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Contact Feature Extraction on a Balancing Manipulation Platform

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Abstract— **The dynamic behavior of an inverted pendulum platform inherently reveals information about its interaction with the environment. The closed loop controller puts the unstable plant into dynamic equilibrium, where very small external forces result in persistent excitation of the system. Our previous work has shown that we are able to detect and estimate external forces on an inverted pendulum base using only dynamic state information from the controller. The Yale Inverted Pendulum Door Opening Robot (YIPDOR) has gained a simple 4 degree of freedom (DOF) arm with the goal of opening and traversing doorways with both heavy and sprung doors. We have explicitly omitted dedicated force sensors. Estimation methods using only the Jacobian and joint torques do not provide adequate estimates of external forces on this system. While improved force estimation continues to be a goal for the project, we propose that traversal of sprung doors may be accomplished with low-level, dynamic postures and detection of changes in dynamics rather than explicit force estimation and control. Changes in the equations of motion and dynamic constraints (contact, unlatching, door movement) are detected by using filtered derivatives of relevant parameters. This feature extraction research increases the safety and performance of the balancing and manipulation system without any additional dedicated sensors.**

I. INTRODUCTION

Mobile manipulation, both teleoperated and autonomous, is an interesting and important area of systems research. When compared to automated systems and machines, humans excel at certain manipulation tasks. Tasks that require dexterity or tasks that have a high degree of variability are relatively easy for humans but often impossible for machines. Consider the task of picking an apple, opening a box or opening a door. Each of these tasks is relatively easy for a child but is challenging for a robot, whether autonomous or teleoperated. Teleoperation systems often address uncertainty by using human perception to address complex environments, though dexterity remains an issue.

Manipulation differs from many robot tasks in that it requires making contact with the environment. A majority of robot systems treat contact conditions as undesirable and focus on navigating around obstacles, or the environment is structured such that contact is avoided entirely.

We have developed a system (the Yale Inverted Pendulum Door Opening Robot, *YIPDOR*) that aims to address a number of challenges in mobile manipulation. The system draws on biological principles of motion control to achieve functions with lower complexity and higher robustness than previous mobile manipulation systems.

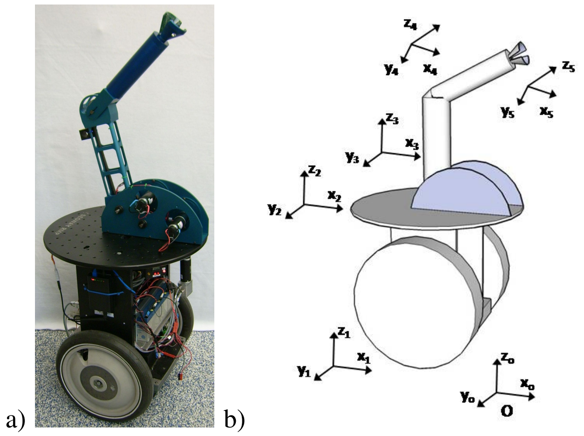

Fig. 1. *YIPDOR & frames.* a) YIPDOR. b) The relevant frames [0-5] of the YIPDOR system, from ground, O, to the end effector, 5. See Table I for entire frame descriptions.

Ref. frame	*Description*
0	Ground coordinates
1	RMP pitch about y_1 (& yaw about z_1)
2	Waist rotation about z_2
3	Upper arm (shoulder) rotation about y_3
4	Lower arm (elbow) rotation about y_4
5	Wrist rotation about z_5

TABLE I

REFERENCE FRAMES OF THE YIPDOR SYSTEM.

In this paper, we will discuss how by combining a balancing platform, equilibrium point control and a simple, low DOF arm, we are able to detect changes in state during automatic door opening. The discussion of the particular controllers is described in [1]. Our main contribution lies in showing that the closed loop, dynamic nature of a balancing platform provides active excitation and dynamic sensing capabilities without force sensors. Furthermore, the naturally low impedance of the balancing platform reduces the performance requirements on the arm actuators when doing force estimation.

II. RELATED WORK

Successful execution of a manipulation task comes from two distinct system attributes: appropriate hardware combined with appropriate control. Further, the appropriate control strategy depends explicitly on the characteristics of the physical hardware, including its nonlinear dynamics.

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Research on human sensory motor learning suggests that humans are able to develop feedforward, dynamically active control schemes for control of the musculoskeletal system [2], [3]. When the dynamics of the human and environment deviate from expected, the human is able to identify the change. We propose that creating dynamic equilibrium points with closed loop control and monitoring the dynamics serves as an effective way to detect changes in the environment. While our system makes use of ideas from model reference parameter estimation methods, our focus is system design and performance, highlighting the benefits of using a passively unstable, persistently excited, closed loop system in order to accomplish greater functionality with fewer components (and lower cost).

The task of door opening and traversal has been studied by several groups, using a range of hardware and strategies. The Yale and Siemens mobile manipulator was one of the earliest mobile robots to open latched doors [4]. Later MIT's Cardea used a basic non-actuated end effector to open similar doors [5]. The Stanford STAIR project completed a similar task, adding a host of visual sensing to characterize the environment [6]. EL-E (Georgia Tech), HERB (Intel), PSR-1 (KIST) and PR2 (Willow Garage) robots have all used onboard sensing to locate and turn latches also [7], [8], [9]. Our strategy differs from theirs in our use of sprung doors and a balancing platform with no dedicated sensing.

In most robotic door opening research, the doors are unsprung. After unlatching, the task is primarily door traversal with minimal door manipulation to push the door ajar. When door spring returns are used, the problem gets more difficult. In addition to door traversal, the door must be manipulated to remain ajar, either at the knob or the actual door. In this type of manipulation, force sensors can become very useful for detecting changes in all phases of task completion. Force sensors are a common accessory for manipulators and most door opening systems, but our system uses a simpler hardware approach to do more with less. Our robotic system, YIPDOR, opens and manipulates sprung doors without a dedicated force sensor. This constrained manipulation problem is robustly handled by using biologically inspired compliance and equilibrium point control. These same techniques have been used to simplify robot control in a broad range of manipulation applications [2], [10], [11], [12], [13]. Our arm uses Whole Arm Manipulation principles by being low degree of freedom and designed for contact along the entire surface [14]. This will allow the manipulator to be robust to unexpected contact over its entire surface and to allow manipulation with many surfaces rather than just the end effector.

YIPDOR is based on a balancing platform, which has an inherently low stiffness when disturbed from equilibrium. The balance gains may also be modified to create a programmable impedance in the locomotion system. By using its high center of gravity, a balancing system can lean against the environment and produce forces that would destabilize a traditional statically stable robot [15]. This allows balancing systems to achieve a larger force workspace with less mass.

Using less hardware requires greater use of available data. It has long been known that joint kinematics and Jacobians can be used to determine joint torques and end point force propagation [16]. These force estimates can be used to detect important events during door opening (knob contact, internal forces, grasp slippage, etc). This is often applied in manipulation systems when force sensors are not present, force sensor validation is required, or for redundancy. If the system is linear and noise free, force estimates can be calculated. But, when the system is noisy, contains non-linearities or other unknown behaviors, the basic estimation model must be expanded, revised or even abandoned. In our previous work, we showed that it is possible to detect and estimate forces on a mobile balancing platform without an arm or dedicated force sensor [17]. By using the pitch angle, wheel motor torque, velocity and position, external torques can be determined over a moderate range (0-25Nm). In our current case, we must again infer important arm contact and force events from available system data.

III. SYSTEM OVERVIEW

For mobility, the base of the system is a Segway RMP 200 balancing platform. The RMP can accept both velocity and turn rate commands, and constantly reports 22 status variables at 100Hz. For manipulation, a custom 4 DOF robotic arm of approximate human dimension was designed and placed atop the RMP baseplate. The arm assembly consists of 4 revolute joints, which we label the waist, shoulder, elbow and wrist. The Maxon EC45 waist motor contains a reduction gearhead (43:1) and an encoder. The shoulder and elbow motors are Maxon RE25 and each contains a reduction gearhead (66:1) and an encoder. A series of toothed pulleys and belts transfer power to the joint axes. For primary arm motor control (waist, shoulder, elbow), a BRD-WHI controller from ELMO Motion Control is used. The wrist motor, which also contains a reduction gearhead (26:1) and encoder, is a Maxon RE40 that is controlled by a PIC Servo SC. Figure 1 and Table I diagram and list the degrees of freedom in the YIPDOR system.

For processing and system integration, a Versalogic Cobra EBX-12g single board computer (SBC) manages all communications and computations. The SBC operates under QNX 6.3.2, and it communicates over CAN and serial ports to relay internal system messages. For operator communications, an Avalon AW900i wireless ethernet bridge connects the system to the network, and a wireless Logitech Rumblepad can be used for full teleoperated control of all DOF and motion.

For power, the RMP balancing base has its own separate, internal supply. To power the remainder of the system components (arm motors and controllers, SBC, wireless connection, etc), four 12V lead acid batteries are connected in series and regulated to various levels. Motor torque is derived from motor commutation data (encoder, motor voltage and current). There are no dedicated force sensors or additional sensing aside from RMP balance sensors.

The YIPDOR system currently relies on the operator to: *1)* maneuver the robot to a position in front of the door, and *2)* align the end effector at the same height as the door knob and <2" away from contact. The remainder of the door opening and traversal process is automated and only requires operator intervention for safety, or if a phase of door opening needs to be retried. The autonomous cycle handles door knob centering, door unlatching, open door manipulation and door frame traversal. The GUI reports on the opening status of YIPDOR and many system variables. In this system, there are a number of variables that can be monitored, and we explore how these can be exploited for force estimation and feature extraction.

The YIPDOR system was designed to traverse the majority of pushing type doors. All of the testing discussed in this paper occurred on a door with a circular, flat faced knob and return spring (see [1] for additional details). In the following sections, we will characterize the 4DOF arm, showing that motor torque and endpoint forces are poorly correlated, making force estimation difficult. We will then present methods that we have used for feature extraction during door opening and traversal.

IV. ARM CHARACTERIZATION

Force measurement is commonly performed with dedicated 1-6 axis force sensors that are often expensive (>$5,000), fragile and would be bulky in our system, for the range of forces expected. Further, these sensors typically are installed at the end effector and thus cannot measure forces applied along the robot arm surfaces. Using the mass properties of the arm, and knowing the arm kinematics and position at all times, an open loop model may be used to estimate theoretical joint torques with the Jacobian [16]. From this, we can estimate when external forces are present on the arm.

In order to estimate the torque on each joint, the following formulation was used:

$$\tau = J^T \cdot F \tag{1}$$

where τ is the joint torque, J^T is the Jacobian transpose, and F is the joint force matrix (based on the link lengths and masses). This predicts the joint torque for all geometric configurations. The theoretical joint torques can be compared with actual torques reported by the motor controllers, revealing when external forces are present. The gearing and belt transmission are included to convert motor torque to joint torque. In these tests, the balancing system was not used, and the base was stationary as the arm was commanded to various poses.

It was found that the model had prediction errors (MSE=0.74 UP(dir#1), MSE=**3.15** DOWN(dir#2), total MSE=1.96) and needed further revision to accurately predict joint torque, which led to the inclusion of Coulombic friction. This improved the model (MSE=0.26 UP(dir#1), MSE=**1.17** DOWN(dir#2), total MSE=0.72), but also made it clear that other factors were present that cause a hysteresis effect (see Figure 2). The actual joint torque at a single position was path dependent, and could take on a range of values. For example, moving an arm joint UP toward a target point resulted in a greater steady state torque to hold that position as compared to moving the arm joint DOWN to get to the same target. The load dependent static and dynamic friction in the arm transmission (planetary gearhead and tooth belts) corrupts the open loop force estimate substantially.

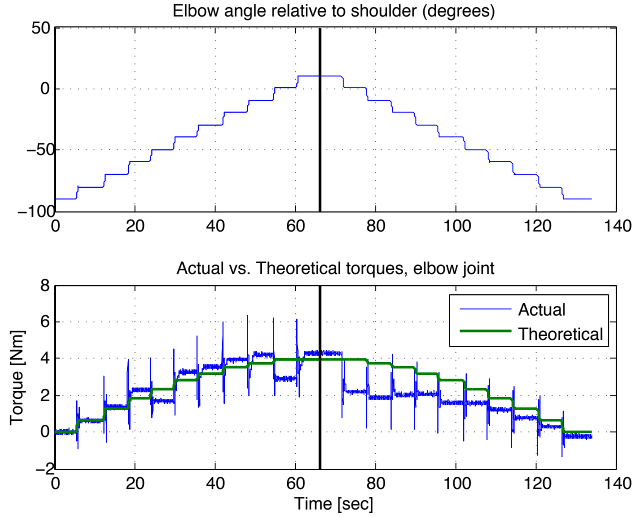

Fig. 2. *Theoretical elbow torque.* (Top) Motion of elbow while maintaining constant shoulder position. (Bottom) Actual torque can vary significantly from the theoretical torque (with friction included) based on the direction of the movement and previous motion. This reveals that a theoretical torque prediction would have to take hysteresis and/or previous motion into account.

In order to explore this behavior more thoroughly, the shoulder and elbow joints were swept through their workspace. The data reveals that there are 2 distinct observable planes of current values. One plane for motion with the joint causing upward arm motion, and another plane where the joint motion is causing arm motion downward (see Figure 3). These two planes can serve as a general bound for the current at any particular arm configuration. While this is useful to know, it makes it very difficult to accurately predict the joint current for any particular target position. And, this in turn makes it harder to predict when an external force has been applied to the arm using only arm torque data. In order to still gain utility from this rich data, we have applied feature extraction techniques to detect key occurrences in our investigation.

V. FEATURE IDENTIFICATION AND DETECTION

The YIPDOR system uses dynamic balance at all times to maintain stability. Whether moving in free space or in contact with the environment, the wheel motors must be actively controlled or the system will fall. This burden of balancing has a benefit. Any force or torque that is applied about the pitch axis of the base will result in control activity and state variable changes that are immediately apparent. Restated, balancing provides persistent excitation about an equilibrium point, and changes in the state trajectory about this operating point may be used to infer environmental changes.

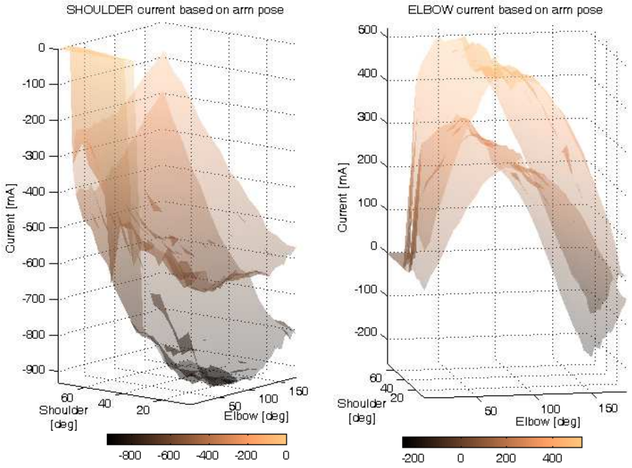

Fig. 3. *Measured current hysteresis.* The measured motor current in the shoulder (left) and elbow (right) joints, based on joint angle. The 2 planes show the hysteresis that is present based on whether the arm motion is up (plane with greater absolute values) or down (lower absolute value plane). This variation in measured current makes it more difficult to predict expected arm torques and thus external forces.

As mentioned previously, our application for the YIPDOR is automated door opening. During door opening, several key events must occur. The door handle must be located and grasped. Next, the handle must be turned to move the latch bolt. Once the door unlatches, the system is less constrained, as the door can swing open. If there is no return spring present, then door traversal becomes a path planning problem, and the door can be sufficiently opened by passive handle or door contact. If there is a return spring present, then some form of active door manipulation must take place in addition to the path planning (e.g. the system may need to robustly modulate the output force vector to keep the door ajar and open it as the system passes through).

In the process of door traversal, the dynamics of the YIPDOR change in discrete ways through contact with stiff (i.e. closed door) and compliant (i.e. open door) objects in the environment. In order to continue safe operation and progress towards a goal, certain contact features need to be recognized during the process. These features are described in detail in the following sections: *a) Handle engagement:* to have an appropriate posture and normal force to enable the wrist to turn the door knob or handle, *b) Latch bolt disengagement:* for sprung and unsprung doors, to go from a stiff manipulation task to a compliant task, and *c) Wheel obstacle detection:* to determine if something is in the path of the wheel.

A. Handle Engagement

In order to unlatch the door by turning the knob, the system must first have a favorable grasp on the knob. A favorable grasp is achieved by a combination of end effector placement and normal force application to generate friction. Other groups have used dedicated optical sensing methods (video, laser, IR, etc) to identify, approach and characterize doors and handles [6], [18], [19], [20], but we chose to use less sensing. In our research we currently rely on the operator to be able to get the end effector close enough to the knob (and at the same height) so that forward motion will create contact with the knob. When autonomous routines begin, the end effector height is maintained as the system drives forward, contacts the knob, and creates the necessary normal force to turn the knob. Without force sensor feedback this can be difficult. We have identified the key parameters and levels, and thus achieved a high unlatch success rate.

In the case of door handle engagement and grasping, we found that the RMP pitch and position errors provide the most salient data. At equilibrium, the pitch and position errors are stationary and known for a given mass distribution, though there is always some persistent oscillation about the mean value. Whenever external forces are present, they can cause significant changes in both the pitch and the position error (as the system shifts its location to balance the torque about the wheel).

In this feature detection investigation, the YIPDOR end effector was placed in contact with the door knob, and the RMP base was given target positions that resulted in pitch and position errors. The arm gains were adjusted to allow some compliance, so that small end effector height changes resulting from RMP pitching would not create excessive internal force. At this point, the wrist was turned clockwise and counter-clockwise for 180^o (i.e. 45^o is required to unlatch the door), and the success of unlatching was recorded. We found that a pitch angle larger than -3^o (i.e. leaning forward) and a negative position error (i.e. slightly behind target position) are good indicators that there is enough normal force (15-17N) to successfully turn our test door knob (15/16 trials). Of course, this is dependent on many factors, such as the type of door handle and coefficient of friction between the materials, but these results serve as a proof of concept that can be expanded to a more general form. In present testing and operation, these two variables were monitored and used in autonomous engagement routines, and also to give the operator feedback as to when it is acceptable to attempt door opening.

B. Latch Bolt Disengagement

In order to create normal force with the YIPDOR (and the friction necessary for turning the handle), we drive the RMP base directly toward the door and establish a dynamic equilibrium point while the arm is controlled with a relatively stiff position control loop. Because we are using an inverted pendulum base, we are able to specify a low impedance along the axis perpendicular to the plane of the door. This controller generally places the target position of the wheels at a point which may intersect the door frame. Therefore, when the door is unlatched and no longer fully constrained, the RMP will seek its target position, colliding with the door frame if no other action is taken. At the same time the door knob and end effector follow an arc as the door opens. This can become an interesting problem when considering a sprung door and a selectively compliant system (the RMP base is only compliant in the fore/aft direction, not laterally; also, the arm is held stiff to maintain friction during turning). For these reasons, the impedance used to provide a stable normal force for turning the knob is unsuitable for controlling the system once the door is unlatched.

When the door is unlatched, there are simultaneous state changes and these can be observed in system variables. Once the important variables have been identified, they can be monitored for abrupt changes by the filtered derivative,

$$\Delta_{X,i} = C_1 \cdot \delta_{X,i} + C_2 \cdot \delta_{X,i-1}, \qquad (2)$$

where $\delta_{X,i} = X_i - X_{i-1}$ is the sample-to-sample difference. Any of the observable system variables can be substituted for the placeholder X. C_i are filter constants that sum to 1.0 and determine the sensitivity. These values can be determined empirically with representative data, taking the signal noise and sampling frequency of the result (Δ_X) into account. In our system, C_1=0.95 and C_2=0.05, and the filtered derivatives are calculated and monitored at a rate of 10Hz. Smaller C_1 values result in missed feature detection, while larger values lead to false positives. Whenever the absolute value of the filtered derivative, $|\Delta_X|$, exceeds a defined limit, a flag can be set to indicate that a certain condition has been met, or a feature detected.

For door unlatching, three variables were identified that could reliably be associated with this feature: average wheel velocity, waist joint torque, and elbow joint torque. For the wheel velocity, the summed average of left and right wheel velocities was used. None of these variables can be used individually as other system occurrences may cause similar variable behavior, but the combination of monitoring all three variables is a strong indicator of latch bolt disengagement.

Prior to latch bolt disengagement, the system is leaning on the door. This is a quasi-static pose; the arm and the base are motionless if there is no commanded arm motion. The door is stationary because the latch is holding it in place. When the latch bolt is no longer holding the door closed, it is free to rotate about its hinge, and the door handle will follow an arc defined by the door width. If the end effector is engaged with the door knob, it is constrained along this arc as the door swings open.

As with any closed loop servo system, the inverted pendulum base will approach its target position when a disturbance is removed - the softer the position gain, the greater the movement. This is characterized by a sudden reduction in position error and simultaneous wheel motion. Thus, the rate of change in the left and right wheel velocity variables is a prime predictor of door opening. However, imperfect grasps on the door handle and wrist rotation can also cause relative motion which creates small wheel motions, so wheel velocity alone is not a sufficient indicator. As shown in [17], the sensitivity of the inverted pendulum base displays the dynamic behavior of a low impedance, low friction position controlled servo.

The change in environmental constraints also results in changes to measured joint torques and displacements in the arm. Despite the challenges described earlier in section IV, there are observable changes in the elbow and waist joint data when the door unlatches.

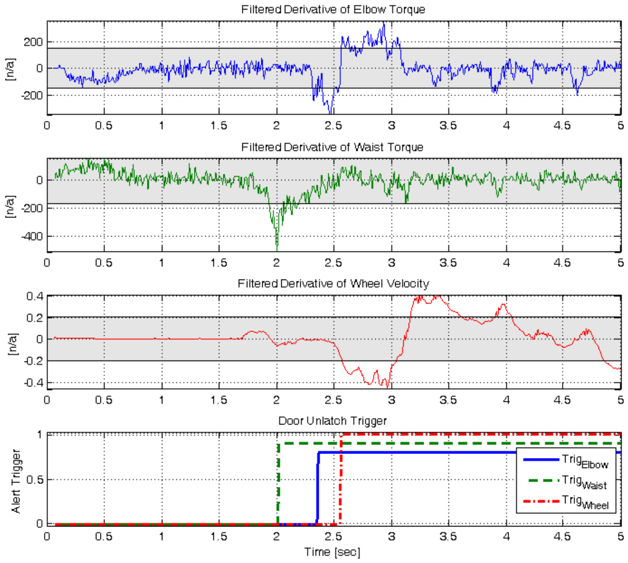

Fig. 4. *Latch bolt disengagement.* When the door unlatches, there is a change in the state variables that can be observed with a filtered derivative. In our door opening system, we use three of these signals to change the behavior of the robot to a new force field/impedance. (Top 3 plots) Filtered derivative of the a) elbow joint torque, b) waist joint torque, and c) summed wheel velocity. The gray areas show the bounds that are considered normal operation. (Bottom) Trigger responses when the filtered derivatives exceed the specified bound. When used together, these triggers are strong indicators for the unlatching of a door.

With an equilibrium point controller used for this phase of door opening, the end effector will remain inline with the base in the absence of external forces. When the latch bolt disengages, the door handle is constrained to follow an arc while the YIPDOR base motion is commanded on a straight line normal to the door. As a result, internal forces are created along two axes, the lateral (left-right, relative to the facing direction of the RMP & arm) and vertical (up-down) axes.

The lateral internal force is detectable in the waist torque variable, and does not greatly affect the inverted pendulum controller variables. The vertical internal force is caused by pitch rotation of the YIPDOR base as the inverted pendulum moves toward the commanded position. This vertical internal force from door knob manipulation can be observed in the elbow torque variable, and in turn can also affect the balancing and positioning of the RMP base.

Due to the varied initial positioning of the RMP base and the end effector on the door knob, neither the elbow or waist torque variables (lateral or vertical internal force) can be used solely to characterize door opening (as false positives occur from grasp changes that are common in the turning process). Thus the combination of wheel velocity, elbow torque and waist torque must be used together to reliably detect a door unlatching, as seen in Figure 4.

C. Wheel Obstacles

In our investigation, bumping into the door frame, or running over a ground obstacle (i.e. foot, large rock, sur-

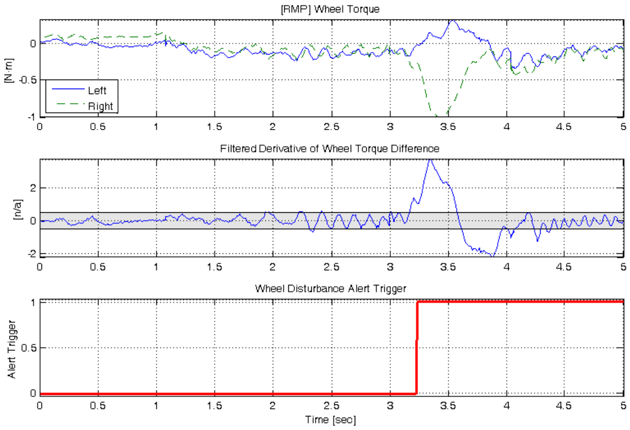

Fig. 5. *Wheel disturbance detection.* (Top) Wheel torque. (Middle) Filtered derivative of the difference in the wheel torques. The gray area shows the bounds that are considered normal operation. (Bottom) Trigger response when the filtered derivative exceeds a specified bound, signifying there is a disturbance at the wheel.

face anomaly) are events that can create problems while manipulating objects and trying to maintain balance. Other groups have used dedicated sensing methods (visual, sonic, capacitive, etc) to map, characterize, or avoid obstacles during motion [21], [22]. YIPDOR currently contains no remote sensing, but still needs to recognize and respond when wheel obstacles are present during manipulation.

For this investigation, several obstacles types were introduced to a single wheel of the RMP and system data was recorded before and after the event. The yaw or steering controller is another closed loop system that operates about an equilibrium point. Analysis of wheel torque data revealed that using the filtered derivative of the difference in the left-right wheel motor torques was a reliable method to detect external disturbances between the wheels (see Figure 5).

VI. CONCLUSIONS AND FUTURE WORK

In this research, we demonstrated that an inverted pendulum base, with its unstable dynamics, persistent movement and closed loop control may be used to detect changes in the environment. We identified several features (latch bolt disengagement, wheel obstacles) of interest to our application, and also found a reliable method to detect these features (filtered derivatives) without the use of dedicated sensors. Future investigations will add to the feature library, and work toward fully autonomous opening of any type of door. Also, work has begun on a manipulator design that can accomplish both pushing and pulling.

See a video of YIPDOR in operation at:
http://hmilab.eng.yale.edu/Downloads/ICRA2010-YIPDOR.mp4

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