent, the physics based model will be only one of the contributing factors.

The physics based model is a nonlinear, coupled set of differential equations and for real time applications local linearization of these equations for discrete applications is being developed. The model based path prediction makes it possible to predict probable paths a few seconds into future. This, when combined with perceptual model of the environment, will play an important role in determining the navigational intent of the Walker's User. An additional issue being considered is the effects of frail versus robust subjects on the model (frailty may be an age related or a disability related phenomenon).

## Acknowledgments

This research was funded by the National Science Foundation (NSF award ID 0004247). The authors would like to thank the staff at the Gait and Motion Analysis Lab, Kluge Children's Rehabilitation Center at the University of Virginia, where experiments are conducted.

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