# Robustness of a Biped Robot Controller Developed by Human Expertise Extraction against Actuator's Malfunctioning

Sarah S. Tabrizi
Tabrizi@ce.sharif.edu

Saeed Bagheri
Bagheri-s@sharif.edu

Sharif University of Technology
Department of Computer engineering, Azadi Ave., Tehran
I. R. Iran

***Abstract*-In many biped control applications, it assumed that internal structure and dynamics of the robot is known to controller, but in real-world problems we don't have exact model of the robot or such model is very complicated and is not useful in real-time control. As a matter of fact, we use many devices without any knowledge about their internal structure or analytical models. This idea motivated us to design a biped controller using human's learning. In the previous works we proposed a linguistic controller designed in this way: a human with no robotics skills tried to control a biped using a joystick; visual information of robot posture was all the available information to the operator; Recognizing that the operator became enabled to control the robot successfully, we extracted his knowledge as 23 fuzzy rules. These rules fed to robot and the robot could walk autonomously. In this paper we show the robustness of this controller against actuator's malfunctioning. To examine controller's robustness, we set some tests upon the robot. These tests include: disabling left ankle, weakening left knee, weakening left hip, disabling both ankles, weakening both knees and weakening both hips. In all cases robot could walk successfully.**

***Index terms*-Biped robot, Fuzzy control, Robustness, Expertise extraction, Linguistic control**

## I. INTRODUCTION

Biped walking has been the most natural human motion for a long time, but it has been passed just 30 years since the first biped robot (WABOT-1, 1973) was physically developed.

Bipeds have many advantages over other legged robots; they usually have less number of actuators, and hence they are lighter and have lower cost. They also require a smaller foothold area for locomotion and thus are more versatile [1]. Since they have human like structure they can *live* in environments specially designed for human (e.g. staircase), and can replace human in dangerous tasks; for example helping people after an earthquake can be entrusted to bipeds.

Another important advantage of bipeds is acceptance by humans; as stated in [2], humans have a tendency to develop affinities based on resemblance.

Despite these advantages, developing legged robots including bipeds started a long time after wheeled ones. Probably this is due to relative control complexity of such robots. As stated in [3], these robots are extremely difficult to control, since they are nonlinear, nominally unstable and Multi Input/Multi Output (MIMO). They operate throughout the range of their state space, act in a gravity field, interact with a semi-structured complex environment, exhibit time variant and intermittent dynamics and require both continuous control and discrete control (for step-to-step transitions).

Two main approaches for solving the legged locomotion control problem are conventional and intelligent control. Conventional control techniques use the equations of motion and feedback from sensors to control the movement. One drawback of the conventional approach is that it does not allow the robot to adapt to changing conditions. If changes occur, such as difference in payload or terrain, the equations used while developing the controller may no longer apply [4]. References [5-9] show some examples of this approach.

Intelligent control techniques do not use motion equations to control movement. Instead, they use general purpose learning algorithms, which enable the robot to learn from experience. Intelligent controllers remember past solutions, so they can be applied to similar situations in the future. Learning enables the robot to adapt to changing conditions, thereby increasing its range of operability [10]; and is critical to achieve autonomous behavior in robots [11]. Some examples of intelligent control can be found in [12-17].

In the previous works, we proposed a linguistic controller to control a seven-link planar biped called Spring Flamingo. This robot developed in MIT Leg Lab. by Jerry Pratt. This robot showed in Figure 1 and table 1 shows its physical parameters. Full description of its structure can be found in [18-20]; and Pratt's approach to control this robot can be seen in [19-21].

We extracted fuzzy rules from the knowledge of the operator who have learned how to control the robot without knowing its internal structure. Then we used these rules to build a fuzzy controller for Spring Flamingo. This controller is proved to be a very suitable and efficient one. In this paper we show its robustness against rough terrain.

The paper is organized as follows: the next section describes designing steps of the controller; Section 3 shows some tests for examining the controller's robustness against actuator's disabling and weakening; and the conclusions come in the last section.

## II. DESIGNING THE CONTROLLER

Despite recent advances in walking and running robots, legged systems in biology continue to outperform our robots in terms of energetic efficiency and their ability to cope with rough terrain. Many researchers believe that this success can be attributed to the ability to learn [22].

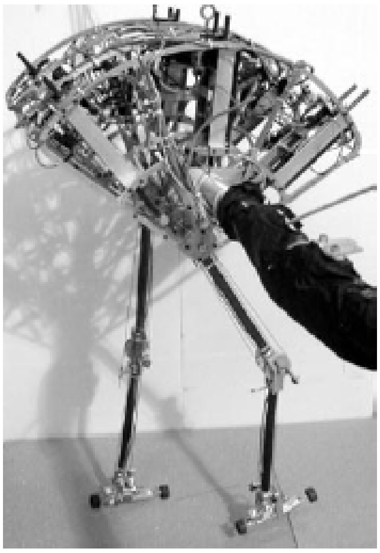

Figure 1: Spring Flamingo

Learning can be seen as the process whereby a system can alter its action to perform a task more effectively due to increase in its knowledge of the task. Learning is considered fundamental to intelligent behavior and the focus of it, is the ability of man-made systems to learn from experience and, based on that experience, improve their performance [11].

Learning to control a physical robot has been proved to be quite a challenge because the real world is unpredictable and physical sensors and actuators are inherently inaccurate [23]; and for a biped robot, the complexity of structure should be added to these problems.

Some various types of learning algorithms have been developed; e.g. Induction, Reinforcement Learning (RL), Case-Based Learning, Explanation-Based Learning, Neural Networks (NN), etc. Almost all learning systems try to model the human's learning mechanism, but they are still far away from this goal because human's learning model is very complex, and nobody can answer this question that "How do we learn?".

In fact our learning system outperforms any learning algorithm in real world applications. After all, in many applications we do not have any knowledge about internal mechanism of the system we learn to control and use it. For example we can drive a car without knowing its engine structure or we can walk without any knowledge about the neuromuscular system of our body.

This motivated us to try to control a biped robot by using the humans' learning process. Our approach consisted of three phases:

### *A. The operator learned to control the robot*

Operator did not have any knowledge about internal structure of the robot. Also he knew nothing about control and robotics. He simply had one joystick, which can open and close each joint separately. The operator was asked to consider the robot as a computer game and by looking at the robot and using the joystick make it walk. It took about 3 weeks for operator to learn how to control the robot on a level rigid (no slip, no bounce) ground.

TABLE 1
PHYSICAL PARAMETERS OF SPRING FLAMINGO

| *Physical Parameter* | *Value* |
|---|---|
| Total mass | 14.2 kg |
| Body mass | 12.0 kg |
| Hip to body center of mass | 0.20 m |
| Body moment of inertia | 0.10 kg $m^2$ |
| Upper leg mass | 0.46 kg |
| Upper leg moment of inertia | 0.13 kg $m^2$ |
| Upper leg length | 0.42 m |
| Lower leg mass | 0.31 kg |
| Lower leg moment of inertia | 0.0095 kg $m^2$ |
| Lower leg length | 0.42 m |
| Foot mass | 0.35 kg |
| Foot moment of inertia | 0.0014 kg $m^2$ |
| Foot height | 0.04 m |
| Foot length forward | 0.17 m |
| Foot length back | 0.06 m |

• **The first week:** At the end of this week, the operator was asked to explain his findings. He was learned that when the swing leg reaches near the ground, the ankle of the leg must be open, and during double support phase the ankle of the frontal leg must be closed so that its foot completely lies on the ground. He learned that the weight of the robot closes its knees and he must send an open signal to knees to make them straight again; but in other situations he didn't use knee joints. The biggest problem was balancing the upper-limb of the robot, and he hadn't found any solution for that problem. .

• **The second week:** After the second week, the operator was asked to describe his knowledge again. This time he used knees to make walking more efficient. Another result was that the operator could keep the robot balance a longer time. He explained that he has found out that he must make the swing leg straight before it contacts the ground. This reduced the balancing problem but didn't solve it.

• **The third week:** After this week the operator was able to make the robot walk some steps without losing its balance. The last problem was solved by finding that the angle between the stance upper-leg and the ground has the main effect on upper-limb balance; and upper-limb bends in the opposite direction of that angle. So adjusting the desired angle during single support phase, maintains balance of the robot.

### *B. The operator expertise is extracted as a fuzzy rule base*

The operator provided us with 23 rules. Some of these rules are as follows:

• **IF** (just one leg -first leg- is on the ground and the other leg -second leg- is behind the first one and its toe is near the ground and its ankle is not closed) **THEN** (close the ankle of the second leg).

• **IF** (just one leg -first leg- is on the ground and the other leg -second leg- is in front of the first one and its ankle is not opened) **THEN** (open the ankle of the second leg fast).

• **IF** (just one leg -first leg- is on the ground and the other leg -second leg- is completely in front of the first one and its knee is not bended) **THEN** (move both legs backward).

• **IF** (just one leg is on the ground and the other leg -second

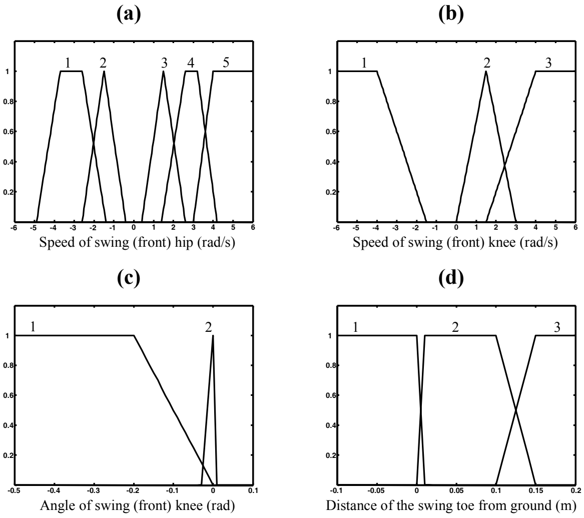


Figure 2: Some membership functions

leg- is in front of the first one and the body is bended backward) **THEN** (move the second leg backward fast).

• **IF** (just one leg is on the ground and the other leg -second leg- is slightly behind of the first one and the body is bended forward) **THEN** (move the first leg forward fast).

• **IF** (both legs are on the ground) **THEN** (move both legs backward and close the ankle of the frontal one).

The complete list of rules can be found in [24].

### *C. Fuzzy rule base was fed to the robot as a fuzzy controller*

We used a Mamdani-type system with Min operator as T-norm, Max operator as S-norm, Centriod operator as Defuzzification method and trapezoid and triangular membership functions.

The controller has 10 inputs and 6 outputs, inputs were: *Support mode*, *Situation of swing (front) Leg relative to other one*, *Distance of the swing toe from ground*, *Distance of the swing heel from ground*, *Situation of the swing (front) knee*, *Situation of the swing ankle*, *Situation of the stance (behind) knee*, *balance*, *Distance of the stance toe from ground* and *Distance of the stance heel from ground*. Outputs were speeds of the joints: *Swing (front) hip*, *Swing (front) knee*, *Swing (front) ankle*, *Stance (behind) hip*, *Stance (behind) knee* and *Stance (behind) ankle*. Membership functions were tuned over a level surface by interacting with the operator. Figure 2 shows some of membership functions.

Implementing the fuzzy logic controller showed that this simple system can control the 6-DOF planar biped efficiently. Snapshots of walking biped are shown in figure 2. Figure 3 shows graphs of a sample try by fuzzy controller. The x axis of all graphs is elapsed time in seconds. The y axis of (a)-(d) are height of robot body, distance traveled by robot, pitch angle of the body and velocity of the robot, respectively[1].

[1] Movies of all samples and tests can be found on: http://ce.sharif.edu/~rcs/Projects/Biped/

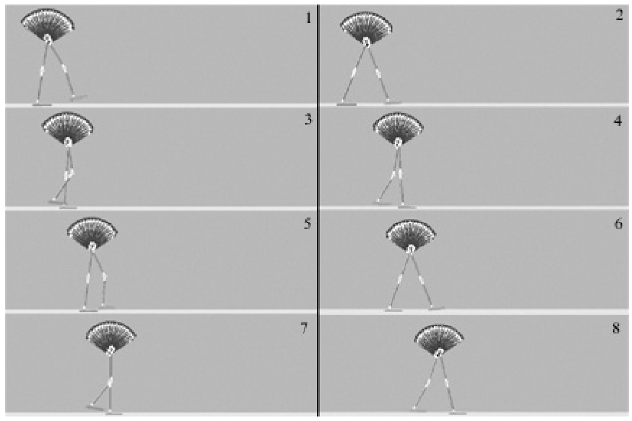


Figure 3: Snapshots of a sample walking by the fuzzy controller

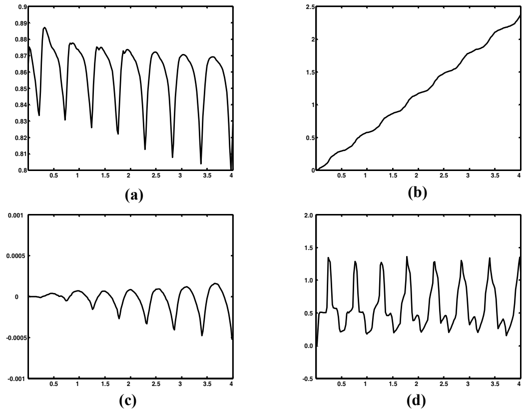


Figure 4: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity

## III. EXAMINING THE CONTROLLER'S ROBUSTNESS AGAINST ACTUATOR'S MALFUNCTIONING

The robot's actuators were working properly during learning phase, and operator learned to control robot on this assumption. All rules were designed and tuned for such a robot. In order to know how much the controller is robust against its actuators' malfunctioning, we disabled or weakened some of its joints. In all these tests the controller knows nothing about changes in robot structure. It assumes that the robot is all right all the time and controls the robot on this assumption. These tests are as follows:

### *A. Disabling the left ankle*

In this test, the left ankle is completely disabled and is affected by external forces only. It means that there is no control signal on it. Robot's success in this test suggests that we can leave support ankle passive in some situations. Snapshots and graphs of walking are shown in figures 4 and 5 respectively.

### *B. Weakening the left knee*

In this test, robot's left knee is weak. It means that it receives a portion of control signal. To determine maximum weakness that robot can accept on each joint we began with a small amount of weakness (about 5%) and increased it gradually. The robot can walk with 40% weakness of one

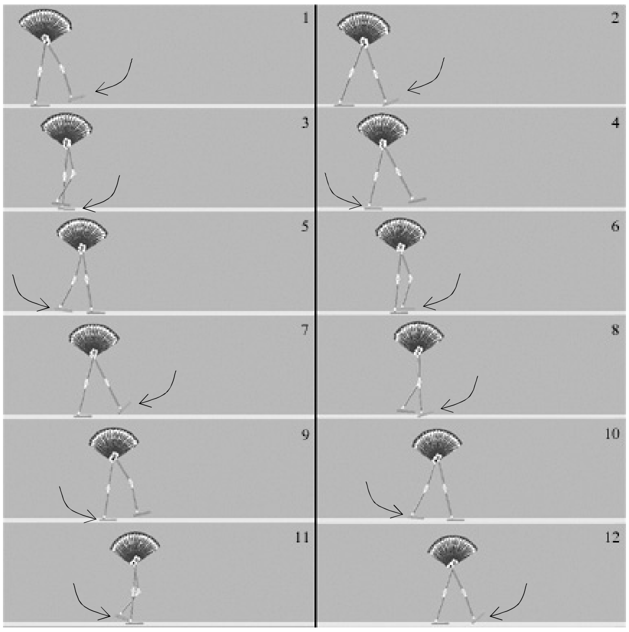

Figure 5: Snapshots of walking with left ankle disabled

Arrow indicates the weak foot

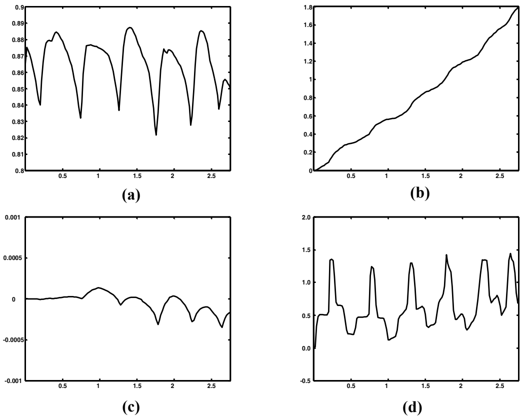


Figure 6: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity

knee, i.e. it can walk with 60% of left knee's control signal. Figures 6 and 7 show snapshots and graphs of movement, respectively.

### C. *Weakening the left hip*

Operator believed that hip joints are the most important joints of the robot. The maximum weakness that robot can bear is 10%, showing that the operator was right. Snapshots and graphs of this test can be seen in figures 8 and 9.

### D. *Disabling both ankles*

In this experience both ankles are completely disabled and do not receive any control signal. Figures 10 and 11 represent the snapshots and graphs of this test.

### E. *Weakening both knees*

After robot's success in walking with one weak knee, we tried to see what happens if both knees are weak. Snapshots of movement are shown in figure 12, and graphs can be seen in figure 13.

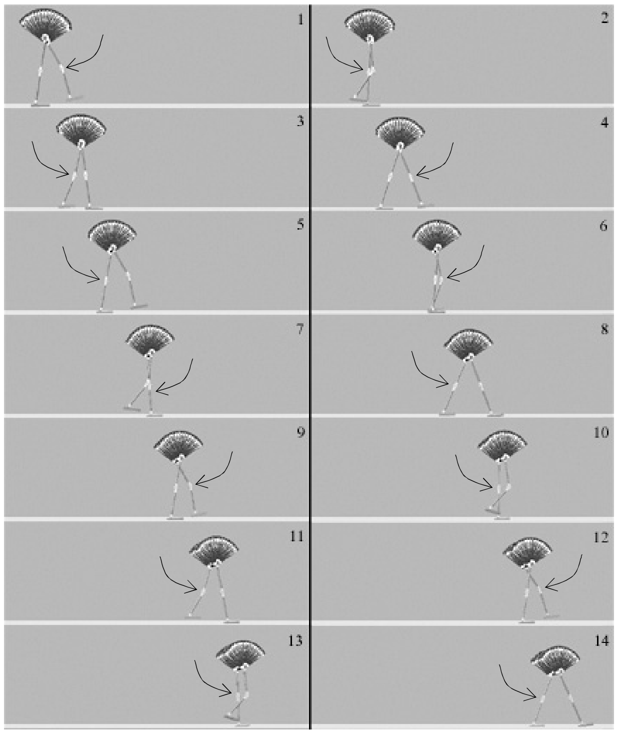

Figure 7: Snapshots of walking with left knee 40% weakened

Arrow indicates the weak knee

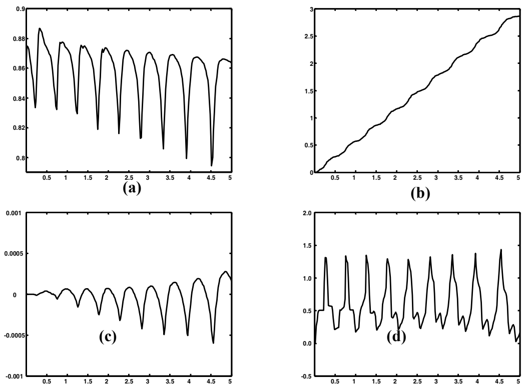


Figure 8: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity

### F. *Weakening both hips*

In experience 3.3 we showed that robot can accept 10% weakness on one of its hips. It seems that robot can not accept more than this weakness on both hips, but in fact it can accept 25% weakness on both hips. It is probably because that the robot do not have waist joint, and rational speed of hip joints controls the balance. Snapshots of movement are shown in figure 12, and graphs can be seen in figure 13.

## IV. Conclusion

We showed that we can control a robot without knowing its internal structure and dynamics in the same way that we use ordinal devices. We used an operator that knew nothing about dynamic equations of the robot and the operator become able to control the robot by looking at it. Finally we extract 23

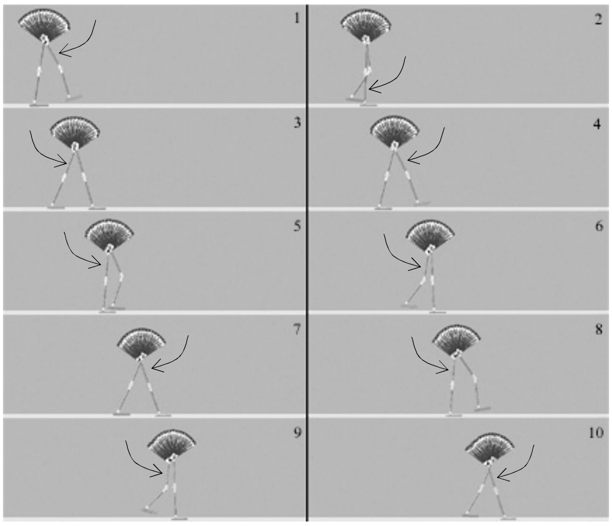

Figure 9: Snapshots of walking with left hip 10% weakened

Arrow indicates the weak leg

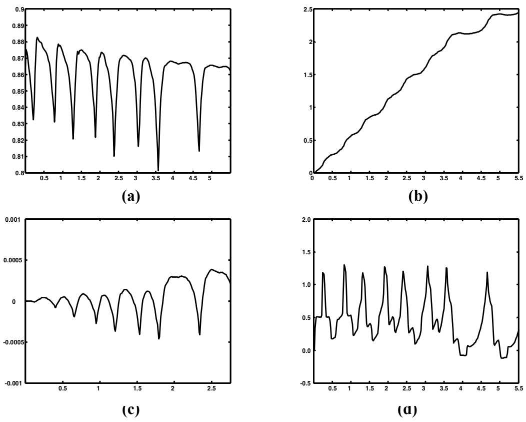

Figure 10: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity

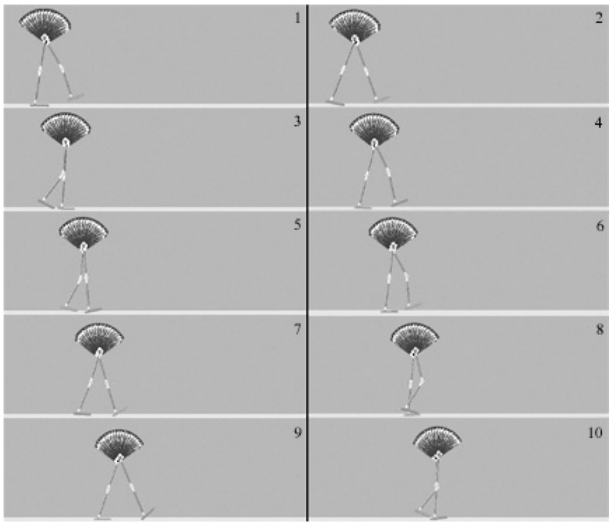

Figure 11: Snapshots of walking with both ankles disabled

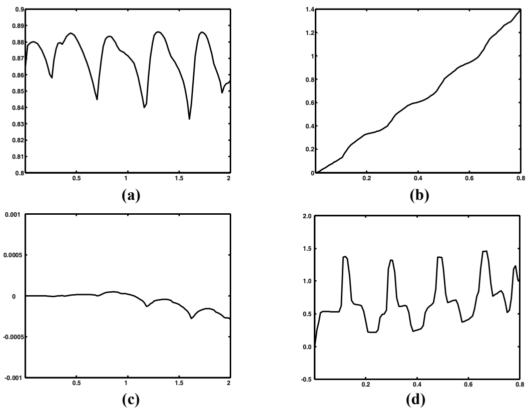

Figure 12: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity

rules and successfully applied them on the robot. We put the robot in unknown terrain without telling it anything about changes in the surface. These tests showed that the controller is robust against changes in terrain.

## REFERENCES

[1] C.M. Chew, Blind walking of a planar biped on sloped terrain, *Masters Thesis, Dept. of Electrical Eng. and Computer Sc. , MIT*, 1998

[2] A. Stoica, Robot fostering techniques for sensory-motor development of humanoid robots, *Robotics and Autonomous Systems* 37: 127–143, 2001

[3] J. Pratt, P. Dilworth, G. Pratt, Virtual model control of a bipedal walking robot, *Proc. of the Int. Conf. on Robotics and Automation (ICRA '97),* 1997

[4] P.I. Doerschuk, V. Nguyen, W. Simon, and F. Kwong, Intelligent ballistic control of a jointed leg, *Proc. of the IEEE Int. Joint Symposia on Intelligence and Systems* , 1996

[5] Y. Fujimoto, S. Obata, A. Kawamura, Robust biped walking with active interaction control between foot and ground, *IEEE Int. Conf. on Robotics & Automation*, 1998

[6] J. Furusho, M. Masubuchi, Control of a dynamical biped locomotion system for steady walking, *J. of Dynamic Systems, Measurement, and Control*, 108:111-118, 1986

[7] P. Gorce, M. Guihard, "On dynamic control of pneumatic bipeds*", J. of Robotic Systems,* 15(7):421–433,1998

[8] C.L. Shih, W.A. Gruver, T.T. Lee, Inverse kinematics and inverse dynamics for control of a biped walking machine, *J. of Robotic Systems*, 10(4):531–555, 1993

[9] Y. Yavin, C. Feangos, Modeling and control of a walking four link robot, *Mathematical and Computer Modeling* 35:393-402, 2002

[10] J. Pepper, Walking algorithms for biped robot, *Bachelor with Honors thesis, Faculty of Engineering and Mathematical Sciences, University of Western Australia,* 1999

[11] P.J. Antsaklis, Intelligent learning control, *IEEE Control Systems*, 15(3):5-7, Jun 1995

[12] M.Y. Cheng, C.S. Lin, Genetic algorithm for control design of biped, *J. of Robotic Systems*, 14(5):365–373,1997

[13] L. Magdalena, F.M. Heulin, A fuzzy logic controller with learning thorough the evolution of its knowledge base, *Int. J. of Approximate reasoning,* 16:335-358, 1997

[14] A.W. Salatian, , K.Y. Yi, Y.F. Zheng, Reinforcement learning for a biped robot to climb sloping surfaces, *Journal of Robotic Systems* 1997;14:283-96

[15] H. Wang, T.T. Lee, W.A. Gruver, A neuromorphic controller for a three-link biped, *IEEE trans on Sys. Man and Cyber.* 22(1):164-169, 1995

[16] C. Zhou, K. Jagannathan, Adaptive network based fuzzy control of a dynamic biped walking, *IEEE Int. Joint Symposia*

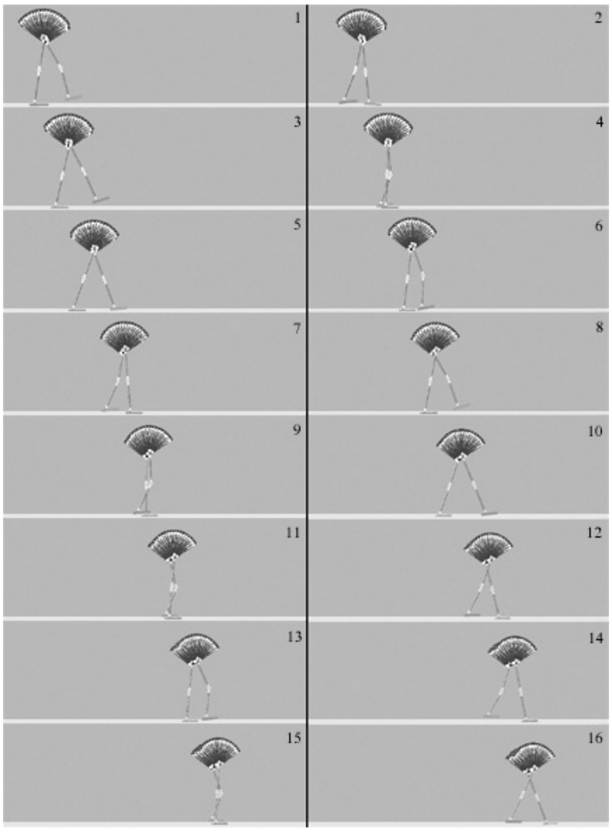

Figure 13: Snapshots of walking with both knees weakened

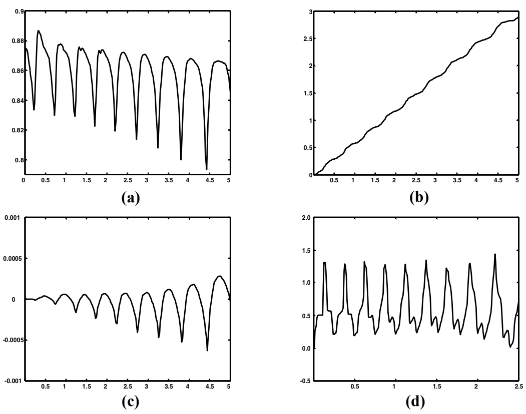

Figure 14: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity


*on Intelligence and Systems (IJSIS '96)* :109-116, 1996

[17] C. Zhou, D. Ruan, Integration of linguistic and numerical information for biped control, *Robotics and Autonomous Systems* 28:53–70, 1999

[18] J. Pratt, Virtual model control of a biped walking robot, *Masters Thesis, Department of Electrical Engineering and Computer Science, MIT,* 1995

[19] J. Pratt, Exploiting inherent robustness and natural dynamics in the control of bipedal walking robots, *PhD. Thesis, Department of Electrical Engineering and Computer Science, MIT*, 2000

[20] J. Pratt, G. Pratt, Exploiting natural dynamics in the control of a planar bipedal walking robot, *Proc. 36th Annual Allerton Conf. on Communication, Control, and Computing*, 1998

[21] J. Pratt, G. Pratt, Intuitive control of a planar bipedal walking robot, *Proc. Int. Conf. on Robotics and Automation*


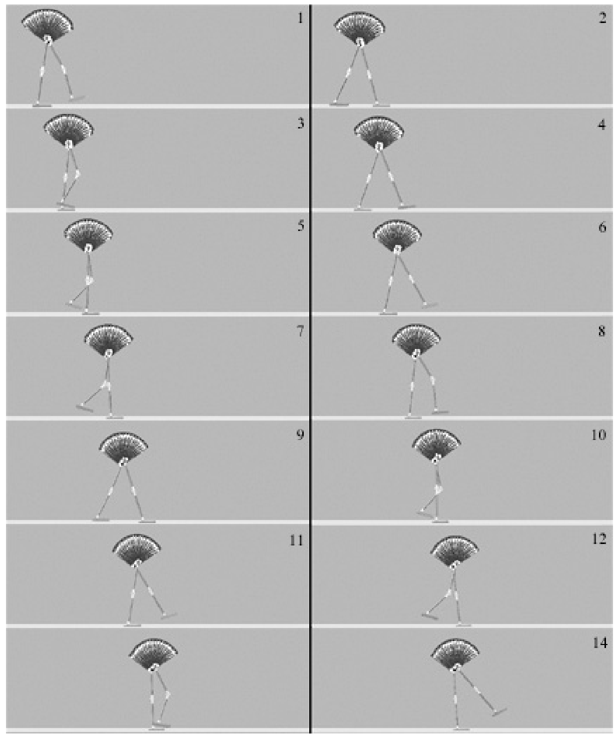

Figure 15: Snapshots of walking with both hips weakened

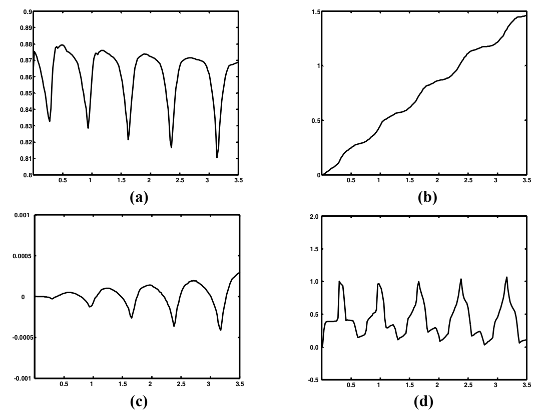

Figure 16: (a) Height, (b) Distance traveled, (c) Pitch, (d) Velocity


*(ICRA'98)*, 1998

[22] R. Tedrake, H.S. Seung, Improved dynamic stability using reinforcement learning, *Proc. Int. Conf. on Climbing and Walking Robots (CLAWAR'02)*, 2002

[23] H. Hexmoor, L. Meeden, Learning in autonomous robots: A summary of the 1996 Robolearn workshop, *Knowledge Engineering Review*, 11(4), 1997

[24] S.S. Tabrizi, S. Bagheri, Developing a fuzzy controller for a planar biped robot using human expertise extraction, *Proc. International Symposium on Computational Intelligence and Intelligent Informatics (ISCIII'03), Nabeul, Tunisia*, 2003