Sensor Filtering for Balancing of Humanoid Robots in Highly Dynamic Environments

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Abstract

This paper is part of our on-going research in balancing of humanoid robots in highly dynamic environments. We focus on balancing of a humanoid robot on a Bongo board. One of the problems with balancing in highly dynamic environments such as the Bongo board is the fact that any control algorithm needs to overcome the inherent latency and jitter in the sensors as well as in the actuators of the robot, since it has very little time to react to disturbances.

The sensor filter method described in this paper allows the robot Jimmy (a DARwIn-OP robot) to balance for several seconds on a Bongo board. A video of the robot Jimmy balancing on the Bongo board can be found at http://www.youtube.com/watch?v= ia2ZYqqF-1w.

1. INTRODUCTION

This paper describes the filtering approaches we developed for our research in balancing of humanoid robots in highly dynamic environments. In recent years, rapid progress in both hardware and software has led to impressive improvements in the performance of humanoid robots. For example, the soccer playing robots participating in the RoboCup competition can walk and turn quickly and stand up after falling. In the HuroCup competition [2], the world record in the sprint event (3 meters walking forward followed by 3m walking backward) has improved from 01:07.50 sec. in 2009 to

00:25.50 sec. in 2013. Similarily, the world record times in the marathon, which is traditionally held outdoors, improved from 37:30.00 over 42.195m in 2007 to 07.34.50 over 120m in 2013. In fact, there are many robots that can move over even and hard terrain.

The problem of gravel roads and debris fields is much harder. So far, the robot Atlas developed by Boston Dynamics has demonstrated the most impressive walking on uneven surfaces. However, the robot uses hydraulic actuators and therefore has a power to weight ratio much higher than that of other robots. Furthermore, the practicality of the robot is limited since it needs a tether which provides a 400V line able to power the robot.

Today no solutions for small electrically powered robots exist. This is not due to a lack of suitable control algorithms as many have been demonstrated in simulation. But the robots do not have sufficiently powerful actuators, nor enough sensors to move over a rubble pile or similar environments.

We therefore focus on balancing in challenging, yet achievable environments. Examples are our robot Tao-Pie-Pie and our ice and inline skating humanoid robot Jennifer [7, 6]. The results of this research have also been used in our robotic competition team Snobots, that won the 2013 HuroCup kid-sized competition [8] in Kuala Lumpur, Malaysia. HuroCup is the most challenging competition for small humanoid robots; a single robot has to compete in eight events (sprint, marathon, lift and carry, weightlifting, wall climbing, penalty kick, basketball, and obstacle run).

We selected the problem of balancing on a Bongo



Figure 1. Jimmy on the Bongo Board

board for our research. A Bongo board consists of a small board that is placed on top of a wheel (fulcrum). Figure 1 shows our humanoid robot Jimmy on top of the Bongo board. The fuclrum can freely move left and right. Balancing on the Bongo board is difficult for humans, so often acrobats in a circus impress spectators by performing various tricks.

Jimmy is a Robotis DARwIn OP [3], a 45cm tall humanoid robot that weighs about 4kg. Robotis MX-28 servo motors power 20 degrees of freedom (DOF). Higher level processing is implemented on a FitPc2 processor board which features an 1.6GHz Intel Atom processor and 1GB of RAM. For active balancing, the robot includes a three axis gyroscope and a three axis accelerometer in the torso. Other sensors include a camera and two microphones. We extended the basic DARwIn OP with two force sensors (FSR) sensors in the feet and replaced the hands with two grippers.

The DARwIn OP uses a two-tiered distributed control architecture for position control of the joints. The higher level processing system sends position and movement commands via a serial link to a low level servo controller based on an ARM Cortex M3 processor running at 72 MHz.

Section 2 shows an analysis of the dynamics of the Bongo board and shows the relationship to other inverted pendulum problems. Section 3 focuses on the specific subproblem of filtering the raw sensor data from the accelerometers and gyroscopes to provide an accurate state estimator for the highly dynamic system.



Figure 2. Bongo Board: The pivot point rotates along the circumference of the fulcrum.

2. ANALYSIS AND RELATED WORK

This section gives a brief introduction to the dynamics of an inverted pendulum [11]. The dynamics of the inverted pendulum problem are well-studied and well understood and form the basis of many motion control algorithms for bipedal humanoid walking robots [12].

The problem of balancing on a Bongo board is similar to the cart and rod problem, as can be seen in Fig. 1. The robot can be modelled as a single point mass balancing on top of the board, and the goal is for the robot and board to balance without touching the ground or the robot falling off the board. In other words, the inverted pendulum system formed by the robot and the Bongo board should balance.

The difference between the Bongo board and the card and rod problem is that when balancing on a Bongo board, (a) the pivot point of the robot will rotate along the circumference of the wheel, and (b) the position of the pivot point cannot be controlled directly - only indirectly by controlling the motion of the humanoid robot balancing on the board.

Figure 2 shows an acrobat balancing on the Bongo board. Acrobats try to maintain their torso in a fixed position as pressure on the board from the legs moves the board sideways.

There has been a lot of theoretical work in the area of highly dynamic balancing [10, 9, 5], but practical implementations are still lacking. Anderson et al. describe an adaptive torque based approach [1] that is able to balance a humanoid robot on a simple see saw. In simulation, their approach is also able to balance a humanoid robot on the more challenging Bongo board.

A similar system that is able to balance a robot on a see saw in the presence of unknown disturbances, is described by Hyon [4].



Figure 3. Raw sensor readings from the accelerometer and the integrated gyroscope readings over an 18 second trial. As can be seen by the spikes in the accelerometer readings, the Bongo board hit the table several times after 3 seconds.

3. FILTERING AND FUSION

This section focuses on the subproblem of filtering and fusing the sensor data from the accelerometers and gyroscopes when balancing on the Bongo board. This is a crucial part of the system. Any control algorithm must use an explicit or implicit state estimator, which depends on fast and accurate sensor feedback.

The DARwIn-OP robot includes a three axis accelerometer and a three axis gyroscope in the torso. Since the movement of the Bongo board is constrained to the left and right (frontal plane), only the readings in those planes were used during the balancing.

Accelerometers measure the linear acceleration of the robot. However, in this and many applications, the accelerometers are used to measure the inclination of the robot by assuming that the robot is static or only moving slowly and measuring the acceleration of the robot due to gravity. As can be seen in Fig. 1, the acceleration due to gravity of a stationary robot on a Bongo board is modulated by the *sine* of the inclination angle.

Gyroscopes use the piezo-electric effect to measure the angular velocity of the robot. Therefore, the gyroscope readings must be integrated to calculate the inclination angle of the Bongo board.

Figure 3 shows the raw sensor data for the accelerometer and the integrated gyroscope readings during one of our trials. The trial took about 18 seconds. The board hit the table after only approximately 3 seconds and several times afterwards.

At first glance it looks as if this sensor data is reasonably accurate and the readings from the accelerometer and the integrated reading from the gyroscopes correlate quite well. Initially, we chose the integrated gy-



Figure 4. The initial raw sensor readings from the accelerometer and the integrated gyroscope readings. It shows that even though the accelerometer registers the initial tilt, the angular velocity is not large enough to register on the gyroscope.

roscope readings as our state estimator, since they were less noisy than the accelerometers.

However, we noticed that the robot would not react quickly enough to disturbances in its position. A close analysis is given in Fig. 4, which shows that the gyroscope does not react at all to the initial tilt (0.0s to 0.2s). The figure also shows that the initial tilt is detected albeit with noise by the accelerometers.

This sensitivity problem is aggravated by the architecture of the DARwIn-OP. The gyroscope and accelerometer sensors are connected to a small embedded microcontroller (CM-730), but all balancing control is executed on the FitPc2 main processor board. The CM730 and the FitPc2 board are connected via a slow serial connection. According to Robotis specifications, the maximum speed of the serial link is 2 MBps, but in our tests we found that there was too much interference on the bus at that speed. Therefore, we limited the speed of the serial link to 1 MBps. To be able to react to disturbances, the main processor board needs to request readings from the CM-730 and the CM-730 transmits the sensor reading back to the FitPc2. This introduces a latency of at least 8 ms, but sometimes as high as 16 ms into the system. The jitter makes accurate control for balancing in highly dynamic environments challenging.

The raw sensor data can be smoothed via exponential smoothing by applying the following formula, where α is the smoothing factor and $x_{raw,i}$ is the raw sensor reading at time t = i and $x_{filtered,i}$ is the output of the filter at time t = i.

 $x_{filtered,i} = \alpha * x_{raw,i} * (1 - \alpha) * x_{filtered,i-1}$

The resulting accelerometer readings of the initial part of the trial for two α values are shown in Fig. 5.



Figure 5. Raw accelerometer readings compared against exponential smoothing with different α parameters.

One drawback of any type of averaging is the fact that the filter will respond slower to changes in the state of the system. Therefore, it was necessary to use both sensors in the control of the robot, which leads to a sensor fusion problem. Most robotics professionals know that their sensors are always lying to them - the question is which sensor to trust more in this situation.

The most common approach to sensor fusion is the original or an extended version of the Kalman filter. Kalman filters use an estimate of the variance of the current sensor to weigh the readings. However, as can be seen from the previous figures, the accuracy of the reading of the gyroscope and accelerometer are dependent on the state of the system. If the robot is almost upright (i.e., inclination angle is close to 0), then the robot moves slowly and the accelerometer is more accurate than the gyroscope, which are unable to measure the slow angular velocity. On the other hand, when the robot is moving quickly, then the gyroscope readings are more accurate.

Furthermore, to further enhance the reactiveness of the robot, we implemented a predictive controller that predicts the state of the robot, thusly compensating for the latency in the DARwIn-OP.

4. CONCLUSIONS AND FUTURE WORK

We described common pitfalls when balancing robots in highly dynamic environments. Our final solution consists of a complementary filter with a predictive control algorithm. Improving the filtering of the sensor data lead to better performance of the robot.

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