EFFECTIVENESS OF COOPERATIVE AND COMPETITIVE SHARED CONTROL

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ABSTRACT

EFFECTIVENESS OF COOPERATIVE AND COMPETITIVE SHARED CONTROL

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Advances in technology place ever increasing demands for effective interactions between humans and machines. Human-machine interaction (HMI) that incorporates shared control, in which the human and machines both simultaneously influence the outcome, may lead to a more natural interaction between people and machines. This natural interaction could be particularly beneficial in assistive devices that are used to increase, maintain, or improve capabilities of individuals.

An interactive computer simulation of an inverted pendulum which takes input from artificial and human controllers was programmed in Matlab to determine the effectiveness of cooperative shared control. A proportional-derivative (PD) controller was used as the artificial/computer side of the shared control. Input from a human operator was obtained using an Xbox 360 controller, with biofeedback provided by a flat panel display. The artificial controller and human worked together to balance the inverted pendulum vertically and prevent it from falling below the horizontal axis. Random perturbations were provided to destabilize the system. The amount of time in which a participant could maintain stability was used as a performance measurement.

In competitive shared control the computer assists the human in completing the primary task. However, in addition, the human works to achieve a secondary task while

working symbiotically with the artificial controller. This may result in conditions where the human is competing with the artificial controller to achieve different goals. Note that this type of shared control is different than the winner takes all competitive control because influence from each source is always present. The amount of time the pendulum is balanced and how long the pendulum remained within the target area was used as a performance measurement.

A total of 20 participants for the cooperative shared control and 12 participants for the competitive shared control were evaluated at 26 different testing conditions in a pseudo-randomized order. Each test condition was repeated three times for each participant and the result for each test condition was averaged. The results from both the cooperative and competitive shared control testing were very promising. The results showed that blended shared control can outperform a human and that higher performance can be achieved by increasing the PD level. Blended shared control can also perform better than an artificial PD controller alone when the difficulty increases beyond the controller's capabilities. This same observation can be made when comparing blended shared control to additive performance. Competitive testing was also able to show that giving the human a secondary task to complete did not interfere with primary task completion. By lightening the load of a primary task, blended shared control could enable someone to perform additional tasks or allow them to perform them better than they could on their own.

CHAPTER 1: INTRODUCTION

Advances in technology place ever increasing demands for effective interactions between humans and machines. This results in the need to improve human-machine interaction (HMI) so that it can keep up with the current technology. Shared control between human and machines is an area of research that could lead to improvements in the way machines assist people at work, in the home, and in every aspect of our daily lives. An automotive cruise control is an example of shared control where control is switched autonomously between an artificial controller and a human. When the driver wishes to increase speed beyond the set cruising speed, the driver pushes the gas pedal and assumes speed control of the vehicle without intervention from the machine until the speed is reduced to the controller's set point. Vehicle speed control is then reverted back to the artificial controller. Shared control could lead to better controller performance allowing certain portions of control to be automatically controlled by an artificial controller while enabling humans to control higher level functions. There are tasks that are too complex for either an artificial control or human control alone. However, some of these tasks may be achievable if humans and machines work together sharing the control. Using this approach, shared control could allow machines to control certain aspects for which they are well adapted to such as those that require high reaction speed or control of multiple degrees of freedom. Humans could then focus their control effort on aspects for which they are well adapted such as high level logic, prediction, and strategy.

One area of technology that could benefit from using a shared control scheme is in the development of assistive devices. These devices are designed to assist people rather than control them. Shared control has been used to control the operation of a walker for the elderly [1]. By using shared control the walker was able to provide assistance only when needed and do so in a natural way without causing instability of the user. Other research shows that shared control may even be able to reduce the visual demands of tasks such as driving [2].

In this research we study a new type of shared control called blended shared control where humans and machines both simultaneously influence the outcome. This type of control scheme may lead to a more natural interaction between people and machines.

CHAPTER 2: LITERATURE REVIEW

2.1 Control Systems

Control systems are an important part of many disciplines of engineering as well as in the natural world. A control system is a system that controls the operation of a system to achieve a desired output [3]. Feedback provides the controller with knowledge of the current state of the system. There are two types of control systems: open loop and closed loop. Open loop systems do not use feedback to make control decisions so the output of the system never affects the input. An automated sprinkler system is an example of open loop system, because it turns on at a specific time regardless of other conditions. It will turn on at a specific time even if the grass already has enough moisture or if it is raining. Closed loop systems take advantage of knowing the output state and use this knowledge to influence the system input so that the desired output is achieved [3]. An oven is an example of a closed loop system. The oven is set to a certain temperature and once the oven reaches this temperature the heat turns off. When the thermometer measures that the oven is below the temperature set point, it heats the oven again until the oven once again reaches the desired temperature. This insures that the oven will maintain the set temperature.

2.2 PID Controllers

The most common type of feedback controller used in industry is a proportional-integral-derivative (PID) controller [4]. The proportional aspect of PID provides a gain that is proportional to the error in the controlled parameter. If the error is large, then the gain will also be large. This is to insure quick reduction of error. However, too large of a gain can lead to instability. The proportional gain can be reduced by taking into account the rate of change in the error, or the derivative part of a PID controller. The derivative gain slows the response by simultaneously incorporating a controller gain corresponding to the rate of change in the error. When this gain is tuned correctly, it will result in a slower transient response and will improve system stability [3]. Integral gain may be used to eliminate steady state error. Integral gain takes into account error that accumulates over time. It is often used in artificial controllers to correct for very small errors that may still be present when the sum of proportional gain and derivative gain is zero [3]. Although the use of PID control is common in engineering systems, in the case of balancing an inverted pendulum, only the proportional and derivative components are essential for system stability [5].

2.3 Assistive Devices

Assistive devices are items or equipment used to increase, maintain, or improve functional capabilities of individuals [6]. Most people only think of assistive devices as items, such as wheel chairs or hearing aids that help disabled people to regain lost functions, such as their ability to walk or hear. However, night vision goggles are also considered an assistive device, because they improve the vision of able bodied people. PDAs and cell phones could also be considered assistive devices because they remind people of appointments. Although not all assistive devices use a high degree of technology, additional research is being conducted to implement cutting edge technology into assistive devices [1, 7, 8].

2.4 Shared Control

Employing shared control in assistive devices may be a better option than using artificial control alone. Blending the artificial assistance with human input could enable assistive devices to be more effective [7]. Shared control is where two or more agents influence the control of the system [9]. This thesis will refer to shared control in which the agents are a human and an artificial controller. Traded control switches sole control between two or more agents depending on the conditions. For example, a pilot will control the plane for takeoff and landings, while the autopilot operates the plane while in the air [9]. Further studies in the area of shared control are being conducted to find other applications as well as evaluating its effectiveness [1, 2, 7–14].

Although there are several published articles on shared control, few investigate the various forms of coordination between humans and machines. Ronald Arkin [15] discusses two main categories: cooperative and competitive. Cooperative coordination is described as a fusion of all controls, similar to superposition of vectors. Competitive coordination is typically defined as winner takes all where two or more controls are competing for dominance and only the winner will be utilized. Nunes [10] and Carreras [11] both propose hybrid control schemes that utilize aspects of both forms of coordination. Nunes proposes using varying forms of coordination in his shared control scheme depending on the hierarchy of the command. Carreras' hybrid approach uses the most beneficial aspects of each type of coordination in order to improve performance.

2.5 Studies of Shared Control in Assistive Devices

We are interested in using shared control on assistive devices; however we are not the first. Glenn Wasson [1, 8] developed the COOL-Aide (CO-Operative Locomotion Aide), an intelligent walker for the elderly that uses shared control on wheeled walkers. Unlike other intelligent walkers that aid the elderly, COOL-Aide senses when assistance is needed and provides it as necessary. On-board sensors are used to determine if walls or other obstacles are close so that braking or steering can be used to avoid them. These sensors are also used to anticipate the user's intended direction and provide a balance between supporting the anticipated position and current position of the user. This provides a more natural feel to the walker and does not make the user feel like he/she is being led. Ana C. Lopes [7] designed and built a robotic wheelchair that uses a brain computer interface (BCI) and shared control to allow people with severe motor disorders to regain mobility. Through BCI the user specifies a certain location in the wheelchair's memory or designates a general direction for the wheelchair to travel. The robotic wheelchair receives the commands from the user and safely navigates to that location or travels in the indicated direction. These two examples use shared control to make adaptive decisions when sensing that assistance is needed. They are a type of shared control in which the human controls higher functions, like direction of travel, and the machine helps to determine the best path.

2.6 Studies of Simulated Shared Control

Besides using shared control in physical devices, it is also being used in simulated environments to test controller efficiency. Navigation is often a complex problem that requires a controller to adapt to various changing circumstances and conditions. When determining the effectiveness of shared control, it is often tested against solely human operation and autonomous control. Aaron Enes [9] used Zermelo's navigation problem where a simulated ship is navigated to a target location while traversing a region of strong current. Enes tested a blended shared control that allowed a human and artificial controller to simultaneously control the ship. The influence of human and artificial controls changed depending on how much the command differed between the artificial controller and the human. If the difference was large, then control was given to the human. This meant that sometimes the human had more influence and at other times commands were given by the artificial controller. This method of shared control resulted in faster completion times than a human navigating without the assistance of an artificial controller.

Yukio Horiguchi [12] tested shared control of a simulated robot navigating a turn in a corridor. The initial testing led to two conclusions; first, that the human was able to perform better when signaled by the robot to turn, and second, operation of the robot by the human was difficult after the robot had decided to ignore human input. These results led to a modification to the shared control that allowed the robot to adapt and predict the human's response to an autonomous movement and enabled better coordination with the human inputs. Further testing showed that this modification alleviated problems in the first test and resulting in improved performance when compared to other forms of control. Gillespie and colleagues [2, 13, 14] investigated shared control through the use of a haptic steering wheel. The artificial controller was able to provide feedback to the human indicating the direction that the controller wished the vehicle to be navigated. Multiple artificial controller schemes were used to determine that haptic feedback can reduce the visual demand of driving. These simulated tests were able to determine the effectiveness of shared control in navigation and shows the benefit of future research using shared control in a variety of forms.

2.7 Blended Shared Control

This thesis research focuses on blended shared control, which is a form of control where human and machine simultaneously influence the outcome of a system [9]. This new form of shared control could lead to more natural interaction between humans and machines. This was investigated in two ways: cooperatively and competitively.

1. Cooperative Shared Control: In the cooperative shared control the computer assists the human in completing the primary goal, both the artificial controller and the human work together to achieve the same goal.

2. Competitive Shared Control: In competitive shared control the computer assists the human in completing the primary goal. However, in addition, the human works toward a secondary goal while working with the artificial controller on the primary

goal. This results in conditions where the human may need to compete with the artificial controller to achieve the secondary goal. Some published research investigated how machines and humans worked together in a cooperative manner [1,2,7–14]. However, we are not aware of any published research investigating the effects of blended shared control with a competitive nature.

CHAPTER 3: METHODS

3.1 Development of a Cooperative Control Computer Simulation of an Inverted Pendulum

An interactive computer simulation of an inverted pendulum which takes input from artificial and human controllers was programmed in Matlab to determine the effectiveness of cooperative shared control.

3.1.1 Description of Pendulum

The model of the planar inverted pendulum, shown in Figure 3.1 consists of a point mass attached to a massless segment that rotates in a single plane around a fixed location.

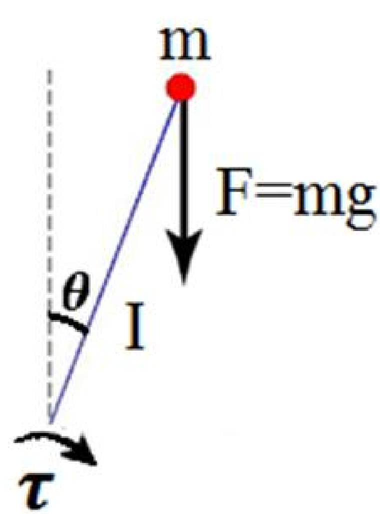

Figure 3.1: Model of Planar Inverted Pendulum

The position of an inverted pendulum is influenced by torque,

$$\tau = mgL\sin\theta \tag{3.1}$$

where the mass, m, and distance from the center of rotation, L, are set to constant values. The acceleration of gravity is g and θ is the angle from the upright vertical position. The mass moment of inertia, I, is a function of both the mass and the distance of the point mass from the center of rotation, where

$$I = mL^2. \tag{3.2}$$

With knowledge of the torque and the inertia, the angular acceleration, α, can be found,

$$\alpha = \frac{\tau}{I}. \tag{3.3}$$

The angular acceleration can then be used to determine the angular velocity, ω, and the angular position. The angular acceleration and current angular velocity is used to calculate the angular velocity at the next time step.

$$\omega_{t+1} = \omega_t + \alpha_{t+1}\Delta t \tag{3.4}$$

This angular velocity and the current angular position are used to calculate position of the pendulum at the next time step.

$$\theta_{t+1} = \theta_t + \omega_{t+1}\Delta t \tag{3.5}$$

3.1.2 Control of the Inverted Pendulum System (PID and Human)

Figure 3.2 shows a block diagram of the feedback system used to control the inverted pendulum. The desired position of the pendulum is fed back into the system then input torque from both the human and PD control are used to change the position of the pendulum. The output torque from the controller is also influenced by the system noise. The human, PD controller, and noise torques are used to influences the physics of the pendulum to change the pendulum's position, velocity, and acceleration. The actual position and actual velocity values are then fed back into the beginning of the loop and used to influence the state of the pendulum at the next time step.

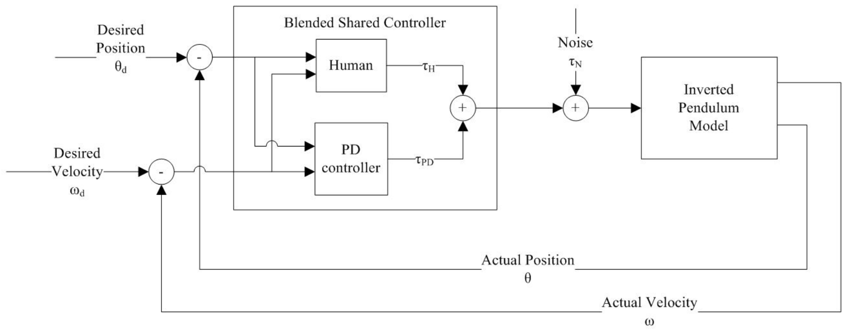

Figure 3.2: Cooperative Block Diagram

The PD control torque, τ_{PD}, corrects for differences between the desired and actual values of the angle and the angular velocity

$$\tau_{PD} = K_P(\theta_d - \theta) + K_D(\omega_d - \omega) \tag{3.6}$$

where K_P and K_D are the proportional and derivative gain constants, respectively. In this case the desired angle, θ_d, and angular velocity, ω_d, will be zero. The proportional gain constant controls how much torque is applied to correct for the difference between the current and desired position. The derivative gain constant effects how fast the pendulum will move by controlling the angular velocity. This helped to reduce overshooting the desired position [3].

In this study, a human uses an Xbox 360 controller, seen in Figure 3.3, to provide input to the system. The left and right movement of the left thumb stick was used to control the torque, τ_H, applied to the pendulum. The Simulink 3D Animation toolbox in Matlab with the commands 'joy = vrjoystick(1)' and 'read(joy)' were used to obtain a values from the human input on the controller. Values for the horizontal axis of the left thumb stick (Figure 3.3) were used to affect the torque of the pendulum.

The axis is analog and generated a value from -1 to 1 that changed based on very slight movements. This value from the axis was multiplied by a factor, called G_H,

Figure 3.3: Xbox 360 Controller

and was used to calculate the amount of torque the human applied. Visual feedback of the current pendulum position was provided using a custom animation program displayed on a computer screen shown in Figure 3.4. The human used the visual feedback of the plot of the pendulum to determine the amount of torque that was needed.

$$\tau_H = G_H \text{axes}(1) \tag{3.7}$$

The noise torque, τ_N, provides instability of the system, representing natural disturbances in real systems. The noise torque was made by multiplying a random number, generated by 'randn' in Matlab, by a noise factor, G_N.

$$\tau_N = G_N \text{randn} \tag{3.8}$$

Equation (3.7) shows the summation of the torques used to determine the acceleration, which when used with equations (3.4) and (3.5) results in a change in position of the pendulum.

$$\alpha = \frac{\tau + \tau_{PD} + \tau_N - \tau_H}{I} \tag{3.9}$$

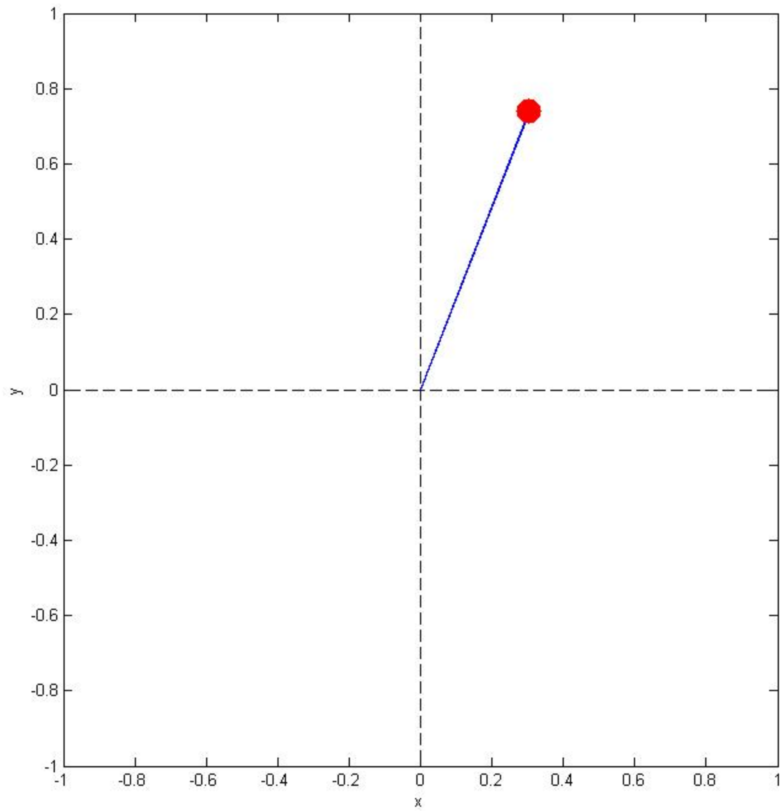

Figure 3.4: Cooperative Pendulum Program Screen, which is used for human input

3.1.3 Cooperative Simulation Description

An interactive Matlab simulation was developed to implement blended shared control into an inverted pendulum. The initial conditions that remained constant for the entire program were defined at the beginning of the program. These constants were the desired position and the desired velocity of the pendulum as well as the derivative gain, which remained 10. Next a loop was set to run continuously and only ended if the pendulum fell below the x axis or if the maximum time limit was reached. The time limit was initially set 5 minutes, or 300 seconds. In this loop the physics and other inputs to the pendulum's torque were calculated. The torque due to gravity was calculated using equation (3.1). The PD control torque was calculated using equation (3.6). The PD controller torque was calculated given the previous time step's position and the previous time step's velocity of the pendulum to determine how much torque needed to be applied. These torques were used by equations (3.4), (3.5) and (3.7) to determine a new position for the pendulum.

The custom animation program worked by taking input data of the time and the theta position of the pendulum and placed a red circle at the location of the pendulum and a blue line was drawn from there to the origin of the figure. The 'drawnow' command was used to immediately update the figure and allowed the program to update the figure quickly enough for human eyes to see continuous movement of the pendulum. Figure 3.5 shows the process of the cooperative computer program.

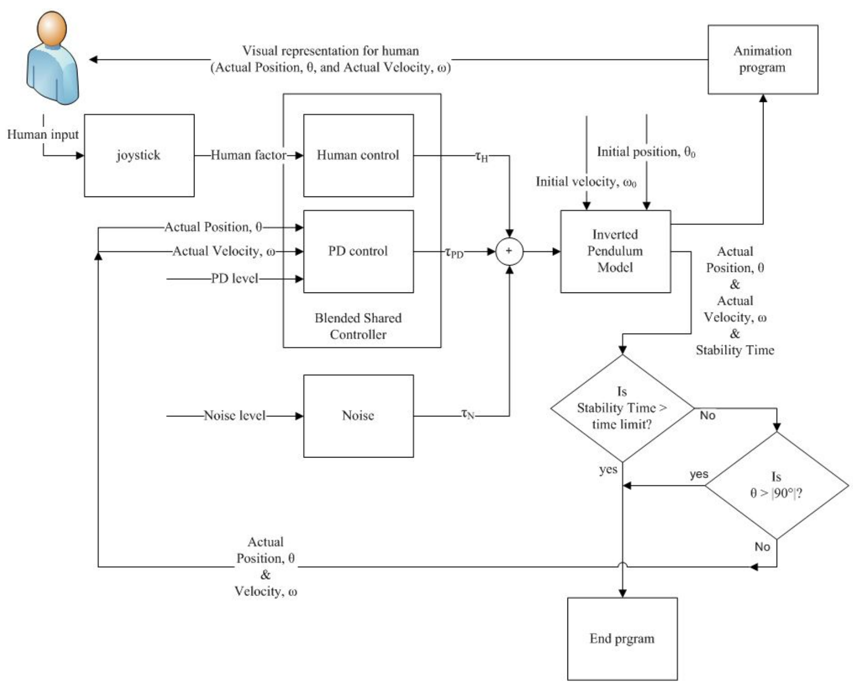

Figure 3.5: Cooperative Program Block Diagram

3.1.4 Sensitivity Analysis

A sensitivity analysis was performed by testing the artificial controller alone over a wide range of noise and PD levels. Only the proportional gain constant was changed, so the PD level indicates the value of K_P while K_D remained fixed at a level of 10.

The noise level indicates the magnitude of G_N used in equation (3.8) to determine the magnitude of random torque noise. This test was used to determine an appropriate range for human participant testing. An optimal region would show a plateau at high performance indicating that the maximum testing time had been achieved. It would also show a flat region of low performance indicating that the challenge was difficult enough for even the highest performer to fail. Finally is would show the transition surface between these two levels. The sensitivity analysis revealed that the region of PD Control / Noise Space where the transition occurred was between a PD level of 0 and 250 and a noise level between 0 and 250 seen in Figure 3.6. Noise levels beyond 250 resulted in very low stability times . PD levels above 250 resulted in times that exceeded 5 minutes except at higher noise. Performance was measured by the number of seconds the controller could keep the pendulum inverted. In order to prevent the test from going indefinitely, a maximum balancing time was placed in the program. This amount of time was chosen to be 5 minutes or 300 seconds. This allowed enough time to determine if a particular test condition was stable or if it would eventually fail by falling below the horizontal axis.

This program was run multiple times for each testing condition. The results for each test condition were averaged together and plotted as a 3D surface in Figure 3.6.

3.1.5 Experimental Protocol Design - Cooperative

We wanted to evaluate the effect of blended shared control (human and artificial controller) over the full controller range of Noise and PD levels. Testing enough points to make a 3D surface would require data collected at 11 different noise values and 11 values of PD. If each test condition was repeated three times, this would require 363 trials. Each trail could last up to five minutes equating to 1815 minutes or over 30 hours to complete a test. This amount of time would be too much of a commitment for each participant, especially if he/she performed well which would prolong

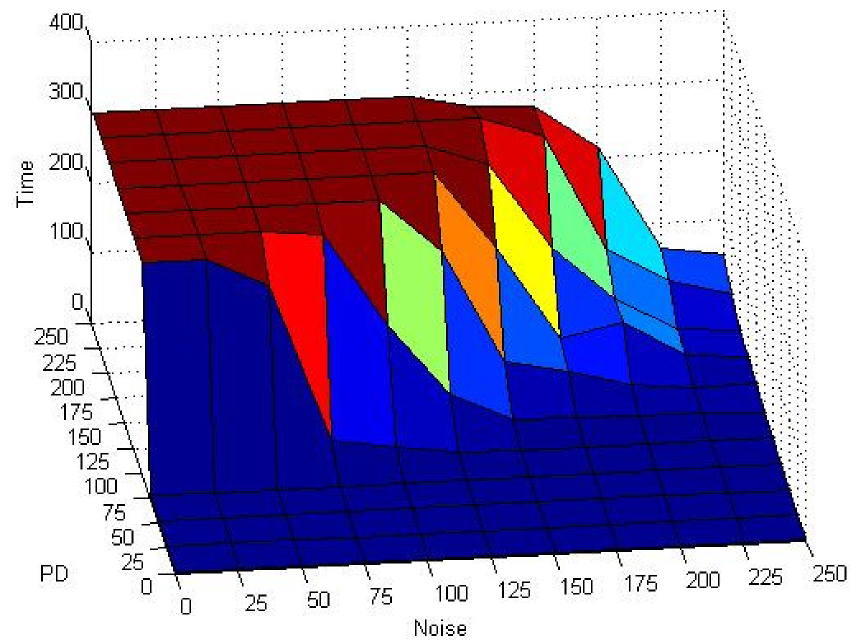

Figure 3.6: Results from Sensitivity Analysis, examining a range of PD and noise from 0 to 250

the amount of time for testing. Therefore, we decided to evaluate cross-section of conditions rather than the entire field. This cross section would allow enough data to sufficiently investigate the transition region and allow cooperative performance to be compared in various ways to highlight its benefits. Nine test conditions were selected to show a transition from high to low values. Using a constant PD level of 100, the noise level was varied from 0 to 200 in increments of 25. Nine test conditions were also chosen at a constant noise level of 150 while the PD level was varied from 0 to 200 in increments of 25. In order to show human performance alone, nine more testing conditions over the same range of noise and with a constant PD level of 0 were also chosen. This resulted in a shape resembling a . This resulted in three sets of nine testing conditions (27 in total), would need to be tested on each participant; however, two of these conditions are in multiple sets so it reduced the number of testing conditions to 25. An average of five trials at each test condition was selected to determine the participants performance.

Initial testing was performed using these test conditions. The initial participant performed as expected; however, five trials resulted in the test exceeding 4 hours. In order to reduce the testing time, the maximum performance time was reduced to three minutes and the number of trials at each testing condition was also reduced to three. This new test protocol was tested and resulted in a test time between 2 and 3 hours.

Preliminary testing was conducted on two more participants. The results were significantly lower than the initial participant and participants commented on the difficulty of balancing the pendulum. It was found that the reaction time needed to balance the pendulum made the task beyond the intended difficulty level. Initially a mass of 12 and length of one was chosen for the pendulum. An increase to the length of the pendulum was used to slow down the pendulum and this decreased the task difficulty. When evaluating how this would affect the results of the experiment the following relationship was derived.

$$\begin{aligned} \alpha &= \frac{\tau + \tau_{PD} + \tau_N - \tau_H}{I} && (3.10) \\ &= \frac{mgL\sin\theta + \tau_{PD} + \tau_N - \tau_H}{I} && (3.11) \end{aligned}$$

By doubling the length and leaving out the human torque, then the PD and noise levels were doubled in order for the acceleration of the pendulum to be halved. By reducing the acceleration to half the value, it made the balancing of the pendulum easier for human participants.

$$\alpha' = \frac{mg(2L)\sin\theta + \tau_{PD} + \tau_N}{m * (4L^2)} \tag{3.12}$$

$$= \frac{2\tau + \tau_{PD} + \tau_N}{4I} \tag{3.13}$$

$$= \frac{1}{2}\Big[\frac{\tau + \tau_{PD} + \tau_N}{I}\Big] \tag{3.14}$$

$$\alpha' = \frac{1}{2}[\alpha] \tag{3.15}$$

It was determined that doubling the current values of noise and PD would insure a transition region similar to the transition region seen with a pendulum of length one. However since this meant a larger range of values, a sensitivity test was performed again to determine the new location of the transitional region. Using the results from the sensitivity analysis, it was decided that a PD and noise range of 100 to 300 with increments of 25 should be used. Therefore this change meant that a range of PD level from 100 to 300 would be tested at a constant noise of 250, a range of noise from 100 to 300 with a constant PD level of 225, and a range of noise from 100 to 300 with a PD level of zero would be the testing conditions. Using this change in PD levels, noise levels, and the change in the length of the pendulum, the two preliminary participants which had difficulty, were tested again. This time they were able to perform considerably better than before and the difficulty level was determined to be sufficiently.

3.2 Experimental Protocol - Cooperative

Description

Each participant was asked to use the Xbox 360 controller to balance the pendulum vertically (at 0 degrees) for as long as possible. If the pendulum fell below the x-axis that test was ended. PD level and noise level were used to the change assistance by the computer and the difficulty of the test. These varied from one test to another. There were 5 minute breaks regularly spaced throughout the testing. The experiment lasted approximately 2 -3 hours.

Pre-Test

1. Find participants
2. There will be 10 males and 10 females
3. Inform participants that the experiment is approximately 2.5 hours long
4. Have participants sign up for an experimentation date

Test

5. Ask participant to sign the informed consent form
6. Ask participant demographic data
7. Ask participant to mark their gaming experience on the visual analog scale
8. Prepare Matlab for experiment
9. Inform participant how the simulation will work

a. Varying levels of difficulties

b. Varying levels of assistance

c. How Xbox controller works

10. Let Participant try at (150,0) , (150,150), (250,150)
11. Begin test on Matlab
12. Let participant have 5 min break after trial
13. Resume test on Matlab
14. Thank participant for their time and participation
15. Record data, labeled for each participant

3.2.1 Participant Testing

Participants from Western Carolina University and the surrounding area were recruited for testing. A total of 20 participants, 10 males and 10 females ranging from ages 17 to 30 were tested for the cooperative testing. Each participant signed an informed consent approved by the IRB prior to beginning testing. Weight and height were also recorded for possible areas of comparison later during analysis. Participants were asked to indicated how well they were feeling and how much gaming experience he/she had by using a visual analog scale, which can be seen in Figure 3.7. The Feeling ratio was calculated by measuring the visual analog scale from the left side, x_{Terrible}, to the participant's mark, x_P, and dividing it by the full length of the visual analog scale line, from $x_{\text{Excellent}}$ to x_{Terrible}, shown in equation (3.16). Gaming ratio was calculated in the same way, shown in equation (3.17), with $x_{\text{No experience}}$ being the left side of the line,and $x_{\text{Playing one right now}}$ being the right side of the line.

$$\text{Feeling ratio} = \frac{|x_P - x_{\text{Terrible}}|}{|x_{\text{Excellent}} - x_{\text{Terrible}}|} \tag{3.16}$$

$$\text{Gaming ratio} = \frac{|x_P - x_{\text{No experience}}|}{|x_{\text{Playing one right now}} - x_{\text{No experience}}|} \tag{3.17}$$

Table 3.1 shows the demographic data, such as age and height, of the cooperative test participants. Figure 3.7 shows the data sheet used to obtain the data in Table 3.1.

Table 3.1: Cooperative Participant's Demographic Information

Number	Gender	Age	Weight (lbs.)	Height (in)	Feeling ratio	Gaming ratio
1	Female	21	105	63	0.78	0.58
2	Female	23	130	63	0.75	0.56
3	Female	24	125	63	0.71	0.73
4	Female	23	146	64	0.76	0.26
5	Male	25	154	70	0.52	0.51
6	Female	25	135	67	0.82	0.15
7	Male	23	208	75	0.64	0.65
8	Male	17	185	71	0.32	0.32
9	Male	17	153	70	0.54	0.42
10	Male	25	163	70	0.79	1.00
11	Female	19	120	64	0.71	0.15
12	Female	20	130	60	0.66	0.03
13	Male	23	160	67	0.56	0.75
14	Female	30	115	63	0.74	0.5
15	Female	21	170	64	0.37	0.14
16	Female	23	125	62	0.52	0.98
17	Male	24	155	67	0.79	0.67
18	Male	22	210	68	0.68	0.67
19	Male	18	210	71	0.92	1.00
20	Male	18	158	70	0.5	0.93

Participant # ________

Shared Control Demographic Data

The total experiment will be performed over approximately 2 hours. Each test will last a maximum of 3 min

Participant information:

Name: ___________________________________

Age: _____________________________________

Gender: __________________________________

Height: ___________________________________

Weight: __________________________________

How are you feeling today?:

Terrible Excellent

Amount of video game experience:

No experience Playing one right now

Figure 3.7: Demographic Data Sheet, filled out by each participant

3.3 Development of a Competitive Control Computer Simulation

The purpose for the study was to investigate the benefits of blended shared control under potentially competitive conditions to evaluate its impact on the performance of the primary and secondary goals. In the competitive simulation, the artificial controller and the human worked together to achieve the primary goal of balancing the inverted pendulum and stopping it from falling below the horizontal axis. The human also worked to achieve a secondary goal of holding the pendulum within a target region that changed location at regular intervals. Like the cooperative simulation, random perturbations were provided during the simulation that moved the pendulum during testing. The amount of time in which a person maintained the pendulum within the target area was used as the performance measurement for the secondary goal. Note that this type of shared control is different than the "winner takes all" competitive control, because influence from each source is always present.

It was expected that the competitive shared control test would improve performance of the primary goal yet decrease the performance of the secondary goal. This was expected because the artificial controller was only working to achieve the primary goal and may be fighting against the human when the human was working to achieve the secondary goal.

3.3.1 Competitive Simulation Description

The program from the cooperative shared control simulation was modified for the competitive shared control simulation. The animation program was modified to add a shaded area to indicate the location of the secondary goal. The size of the target was set to be 20 degrees wide. This target area can be seen as a green pie shaped area in Figure 3.8.

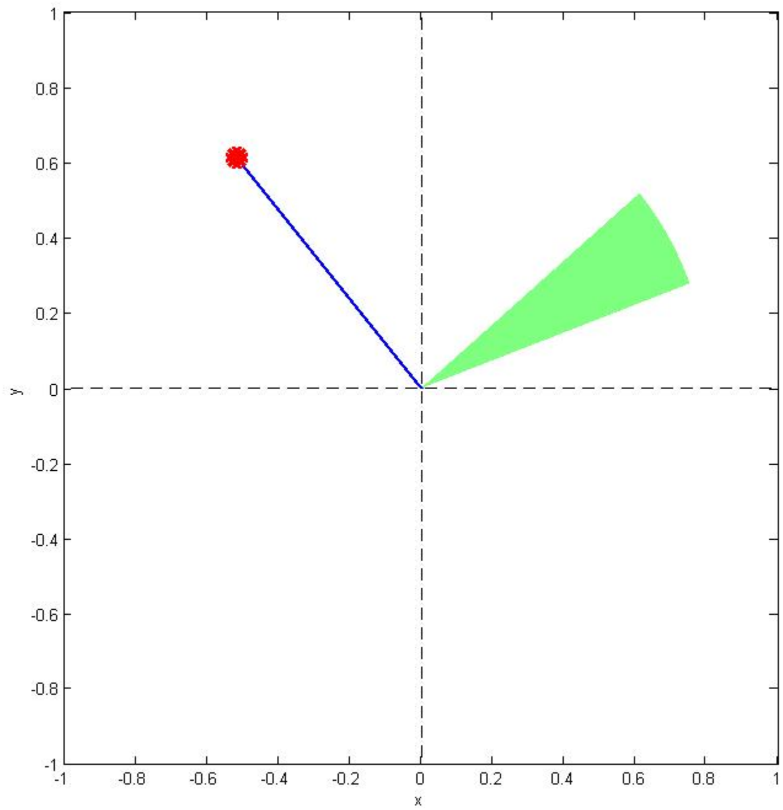

Figure 3.8: Competitive Pendulum Program Screen, which is used for human input

This target area's location was randomized using the 'rand' function in Matlab. A boundary was set at 75 degrees so that the random location was not too close to the horizontal axis. This would cause the human to fail the test too quickly if the area was randomly placed too close to the horizontal axis. The target area changed location every 200 loops, approximately 3.5 seconds.

A score was generated by recording the number of times the pendulum was within the target area during each loop of the program. After the program ended, this score was then converted into the amount of time in the target area by multiplying the score by the total time divided by the number of loop iterations. Figure 3.9 shows a diagram of the competitive computer simulation.

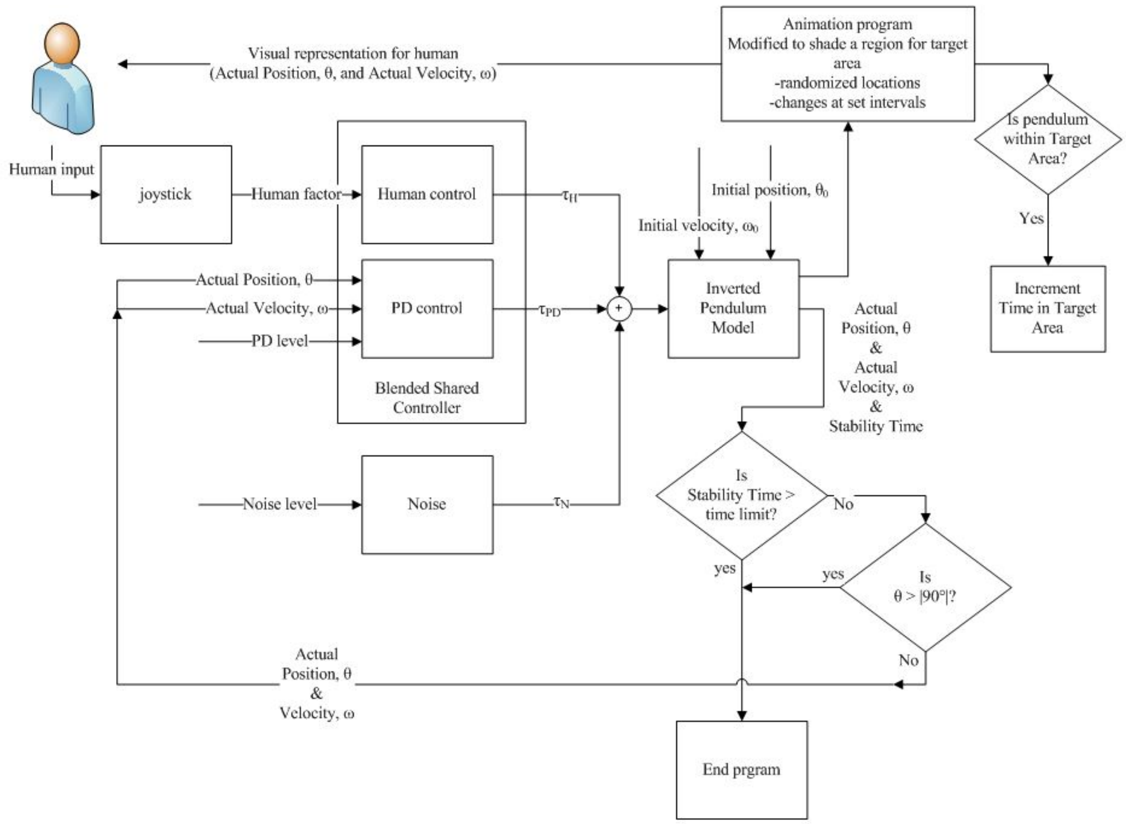

Figure 3.9: Competitive Program Block Diagram

3.3.2 Testing Protocol Design - Competitive

The same input parameters from the cooperative experiment were used in the competitive experiment. This meant PD levels of range 100 to 300 with a constant noise level of 250, a range of noise levels from 100 to 300 with a constant PD level of 225, and a range of noise levels from 100 to 300 with a PD level of zero were used as testing conditions.

3.4 Experimental Protocol - Competitive

Description

Each participant was asked to use the Xbox 360 controller to complete the primary goal of preventing the pendulum from falling below the x-axis while simultaneously trying to achieve that secondary goal of keeping the pendulum within the target area. Participants were tested over a range of PD and noise levels as described above. Five minute breaks were regularly spaced throughout the testing. The experiment lasted approximately 2-3 hours.

Pre-Test

1. Find participants
2. There will be 6 males and 6 females
3. Inform participants that the experiment is approximately 2.5 hours long
4. Have participants sign up for an experimentation date

Test

5. Ask participant to sign the informed consent form
6. Ask participant demographic data
7. Ask participant to mark their gaming experience on the visual analog scale
8. Prepare Matlab for experiment
9. Inform participant how the simulation will work

a. Varying levels of difficulties

b. Varying levels of assistance

c. How Xbox controller works

10. Let Participant try at (150,0) , (150,150), (250,150)
11. Begin test on Matlab
12. Let participant have 5 min break after trial
13. Resume test on Matlab
14. Thank participant for their time and participation
15. Record data, labeled for each participant

3.4.1 Participant Testing

Participants from Western Carolina University and the surrounding area were recruited for testing. A total of 12 participants, 6 males and 6 females ranging from ages 18 to 30 were tested for the competitive control study. Each participant signed an informed consent approved by the IRB prior to beginning testing. The same data sheet used in the cooperative control study (Figure 3.7), was used for this study. The Feeling ratio was calculated by using equation (3.16) and the Gaming ratio by equation (3.17). The resulting demographic data and ratios are shown in Table 3.2.

Table 3.2: Competitive Participant's Demographic Information

Number	Gender	Age	Weight (lbs.)	Height (in)	Feeling ratio	Gaming ratio
1	Female	24	132	63	0.63	0.46
2	Female	21	105	63	0.76	0.62
3	Female	23	125	63	0.62	0.35
4	Female	26	135	67	0.76	0.20
5	Male	30	220	73	0.77	0.25
6	Male	23	147	72	0.96	0.94
7	Female	23	147	64	0.69	0.27
8	Male	19	172	71	0.80	0.65
9	Male	23	158	67	0.79	0.61
10	Male	18	140	67	0.92	0.67
11	Male	18	200	70	0.81	0.82
12	Female	23	115	62	0.51	0.81

CHAPTER 4: RESULTS

4.1 Cooperative Shared Control

4.1.1 Influence of Increasing PD Level on Cooperative Performance

The results show that the human participants, at a noise level of 250, were able to balance the inverted pendulum for an average of 13.7 seconds without assistance of an artificial controller shown in Figure 4.1 and Table 4.1. When a PD controller with a PD level of 100 was used to assist the participants, their average performance increased to 60.8 seconds, which was an increase of over four times. Similar results were observed for all PD levels. At the maximum PD level of 300, performance time was increased over nine times.

Table 4.1: Average Performance of All Participants – Cooperative Control Study

Noise level	PD level	Coop (sec)
250	0	13.6950
250	100	60.8088
250	125	68.5419
250	150	70.6108
250	175	81.6798
250	200	101.5989
250	225	80.7118
250	250	105.6846
250	275	133.3748
250	300	126.3517

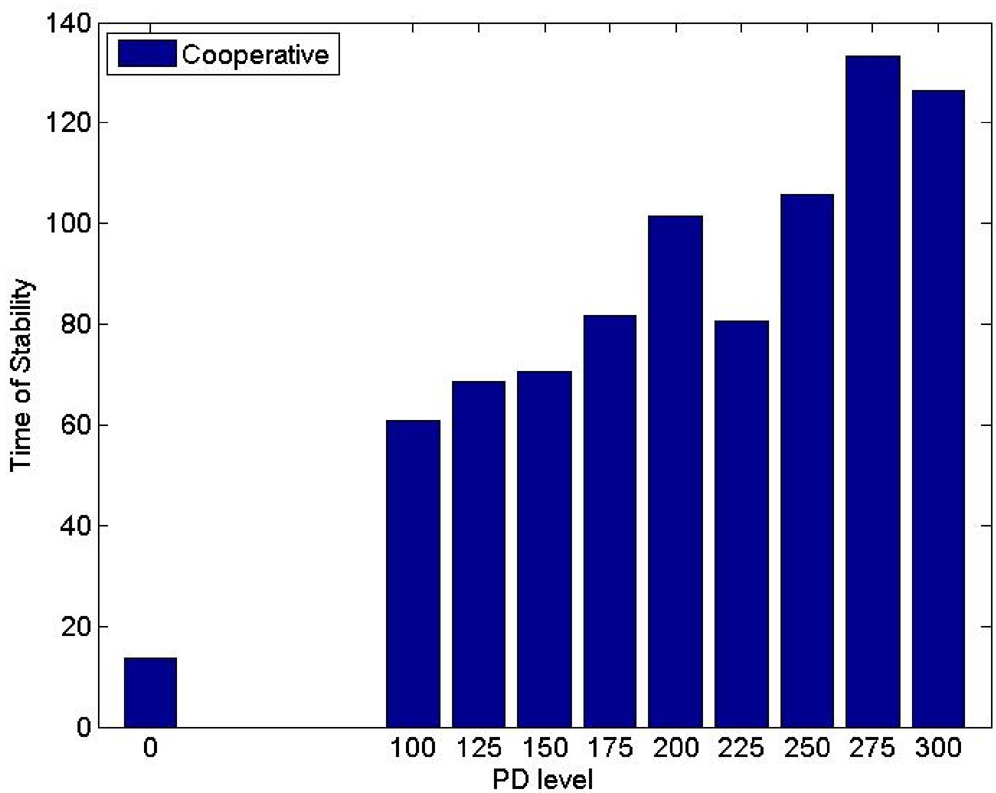

Figure 4.1: Cooperative Performance at Increasing Levels of PD

A statistical analysis was performed on the data in Table 4.1 with the results shown in Tables 4.2 and 4.3. A paired samples t-test was used to determine if human performance was significantly improved when assisted by an artificial controller. The t-test determines whether the means of two groups are statistically different from each other. Table 4.3 shows the t value, t, the degrees of freedom, df, and the p-value, p. The cooperative and human performances were compared at each level of PD. The paired samples correlation results showed that for the condition pairs 1, 2, 3, 4, and 6 the performance varied between each participant (Table 4.3). However, for the condition pairs 5, 7, 8, and 9 indicated that performance was not impacted by the participant contributing to the cooperative shared control. This means that as PD level increases, the differences between individual performance capabilities has less of an impact on the overall performance. The paired samples t-test indicated that for every level of PD, blended shared control was significantly better ($p=0.000$) than performance by a human alone (Table 4.3).

Table 4.2: Paired Samples Statistics of Human Participant Performance – Cooperative Control Study

		Noise	PD	N	Mean	Std. Deviation
Pair 1	Coop	250	100	20	60.8087	52.1844
	Human	250	0	20	13.6950	27.3252
Pair 2	Coop	250	125	20	68.5419	51.2684
	Human	250	0	20	13.6950	27.3252
Pair 3	Coop	250	150	20	70.6108	53.4791
	Human	250	0	20	13.6950	27.3252
Pair 4	Coop	250	175	20	81.6798	58.2335
	Human	250	0	20	13.6950	27.3252
Pair 5	Coop	250	200	20	101.5989	55.9579
	Human	250	0	20	13.6950	27.3252
Pair 6	Coop	250	225	20	80.7118	50.1116
	Human	250	0	20	13.6950	27.3252
Pair 7	Coop	250	250	20	105.6845	48.7928
	Human	250	0	20	13.6950	27.3252
Pair 8	Coop	250	275	20	133.3748	49.7260
	Human	250	0	20	13.6950	27.3252
Pair 9	Coop	250	300	20	126.3517	54.9396
	Human	250	0	20	13.6950	27.3252

Table 4.3: Paired Samples t-Test of Human Participants' Performance – Cooperative Control Study

				Paired Samples Correlations		Paired Samples Test		
		Noise	PD	Correlation	Sig.	t	df	p
Pair 1	Coop	250	100	0.563	0.010	4.878	19	0.000
	Human	250	0					
Pair 2	Coop	250	125	0.558	0.011	5.762	19	0.000
	Human	250	0					
Pair 3	Coop	250	150	0.573	0.008	5.793	19	0.000
	Human	250	0					
Pair 4	Coop	250	175	0.467	0.038	5.904	19	0.000
	Human	250	0					
Pair 5	Coop	250	200	0.415	0.069	7.696	19	0.000
	Human	250	0					
Pair 6	Coop	250	225	0.447	0.048	6.646	19	0.000
	Human	250	0					
Pair 7	Coop	250	250	0.419	0.066	9.178	19	0.000
	Human	250	0					
Pair 8	Coop	250	275	0.305	0.192	10.944	19	0.000
	Human	250	0					
Pair 9	Coop	250	300	0.305	0.190	9.440	19	0.000
	Human	250	0					

We were also interested in developing a better understanding of how increasing PD levels influenced cooperative performance. A linear trendline with an R^2 value equal to 0.8557 was fit to the average of the participants' cooperative performance over the range of PD levels, shown in Figure 4.2. The coefficient of determination, R^2, was calculated in order to determine how well the model fits the data. A value of one means the model is an exact match of the data. By looking at the y-intercept of the cooperative performance, it can be seen that the trendline predicts that a human participant with no assistance by an artificial controller will be able to balance the pendulum on his/her own for 22.0 seconds. This is fairly close to the actual human participant result which was 13.7 seconds.

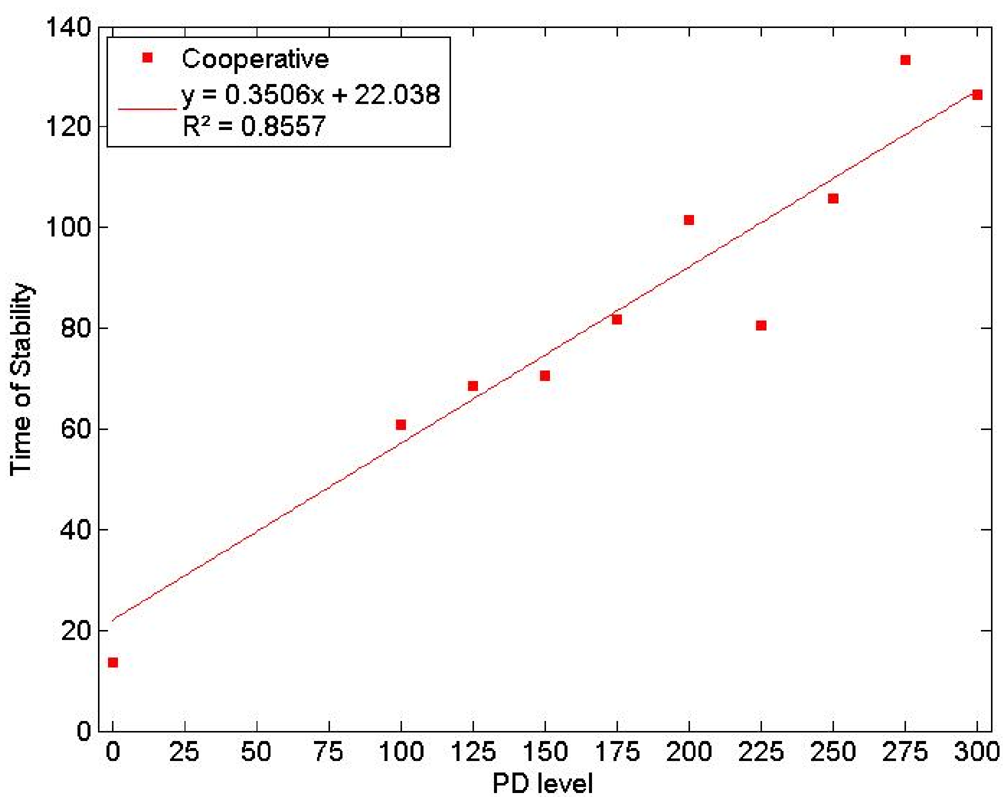

Figure 4.2: Cooperative Trendline Over PD Level Range

4.1.2 Performance of an Artificial Controller was Improved with Human Assistance

The results show that the artificial controller with a PD level of 225 was able to balance the inverted pendulum very well at the lowest noise level for an average of 170.6 seconds, as shown in Figure 4.3 and Table 4.4. As noise increased the artificial controller's performance fell off sharply and at the maximum noise level of 300, performance time was only 8.0 seconds. When the PD controller was assisted by a human participant, the average performance at a noise level of 100 was 139.7 seconds. As the noise level increased, cooperative performance of the artificial controller and human participants working together decreased at a much slower rate than the PD controller alone. At the maximum noise level of 300, performance time was 90.0 seconds, an increase of over 11 times when compared to the artificial controller alone.

Table 4.4: Average Performance of the Artificial Controller Alone and the Artificial Controller Working Along with Human Participants– Cooperative Control Study

PD level	Noise level	PD time (sec)	Coop (sec)
225	100	170.5948	139.768
225	125	112.4509	145.1179
225	150	57.5807	145.9698
225	175	35.1576	118.4025
225	200	22.7338	105.0486
225	225	14.2444	121.2332
225	250	12.2793	80.7118
225	275	11.7426	101.9527
225	300	8.0022	90.0054

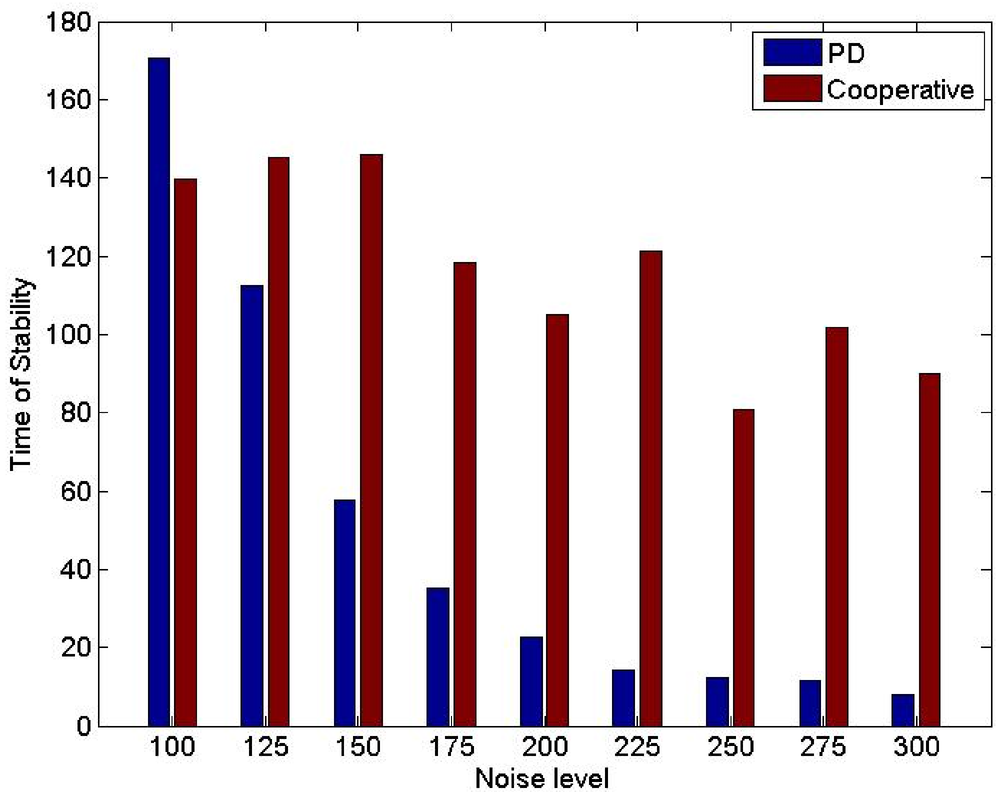

Figure 4.3: Artificial Controller and Cooperative Performance Over Noise Range

A statistical analysis was performed on the data in Table 4.4 with the results shown in Table 4.5. An independent samples test indicated that at the lowest level of noise, the artificial controller performed better than the blended shared control (p=0.007). At a noise level of 125 the blended shared control was better (p=0.011) than performance by the artificial controller alone. From a noise level of 150 to 300 the blended shared control was also significantly better (p=0.000) than the artificial controller (Table 4.5).

Table 4.5: Group Statistics and Independent Samples Test of Artificial Controller and Cooperative Performance

				Group Statistics			t-test for Equality of Means		
		Noise	PD	N	Mean	Std. Deviation	t	df	p
Pair 1	Coop	100	225	20	139.7679	43.2488	-2.928	26	0.007
	PD	100	225	60	170.5948	32.2411			
Pair 2	Coop	125	225	20	145.1178	42.0354	2.63	49	0.011
	PD	125	225	60	112.4508	62.8972			
Pair 3	Coop	150	225	20	145.9698	49.0340	6.855	78	0.000
	PD	150	225	60	57.5806	50.2250			
Pair 4	Coop	175	225	20	118.4024	50.2532	7.046	23	0.000
	PD	175	225	60	35.1575	28.2442			
Pair 5	Coop	200	225	20	105.0485	55.3554	6.55	20	0.000
	PD	200	225	60	22.7337	16.8495			
Pair 6	Coop	225	225	20	121.2332	49.5899	9.543	19	0.000
	PD	225	225	60	14.2444	12.7969			
Pair 7	Coop	250	225	20	80.7118	50.1116	6.079	19	0.000
	PD	250	225	60	12.2792	8.3526			
Pair 8	Coop	275	225	20	101.9526	58.7127	6.834	19	0.000
	PD	275	225	60	11.7425	10.5926			
Pair 9	Coop	300	225	20	90.0053	57.1136	6.406	19	0.000
	PD	300	225	60	8.0022	6.7590			

We were also interested in developing a better understanding of how increasing noise levels influenced the performance of the artificial controller and cooperative control. An exponential trendline with an R^2 value equal to 0.9527 was fit to the average of the artificial controller's performance over the range of noise levels, shown in Figure 4.4. A linear trendline with an R^2 value equal to 0.7574 was fit to the average of the cooperative performance over the range of noise levels (Figure 4.4). The exponential trendline predicts that the artificial controller alone will only be able to balance the pendulum effectively over a small range of noise levels. On the other hand, the linear trendline of the cooperative shared control shows adequate performance over a much larger noise level range.

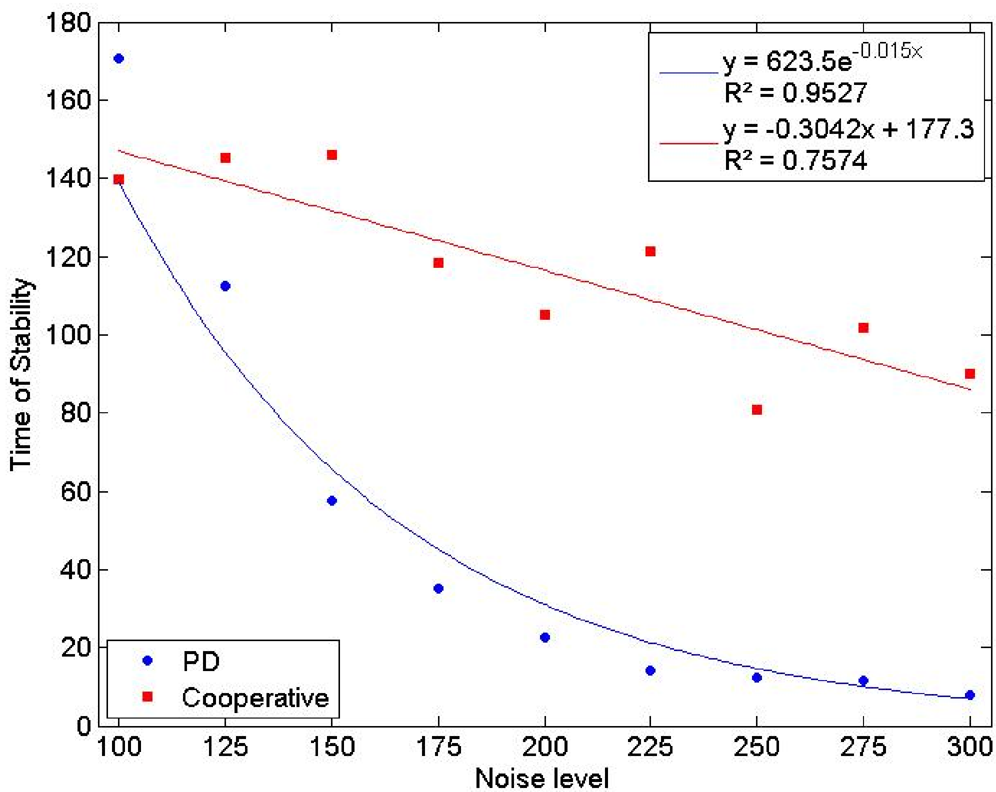

Figure 4.4: Cooperative and PD Trendlines Over Noise Range

4.1.3 Individual Additive Performance Compared to Cooperative Shared Control Performance

The results show that the human participants, without assistance of an artificial controller, were able to balance the inverted pendulum for a maximum time of 38.8 seconds and a minimum time of 14.3 seconds, shown in Figure 4.5 and Table 4.6. These times correspond to the minimum and maximum levels of noise, respectively. The artificial controller with a PD level of 225 was able to balance the inverted pendulum very well at the lowest noise level of 100 for an average of 170.6 seconds. As noise increased the artificial controller's performance fell off sharply and at the maximum noise level of 300, performance lasted only 8.0 seconds. The average results of the human working alone and the artificial controller working alone were added at each level of noise. This resulted in the additive performance time.

The additive performance at the lowest level of noise exceeded the maximum time of 180 seconds, therefore it was rounded down to 180.0 seconds. The additive performance at the next noise level was also high with an average of 147.3 seconds. As noise level continued to increase the additive performance fell sharply and at the maximum noise level of 300, performance time was 14.27 seconds. When the human and artificial controller worked together in a cooperative manner there was a much slower decline in performance as noise level increased. At a noise level of 100, cooperative performance was 139.7 seconds, considerably less than the additive performance. However at the next noise level of 125, cooperative performance was 145.1 seconds and very similar to the additive performance. At the maximum noise level of 300, performance time was 90.0 seconds, an increase of over six times when compared to the additive performance of the human and artificial controller working independently.

Table 4.6: Average Performance of Human Alone, Artificial Controller Alone, the Additive Performance of the Two Working Independently, and the Cooperative Performance of the Two Working Together

Noise level	Human (sec)	PD time (sec)	Human+PD (sec)	Coop (sec)
100	38.8420	170.5948	180.0000	139.7680
125	34.8721	112.4509	147.3230	145.1179
150	29.4240	57.5807	87.0047	145.9698
175	30.9817	35.1576	66.1393	118.4025
200	19.6651	22.7338	42.3989	105.0486
225	18.5855	14.2444	32.8299	121.2332
250	13.695	12.2793	25.9743	80.7118
275	10.5359	11.7426	22.2785	101.9527
300	6.2691	8.0022	14.2713	90.0054

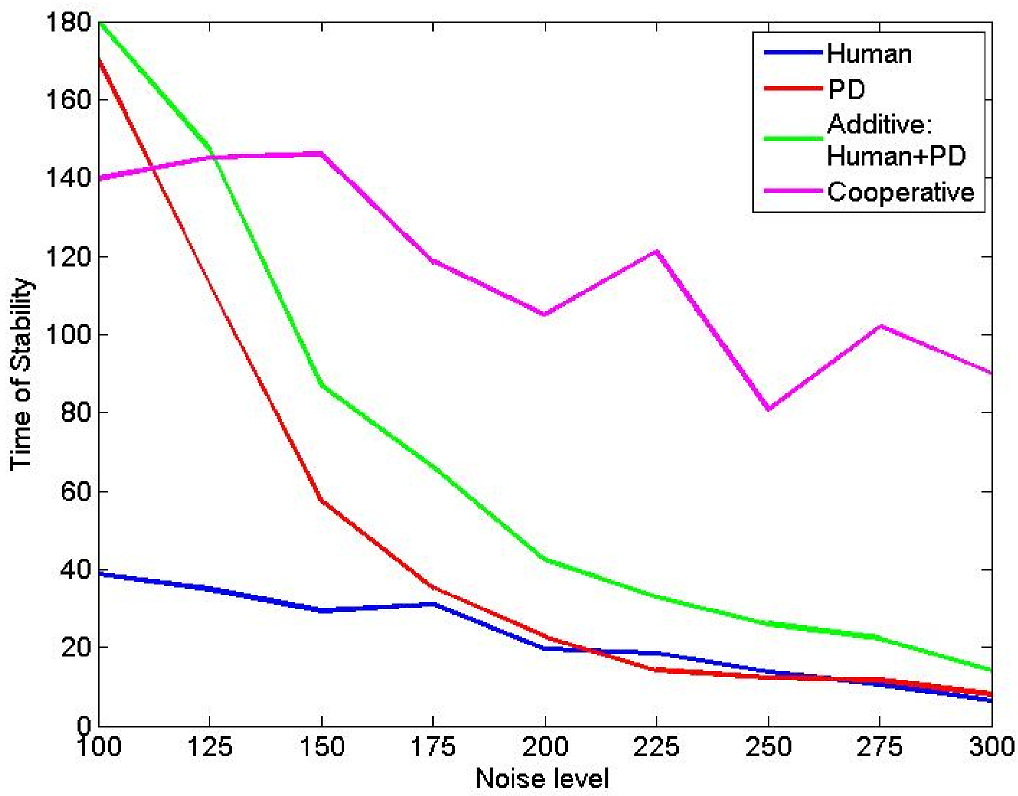

Figure 4.5: Cooperative vs. Additive Over Noise Range

A statistical analysis was performed on the data in Table 4.6 with the results shown in Table 4.7. An independent samples test indicated that at the lowest level of noise, the additive performance of the human and artificial controller working independently was significantly better (p=0.001) than the blended shared control. At the next noise level of 125, the additive and blended shared control had similar performance (p=0.401). From a noise level of 150 to 300 the blended shared control was significantly better ($p \leq 0.001$) than the artificial controller (Table 4.7).

Table 4.7: Group Statistics and Independent Samples Test of Additive and Cooperative Performance

				Group Statistics			t-test for Equality of Means		
		Noise	PD	N	Mean	Std. Deviation	t	df	p
Pair 1	Coop	100	225	20	139.7679	43.2488	-3.894	19	0.001
	Add	100	225	20	177.5309	3.1862			
Pair 2	Coop	125	225	20	145.1178	42.0354	0.849	38	0.401
	Add	125	225	20	135.7228	26.1219			
Pair 3	Coop	150	225	20	145.9698	49.0340	4.175	38	0.000
	Add	150	225	20	86.6521	40.4082			
Pair 4	Coop	175	225	20	118.4024	50.2532	3.662	38	0.001
	Add	175	225	20	64.3810	42.7390			
Pair 5	Coop	200	225	20	105.0485	55.3554	4.325	32	0.000
	Add	200	225	20	41.2619	35.8704			
Pair 6	Coop	225	225	20	121.2332	49.5899	6.735	38	0.000
	Add	225	225	20	32.8299	31.4136			
Pair 7	Coop	250	225	20	80.7118	50.1116	4.289	29	0.000
	Add	250	225	20	25.9743	27.3252			
Pair 8	Coop	275	225	20	101.9526	58.7127	5.804	22	0.000
	Add	275	225	20	22.2784	17.9514			
Pair 9	Coop	300	225	20	90.0053	57.1136	5.870	19	0.000
	Add	300	225	20	14.2713	8.2281			

We were also interested in developing a better understanding of how increasing noise levels influenced the performance of the additive control and cooperative control. An exponential trendline with an R^2 value equal to 0.9864 was fit to the average of the additive performance over the range of noise levels, shown in Figure 4.6. A linear trendline with an R^2 value equal to 0.7574 was fit to the average of the cooperative performance over the range of noise levels (Figure 4.6). These trendlines are similar to the trendlines in the previous section. Adding human alone performance to the artificial controller alone performance did not result in a large difference in the trendlines. This meant that the cooperative trendline shows a much larger region in which the pendulum could be balanced when compared to the additive performance.

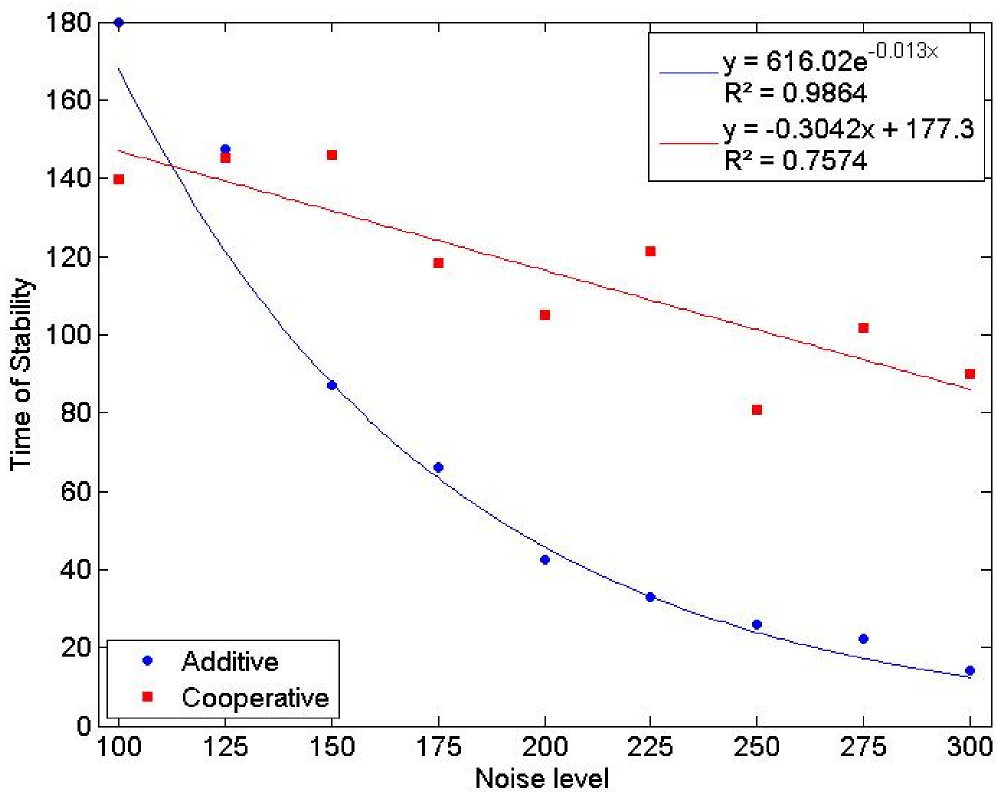

Figure 4.6: Cooperative and Additive Trendlines Over Noise Range

4.2 Competitive Shared Control Data

4.2.1 Influence of Increasing PD Level on Competitive Performance

For the competitive shared control data, the human participants and artificial controller worked to achieve the primary goal of balancing the inverted pendulum for as long as possible. The human participants also were working to keep the pendulum within the target area. The results show that the human participants, at a noise level of 250, were able to balance the inverted pendulum for an average of 14.3 seconds without assistance of an artificial controller shown in Figure 4.7 and Table 4.8. When a PD controller with a PD level of 100 was used to assist the participants, their average performance increased to 38.9 seconds, which was an increase of close to three times. Similar results were observed for all PD levels. At the maximum PD level of 300, performance time was increased over seven times.

Table 4.8: Average Performance of All Participants – Competitive Control Study

Noise level	PD level	Comp (sec)
250	0	14.3014
250	100	38.9488
250	125	49.1482
250	150	68.7320
250	175	80.7666
250	200	126.1845
250	225	115.0430
250	250	108.7013
250	275	145.2630
250	300	148.0025

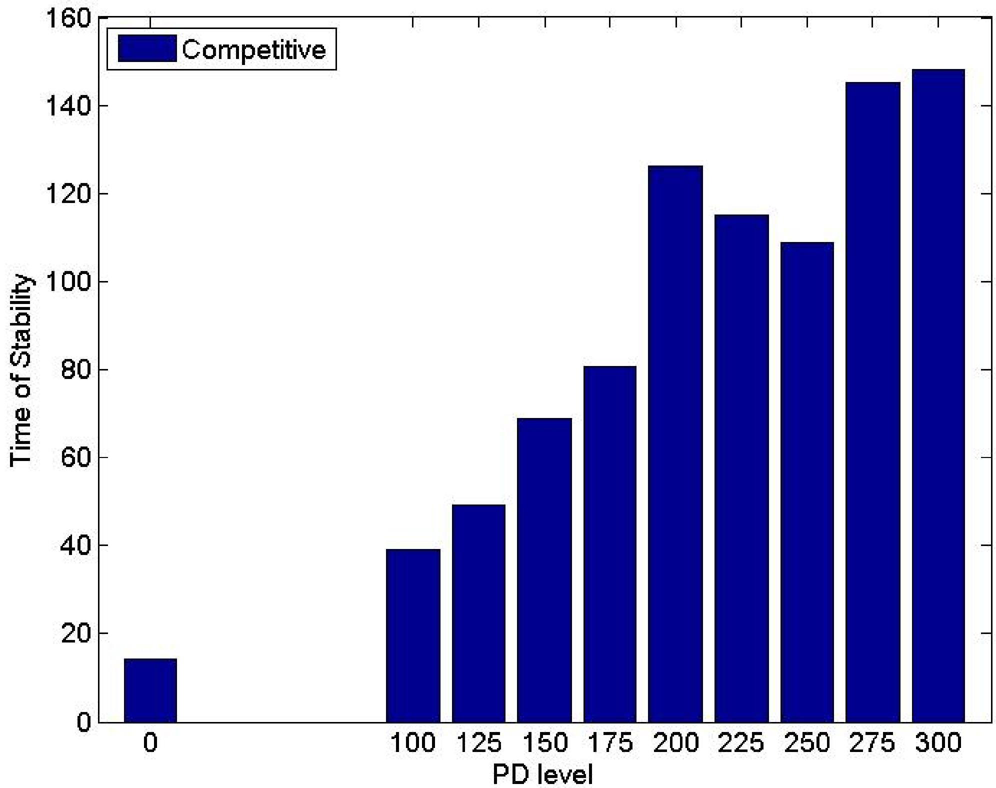

Figure 4.7: Cooperative Performance at Increasing Levels of PD

A statistical analysis was performed on the data in Table 4.8 with the results shown in Tables 4.9 and 4.10. A paired samples t-test was used to determine if human performance was significantly improved when assisted by an artificial controller. The competitive and human performance was compared at each level of PD. The paired samples correlation results showed that for the condition pairs 1 - 3 the performance varied between each participant (Table 4.10). However, for the condition pairs 4 - 9 indicated that performance was not impacted by the participant contributing to the competitive shared control. This means that as PD level increases, the differences between individual performance capabilities has less of an impact on the overall performance. The paired samples t-test indicated that for every level of PD, blended shared control was significantly better (p=0.000) than performance by a human alone (Table 4.10).

Table 4.9: Average Performance of All Participants – Competitive Control Study

		Noise	PD	N	Mean	Std. Deviation
Pair 1	Comp	250	100	20	38.9487	32.6057
	Human	250	0	20	14.3013	27.2595
Pair 2	Comp	250	125	20	49.1482	47.4998
	Human	250	0	20	14.3013	27.2595
Pair 3	Comp	250	150	20	68.7320	52.8029
	Human	250	0	20	14.3013	27.2595
Pair 4	Comp	250	175	20	80.7666	54.8872
	Human	250	0	20	14.3013	27.2595
Pair 5	Comp	250	200	20	126.1845	41.7886
	Human	250	0	20	14.3013	27.2595
Pair 6	Comp	250	225	20	115.043	48.5209
	Human	250	0	20	14.3013	27.2595
Pair 7	Comp	250	250	20	108.7013	46.4105
	Human	250	0	20	14.3013	27.2595
Pair 8	Comp	250	275	20	145.2629	43.4040
	Human	250	0	20	14.3013	27.2595
Pair 9	Comp	250	300	20	148.0024	50.6149
	Human	250	0	20	14.3013	27.2595

Table 4.10: Paired Samples t-Test of Human Participants' Performance – Competitive Control Study

				Paired Samples Correlations		Paired Samples Test		
		Noise	PD	Correlation	Sig.	t	df	p
Pair 1	Comp	250	100	0.845	0.001	4.893	11	0.000
	Human	250	0					
Pair 2	Comp	250	125	0.893	0.000	4.604	11	0.001
	Human	250	0					
Pair 3	Comp	250	150	0.676	0.016	4.737	11	0.001
	Human	250	0					
Pair 4	Comp	250	175	0.495	0.101	4.829	11	0.001
	Human	250	0					
Pair 5	Comp	250	200	0.244	0.445	8.814	11	0.000
	Human	250	0					
Pair 6	Comp	250	225	0.450	0.142	7.990	11	0.000
	Human	250	0					
Pair 7	Comp	250	250	0.507	0.093	8.137	11	0.000
	Human	250	0					
Pair 8	Comp	250	275	0.288	0.364	10.284	11	0.000
	Human	250	0					
Pair 9	Comp	250	300	0.253	0.428	9.070	11	0.000
	Human	250	0					

We were also interested in developing a better understanding of how increasing PD levels influenced the competitive performance of the primary goal, when the human participant was also concerned about the secondary goal. A linear trendline with an R^2 value equal to 0.9047 was fit to the average of the participants' competitive performance over the range of PD levels, shown in Figure 4.8. In the competitive study it can be seen there is much more deviation between the predicted and actual human alone performances can be seen in the trendline, with the y-intercept being -13.9 seconds and the actual being 14.3 seconds. This could possibly be a result of having a secondary goal in the competitive control study.

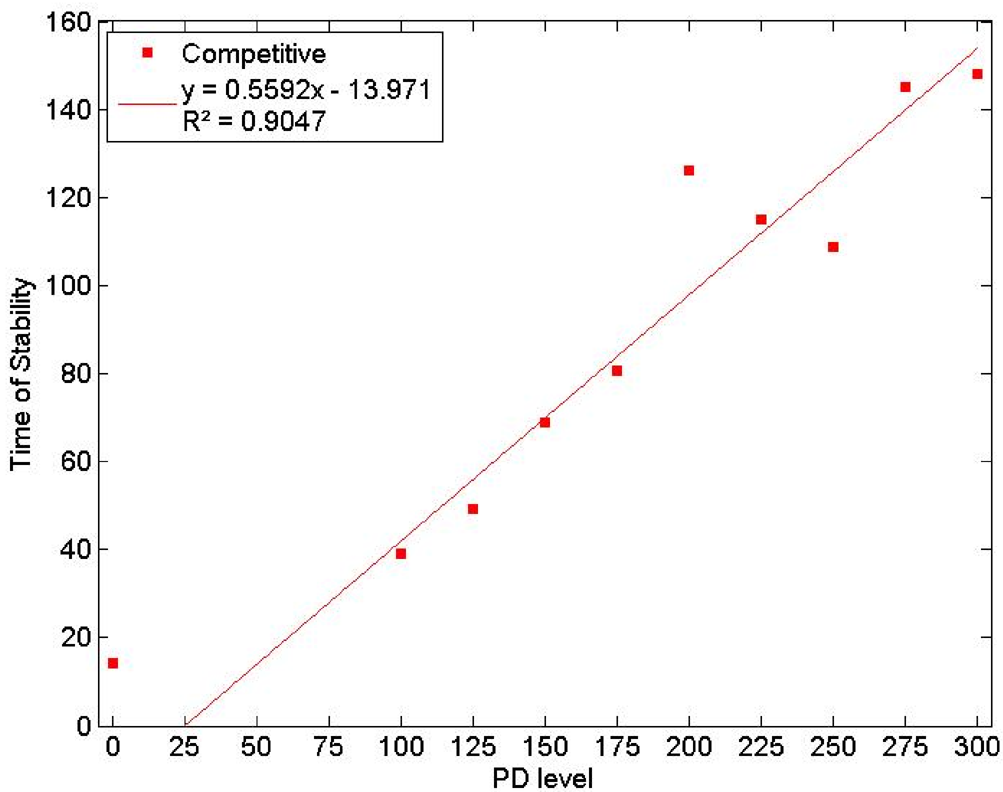

Figure 4.8: Competitive Trendline Over PD Level Range

4.2.2 Performance of an Artificial Controller was Improved with Human Assistance

The results show that the artificial controller with a PD level of 225 was able to balance the inverted pendulum very well at the lowest noise level for an average of 170.6 seconds, shown in Figure 4.9 and Table 4.11. As noise increased the artificial controller's performance fell off sharply and at the maximum noise level of 300, performance time was only 8.0 seconds. When the PD controller worked with human participants, their average performance at a noise level of 100 was 165.6 seconds. However as noise increased competitive performance of the artificial controller and human participants working together decreased at a much slower rate. At the maximum noise level of 300, performance time was 93.5 seconds, an increase of over 11 times when compared to the artificial controller alone.

Table 4.11: Average Performance of the Artificial Controller Alone and the Artificial Controller Working Along with Human Participants– Competitive Control Study

PD level	Noise level	PD time (sec)	Comp (sec)
225	100	170.5948	165.5936
225	125	112.4509	144.0967
225	150	57.5807	151.5216
225	175	35.1576	131.9590
225	200	22.7338	142.7777
225	225	14.2444	119.8004
225	250	12.2793	115.0430
225	275	11.7426	106.9609
225	300	8.0022	93.4986

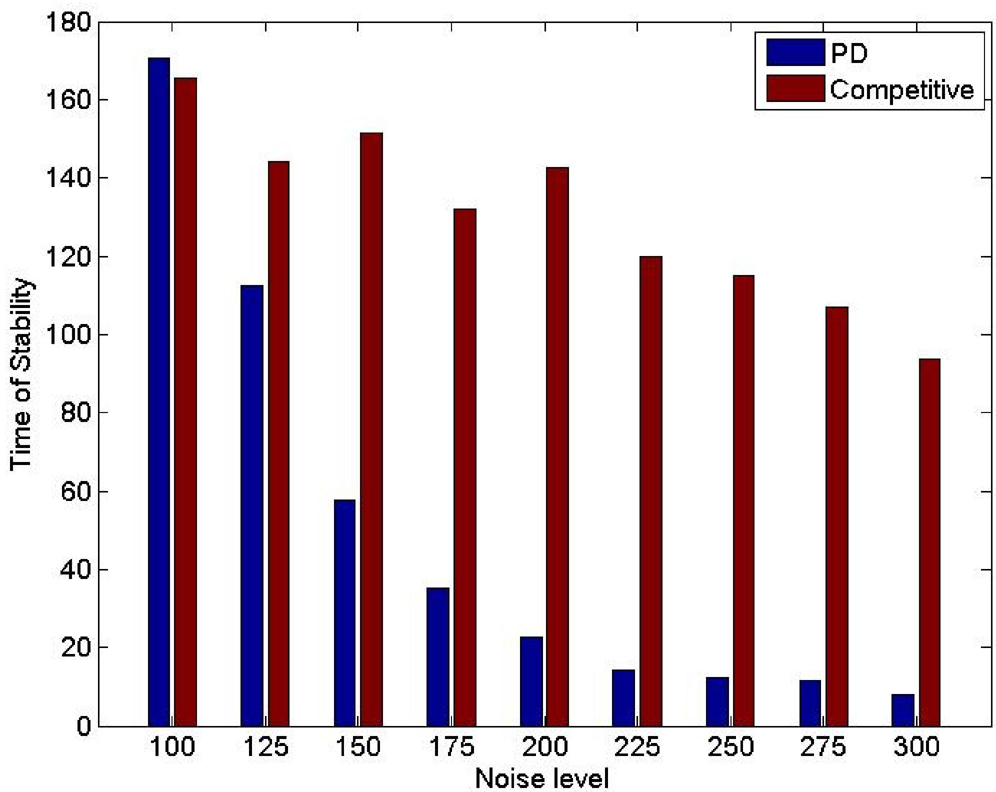

Figure 4.9: Artificial Controller and Competitive Performance Over Noise Range

A statistical analysis was performed on the data in Table 4.11 with the results shown in Tables 4.12. An independent samples test indicated that at the lowest level of noise, the artificial controller and the blended shared control had similar performance (p=0.625). At a noise level of 125 the blended shared control was better (p=0.014) than performance by the artificial controller alone. From a noise level of 150 to 300 the blended shared control was significantly better (p=0.000) than the artificial controller (Table 4.12).

Table 4.12: Group Statistics and Independent Samples Test of Artificial Controller and Competitive Performance

				Group Statistics			t-test for Equality of Means		
		Noise	PD	N	Mean	Std. Deviation	t	df	p
Pair 1	Comp	100	225	12	165.5936	32.2336	-0.491	70	0.625
	PD	100	225	60	170.5948	32.2411			
Pair 2	Comp	125	225	12	144.0966	31.2165	2.609	32	0.014
	PD	125	225	60	112.4508	62.8972			
Pair 3	Comp	150	225	12	151.5215	47.2795	5.968	70	0.000
	PD	150	225	60	57.5806	50.2250			
Pair 4	Comp	175	225	12	131.959	45.2163	7.143	13	0.000
	PD	175	225	60	35.1575	28.2442			
Pair 5	Comp	200	225	12	142.7776	43.4208	9.436	12	0.000
	PD	200	225	60	22.7337	16.8495			
Pair 6	Comp	225	225	12	119.8004	54.7883	6.638	11	0.000
	PD	225	225	60	14.2444	12.7969			
Pair 7	Comp	250	225	12	115.043	48.5209	7.315	11	0.000
	PD	250	225	60	12.2792	8.3526			
Pair 8	Comp	275	225	12	106.9608	43.9897	7.455	11	0.000
	PD	275	225	60	11.7425	10.5926			
Pair 9	Comp	300	225	12	93.4985	60.4805	4.891	11	0.000
	PD	300	225	60	8.0022	6.7590			

We were also interested in developing a better understanding of how increasing noise levels influenced the performance of the artificial controller and competitive control. An exponential trendline with an R^2 value equal to 0.9527 was fit to the average of the artificial controller's performance over the range of noise levels, shown in Figure 4.10. A linear trendline with an R^2 value equal to 0.9142 was fit to the average of the competitive performance over the range of noise levels (Figure 4.10). The trendlines showed that although the human participants had a secondary goal, it did not impact the primary goal very much. The artificial controller and human participant working together were able to maintain stability of the pendulum over a much greater range then the artificial controller working alone.

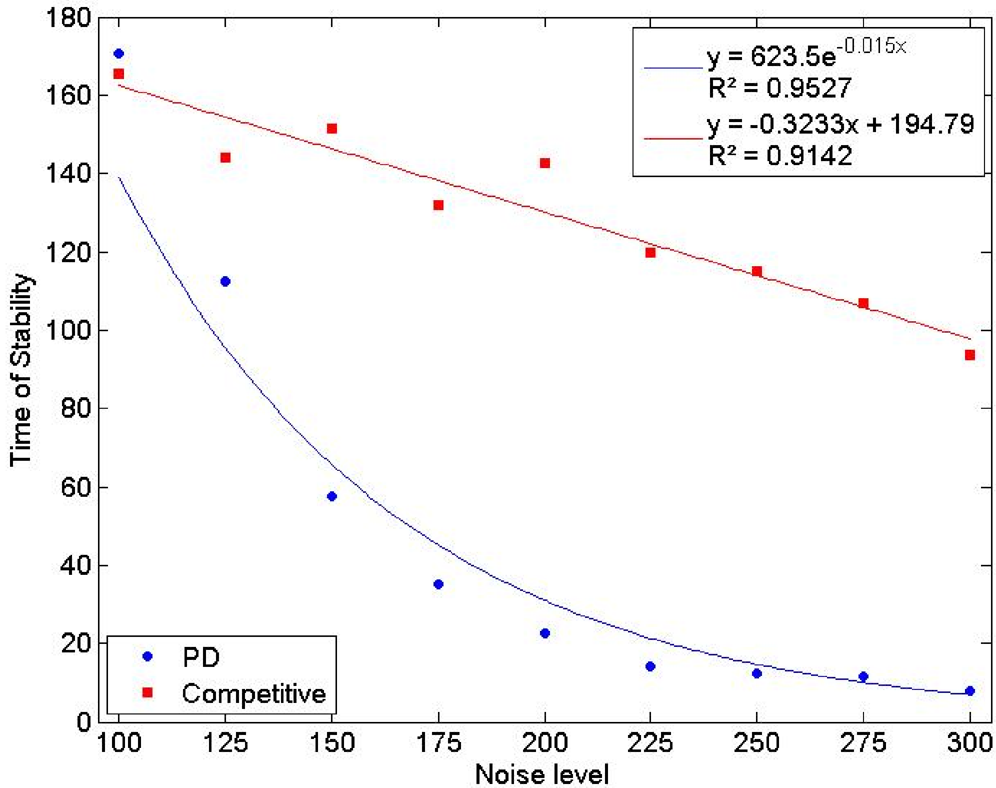

Figure 4.10: Competitive and PD Trendlines Over Noise Range

4.2.3 Individual Additive Performance Compared to Competitive Shared Control Performance

The results show that the human participants, without assistance of an artificial controller, were able to balance the inverted pendulum for a time of 16.46 seconds at the lowest level of noise and a minimum time of 7.5 seconds, shown in Figure 4.11 and Table 4.13. The maximum performance time of 23.3 seconds occurred at a noise level of 150. The artificial controller with a PD level of 225 was able to balance the inverted pendulum very well at the lowest noise level of 100 for an average of 170.6 seconds. As noise increased the artificial controller's performance fell off sharply and at the maximum noise level of 300, performance time was only 8.0 seconds. The average results of the human working alone and the artificial controller working alone was added at each level of noise. This resulted in the additive performance time.

The additive performance at the lowest level of noise exceed the maximum time of 180 seconds, therefore it was rounded down to 180.0 seconds. As noise level continued to increase the additive performance fell sharply and at the maximum noise level of 300, performance time was 15.5 seconds. When the human and artificial controller worked together in a competitive manner there was a much slower decline in performance as noise level increased. At a noise level of 100, competitive performance was 165.6 seconds, similar to additive performance. At the maximum noise level of 300, competitive performance time was 93.5 seconds, an increase of over 6 times when compared to the additive performance of the human and artificial controller working independently.

Table 4.13: Average Performance of Human Alone, Artificial Controller Alone, the Additive Performance of the Two Working Independently, and the Competitive Performance of the Two Working Together

Noise level	Human (sec)	PD time (sec)	Human+PD (sec)	Comp (sec)
100	16.4630	170.5948	180.0000	165.5936
125	17.6160	112.4509	130.0669	144.0967
150	23.3373	57.5807	80.9180	151.5216
175	13.5984	35.1576	48.7560	131.9590
200	12.5547	22.7338	35.2885	142.7777
225	13.0025	14.2444	27.2469	119.8004
250	14.3014	12.2793	26.5807	115.0430
275	8.7487	11.7426	20.4913	106.9609
300	7.5098	8.0022	15.5120	93.4986

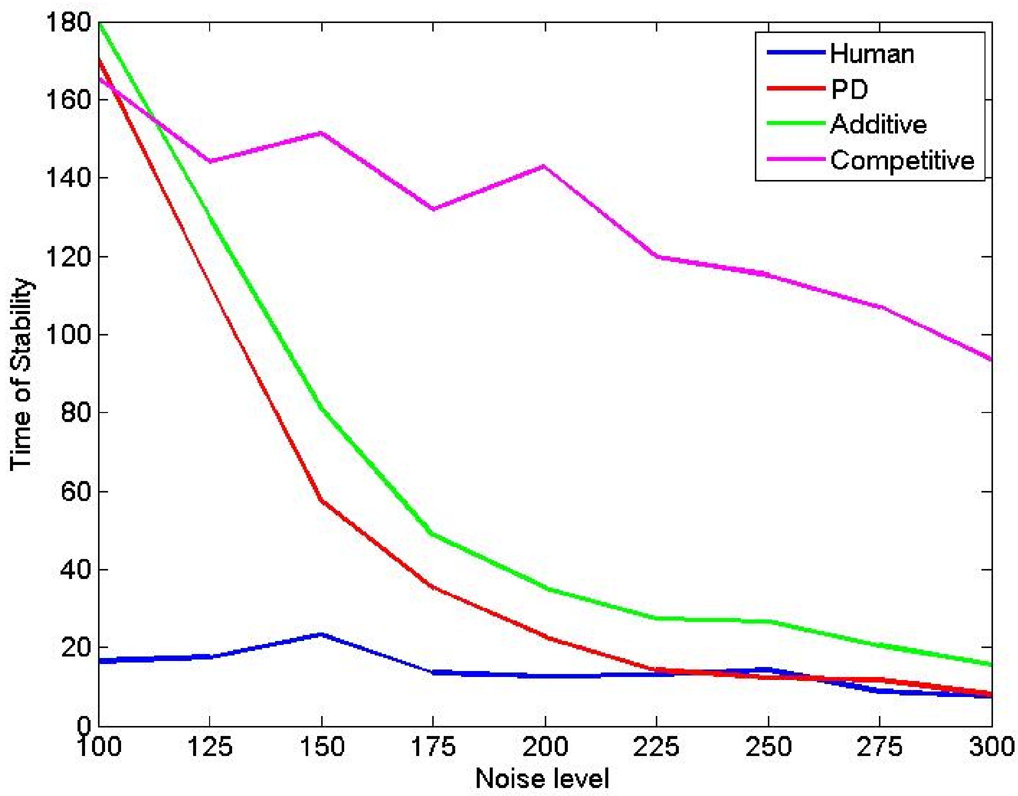

Figure 4.11: Competitive vs. Additive Over Noise Range

A statistical analysis was performed on the data in Table 4.13 with the results shown in Table 4.14. An independent samples test indicated that at the two lowest levels of noise, the additive performance of the human and artificial controller working independently and the performance of the blended shared control were similar (p=0.259 and p=0.087). From a noise level of 150 to 300 the blended shared control was significantly better ($p \leq 0.001$) than the artificial controller (Table 4.14).

Table 4.14: Group Statistics and Independent Samples Test of Additive and Competitive Performance

				Group Statistics			t-test for Equality of Means		
		Noise	PD	N	Mean	Std. Deviation	t	df	p
Pair 1	Comp	100	225	12	165.5936	32.2336	-1.19	11	0.259
	Add	100	225	12	176.7206	3.1287			
Pair 2	Comp	125	225	12	144.0966	31.2165	1.813	17	0.087
	Add	125	225	12	125.1816	18.2179			
Pair 3	Comp	150	225	12	151.5215	47.2796	4.241	22	0.000
	Add	150	225	12	82.1727	31.2058			
Pair 4	Comp	175	225	12	131.959	45.2163	5.884	15	0.000
	Add	175	225	12	47.3991	20.8344			
Pair 5	Comp	200	225	12	142.7776	43.4208	7.569	22	0.000
	Add	200	225	12	34.9529	23.4547			
Pair 6	Comp	225	225	12	119.8004	54.7883	5.608	13	0.000
	Add	225	225	12	26.1297	18.5974			
Pair 7	Comp	250	225	12	115.043	48.5209	5.565	22	0.000
	Add	250	225	12	25.4822	27.4499			
Pair 8	Comp	275	225	12	106.9608	43.9897	6.845	11	0.000
	Add	275	225	12	19.0656	6.5852			
Pair 9	Comp	300	225	12	93.4985	60.4805	4.422	11	0.001
	Add	300	225	12	15.0971	10.7257			

We were also interested in developing a better understanding of how increasing noise levels influenced the performance of the additive control and competitive control, when the human participant had a secondary goal. An exponential trendline with an R^2 value equal to 0.9573 was fit to the average of the additive performance over the range of noise levels, shown in Figure 4.12. A linear trendline with an R^2 value equal to 0.9142 was fit to the average of the competitive performance over the range of noise levels (Figure 4.12). These trendlines show a similar trend to the cooperative study in which the two agents working simultaneously can balance the pendulum better over the full range of noise when compared to the two agents working independently. This again seems to indicate that the secondary goal did not interfere with primary goal completion.

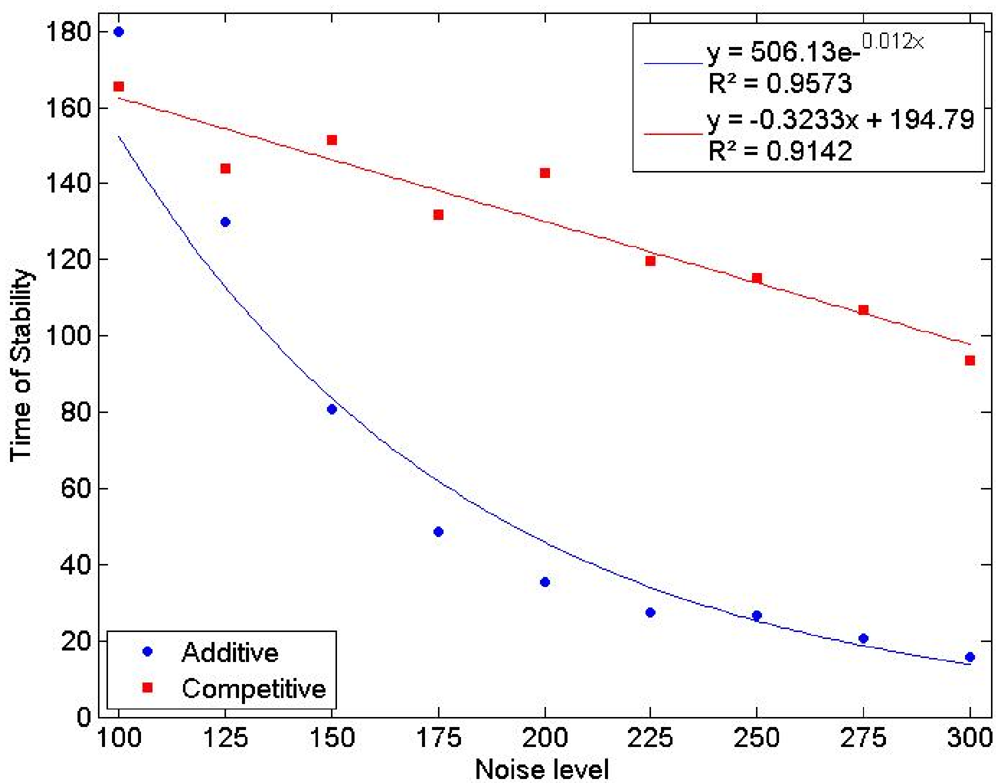

Figure 4.12: Competitive and Additive Trendlines Over Noise Range

4.2.4 Secondary Goal Performance Over the Range of PD Levels

The results show that the human participants, at a noise level of 250, were able to maintain the inverted pendulum within the target area for an average of 10.9 seconds with assistance from an artificial controller shown in Figure 4.13 and Table 4.15. As PD level increased their average performance increased to a maximum time of 48.2 seconds, which was close to five times greater. This maximum time was seen at the highest level of PD.

Table 4.15: Secondary Goal Performance Over Range of PD Levels

Noise level	PD level	Comp (sec)
250	100	10.9492
250	125	12.8796
250	150	20.5019
250	175	26.7973
250	200	44.6813
250	225	38.7538
250	250	35.2984
250	275	42.4298
250	300	48.1751

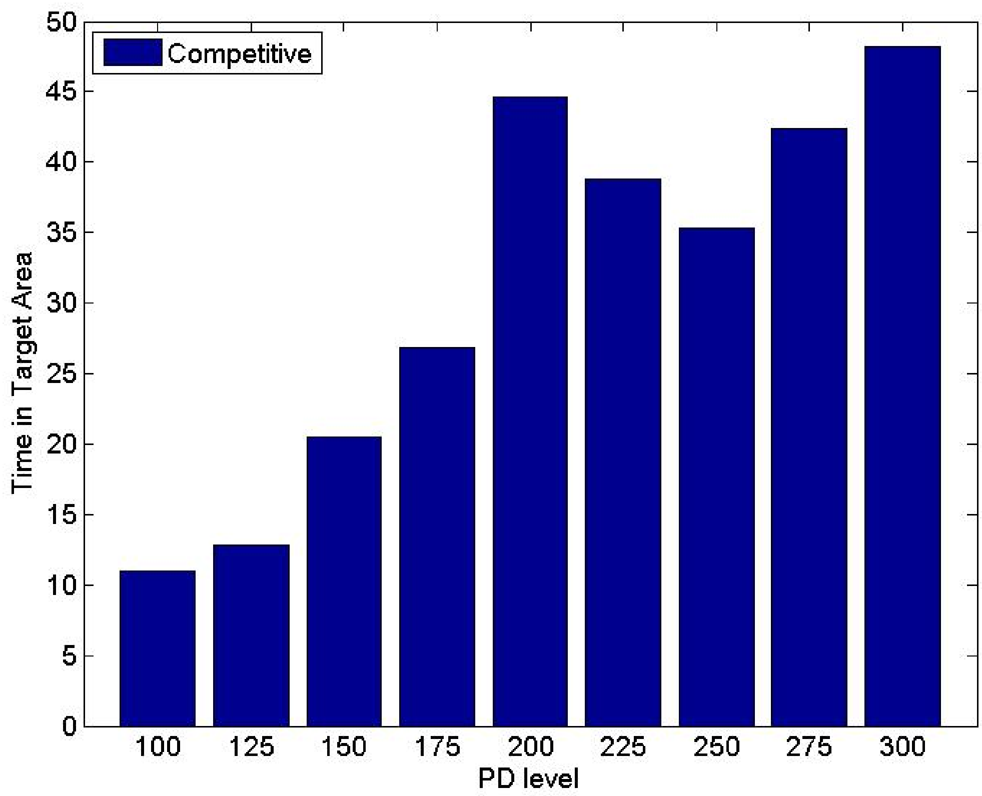

Figure 4.13: Secondary Goal Performance Over Range of PD Levels

We were also interested in developing a better understanding of how increasing PD levels influenced the secondary goal performance. A linear trendline with an R^2 value equal to 0.8379 was fit to the average of the secondary goal performance over the range of PD levels, shown in Figure 4.14. The linear trendline has a slope of 0.18 and this will be compared to the trendline slope in the next section which investigates secondary goal performance over a range of noise levels.

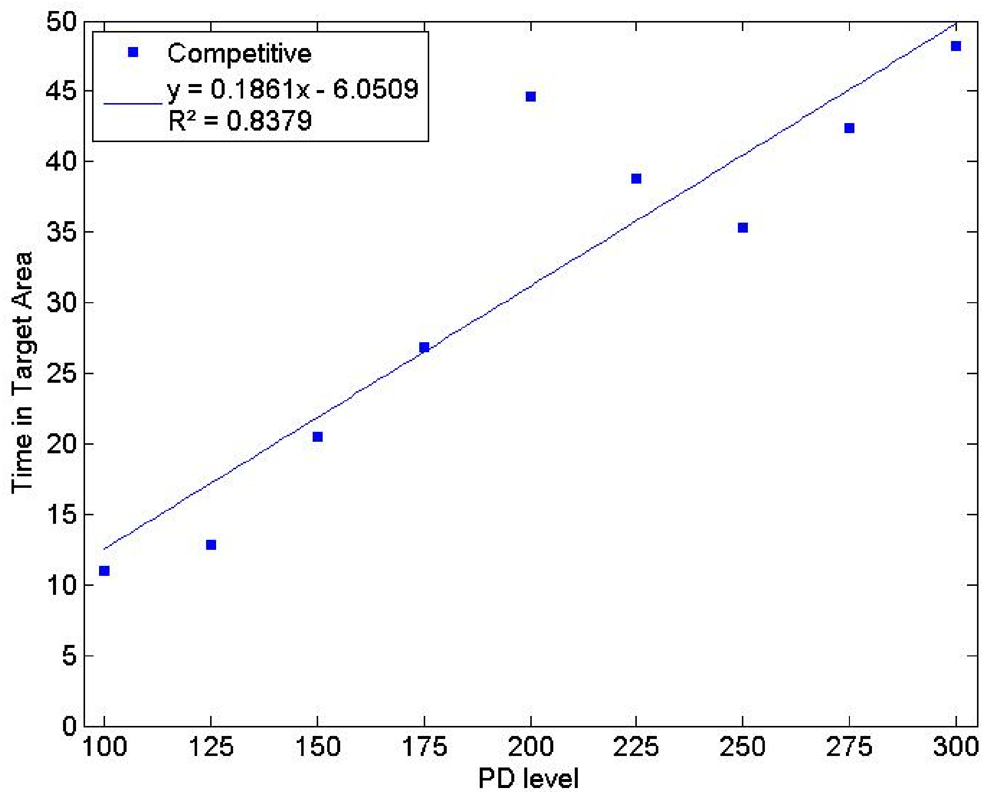

Figure 4.14: Competitive Secondary Goal Performance Trendline Over Range of PD Levels

4.2.5 Secondary Goal Performance of Range of PD Levels

The results show that the human participants, at a PD level of 225, were able to maintain the inverted pendulum within the target area for an average of 70.4 seconds with assistance from an artificial controller shown in Figure 4.15 and Table 4.16. As noise level increased their average performance decreased to a minimum time of 27.7 seconds. This minimum time was seen at the highest level of noise.

Table 4.16: Secondary Goal Performance Over Range of Noise Levels

PD level	Noise level	Comp (sec)
225	100	70.4403
225	125	62.3897
225	150	61.0438
225	175	51.2379
225	200	55.5237
225	225	44.8732
225	250	38.7538
225	275	34.4619
225	300	27.7289

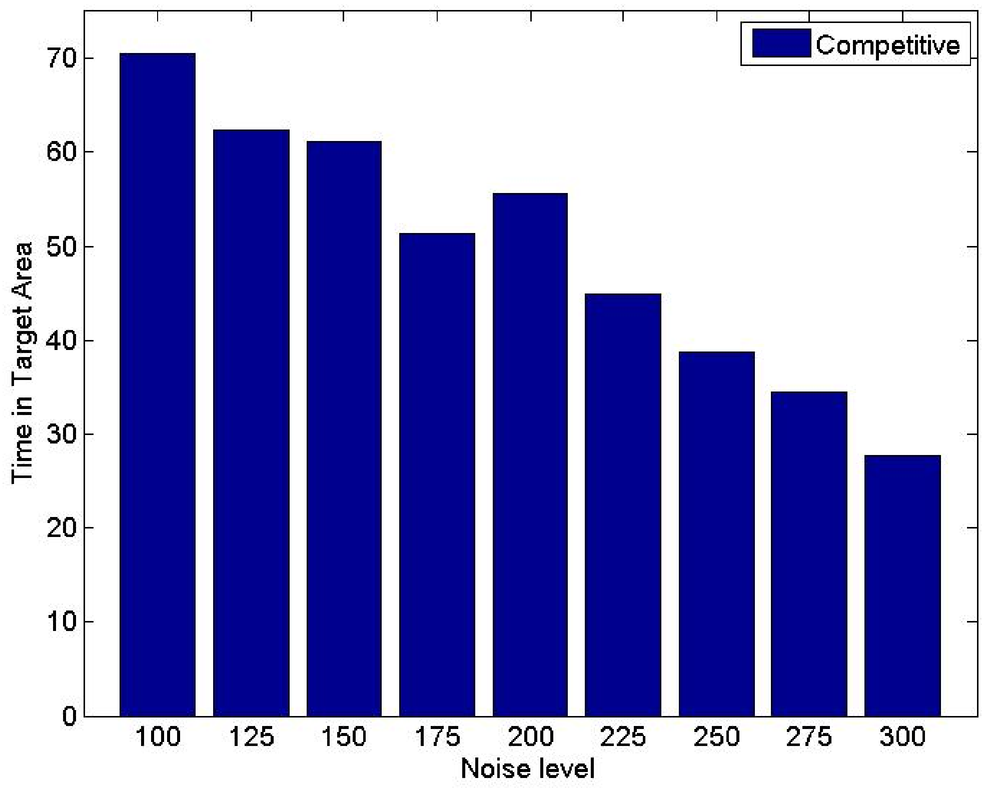

Figure 4.15: Secondary Goal Performance Over Range of Noise Levels

We were also interested in developing a better understanding of how increasing noise levels influenced the secondary goal performance. A linear trendline with an R^2 value equal to 0.9642 was fit to the average of the secondary goal performance over the range of noise levels, shown in Figure 4.16. The linear trendline over a range of noise has a slope of -0.2. When this is compared to the trendline slope over the range of PD levels, which is 0.18, a relationship may be observed. This seems to indicate that if PD level is increased at the same rate as noise level is increased then a constant level of performance can be achieved in the completion of the secondary goal.

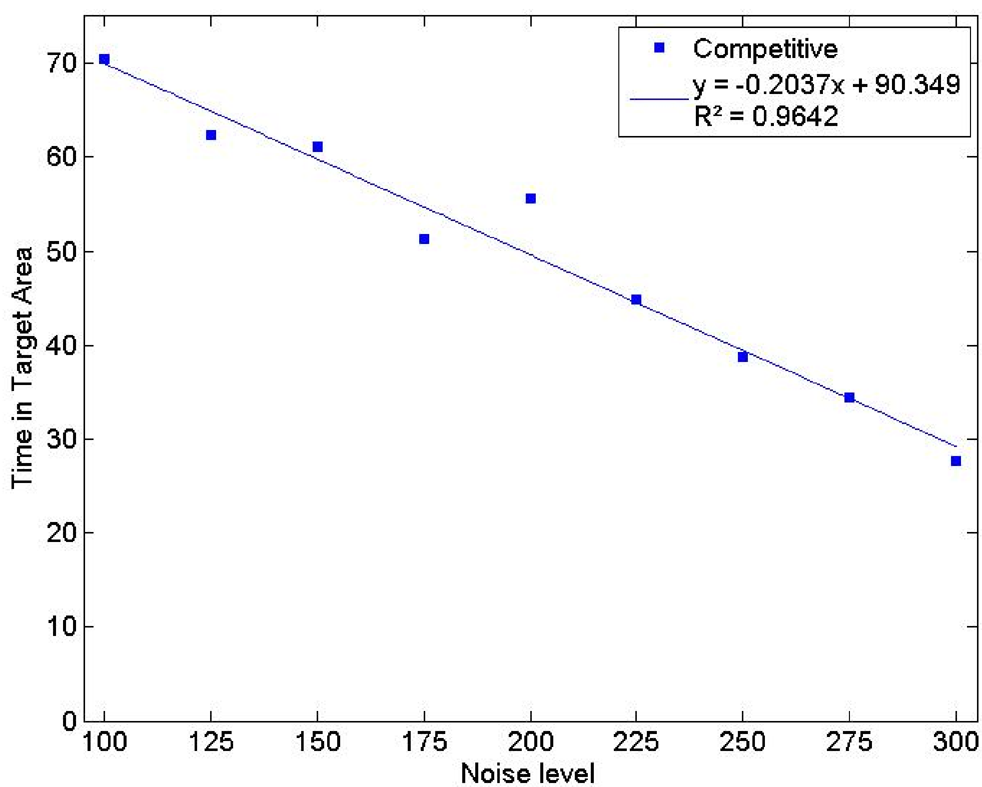

Figure 4.16: Competitive Secondary Goal Performance Trendline Over Range of Noise Levels

4.2.6 Investigating Target Area Location Difficulty

The results were looked at to determine the position of the target area when a participant fails. It can be seen in Figure 4.17 that participants were more likely to fail when the target area was closer to the horizontal axis. For this experiment the vertical axis represents 0 degrees with the right of the axis being in the positive and the left of the axis being in the negative direction. Figure 4.17 is a graph of the absolute value of the degrees. Figure 4.18 shows the frequency of failures when the target area is in a particular area.

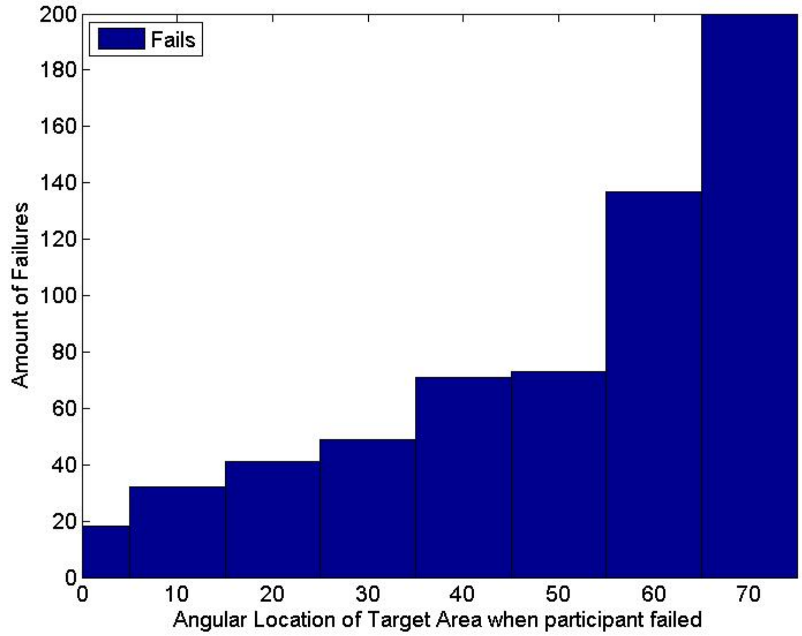

Figure 4.17: Histogram of Absolute Valued Positions of Target Area and the Number of Failures Associated at Each Interval

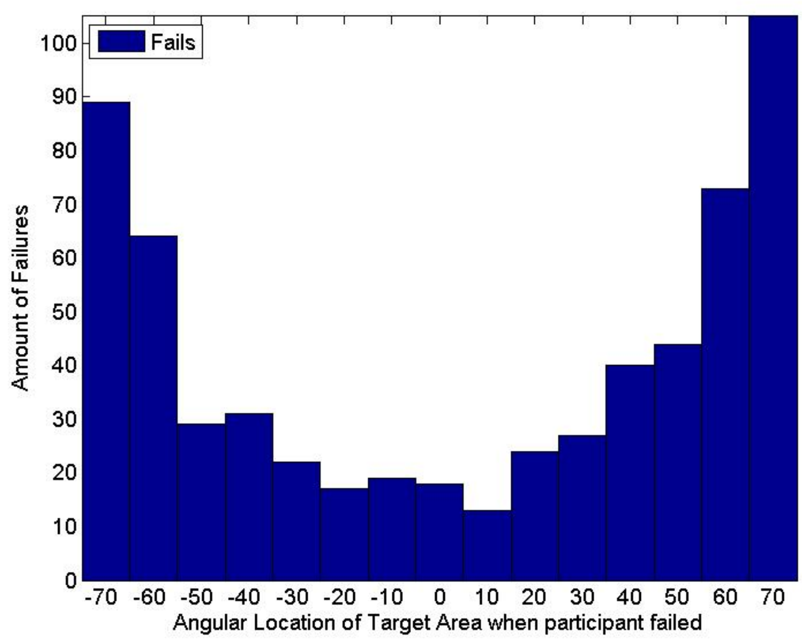

Figure 4.18: Histogram of Positions of Target Area and the Number of Failures Associated at Each Interval

CHAPTER 5: DISCUSSION AND CONCLUSION

5.1 Discussion of Results

The cooperative control study showed very promising results. By using blended shared control a human participant's performance was shown to increase 4 to 9 times that of human-only control. The amount of improvement depended on the PD level of the artificial controller. Artificial controllers showed that, as noise increased, performance of balancing the pendulum fell very quickly. However, by supplementing the artificial controller with a human participant, performance dropped at a much lower rate as noise increased. This can be seen at the highest level of noise which shows that cooperative performance is over 11 times greater than the artificial controller alone. Finally, the individual performance of the human participants working alone and the performance of the artificial controller working alone was compared to the cooperative performance of the two working together simultaneously. This showed that cooperatively the two controllers were able to work much more efficiently, and at the highest levels of noise performance, was increased by 2.5 - 6 times.

Performance in achieving the primary goal for the competitive control study showed very similar results to the cooperative control study. Human alone performance could be increased substantially by working with an artificial controller, and increasing the PD level of the artificial controller enabled higher levels of performance to be achieved. The same increase in performance could be seen by comparing an artificial controller alone to an artificial controller working with a human participant. Additive control was also outperformed by the two controllers working at the same time. This shows that although the human had a secondary goal of maintaining the pendulum within a target area, primary goal performance was not adversely affected. This may mean that what was called competitive shared control was actually just an extension of cooperative control.

Secondary goal performance was influenced by the PD level of the artificial controller. When a human participant worked with an artificial controller with a higher PD level, secondary goal performance was increased. This means that even though the artificial controller was not aware of a secondary goal, it was actually able to increase its performance. Secondary goal performance was also affected by two parameters, the noise level and the target location. Increasing the noise level resulted in a decrease of secondary goal performance because the random perturbations produced a torque which was too large and unpredictable to maintain the pendulum within the target area for very long. Results showed that when the target region was closer to the x-axis, participants were more likely to fail. This was possibly from the random perturbations caused by noise which would make the human participant fail when the pendulum was moved to the target areas close to the x-axis. This study was able to show that blended shared control can increase performance of a primary goal while also allowing a secondary goal to be achieved.

The results from both the cooperative and competitive shared control testing were very promising. The results showed that blended shared control can outperform a human and that higher performance can be achieved by increasing the PD level. Blended shared control can also perform better than an artificial PD controller alone when the difficult increases beyond the controller's capabilities. This same observation can be made when comparing blended shared control to additive performance. Competitive testing was also able to show that giving the human a secondary task to complete did not interfere with primary task completion. By lightening the load of a primary task, blended shared control could enable someone to perform additional tasks or allow them to perform them better than they could on their own.

5.2 Future Work

5.2.1 Modeling a Higher Order Inverted Pendulum

Future work on the topic of blended shared control and its benefits could be focused in several areas. One area would be to investigate the effectiveness of shared control on a 3D model of an inverted pendulum. This could greatly increase the complexity of the pendulum and lead to using high order equations. While the motion of the pendulum would be in three dimensions, the inputs to the model need only deal with two dimensions to indicate torques in the x-z and y-z planes. This would mean the Xbox 360 controller could use both x and y components of the analog stick as human input.

A two dimensional pendulum that could be modeled is by using ordinary differential equations or specifically delay differential equations. The most common type of mathematical model used is an ordinary differential equation [3]. An ordinary differential equation (ODE) is an equation containing a function of one independent variable and its derivatives. An example of an nth order ODE is $F(x, y, y', y^{(n)}) = 0$ where y is a function of x and y' is the derivative of y with respect to x [16]. A higher order ODE can be simplified by turning it into a system of first order ODEs by introducing new unknown functions; this allows the higher order ODE to be solved more easily. A delay differential equation (DDE) is a specific type of ordinary differential equation whose derivative depends on solutions at past times [17]. A simple example of a DDE with only a single delay is $\frac{d}{dt}x(t) = f(x(t), x(t-\tau))$ where $\tau \geq 0$. Certain DDEs can be transformed into a system of ordinary differential equations. Both types of equations can be used to model the real world in various applications. For DDEs the past values, or delays, can typically be measured in the physical world and may be constant, a function of t, or a function of t and y [18]. ODEs and DDEs can be compared in Table 5.1.

ODEs and DDEs can be solved several different ways depending on the characteristics

Table 5.1: Comparison of ODE and DDE [18]

ODE Model	DDE Model
Assumes: effect of any changes to the system is **instantaneous** (A principle of causality)	**Assumes:** effect of any change to the system is **not instantaneous**. i.e. past history is taken into account
Generates a system that is **finite** dimensional	**Generates** a system that is **infinite** dimensional
Needs an initial condition (to determine a unique solution)	**Needs an initial function** (to determine a unique solution
	Advantage: Enables a more accurate reflection of the system being modeled
	Disadvantage: The analytical theory is less well developed

of the equation. ‘ode45’ is typically the first and most commonly used method of solving ODEs in Matlab; however, ‘ode23’ can also be used to obtain a solution of lower accuracy. These codes use Runge-Kutta-Fehlberg method to solve first order ODE or a system of first order ODEs. The 45 and 23 correspond to the use of 4th and 5th order formulas and 2nd and 3rd order formulas used in the Runge-Kutta method. The Runge-Kutta method is able to automatically determine the necessary step size to obtain a solution within the given tolerance, which is defaulted to 10^{-3}. DDEs can be solved using a code similar to ‘ode23’ which is called ‘dde23’ [17]. ‘dde23’ is limited to solving problems with constant delays. The solutions of ODEs and DDEs can be used by a PID controller to provide feedback to a system.

5.2.2 Implementing Various Artificial Controllers

Another modification to the program could be made by using a different type of artificial controller. A PD controller was chosen because they are common and relatively simple to implement; however, a more complex artificial controller could be used. It was seen by observing the human participants that their input was sometimes influenced by what they expected the PD controller to do. By utilizing this same idea, an artificial controller could be able to anticipate human input and account for it. Adaptive artificial controllers that employ a simple controller such as a PD controller that adapts the level of PD could also be tested.

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Appendices

APPENDIX A: SUPPLEMENTAL INFORMATION

A.1 Matlab and Xbox 360 Controller Interaction

The vrjoystick function enables Matlab to take input from up to 10 buttons and 5 axis. There are two thumbsticks on the controller, both of which have an x and y component that is on a range from -1 to 1 depending on the direction and amount of movement applied to the thumbstick in that direction. The left and right triggers also use an analog system that allows Matlab to determine how much each trigger is held down. The triggers share the same axis, where pressing on the left trigger indicates a negative value on the axis and the right trigger indicates a positive value. If both are completely held down the resulting value for that axis is 0. There are a total of 10 buttons on the Xbox 360 controller that are able to interact with Matlab. They are momentary push buttons that when held down send a 1 and when left untouched send a 0. The directional pad, or d-pad, uses what is called POV in Matlab. A -1 is sent to Matlab if the d-pad is not touched. There are 8 directions that Matlab recognizes when pressed, with straight up sending a 0. Pressing the d-pad to the upper-right sends a 45. Each additional direction in a clockwise motion, of the 8 which can be chosen, adds 45 to the value sent to Matlab, with the upper-left having a value of 315.

Referring to Figure A.1, buttons (1& 3) are the left and right thumbsticks, respectively. There is also a directional pad (2), or d-pad. Buttons 5-10, 13, and 14 are normal momentary buttons. The Xbox home button (4) but it has no functionality in Matlab. Analog triggers (11 & 12) function as an axis in Matlab.

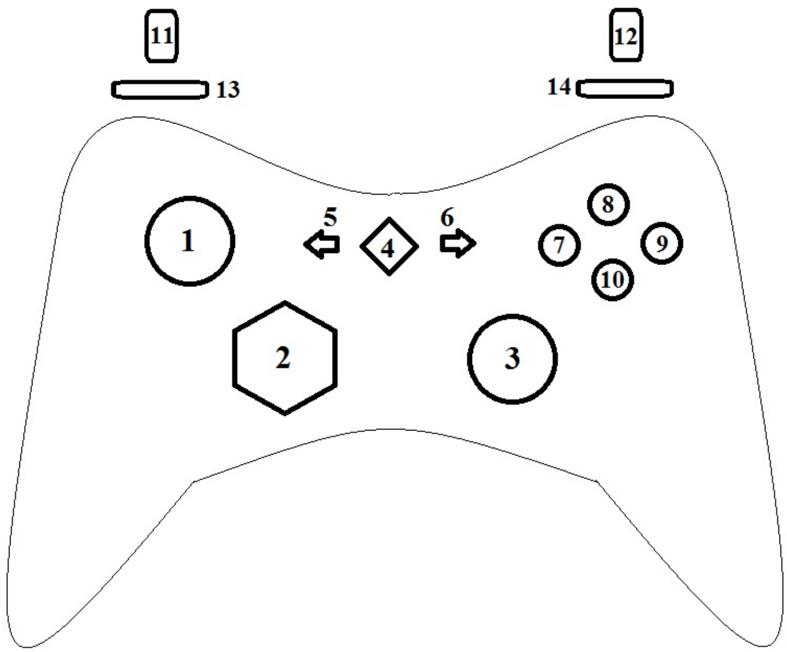

Figure A.1: Layout of Xbox 360 Controller with Labeled Buttons