

# Neural Network Control of a Biped Robot Model with Composite Adaptation Low

Ahmad Forouzentabar<sup>1,2</sup>

1-Faculty of Electrical Engineering, Islamic Azad University, Fars Science and Research Branch, Fars, Iran

2-Young Research Club, Islamic Azad University, Fars Science and Research Branch, Fars, Iran

Phone: +98-7284692104 e-mail: a.forouzentabar@srbiau.ac.ir

**Abstract**—this paper presents a novel neural network controller with composite adaptation low to improve the trajectory tracking problems of biped robots comparing with classical controller. The biped model has 5 link and 6 degrees of freedom and actuated by Plated Pneumatic Artificial Muscle, which have a very high power to weight ratio and it has large stroke compared to similar actuators. The proposed controller employ a stable neural network in to approximate unknown nonlinear functions in the robot dynamics, thereby overcoming some limitation of conventional controllers such as PD or adaptive controllers and guarantee good performance. This NN controller significantly improve the accuracy requirements by retraining the basic PD/PID loop, but adding an inner adaptive loop that allows the controller to learn unknown parameters such as friction coefficient, therefore improving tracking accuracy. Simulation results plus graphical simulation in virtual reality show that NN controller tracking performance is considerably better than PD controller tracking performance.

**Keywords**—Biped robot, Neural network, Plated Pneumatic Artificial Muscle, Composite adaptation

## I. INTRODUCTION

OVER the past few years the field of robotics encounters new direction in which new robot models are emerged.

Legged robot and especially biped robot nowadays are exclusive research topic for academic and even military world.

The mechanical complexity of legged locomotion systems is one of the characteristics that make their design and control very difficult. Specially, the existence of a non (directly) controllable degree of freedom in biped systems plays a significant role in the determination and improvement of their stability properties. On the other hand, during the motion of any walking robot, a number of sudden geometric constraints are imposed, e.g. stepping on the ground, knee locking, etc. These constraints, which are inherent in all walking machines, give rise to impulse-like disturbances that make the control by standard PD or PID controllers an extremely difficult problem.

Most of the legged robots nowadays use electrical drives. The most well-known robots are HRP-2P [1], Johnnie [2], Qrio [3], and Asimo[4].

Liu and Zhang [5] proposed a type-2 fuzzy switching control system for a biped robot, which includes switched nonlinear system modeling, type-2 fuzzy control system design, and a type-2 fuzzy modeling algorithm.

Author is with the Faculty of Electrical Engineering, Islamic Azad University, Fars Science and Research Branch, Fars, Iran. Phone: +98-7284692104 e-mail: a.forouzentabar@srbiau.ac.ir

A new switched system model was proposed to represent the continuous-time dynamic and discreteevent dynamic of a walking biped as a whole, which is useful to analyze the closed-loop stability of the biped locomotion. Then, a type-2 fuzzy switching control system was proposed for the switched system model to guarantee the gait stability and to achieve a robust control performance with a simplified control scheme. Because the torque density of the drives is too low to actuate legs, gearboxes are used to deliver the required torque at low rotation speeds, therefore making the joint stiff and losing joint compliance. While the compliance characteristics actually can be useful for legged locomotion to reduce shocks and decrease energy consumption by exploiting the natural dynamics of the system[7].

The research group Multibody Mechanics of the Vrije University Brussel has built the planar walking biped Lucy. This biped model is actuated by pleated pneumatic artificial muscles (PPAM) [7]. The goal of the biped project is to achieve a lightweight bipedal robot able to walk in a dynamically stable way while exploiting the passive behavior of the pleated pneumatic artificial muscles in order to reduce energy consumption and control effort. A picture of the complete set-up is given in Fig.1. The movement of Lucy is restricted to the sagittal plane by a sliding mechanism. The robot, all included, weighs about 30kg and is 150 cm tall. The robot has 12 pneumatic actuators for 6 DOF's [9-11]. The Pleated Pneumatic Artificial Muscle (PPAM) is depicted in Fig.2.

In this paper, a novel control structure, with composite adaptation low, for a new biped robot model is proposed. In this regard, a stable neural network is employed to approximate unknown nonlinear functions in the robot dynamics; hence overcoming some limitation of conventional controllers and improve biped robot tracking performance. This controller can easily reject disturbance and also robust to dynamic exchange in walking process.

The rest of this paper organized as follows. Section II describes 6DOF biped robot with Pleated Pneumatic Artificial Muscle introduced by Verrelst *et al.* [7]. In Section III we describe the structure of stable neural network controller with composite adaptation low. In Section IV shows the simulation results. And finally, Section V draws conclusions and sum up the whole paper.



Fig. 1. Photograph of Lucy



Fig. 2. Photograph of deflated and inflated state of the PPAM

## II. KINEMATICS AND DYNAMICS OF THE BIPED ROBOT MODEL

The biped robot has 5-link and 6 DOF. Center of gravity for each link is located in the middle of it. The biped robot model with 6 degree of freedom during single phase is shown in Fig 3. This model has a torso and two legs. Each leg has two links and one ankle [8-13].

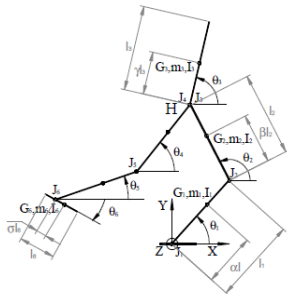


Fig. 3. Biped robot model during single phase

### A. Kinematics

It is assumed that both legs are identical. So, all inertial properties and the length of the upper and lower leg to be pair wise equal. The hip takes a central position and considered as a reference point.

$$\begin{aligned} X_H &= l_1 \cos \theta_1 + l_2 \cos \theta_2 \\ Y_H &= l_1 \sin \theta_1 + l_2 \sin \theta_2 \end{aligned} \quad (1)$$

with this reference point, the position of the global center of gravity (COG) of the robot, stance foot not included, is given by

$$\begin{aligned} X_G &= X_H + a_1 \cos \theta_1 + a_2 \cos \theta_2 + a_3 \cos \theta_3 + a_4 \cos \theta_4 + a_5 \cos \theta_5 + a_6 \cos \theta_6 \\ Y_G &= Y_H + a_1 \sin \theta_1 + a_2 \sin \theta_2 + a_3 \sin \theta_3 + a_4 \sin \theta_4 + a_5 \sin \theta_5 + a_6 \sin \theta_6 \end{aligned} \quad (2)$$

where  $a_i$ ,  $i = 1, 2, \dots, 6$  is depend on lengths and masses of the robot links [12].

### B. Dynamics

The motion of the robot is limited to the sagittal plane. During walking, there is two major phase: single support phase and double support phase. In low-speed human walking the single support phase is chosen to cover 80% of total step duration, while the double support phase lasts for the remaining 20 %.

#### B.1 Single support phase

During the single support phase the robot's supporting foot is assumed to remain in full contact with the ground. It is assumed that the friction of the ground is sufficiently large to ensure no slipping of the supporting foot. The Lagrange dynamic model describing the motion of the biped in this phase is written as [12]:

$$D(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau \quad (3)$$

with  $q = [q_1, q_2, q_3, q_4, q_5, q_6]$ ,  $\tau = [\tau_1, \dots, \tau_6]$  and  $D(q)$  the inertia matrix,  $C(q, \dot{q})$  the centrifugal/coriolis matrix,  $G(q)$  the gravitational torque/force vector and  $\tau$  the torque vector.

#### B.2 Double support phase

Immediately after impact of the swing leg, three geometrical constraints are imposed on the motion of the system. The three constraints are summarized as follows:

$$l_1 \cos(\theta_1) + l_2 \cos(\theta_2) - l_2 \cos(\theta_4) - l_1 \cos(\theta_5) - X_{AF}^{td} = 0 \quad (4.1)$$

$$l_1 \sin(\theta_1) + l_2 \sin(\theta_2) - l_2 \sin(\theta_4) - l_1 \sin(\theta_5) - Y_{AF}^{td} = 0 \quad (4.2)$$

$$\theta_6 - C^{\alpha} = 0 \quad (4.3)$$

with  $X_{AF}^{td}$  and  $Y_{AF}^{td}$  the actual horizontal and vertical position of the front ankle point at touch down. The number of DOF during double support is reduced to 3, but the same 6 Lagrange coordinates ( $q = [q_1, q_2, q_3, q_4, q_5, q_6]$ ) are used. The equations of motion of single support are adapted with the three geometrical constraints as follows [12]:

$$D(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau + J^T \psi \quad (5)$$

With  $J(q)$  the Jacobian matrix, which is calculated by taking the derivative of the constraint equations with respect to the generalized Lagrange coordinates:

$$J(q) = \begin{bmatrix} -l_1 \sin(\theta_1) & -l_2 \sin(\theta_2) & 0 & l_2 \sin(\theta_4) & l_1 \sin(\theta_5) & 0 \\ l_1 \cos(\theta_1) & l_2 \cos(\theta_2) & 0 & -l_2 \cos(\theta_4) & -l_1 \cos(\theta_5) & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)$$

and  $\psi$  the vector of Lagrange multipliers.

### III. NEURAL NETWORK CONTROL STRUCTURE

The robot dynamic has

$$M(q)\ddot{q} + V_m(q, \dot{q})\dot{q} + F(\dot{q}) + G(q) + \tau_d = \tau \quad (7)$$

In this dynamic,  $M(q)$  is the inertia matrix,  $V(q, \dot{q})$  is the centrifugal/coriolis matrix,  $G(q)$  the gravitational force vector,  $F(\dot{q})$  is friction term,  $\tau_d$  represents disturbances and  $\tau$  the torque vector.

To make robot manipulator follow a prescribed desired trajectory  $q_d(t)$ , define the tracking error  $e(t)$  and filtered tracking error  $r(t)$  by

$$e = q_d - q \quad (8)$$

$$r = \dot{e} + \Lambda e \quad (9)$$

with  $\Lambda > 0$  a positive definite design parameter matrix. The robot dynamics are expressed in terms of the filtered error as

$$M\dot{r} = -V_m r + f(x) + \tau_d - \tau \quad (10)$$

Where the unknown nonlinear robot function is defined as

$$f(x) = M(q)(\ddot{q}_d + \Lambda\dot{e}) + V_m(q, \dot{q})(\dot{q}_d + \Lambda e) + F(\dot{q}) + G(q) \quad (11)$$

One may define  $x \equiv [e^T, \dot{e}^T, q_d^T, \dot{q}_d^T, \ddot{q}_d^T]^T$ .

A general sort of approximation- based controller is derived by setting

$$\tau = \hat{f} + K_v r - v(t) \quad (12)$$

with  $\hat{f}$  an estimate of  $f(x)$ ,  $K_v r = K_v \dot{e} + K_v \Lambda e$  an outer PD tracking loop, and  $v(t)$  an auxiliary signal to provide robustness in the fact of disturbances and modeling error [14]. The multi loop control structure implied by this scheme is shown in fig. 5. Using this controller, the closed-loop error dynamics are

$$M\dot{r} = -V_m r - K_v r + \tilde{f} + \tau_d + v(t) \quad (13)$$

Where the function approximation error is given by

$$\tilde{f} = f - \hat{f} \quad (14)$$

According to the universal approximation property of NN, if the  $\phi(\cdot)$  provides a basis, then a smooth function  $f(x)$  from  $\mathfrak{R}^n$  to  $\mathfrak{R}^m$  can be approximated on a compact set  $S$  of  $\mathfrak{R}^n$ , by

$$f(x) = W^T \phi(x) + \varepsilon \quad (15)$$

for some ideal weights and thresholds  $W$  and some number of hidden layer neurons  $L$ . In fact, for any choice of a positive number  $\varepsilon_N$ , one can find a feed forward NN such that

$$\|\varepsilon\| < \varepsilon_N \quad (16)$$

For all  $x$  in  $S$  [15].

The One-layer functional-link neural network (FLNN) structure is shown in fig. 4.

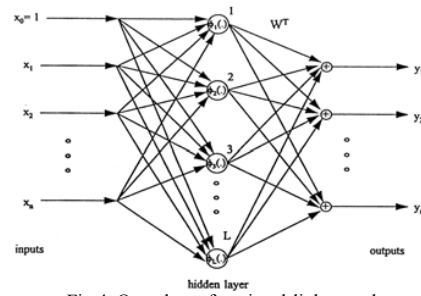


Fig.4. One-layer functional-link neural net

It has been shown that the sigmoid can form a basis set [16]. In Sanner and Slotine [17] it was shown that radial basis functions can form a basis. Determining the number of hidden layer neuron required for good approximation in an open problem for general fully connected two-layer NN. If we want a good approximation for  $f(x)$ , the number of hidden layer neuron should be large enough. Extracting the NN weight tuning algorithm, some assumptions and lemmas are needed. These assumptions are true in every practical situation [13].

*Assumption 1:* The desired trajectory is bounded so that

$$\begin{bmatrix} q_d(t) \\ \dot{q}_d(t) \\ \ddot{q}_d(t) \end{bmatrix} < q_B \quad (17)$$

With  $q_B$  a known scalar bound.

The desired trajectory generates joint motion patterns based on objective locomotion parameters. The objective locomotion parameters are average forward speed of the hip, step-length, step-height and intermediate foot-lift. These parameters are calculated by a higher level gait planning control unit. It is important to mention that the trajectory generator ensures dynamically stable walking for a wide range of objective locomotion parameter combinations. For the calculation of the joint trajectories, the motion of the swing foot during the single support phase is not considered; it is kept in a horizontal position [18].

Suppose that a FLNN is used to approximate the nonlinear biped robot functions (11) according to (15), with  $W$  the ideal approximating weights. The ideal weights are unknown and may even be non unique. Assume they are constant and bounded so that

$$\|W\|_F \leq W_B \quad (18)$$

with  $W_B$  known and  $\|\cdot\|_F$  the Frobenius norm.

Then, an estimate of  $f(x)$  is given by

$$\hat{f}(x) = \hat{W}^T \phi(x) \quad (19)$$

With  $\hat{W}$  the actual values of the NN weights given by the tuning algorithm to be specified. Select the control input

$$\tau = \hat{W}^T \phi(x) + K_v r - v \quad (20)$$

The proposed NN control structure is shown in fig. 5, where  $q = [q^T \dot{q}^T]^T$ ,  $e = [e^T \dot{e}^T]^T$

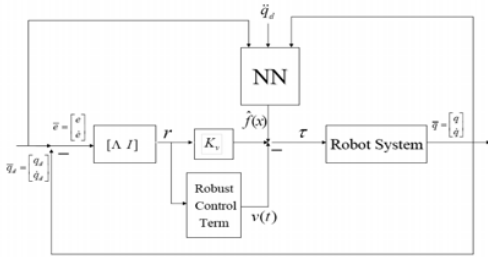


Fig. 5. NN controller structure

It is now necessary to show how to tune the NN weights  $\hat{W}$  on-line so as to guarantee stable tracking. The tuning algorithm found will presumably modify the actual weights  $\hat{W}$  so that they become close to ideal weights  $W$ , which are unknown. To this end, define the weight deviations or weight estimation error as

$$\tilde{W} = W - \hat{W} \quad (21)$$

Then,  $f - \hat{f} = W^T \phi(x) + \varepsilon - \hat{W}^T \phi(x)$  and the close loop filtered error dynamics (13) becomes

$$M\dot{r} = -(K_v - V_m)r + \tilde{W}^T \phi(x) + (\varepsilon + \tau_d) + \nu \quad (22)$$

Now we give a FLNN weight tuning algorithm with composite adaptation law that guarantee the tracking stability of the closed loop system. It is required to demonstrate that the tracking error  $r(t)$  is suitably small and that the FLNN weights  $\hat{W}$  remain bounded, for then the control  $\tau(t)$  is bounded.

The resulting controller is given in below theorem. In this case the tracking error does not go to zero with time, but is bounded by a small enough value.

*Theorem:*

Let the desired trajectory  $q_d(t)$  be bounded by  $q_B$  as in Assumption1. Assume the ideal target NN weights are bounded by  $W_B$  as in (18) and the initial tracking error  $r(0)$  is bounded. Let the estimate error bound  $\varepsilon_N$  and the disturbance bound  $d_B$  be constants. Let the control input for the biped robot with  $\nu = 0$  be given by

$$\tau = \hat{W}^T \phi(x) + K_v r \quad (23)$$

with gain satisfying

$$\sigma_{\min}(K_v) \geq \frac{(\varepsilon_N + d_B)}{b_r} \quad (24)$$

Let NN weight tuning be provided by

$$\dot{\hat{W}} = F \phi r^T - \kappa F \phi^T \phi \tilde{W} \quad (25)$$

with any constant matrices  $F = F^T > 0$  and  $\kappa > 0$  a small scalar design parameter. Then the filtered tracking error  $r(t)$  and NN weight estimates  $\hat{W}$  are UUB with practical bounds. Moreover the tracking error may be kept as small as desired by increasing the gain  $K_v$ .

*Proof:*

Let the NN approximation property (15) hold for the function  $f(x)$  given in (11) with a given accuracy  $\varepsilon_N$  for all

$x$  in the compact set  $S_x \equiv \{x \mid \|x\| < b_{x_2}\}$  with  $b_{x_2} > q_B$ . Define  $S_r \equiv \{r \mid \|r\| < b_r\}$  and  $r(0) \in S_r$ .

Select the Lyapunov function candidate

$$L = \frac{1}{2} r^T M r + \frac{1}{2} \text{tr} \{ \tilde{W}^T F^{-1} \tilde{W} \} \quad (26)$$

Differentiating yields

$$\dot{L} = r^T M \dot{r} + \frac{1}{2} r^T \dot{M} r + \frac{1}{2} \text{tr} \{ \tilde{W}^T F^{-1} \dot{\tilde{W}} \} \quad (27)$$

Substituting from (25) yields

$$\dot{L} = -r^T K_v r + \frac{1}{2} r^T (M - 2V_m) r + \text{tr} \{ \tilde{W}^T (F^{-1} \dot{\tilde{W}} + \phi r^T) \} + r^T (\varepsilon + \tau_d) \quad (28)$$

The skew symmetry property makes the second term zero. Using tuning rule (25) yields

$$\dot{L} = -r^T K_v r - \kappa \text{tr} \{ \tilde{W}^T \phi^T \phi \tilde{W} \} + r^T (\varepsilon + \tau_d) \quad (29)$$

Now,

$$\dot{L} \leq -\sigma_{\min}(K_v) \|r\|^2 + \|r\| (\varepsilon_N + d_B) - \kappa \text{tr} \{ \tilde{W}^T \phi^T \phi \tilde{W} \} \quad (30)$$

with  $\sigma_{\min}(K_v)$  the minimum singular value of  $K_v$ . Since  $(\varepsilon_N + d_B)$  is positive constant,  $\dot{L} < 0$  as long as

$$(31) \|r\| > \frac{(\varepsilon_N + d_B)}{\sigma_{\min}(K_v)} \equiv b_2$$

Thus,  $\dot{L}$  is negative outside a compact set. Selecting the gain according to (24) ensure that the compact set defined by  $\|r\| \leq b_2$  is contained in  $S_r$ , so that approximation property holds throughout. This demonstrates the UUB of both  $\|r\|$

and  $\|\tilde{W}\|_F$ . As a result, the biped tracking error  $r(t)$  is bounded and continuity of all functions shows as well the boundedness of  $\dot{r}(t)$ . Boundedness of  $r(t)$  guarantees the boundedness of  $e(t)$  and  $\dot{e}(t)$ , therefore boundedness of desired trajectory in biped robot shows  $q$  and  $\dot{q}$  are bounded. Moreover,  $\tilde{W}$  is bounded and therefore  $\hat{W}$  and  $\hat{f}$  are bounded.

Note that NN control with composite adaptive law guarantees prediction error ( $\tilde{f} = f - \hat{f}$ ) and tracking error ( $r(t)$ ) are bounded, while direct adaptive or NN control only guarantees that of the tracking error. This is because the fact that NN composite adaptation law explicitly pay attention to both tracking and prediction error.

This NN controller has no preliminary off-line learning phase. The weights can simply initiated at zero. Because of the PD controllers in (23) the closed loop system remains stable until the neural networks began to learn. The weights are tuned online in real time as the system tracks the desired trajectory. As the NN learns  $f(x)$ , the tracking performance improves.

IV. SIMULATION

In this simulation, we consider the biped robot during walking in the smooth ground. The desired trajectory produced by using Spline Toolbox in MATLAB.

The presented NN controller had implemented in biped robot. The hidden layer of neural network has 40 neuron and controller parameters selected as below

$$F = 500 \times I_{10 \times 10}, \kappa = 0.0001, K_v = 35 \times I_{6 \times 6},$$

$$\Lambda = 5 \times I_{6 \times 6}, L = 40$$

The initial condition is selected as below

$$q(0) = [74 \ 102.8 \ 90 \ 110.2 \ 85 \ 0]^T$$

$$\dot{q}(0) = [-26.77 \ -12.6 \ -12.6 \ -87.18 \ -21.22 \ 0]^T$$

Reference and output signals of NN controller are depicted in fig.6, fig.7 (for four angels) and the NN weights shown in fig.8. The tracking response is good and the weights reach bounded values. No initial NN training or learning phase was needed. The NN weights were simply initialized at zero in this simulation. To study the contribution of the NN in the controller in fig.5, we simulated the PD controller  $\tau = K_v r$ , which has no neural network inner loop. Fig.7 and fig.8 shows the result. The tracking performance is not good.

It is clear that the addition of NN makes a significant improvement in the tracking performance. Fig.11 shows biped robot, Lucy, which is graphically simulated by VRML in MATLAB.

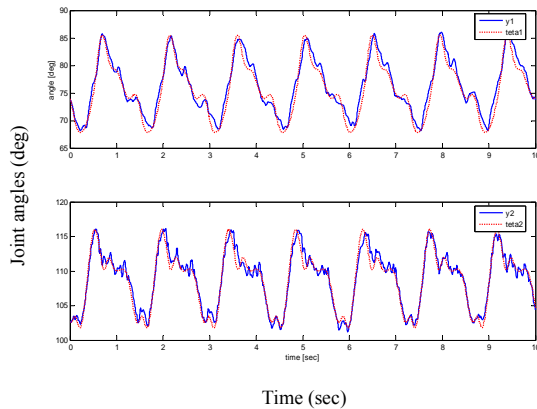


Fig. 6. Response of NN controller: actual and desired joint angles.

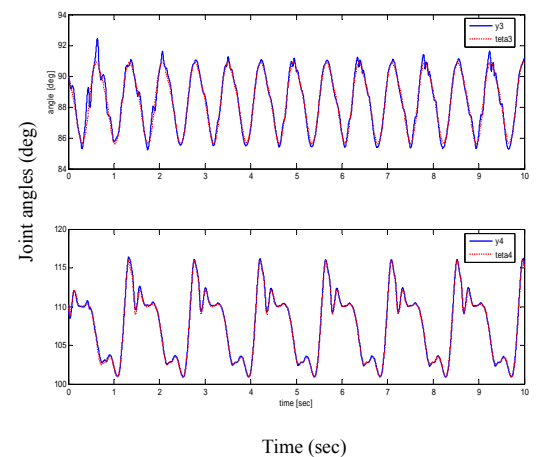


Fig. 7. Response of NN controller: actual and desired joint angles.

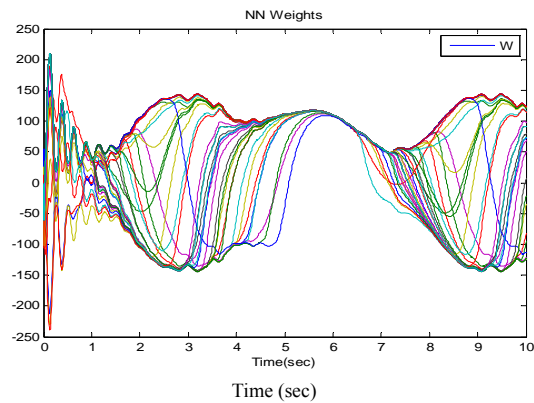


Fig. 8. NN Weight estimation W.

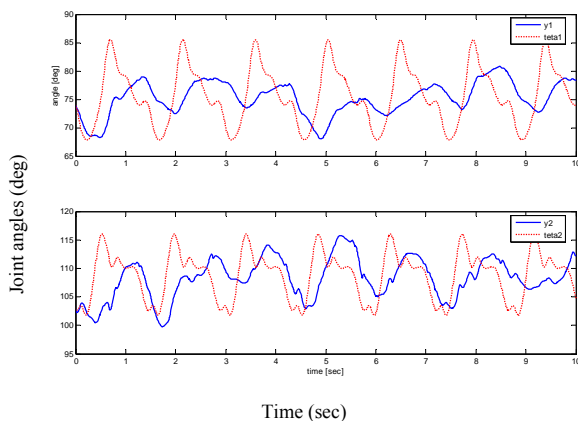


Fig. 9. Response of PD controller: actual and desired joint angles.

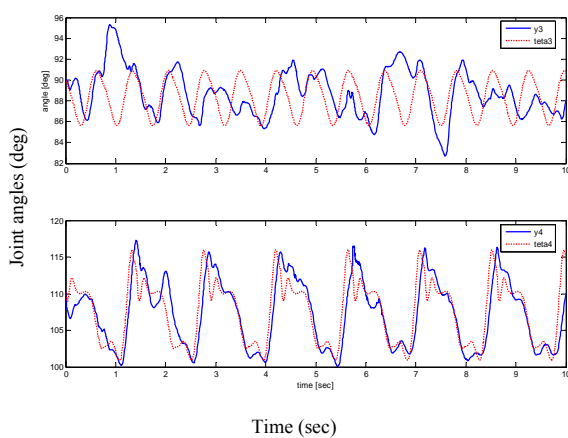


Fig. 10. Response of PD controller: actual and desired joint angles.

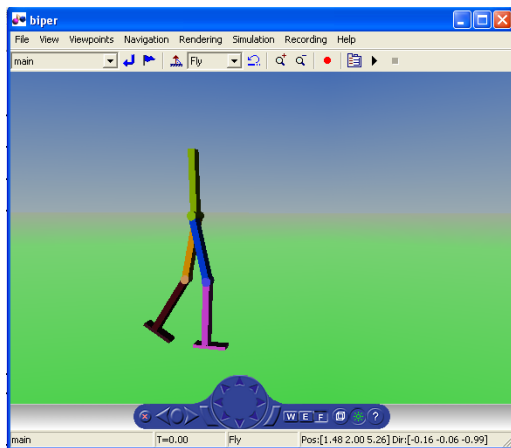


Fig. 11. Graphical simulation of biped robot by VRML

## V. CONCLUSION

In this paper, we have introduced a stable neural network controller with composite adaptive law that improved tracking performance of biped robot. The biped robot has 5\_link and 6

degrees of freedom and actuated by Plated Pneumatic Artificial Muscle. This NN controller guarantee boundedness of both tracking error and prediction error, therefore allows accurate and dynamic following of prescribed trajectories. Comparing to PD controller, the proposed controller has significantly better tracking performance. Simulation results and graphical simulation by virtual reality in MATLAB showed the validity and effectiveness of the proposed controller.

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