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Real time Virtual Simulation of an Underactuated Pendulum-Driven Capsule System

Keattikorn Samarnggoon and Hongnian Yu

Abstract— **In this paper, a real time virtual simulation framework which is the foundation for studying human adaptive mechatronics (HAM) is proposed. This framework allows researchers to interact and experiment with the system in real time. Thus, motion control patterns can be identified and learned with, for example, a heuristic strategy. The prototype is developed with an underactuated pendulum-driven capsule robot model. Motion control patterns are identified and presented. The experimentation results demonstrate the proposed concept.**

Keywords-human adaptive mechatronics, pendulum capsule robot, underactuated systems, virtual environment, real time system (key words)

I. INTRODUCTION

Human adaptive mechatronics (HAM) is defined as an intelligence human machine system in which the system can be self-adapted intelligently based on the current user competency level to obtain optimum performance [1–5]. To achieve the HAM requirements, there must be several mechanisms working together. The main components of a HAM system are human operators, the intelligent discrimination of operator actions, competency evaluation metrics, human machine interaction mechanisms, and the machine system.

The work presented in this paper is a part of HAM research which covers a real time virtual system for understand the functions of human operators in HAM which has many invaluable advantages. This kind of virtual simulation systems running in real time allows researchers to experiment with dynamic of the modelled system in an immediate and interactive manner. Robotic researchers usually design mechanical systems by modelling mathematical relation of system parts but there exists troublesome to find control patterns for human operating a robot. This issue can be overcome by the help of real time virtual simulation systems. Motion control patterns could be identified by trial and error (heuristic) experimentation strategies using this virtual system. Moreover, apart from the robot mechanical simulation itself, dynamics of the environment can also be integrated into the simulation, for examples, different frictions of ground areas, dynamic of fluid while controlling robot movements, and capsule bots moving on a simulated deformable surface in medical application robotics.

Virtual training is also capable with this real time simulation based on the human-in-the-loop concept of mechanical systems. Training scenarios can be implemented with little effort or at no cost. Measurement of performance improvements can also be done from the feedback within the environments. This allows users to practice as much as they want. As a result, the user learning curve could be improved drastically. Regarding training environment with virtual real time simulation, it is a novel concept called human adaptive mechatronics that could further help optimise the learning curve of a user while training by its assisting behaviours.

The main contributions of the paper are

- Proposing a real time virtual human and machine interactions framework. The proposed framework will be a basis for development and realisation of the HAM concept.
- Developing a human heuristic learning strategy for learning motion control patterns.
- Conducting the experimental tests to demonstrate the framework and the HAM concepts.

II. RELATED WORKS

Human is considered the main component of the HAM systems because the aim of this system is a combination of an automatic control and adaptive manual control system which is operated by humans. Normally, humans are complex and unpredictable, but if they are involved in a goal oriented task, it is possible to recognise their intentions. Human has been long studied in many related fields e.g., neurophysiological, neuroscience, cognitive science, and psychophysical. In neuroscience study, Haynes and colleague successfully read human covert intention by decoding brain images from various sections simultaneously [6], [7]. The pattern recognition technique is used in decoding those human intentions by discriminate patterns from spatial information from various brain activity areas. This method of using spatial brain information is claimed to be more accurate than analysing only specific area of the human brain. The reason is that when human performing an activity, several of brain areas are working together according to its functions. Additionally, human intentions are influenced from personal experiences. This is indicated by Blakemore and Decety analysis of the evidences of brain activity [8]. The evidences show that when human perceive biological motions there exists brain activity that try to simulate these motions internally. As a consequence, this internal simulation would reflect as intentions in future actions. This basically works in the same way as training activity to improve personal experience.

Human has good abilities to learn, predict, and process information. However, these capabilities are depended on individual. A task that is performed by different persons might return different results because of individual ability. Individual ability is usually denoted by word ‘skill’ and the outcome from using skill to perform an action is called ‘performance’. Learning capability is another magnificence aspect of human being in which humans have learnt to improve their skills and as an overall result i.e., overall

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performance improvement. The most important part that ruled all of these capabilities is the thinking inside the human brain. Consequently, as mentioned earlier, internal thinking would reflect out as the intentions to do a specified task. This intended output actions could be identified by pattern recognition techniques. The intention recognition is also considered as part of the HAM system.

For the intelligent machine to serve or adapt to human appropriately, it needs to know human intentions by estimating from various kinds of related information. Fortunately, sensor technologies have advanced significantly along with the matured field of pattern recognition. These two combinations are essential for online human intention recognition. Observations and measurements from sensors are the inputs to pattern recognition algorithms to identify or estimate human intention at time. There exist numbers of information to be monitored and measured which is depended on the type of tasks. For examples, patterns of force signals exert on an arm gripper are recognised to discriminate human operator actions when performs industrial weight loading operation using Hidden Markov Models [9], motion and velocity pattern profiles are the information used to classify human actions in telemanipulation tasks [10]. The identified actions are useful for switching among virtual fixture models which help in different mode of operations. Once the machine has ability to identify human intention in which step the human operator is performing. It is functionality of the next component of the HAM system to evaluate how well the performing competency.

The aim of competency evaluation is to measure how well the operator is performing a step of the task so that the next component of the HAM system can make adaptations for assisting the operator. A generic performance evaluation framework, human performance index (HPI), is proposed in [11]. The framework consists of two layers of evaluation. The first layer is the collection of performance variables that evaluate raw competency of actions. The second layer is the weighted conditional integral of those variables in the first layer for specific area of measurement e.g. speed, and accuracy. This layer is called performance criterions. Final performance conclusion, HPI, is then weighted and accumulated from the second layer values. On the other hand, this HPI measurement concept can be viewed as grading evaluation in education such as school. Evaluations such as paper works, examinations, and attendance are scored. These scores are weighted with different percentage values according to its importance. The subject's grade is calculated from these values. Grading point average (GPA) is finally calculated from weighted credits of each subject. Therefore, the HPI is viewed as the GPA while performance criterions are viewed as subjects, and raw evaluations are viewed as those scorings. In addition, this HPI framework could be used in two modes, open form and closed form. The open form is located at the second layer in which these performance criterions can be used in any applicable future closed form. The closed form is located at the final accumulation evaluations, HPI or GPA. Performance criterions such as speed and accuracy are the example of competency measurement metric. This metric is a basis for the next step of the HAM system, adaptive tuning.

Intelligent adaptation of the HAM system is tuned based on current operator competency. There are two types of adaptation i.e., passive and active adaptation. Tuning parameters inside the machine without interfering the operator is a passive adaptation [12]. An active adaptation works in the opposite way. It actively assists the operator by, as an example, pushing small amount of force to the controller grip to help achieving the aimed intention easily [13–15].

The basis system model for this paper is an underactuated modelling approach and a 6-step motion control strategy to develop a desired driving profile studied in [16].

Underactuated mechanical systems are a system that has less control inputs than degrees of freedom of the system to be controlled. This system may also occur in a full actuated system because it losses some freedom of control due to some reasons such as accident or system failure.

III. Proposed Real Time Virtual Simulation System

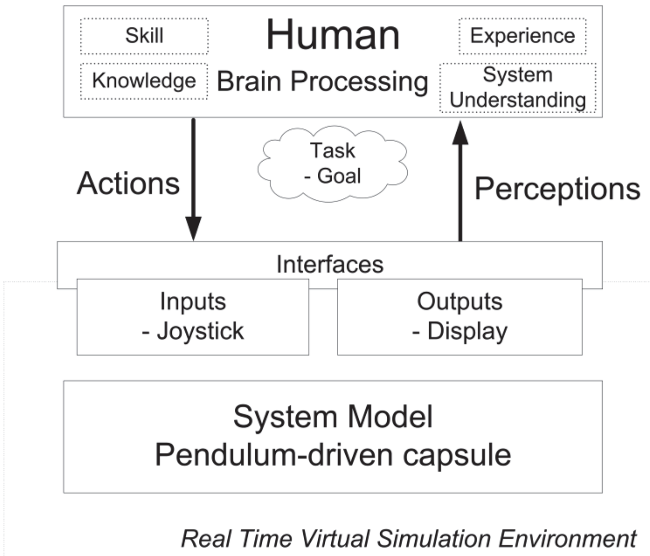

Figure 1. Diagram of the proposed real time virtual simulation based on HAM.

In this paper, the framework for the human machine controlling system in real time virtual simulation environment is proposed. Fig.1 shows a diagram and components of the system. The human operator interacts with a real time virtual simulation via the provided interfaces while perceiving information from the controlling system through a display monitor. It is the human operator's brain that processes information and orders the muscles to take actions to control an interface to manipulate the machine for accomplishing the desired task. Information is retrieved through various perception channels, e.g., eyes looking at meaningful data on the display screen, ears hearing the alert sound signal, and feeling of touching control interfaces. The human operator then observes, interprets, and processes this information and reacts with appropriate actions with the aimed goal in mind. Overall, these activities can be viewed as a human-in-the-loop control scheme and they are working together to be a system. Lacks of one of these components could cause the system failure.

The human block in the proposed framework diagram (Fig.1) acts as a controller that controls the underlying virtual simulation system. Loop of brain processing, perceptions, and actions that related to the human block is performed simultaneously. To control the system, the human operator first needs to know the goal of the controlling task. Then, the control strategy is planned to reach the goal. For example, the heuristic strategy is one of many strategy selections. Based on the planned strategy, series of actions are performed repeatedly. Outcome of each action may not be as planned but it can be adapted according to the situation because of adaptability of human. This process can be viewed as a learning process to control the system. It is individual skills that affect all blocks in the human related loop i.e., skill for perceptions, skill for information processing, and skill for conducting actions. These inputs (perceptions), outputs (actions), and internal flows (brain activities) work as a control system that interacts with the underlying virtual simulation environment.

There is a 'task' block located in conjunction between a human controller and the system (Fig.1). Task understanding is needed to be given first so that the human operator is able to plan actions ahead in mind. For example, the given task as controlling a robot to the right, an operator might think ahead about how to control to reach the given goal. Thus, it is very important to describe the task goal to the human operator.

The proposed real time virtual simulation environment needs software components to compose the system. These components are responsible to simulate the dynamical system, in this case the pendulum-driven capsule robot, to interface with the input system, to render the outputs to the display interface, and in the future functionalities; to recognise human intention and to calculate assisted tuning parameters and forces. The blocks component of this simulation environment from the software architecture point of view is shown in Fig.2.

Software architecture design for this proposed system in Fig.2 is designed centred on the following system functional requirements: 1) simulating dynamics in real time, 2) allowing the user to interact with the simulated dynamic via some controlling interfaces, 3) displaying adequate information for the user to perceive, 4) recognising and adapting the system behaviour based on the current user's competency, and 5) logging and saving experiment data for future analysis. It starts with initial conditions and enters the main simulation loop with the aimed sampling time step. The simulation loop continues running until the software is terminated. Inside of the simulation loop, there are particular components executing to serve the whole functionalities of this virtual system. The ordinary differential equation solver, ODE Solver block, is used for solving ordinary differential equations with the implemented method and algorithm. The equations are based on the mathematical model of the mechanical system. The input system is responsible to handle an interface between the human operator and the virtual system. The input values from the device are transformed into the model's input at every single step of simulation loops. The display output is drawn by the underlying graphic rendering system to visualize the simulating environment. Additional features such as the log system and the real time oscilloscope alike, the graphing system are essential for analysing immediate simulating values as well as logged values for later analysis. Realisation of HAM cannot be achieved without the following components; adaptation computation based on human intention and its corresponding competency, adaptation computation which is divided into passive and active tuning (Shaded blocks in Fig.2).

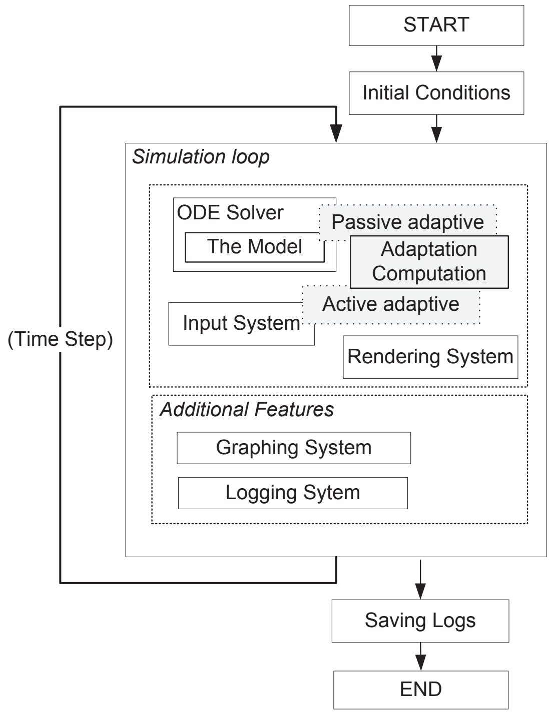

Figure 2. The software architecture.

IV. MODEL OF THE DYNAMICAL SYSTEM

The schematic diagram of the underactuated pendulum-driven capsule system [16] shown in Fig.3 is adopted as a machine to the proposed virtual simulation system. M is mass of a capsule body. The mass m is on the top of the weightless link L. The link can rotate 360 degrees around the centre. One dimensional movement is defined by a position denoted by x and friction f is modelled to point in an opposite direction of the body movement base on the Coulomb's friction model. The system is driven only by the force from the movement of the ball which is exerted by input torque τ and its moving momentum that causes forces.

The movement is possible because of both pendulum force and surface friction force.

From Fig.3, the ball position is defined in terms of cart position x at the centre as shown in equation (1). Then, the ball position equation is differentiated to get velocity and acceleration as in equations (2) and (3) respectively.

$$ball\ position = (x - Lsin\theta)\hat{\imath} + (Lcos\theta)\hat{\jmath} \qquad (1)$$

$$ball\ velocity = \left(\dot{x} - L\dot{\theta}cos\theta\right)\hat{\imath} - (L\dot{\theta}sin\theta)\hat{\jmath} \qquad (2)$$

$$ball\ acceleration = (\ddot{x} - L\ddot{\theta}cos\theta + L\dot{\theta}^2sin\theta)\hat{\imath} - (L\ddot{\theta}sin\theta + L\dot{\theta}^2cos\theta)\hat{\jmath} \qquad (3)$$

Equation (3) and Newton's law of motion give forces from motion of pendulum ball in both x and y directions as follows.

$$F_{bx} = -m\ddot{x_b} \text{ , and } F_{by} - mg = m\ddot{y_b}$$

$$F_b = \begin{bmatrix} F_{bx} \\ F_{by} \end{bmatrix} = \begin{bmatrix} -m\ddot{x} + mL\ddot{\theta}cos\theta - mL\dot{\theta}^2sin\theta \\ mg - mL\ddot{\theta}sin\theta - mL\dot{\theta}^2cos\theta \end{bmatrix}$$

Also, the input torque to the joint is calculated as follows.

$$\tau = (-mLcos\theta)\ddot{x} + (mL^2)\ddot{\theta} - mgLsin\theta$$

$$F_{bx} - f = M\ddot{x}\ ; \quad \text{where } f = \mu Nsgn(\dot{x})$$

$$N = Mg + F_{by}$$

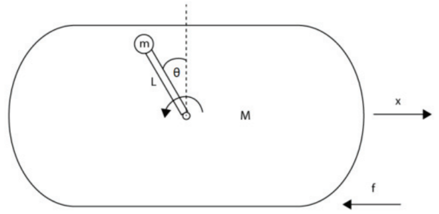

Figure 3. Pendulum-driven capsule system.

From above equations, we have

$$\ddot{x} = \frac{f\sigma_1 + \ddot{\theta}Lmcos\theta - \dot{\theta}Lmsin\theta}{M + m} \qquad (4)$$

where $\sigma_1 = -g(M + m) + \dot{\theta}^2Lmcos\theta + \ddot{\theta}Lmsin\theta$

$$\ddot{\theta} = \frac{Lmcos\theta\ddot{x} + \tau + gLmsin\theta}{L^2m} \qquad (5)$$

Equations (4) and (5) are the system equations with the single control input torque τ.

V. IMPLEMENTATION OF REAL TIME SIMULATION

To conduct real time simulation, the forth order Runge Kutta numerical approximation method of ODEs [17] is used. From the system model (4) and (5), we have

$$\dot{v} = \frac{(2M + 2m)(\sigma_2 + \mu S\sigma_3) - \omega^2Lmsin\theta}{(M + m)(2M + m - mcos2\theta - \mu Smsin2\theta)} \qquad (6)$$

$$where\ \sigma_2 = \frac{cos\theta(\tau + gLmsin\theta)}{L}$$

$$and\ \sigma_3 = \frac{gLmsin^2\theta + \tau sin\theta}{L} - g(M + m) + \omega^2Lmcos\theta$$

$$\dot{\omega} = \frac{(2M + 2m)(\tau + gLmsin\theta - \sigma_4)}{L^2m(2M + m - mcos2\theta - \mu Smsin2\theta)} \qquad (7)$$

$$where\ \sigma_4 = \frac{Lmcos\theta(\mu S(Mg + mg - \omega^2Lmcos\theta) + \omega^2Lmsin\theta)}{M + m}$$

$$\dot{x} = v \qquad (8)$$

$$\dot{\theta} = \omega \qquad (9)$$

where $S = sgn(\dot{x})$

Equations (6), (7), (8), and (9) are then solved by the forth order Runge Kutta numerical approximation algorithm.

An implementation of this real time virtual simulation system is developed using the industry leading application programming interface named Microsoft XNA and C# programming language. Sampling time is chosen at 10ms although it might change depending on the system performance but the system implementation is coded to compensate the issue by using elapsed time of each loop as a time step. The system parameters are as follows; M=0.5kg, m=0.05kg, L=0.3m, g=9.81m/s^2, μ=0.01 N*m/s.

The proposed real time virtual simulation system is controlled by the gaming joystick. The only system input is the amount of torque applied to the joint. The amount of torque can be varied by pushing an analogue stick in which its value is range between -1.0 and 1.0 N. In this case, the mapping is straightforward i.e. [-1.0, 1.0], value from an analogue stick is mapped to the input torque, τ, to drive the underactuated pendulum-driven capsule robot. However, it is noticed that the aimed system time step is 10ms. Therefore, the torque pushed by the joystick in real time is applied to the system at every time step of the system loop.

The screenshot of the simulation display is shown in Fig.4 when the system is simulated. The capsule body and its inner swinging shaft with the attached pendulum ball are displayed for the user to observe the capsule robot. Also, additional features for output information data are shown as online oscilloscope like a graphing system for both user observation and validation purposes.

Observations and manual controls are an inevitable couple in the human-in-the-loop control system. The proposed online simulation system displays necessary information on the monitor for observation while the user control amount of input torque via a joystick is shown in Fig.4. The user has an assigned task in mind while observing the pendulum movement on the screen and react to the dynamic behaviour of the system in real time to achieve desire control motions. In this case motion is in one dimensional movement i.e. moving to the left or vice versa.

Both input and output raw data during runtime experimentation of controlling are logged and saved for further analysis. Angle θ, angular velocity ω, capsule position x, capsule velocity v, and input torque τ are those variables that have been recorded. Also, an extra variable such as sign ($sgn\dot{x}$) of the friction term is logged for more clarification and validation of the implemented friction model.

VI. LEARNING OF MOTION CONTROL PATTERNS

One of the useful functionality of the real-time simulation system is apparent for heuristic strategy experimentation. In the following section, searches and results of motion control patterns for the pendulum-driven capsule system are presented. Control characteristics were experimented by the heuristic strategy. Ability to control this dynamical system is depended on the user's skill and understanding of the system. However, once understood, control characteristics can be identified and used as a pattern of control strategy.

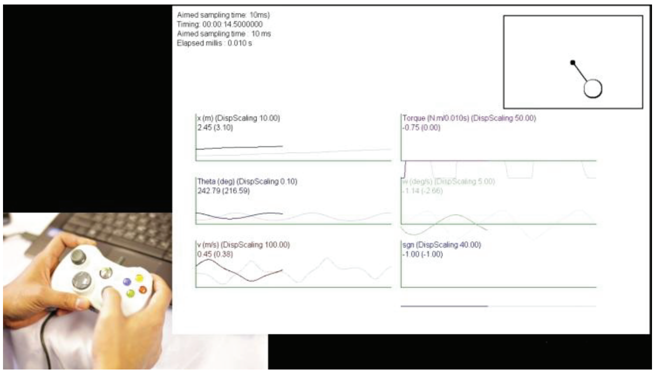

Figure 4. User using the joystick to control virtual simulation system.

The system initial values θ, ω, x, v, and τ are 180 degrees, 0 rad/s, 0 m, 0 m/s, and 0 N.m/s respectively. At the beginning the system stays still with the pendulum shaft and the ball lying straight down. When a small torque is applied, the pendulum begins to swing and the capsule start to move to the left and to the right repeatedly according to forces from the ball and the surface friction model as shown in Fig.5. The capsule is unintentionally displaced to the right by small torque after it finally comes to the steady state.

After several tries to control movement of the pendulum-driven capsule, the control strategy is developed. The system begins at the steady state and is intentionally controlled using the identified control patterns to move a capsule to the left and then to the right (Appendix 1). The identified control patterns to move a capsule by an input torque is summarised by the following strategies.

Step 1) Generate a torque by pushing the joystick to allow the pendulum to swing freely around, and then release the joystick (Fig.6).

Step 2) If one wants to move the capsule to the left, while the pendulum is freely swinging to the left side, the human operator needs to push the torque backward suddenly only in an appropriate short period of time. Moving to the right is done in the opposite way (Fig.7).

More precisely, to move to the left, the user needs to push the torque in the middle of rising or falling of angular velocity. In other words, one needs to push the torque at the edge of sine curves. These torque control strategies allow the user to control the pendulum driven capsule in the desired directions.

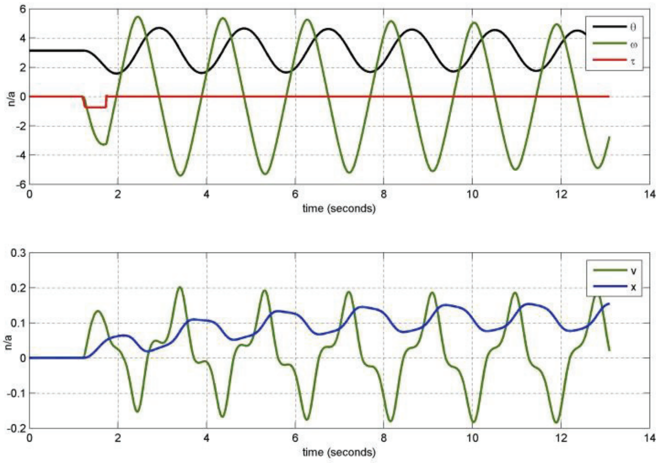

Figure 5. Single pushed torque.

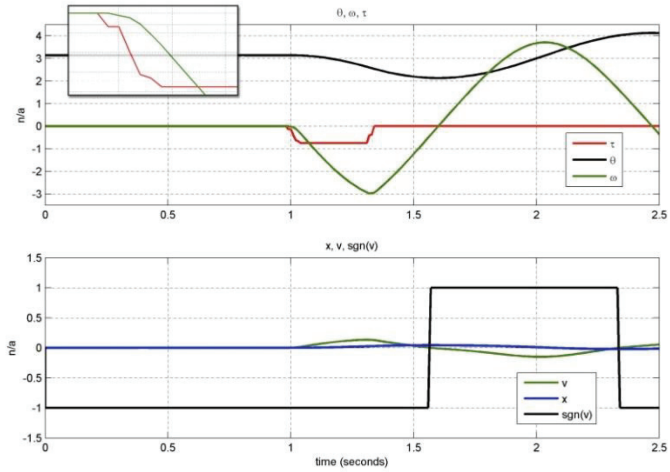

Figure 6. Control characteristics for step 1.

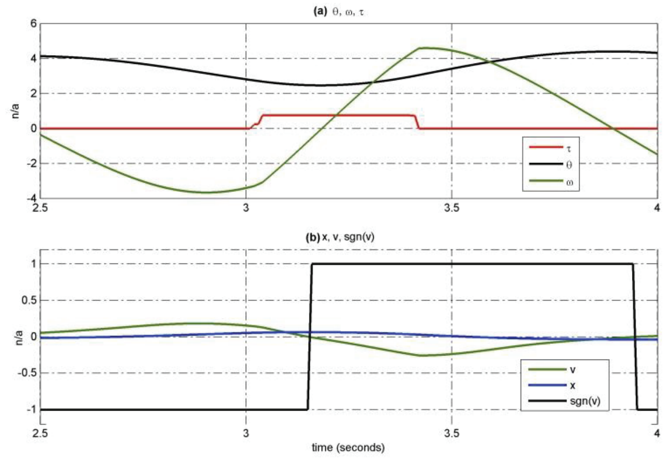

Figure 7. Control characteristics for step 2.

VII. CONCLUSIONS AND FUTURE WORK

A framework of the human-in-the-loop control scheme using real time virtual simulation has been proposed. The software architecture and implementation of the underactuated pendulum-driven capsule robot system have been developed. Usefulness of real time simulation is apparent because of an interactivity nature of this type of systems. The system dynamic model can be realised experimentally. As a result, systematic motion control patterns can be identified. The system also exposes an important of human controlling ability. Different user controlling skills appear to be an important factor in the human-in-the-loop system control. The human controlling skill is depended on user's perceptions, brain processing of particular circumstances, and control actions. Overall performance of the system is another aspect compared to user skills that control the system.

The identified patterns of motion control for the joint torque seem similar to a walking cycle of human. The inverted bottom half circle of leg movements is shown in Fig.8. For example, given that desired movement is to move to the right, at first push the pendulum to swing freely from A to B and vice versa. At the moment that the pendulum ball nearly reaches point B, the torque should add in the opposite way. This will make the capsule move to the right because of both pushed torque and friction. This is working in the same way as human walking habits.

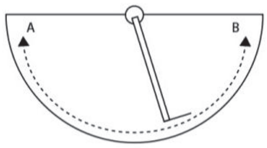

Figure 8. Human walk cycle.

In future works, closed loop control of an underactuated pendulum-driven capsule robot and a more complex model of double underactuated pendulum-driven robot [18] will be implemented as well as realization of an assisting control system based on human adaptive mechatronics. Also, the important adaptive mechanisms that would affect and optimise the learning curve of training will be experimented.

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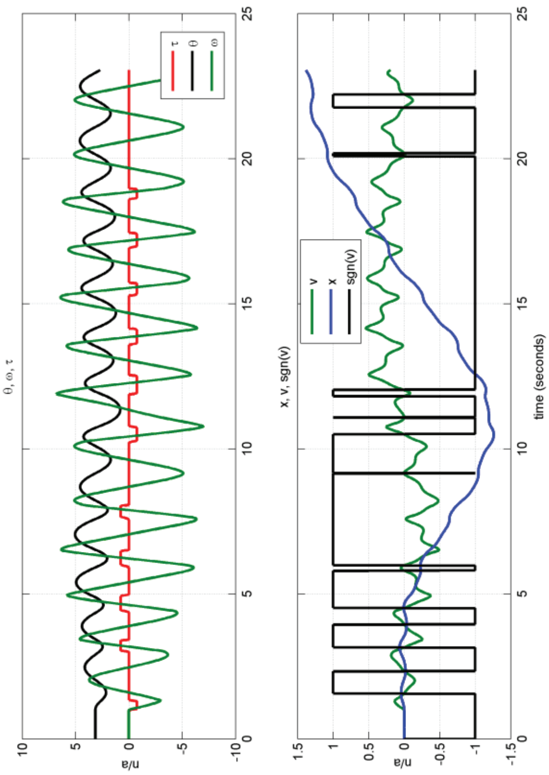
Appendix 1



Graph of all logged variables of operation move to the left and then right.