Implementation of Evolutionary Active Force Control in a 5-Link Biped Robot

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IN A 5-LINK BIPED ROBOT

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ABSTRACT—In this paper, the application of Active Force Control (AFC) incorporated with a conventional Proportional-Derivative (PD) controller to a five-link biped robot has been studied and simulated. The efficacy and robustness of the AFC strategy in suppressing external disturbances was examined on a model using Crude Approximation (CA) method. However, the task of tuning the PD controller parameters and the inertia matrix coefficient is tedious and time-consuming. Thus, an evolutionary strategy - Differential Evolution (DE) has been proposed in order to tune automatically the parameter gains in a systematic approach. The effectiveness of the proposed method is investigated, and it is found that the system is robust and stable even under influence of disturbances.

Key Words: Biped, Proportional-Derivative Control, Active Force Control, Crude Approximation, and Differential Evolution

1. INTRODUCTION

Active research in mobile robots has been conducted since a few decades ago. These robots have been designed with wheels, tracks or multiple legs. Of all the mobile robots, biped robots possess the potential of human-like mobility, especially when moving on rough terrain, steep stairs and obstructed environments. Since the biped robots can realize the walking gait similar to that of human beings, they could operate in the irregular or hazardous environments such as nuclear power plants and polluted areas.

Several techniques have been utilized for the bipedal walking control. Many attempts have been made on computed torque control ([1] and [2]). However, the success of its application relies heavily on the availability of an accurate model. Robust variable structure control proposed by Lum et al. [3] outperforms the computed torque scheme especially in the existence of parametric uncertainty. Chan [4] proposed a sliding mode control using an integral term. The superiority of the proposed control scheme over the computed torque scheme was strengthened with large parametric uncertainty. Chan [4] proposed a sliding mode control using an integral term. The superiority of the proposed control scheme over the computed torque scheme was strengthened with large parametric uncertainty.

Kun and Miller studied robot walking with both static and dynamic balance using a 10-axis biped with foot force sensing [5]. They designed a neural network learning system for the biped that was capable of learning the balance for side-to-side and front-to-back motion. The control scheme used pre-planned but adaptive motion sequences while Celebellar Model Articulation Controller (CMAC) neural networks were responsible for the adaptive control as well as for maintaining good foot contact. On the other hand, the Adaptive Virtual Model Controller (AVMC) proposed by Hu et al. [6] managed to respond to time varying parameters and external disturbances. With the proposed Radial Basic Function (RBF) Neural Network Adaptive Control (NNAC) method, compensation of the unpredictable external disturbance was ameliorated [7]. Both RBF and CMAC methods succeed in giving satisfactory performance, however, high computational burden in terms of time as well as memory is required.

Zhou proposed a general genetic algorithm-based fuzzy reinforcement learning (GAFRL) agent [8]. He demonstrated the incorporation of the expert knowledge and measurement-based information into the proposed GAFRL agent in order to accelerate the learning process. By making use of the global optimization capability of the GAs, the GAFRL managed to solve the local minima problem in traditional actor-critic reinforcement learning. Survey on other conventional as well as intelligent control techniques applied in bipedal walking control could be referred to works [9] and [10].
In this study, Active Force Control (AFC) strategy is proposed as an alternative control method for bipedal tracking problem. The application of a classical Proportional-Derivative (PD) controller incorporated with an AFC scheme in a 5-link biped model has been investigated and simulated. A distinctive feature of the AFC strategy is - it manages to eliminate unpredictable external disturbances using a simple control algorithm [11]. AFC strategy is impervious to parameter variations and external disturbances. The implementation of AFC does not involve excessive computing time and memory. In addition, an accurate dynamic model is not required.

The approach of AFC depends exclusively on measurement and estimation of control parameters, thus reducing the computational burden. The effectiveness of the AFC strategy relies on the estimated inertia matrix of the biped model that is required for the AFC feedforward loop. Several methods could be used to estimate the inertia matrix, vary from conventional techniques such as perfect modeling of the inertia matrix, crude approximation, etc, to intelligent mechanisms like neural network, iterative learning, etc [13]. In work [14], the application of AFC, with an iterative learning algorithm as the inertia matrix estimator, in a biped-tracking problem has been discussed. In this paper, a comparative study on the implementation of AFC with Crude Approximation (CA) as well as an evolutionary method - Differential Evolution (DE) will be presented.

The paper is structured as follows. A brief description of the biped model used in this simulation study will be discussed in Section 2. Then, the fundamentals of PD, AFC, CA, and DE will be presented in Section 3. In Section 4, the efficacy of the proposed technique is demonstrated in a series of simulation studies. The results obtained from both of the mentioned control schemes are analyzed and compared in the following section. Finally, conclusions are made, and some suggestions for further work are recommended in Section 6.

2. THE 5-LINK BIPED MODEL

In order to achieve a stable biped locomotion, it is useful and necessary to derive a mathematical dynamic model, and then simulate and evaluate the performance of the system. In this case, Lagrange's equation of motion has been used to obtain the mathematical model of the biped system.

2.1 The Kinematics Model of the Biped

Figure 1 illustrates the planar biped model employed in this study. The biped consists of five links, namely the torso (link 3) and two links in each leg (thighs, that are links 2 and 4, and shanks, that are links 1 and 5). These links are connected via four rotating joints (two hip joints and two knee joints). These rotating joints are considered to be friction free and are driven by independent DC motors.
In Figure 1, \( m_i \) is mass of link \( i \), \( l_i \) is length of link \( i \), \( d_i \) is distance between the center of mass of link \( i \) and its lower link, \( I_i \) is moment of inertia with respect to an axis passing through the mass center of link \( i \) and perpendicular to the motion plane, \( \theta_i \) is angle of link with respect to the vertical (the positive direction of \( \theta_i \), \( i = 1,2,3,4,5 \), is the one shown in Figure 1), \( O_o-x_o y_o z_o \) is the fixed coordinate frame (that is the inertia reference system), \((x_o,y_o)\) is position of the point of support, \((x_e,y_e)\) is position of the free end.

Some assumptions have been made in order to simplify the analysis: (1) the locomotion of the biped is constrained within the sagittal plane; (2) both of the left and right sides of the biped are symmetric; (3) the line contact between the tip of the support leg and the walking surface is represented by an equivalent point contact in the sagittal plane to simplify the analysis of the effect of impact but without loss of generality; (4) the base areas of the legs (links 1 and 5) are large enough to maintain its balance at vertical positions (to ensure no slippage); (5) the stability of the biped in frontal plane is ensured assuming that the biped is shifting its center of mass between two large foot areas in a "penguin walk" manner (moving side-to-side) while it is walking in the sagittal plane (as in Figure 1(b)).

From Figure 1(a), the position of the free end is given as follows,

\[
\begin{align*}
{x_e} &= x_o + l_1 \sin \theta_1 + l_2 \sin \theta_2 + l_4 \sin \theta_4 + l_5 \sin \theta_5 \\
{y_e} &= y_o + l_1 \cos \theta_1 + l_2 \cos \theta_2 - l_4 \cos \theta_4 - l_5 \cos \theta_5
\end{align*}
\]

By differentiating Equation (1) with respect to time, the linear velocity of the free end of the swing leg can be formulated. The derivation for the coordinates of the center of the mass of the biped \((cg x,cg y)\), could be obtained from works [1] and [14].

### 2.2 The Motion Equations

The gait of biped robot is achieved through the phased movements of the legs. The legs must alternate between support phase (on the ground), and swing phase (in the air) in order to propel the robot forward. Generally, the walking motion of the biped is divided into three distinct phases: single-leg support, the biped with both legs in the air, and exchange of the supporting leg.

In this study, the biped dynamic modeling is simplified by only considering the single-leg support phase. During the single-leg support phase, the biped has one leg (the support leg) in contact with the walking surface carrying all the biped's weight while the other leg (the swing leg) in the air is in the forward walking direction [4]. The biped is assumed to be walking in a flat horizontal surface, and the locomotion is constrained in the sagittal plane. This phase is illustrated in Figure 1(a).

By applying the Lagrange's equation of motion, the dynamic model of the biped in the single support phase could be expressed as follow,

\[
D(\theta)\ddot{\theta} + h(\theta, \dot{\theta}) + G(\theta) = T_\theta
\]

where \( \theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T \) is the joint angle vector, \( T_\theta = [T_{\theta_1}, T_{\theta_2}, T_{\theta_3}, T_{\theta_4}, T_{\theta_5}]^T \) is the generalized torque that corresponds to \( \theta_i \), \( D(\theta) = [D_{ij}(\theta)] \), (where \( i,j = 1,2,...,5 \)) is a symmetric, positive-definite inertia matrix, \( h(\theta, \dot{\theta}) = col\left[ \sum_{i \neq j} h_{ij}(\theta, \dot{\theta})^2 \right] \) is a column vector consisting of coriolis and centripetal torques.

It is noted that only four of the five degrees of freedom, \( \theta_1, \theta_2, \theta_3, \theta_4 \), and \( \theta_5 \), can be controlled directly by the 4 driving torques at each joints. The angle \( \theta_1 \) at the contact point with the walking surface (hypothetical joint 0) is controlled indirectly using the gravitational effects.

For the control purpose, the model in Equation (2) is transformed using the relative angle,

\[
D_q(q)\ddot{q} + h_q(q, \dot{q}) + G_q(q) = T_q
\]

where \( D_q(q) \) is the 5x5 symmetric, positive definite inertia matrix, \( h_q(q, \dot{q}) \) is the vector of centrifugal and coriolis torques, \( G_q(q) \) is the vector of gravitational torques, and \( T_q \) is the vector of applied torques at each joints, \( q = [q_0, q_1, q_2, q_3, q_4]^T \) is the vector for relative angle deflections of the corresponding joints. The relationship between the relative angles \( q_i \) and the absolute angles \( \theta_i \) are as follow,
\[ q_0 = \theta_1; \quad q_1 = \theta_1 - \theta_2; \quad q_2 = \theta_2 - \theta_3; \quad q_3 = \theta_3 + \theta_4; \quad q_4 = \theta_4 - \theta_3 \] (4)

The detailed procedure of deriving the Lagrange's equation of motion as well as the transformation of the equations of motion (3) could be found in works [1] and [9].

3. THE CONTROL

The main goals of the control techniques are to ensure that the realization of a walking process is preserved, such that the movement of the biped follows the prescribed trajectory profile, and thus the tracking error converges to zero. However, the uncertainties of the system as well as the existence of unpredictable external disturbances make the control action a challenging task. Therefore, a successful controller must be able to eliminate the uncertainties and disturbances efficiently and rapidly.

In this study, a conventional proportional-derivative controller, and an active force control scheme have been used to evaluate a biped-tracking control problem.

3.1 The Proportional-Derivative (PD) Control

For a predefined trajectory, the desired angular positions, desired joint velocities, and the desired joint accelerations of the links can be known exactly. In order to reduce the angular error of the biped, the input torques or forces have to make the actual angular accelerations of the links \( \ddot{q}(t) \), to satisfy

\[ \ddot{q}(t) = \ddot{\bar{q}}(t) + K_D(q_{\text{bar}}(t) - \dot{q}(t)) + K_P(q_{\text{bar}}(t) - q(t)) \] (5)

where \( K_D \) and \( K_P \) are 5x5 derivative and position feedback gains respectively. \( q_{\text{bar}}, \dot{q}_{\text{bar}} \), and \( \ddot{q}_{\text{bar}} \) are vector of the desired reference relative joint trajectory, desired reference velocity, and desired reference acceleration respectively, while \( q, \dot{q}, \) and \( \ddot{q} \) are their actual counterparts.

In order to obtain a critically damped closed-loop performance, the PD gains must be chosen as [1],

\[ K_D = \text{diag}[2\lambda] \quad \text{and,} \quad K_P = \text{diag}[\lambda^2] \] (6)

where \( \lambda \) is the desired bandwidth. The computed acceleration command vector provides the signal into the AFC loop (as shown in Figure 2). One of the main disadvantages of the conventional PD control is - the feedback gains are constant and pre-specified. It does not have the capability of updating the feedback gains under varying speeds, payloads and disturbances. Thus, the above control scheme using constant feedback gains to control a highly nonlinear biped system does not perform well.

3.2 Active Force Control (AFC)

The idea of Active Force Control (AFC) was first explored by Hewit and Burdess [11]. The goal of this control scheme is to ensure that a system remains stable and robust even in the presence of disturbances. It is based upon a method of measuring and estimating a number of identified parameters to affect its compensation actions, and hence reducing the computational burden.

Figure 2. The block diagram of the PD and AFC strategies applied to a biped.
In general, the motion equation of a robot system with \( n \) degrees of freedom can be described as,

\[
IN(q) \cdot \ddot{q} = Q(q, \dot{q}) + T_q
\]  

(7)

where \( IN(q) \) is an \( nxn \) inertia matrix of the robot, \( Q(q, \dot{q}) \) is an vector of coriolis, centrifugal, frictional, and other internal and disturbance torques, \( T_q \) is the vector of applied torques, and \( q \) is an vector of the relative joint coordinates. Equation (7) could be rewritten as,

\[
Q(q, \dot{q}) = -T_q + IN(q) \cdot \ddot{q}
\]  

(8)

Equation (8) shows that \( Q \) can be deduced provided that the torque vector and the acceleration vector can be measured directly, and \( IN \) is available. The applied torque \( T_q \) is generated by,

\[
T_q = V \cdot C = V \cdot (C_c + C_a)
\]  

(9)

where \( V \) is a diagonal matrix representing the transfer functions of the actuators, and \( C \) is the controller output vector, with \( C_c \) is the "control" signal that will be used to drive the system along the desired trajectory, and \( C_a \) is the "absorption" signal that will be used to compensate the unknown disturbances.

The idea of AFC is to generate the command vector \( C \) so that the robot can be controlled to perform the prescribed task even in the presence of unknown disturbance torques.

From Equation (8), the disturbance torque \( Q' \) could be estimated as,

\[
Q'(q, \dot{q}) = -T_q + IN(q) \cdot \ddot{q}
\]  

(10)

The estimated disturbance \( Q' \) is used to decouple the actual disturbance torque. In this context, the applied torque \( T_q \) could be estimated by using a force sensor, and the angular acceleration \( \ddot{q} \) could be measured by using an accelerometer. On the other hand, the inertia matrix \( IN \) could be estimated using crude approximation, iterative learning, neural network [11].

The \( Q' \) estimation is used directly to compute the absorption command vector \( C_a \) as,

\[
C_a = -Q'
\]  

(11)

Figure 2 shows the block diagram of AFC and PD controllers applied to a biped system. The PD controller calculates the reference acceleration command \( \ddot{q}_{ref} \), which when multiplied with a decoupling transfer function \( \frac{W(s)}{K_m} = \frac{IN}{K_m} \) (where \( K_m \) is the motor constant), gives the required command current vector \( I_c \). On the other hand, the AFC loop compensates the actual disturbance \( Q \) from an estimated value, which is obtained from the error between the ideal and actual force vectors, as in Equation (10).

The applied control torques \( T_q \) is given by,

\[
T_q = K_a I_c = K_m (I_c + I_a)
\]  

(12)

where \( I_c \) is the sum of the command current vector \( I_c \) and the compensating current vector \( I_a \).

The concept of AFC has been implemented successfully in robotic systems via simulation and experimental works [11,12,13,14]. However, a good estimation of \( IN \) is essential for effective implementation of AFC. In this study, comparative studies on the applications of AFC, in conjunction with a Crude Approximation method, and Differential Evolution, in a 5-link biped robot are investigated.

### 3.3 The Crude Approximation (CA) method

The inertia matrix of the links of the biped, which is required in the AFC loop, can be estimated using a crude approximation method [13],

\[
IN = K_m \times \text{diag}(D_q)
\]  

(13)

where \( K_m \) is a coefficient of the estimated inertia matrix, \( \text{diag}(D_q) \) is a vector representing the diagonal elements of matrix \( D_q \).
In order to evaluate the tracking performance, a performance index $f$ that reflects small steady-state errors, short rise-time, low oscillations, low overshoots, and good relative stability, has been chosen [15],

$$f = \exp\left(\frac{a}{N} \sum_{i=0}^{N} \left( e_i^2 + w \Delta e_i^2 \right) \cdot i \right)$$  \hspace{1cm} (14)$$

where $N$ is the number of time step for the simulation period, $a$ is a positive number used to scale the maximum performance index up or down, $i$ is the time index in the simulation, $e_i$ is the error between the desired signals and the actual signals at simulation step $i$, and $\Delta e_i$ is the change-of-error at simulation step $i$, and $w$ is a positive constant used for weighting between the error and the change-of-error. The term of $\Delta e_i$ can be distinctively weighted to suppress oscillations. The multiplication of the time index $i$ is used to ensure smaller steady-state errors, and to avoid oscillations to grow towards infinity.

This definition of fitness yields a value between 0 and 1, with higher performance index values corresponding to better controller performance.

The procedures of obtaining the optimum $K_{in}$ are given below:

1. The diagonal terms of the inertia matrix from the model $D_q$ are derived mathematically.
2. A coefficient $K_{in}$ is embedded into the simulation program. This factor will be multiplied with $D_q$, and subsequently fed into the AFC loop.
3. Initially, $K_{in}$ is set as 0.1, and the simulation program (will be discussed in Section 4) is executed. The resulting performance index is recorded.
4. Procedure 3 is repeated using various $K_{in}$ values, in which $K_{in} = 0.1, 0.2, ..., 0.8$ with a step of 0.1.
5. Finally, a graph of performance index vs. $K_{in}$ representing the performance curve is plotted. Based on the performance curve obtained, the optimum $K_{in}$ value can be determined. The optimum $K_{in}$ value refers to the corresponding maximum performance index.

The implementation of this method is straightforward. Thus, it could be easily accomplished in real time applications. Nevertheless, the scheme needs trial-and-error and tedious efforts to determine the optimum $K_{in}$ (and hence $IN$). Furthermore, the coefficient factor is constant and pre-determined. It is not updated adaptively based on the errors. Thus, better ways of obtaining the estimated $IN$ are sought.

### 3.4 The Differential Evolution (DE) method

Differential Evolution (DE) developed by Storn and Price has been proven to be a simple yet powerful population-based, direct-search algorithm for globally optimizing real-valued multi-modal objective function [16]. It was the best genetic type of algorithm for solving the real-valued test function suite in the First International Contest on Evolutionary Computation that was held in Nagoya, in 1996. DE introduces a novel, self-referential mutation scheme that is able to produce good convergence properties.

There are several variants of DE schemes. In this study, the DE/rand/1/bin scheme is utilized. The notation of DE/rand/1/bin specifies that a DE algorithm with the perturbed vector is selected randomly, mutated and recombined using a binomial distribution, and the perturbation consists of one weighted difference vector. The following section describes the procedures for the DE/rand/1/bin scheme,

#### 3.4.1 Input

DE settings, i.e. number of parameters in an object vector $D$; number of object vectors in a population $NP$; number of populations $G_{max}$; scaling factor $F \in [0,1]$ that controls the amplification of the differential variation; crossover constant $CR \in [0,1]$; upper and lower parameter bounds $x^{lo}$ and $x^{hi}$, are identified.

#### 3.4.2 Initialization

DE creates a randomly distributed initial population $P_{G=0}$ of a NP $D$-dimensional object variable vectors $x_{j,i,G}$ for the potential solutions, as follow,

$$P_G = \{\bar{x}_{1,G}, \bar{x}_{2,G}, ..., \bar{x}_{NP,G}\}$$

$$\bar{x}_{j,i,G} = x_{j,i,G}$$

Where $1 \leq j \leq D$, $1 \leq i \leq NP$, and $G = 0$. The initialization is repeated sequentially from $G = 1$ to $G = G_{max}$.
where \( i = 1, 2, \ldots, N P, \ j = 1, 2, \ldots, D, \) and \( \text{rand} \{0,1\} \) represents a uniformly distributed random variable that ranges from zero to one. The subscript \( j \) indicates that a new random value is generated for each value of \( j \) that is, for each object variable.

### 3.4.3 Mutation and Recombination

After initialization, the population is subjected to repeated generations \( G = 1, 2, \ldots, G_{\text{max}} \) of mutation, recombination, and selection. For \( \text{DE/rand/1/bin} \), the perturbed vector \( v_{j,i,G+1} \) is created as follow,

\[
v_{j,i,G+1} = x_{j,i,G} + F (x_{j,i,G} - x_{j,r_2,G})
\]

with \( r_1, r_2, r_3 \in [0, NP] \), and randomly selected, except \( r_1 \neq r_2 \neq r_3 \neq i \), and \( F \) is a scaling factor with \( F \in [0,1] \) that controls the amplification of the differential variation \( (x_{j,r_1,G} - x_{j,r_2,G}) \).

The concept of crossover is introduced to increase the potential diversity of the perturbed vectors. A user-defined crossover constant \( CR \) is used to mediate the optimization process. The binomial scheme takes parameters from \( v_{j,i,G+1} \) every time that \( \text{rand} \{0,1\} < CR \); otherwise, the parameter comes from \( x_{j,i,G} \).

### 3.4.4 Selection

If the new vector \( v_{j,i,G+1} \) yields a better objective value than that of \( x_{j,i,G} \), it will become a population member of the next generation or \( x_{j,i,G+1} \), otherwise, the old value \( x_{j,i,G} \) is retained. The similar performance index as given in Equation (14) has been used as the fitness function.

Therefore, with the membership of the next generation selected, the evolutionary cycle in \( \text{DE} \) repeats until a stopping criterion is achieved. In this study, the \( \text{DE} \) algorithm has been used together with AFC, which is known as Evolutionary Active Force Control (EAFC), to tune the controller parameters \( (K_P \) and \( K_D) \) as well as the inertia matrix coefficient \( (K_m) \) automatically.

### 4. SIMULATION

The simulation work is performed using the MATLAB and SIMULINK software packages.

### 4.1 The Simulation Parameters

The robot parameters are obtained from work [1], thus they are eliminated here. The PD gains are obtained from Equation (6) using \( \lambda = 30 \text{rad} / \text{s} \). The motor torque constant \( K_m \) is obtained from the actual data sheet for the DC torque motor [13]. The parameters utilized in the simulations are given as follow,

- **For PD Controller**,
  - Controller gains: \( K_p = 900 / \text{s}^2 \), \( K_d = 60 / \text{s} \)

- **For AFCCA scheme**,
  - Motor torque constant, \( K_m = 0.263 \text{Nm} / \text{A} \)
  - AFC constant \( K_v = 1.0 \) (indicates 100% AFC or full AFC)
  - Optimum inertia matrix factor \( K_m = 5.2 \) (for the step input); \( K_m = 8.0 \) (for the spline trajectory)

- **For EAFC scheme**,
  - Number of parameters \( D = 3 \)
  - Number of object vectors \( NP = 30 \)
  - Upper initial parameter bound \( x^{(hi)} = [1000 \ 400 \ 8] \)
  - Lower initial parameter bound \( x^{(lo)} = [250 \ 30 \ 0.5] \)
  - Number of populations \( G_{\text{max}} = 100 \)
  - Scaling factor for the differential variation \( F = 0.8 \)
  - Crossover constant \( CR = 0.8 \)
4.2 Prescribed Trajectory

In this study, two different reference input have been considered. First, a standard test input, i.e. a step input, is used. Then, a steady walking trajectory for the biped on a horizontal plane surface has been considered. For the latter case, the biped is required to follow a prescribed joint profile generated using a periodic cubic spline function.

4.2.1 Step response evaluation

In order to examine the stability of the biped system, a step input has been used as the reference input. For convenience in comparing transient responses of the system, the system is assumed at rest initially with output, and all time derivatives thereof zero. In this case, the reference relative joint angles, $q_i$, have been set such a way that $q_{bar1} = 0.015\text{rad}$, $q_{bar2} = 0.270\text{rad}$, $q_{bar3} = 0.360\text{rad}$, and $q_{bar4} = 0.210\text{rad}$.

4.2.2 Steady walking on a horizontal plane

The human walking motion is a periodic function, therefore a periodic cubic spline function, which can guarantee the smoothness of velocity and acceleration of the biped [17], has been used to generate the reference trajectory of joint variables as follows,

$$q_i = \text{spline}(y_j, t) \quad \text{where} \quad j = 1, \cdots, n$$

where $\text{spline}(y_j, t)$ denotes the periodic cubic spline function, that expresses joint $i$, $n$ is the number of spline-interpolated points, and $y_j$ is spline-interpolated points. $y_j$ are selected based on the constraint parameters considered during the trajectory planning, i.e. step length $L$, highest position of swing leg $H$, etc, as illustrated in Figure 3(a).

A periodic condition has been chosen as the boundary condition, in which velocity $\dot{q}_i(t_s) = \dot{q}_i(t_s)$, and acceleration $\ddot{q}(t_s) = \ddot{q}(t_s)$, with $(t_s - t_s)$ representing the walking period. In this study, each steady walking step requires $t_s = 0.5014s$, and the biped needs $0.2507s \left(\frac{1}{2}t_s\right)$ to move from its initial position (all links are in vertical position) to the steady walking phase. Figure 3(b) shows the generated trajectory.

4.3 Disturbances

In order to further examine the effectiveness and robustness of the proposed control schemes, a number of typical external disturbance modes encountered are introduced in the simulation studies (only apply to the case of steady walking trajectory). The disturbances considered are,

- constant torque at the joints, $Q_c = 100N$
- harmonic torque at the joints, $Q_h = 100\sin(10t)N$
- pulsating torque, $Q_p = 50N$, 10% duty cycle of period of 0.5s

![Figure 3. (a) The walking parameters, (b) The generated steady walking trajectory.](image-url)
5. RESULTS AND DISCUSSIONS

The results and discussions are divided into two parts. In the first part, the step response of the biped is analyzed. Consequently, the results obtained for the steady-walking trajectory is presented.

5.1 Step response evaluation

For the AFCCA control scheme, the optimum value of $K_m = 5.2$ has been determined from the performance curve [9]. The simulation program has been repeated by using this optimum value.

Figures 4 shows the graphical results obtained from the simulation by using the AFCCA control scheme for the case of no external disturbance. Figure 4(a) illustrates the actual joint angles of the biped. It is noticed that the biped, using AFCCA strategy, succeeds in giving satisfactory tracking performance, and provides a tracking resembling the desired one, i.e., for joint 1, the biped takes 0.11s to remain within 10% of its desired reference value. The corresponding tracking error generated is shown in Figure 4(b). It manages to keep the error margin to be below 0.01 rad (for all of the 4 axes) after 0.18s.

On the other hand, the optimum values of the parameter gains as determined from the EAFC scheme are such that $K_P = 1000.00 / s^2$, $K_D = 37.91 / s$, and $K_m = 8.00$ [9]. The simulation program is repeated by using these values. The graphical results obtained are shown in Figure 5. The actual joint angle of all of the links of the biped exhibit overshoot problems. However, the biped has a fast response, and manages to give an excellent tracking performance after a short time - 0.20s. From Figure 5(b), the generated tracking error appears to be similar as that of the AFCCA scheme. After 0.22s, the tracking errors generated by the biped (of all axes) do not exceed 0.005 rad.

The performance of the proposed AFC schemes has been compared from the aspect of maximum percent overshoot, rise time, settling time, average tracking error, and the performance index (or fitness value). The maximum percent overshoot is the percentage of the difference between the maximum peak value of the response curve and its final value with respect to its final value. Rise time refers to the time required for the response to rise from 10% to 90% of its final value. Settling time is the time required for the response to reach, and stay at less than 5% of the final value. While, the average tracking error (ATE) is defined as the average tracking error generated by all joints of the biped throughout the simulation.

![Figure 4. (a) Actual Joint Trajectory, (b) Tracking Error, using AFCCA (step input).](image1)

![Figure 5. (a) Actual Joint Trajectory, (b) Tracking Error, using EAFC (step input).](image2)
The results are summarized in Table I. It is noted that the EAFC scheme outperforms AFCCA in most of the performance criterions. EAFC yields a lower ATE value of 0.0491 rad compared to 0.0611 rad for the AFCCA counterpart. The higher performance index given by the EAFC scheme indicates that the biped could satisfy the predefined fitness function better than that of the AFCCA.

Table I. Results summary obtained from the AFC schemes for step input.

<table>
<thead>
<tr>
<th>Percentage Overshoot (%) of each link</th>
<th>Rise Time (s) of each link</th>
<th>Settling Time (s) of each link</th>
<th>Average Tracking Error (rad) of all links</th>
<th>Fitness value of all links</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFCCA</td>
<td>0.0202</td>
<td>0.11</td>
<td>0.15</td>
<td>0.0611</td>
</tr>
<tr>
<td></td>
<td>0.0058</td>
<td>0.11</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0207</td>
<td>0.11</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0357</td>
<td>0.12</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>EAFC</td>
<td>12.7407</td>
<td>0.05</td>
<td>0.15</td>
<td>0.0491</td>
</tr>
<tr>
<td></td>
<td>10.3650</td>
<td>0.06</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10.9804</td>
<td>0.05</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9.9704</td>
<td>0.08</td>
<td>0.20</td>
<td></td>
</tr>
</tbody>
</table>

5.2 Steady walking on a horizontal plane

The overall performance of both the AFCCA and EAFC schemes applied to the biped is compared by considering the ATE values and the performance index. In this case, various external disturbances as described in Section 4.3 have been applied on the biped. The results are summarized as in Table II. Generally, both of the AFCCA and EAFC control schemes demonstrate a high degree of accuracy and robustness even under the influence of various disturbances. The performance of the EAFC scheme is more superior to that of the AFCCA scheme in all cases.

Under the AFCCA control, the minimum ATE value is 0.0127 rad for the case of without disturbance, and maximum ATE is recorded as 0.0254 rad when the harmonic disturbance is acting on the biped. On the other hand, the ATE generated by the EAFC scheme ranges from 0.0086 rad to 0.0099 rad in all cases. For both of the AFC schemes, the highest ATE values have been recorded for the case of harmonic disturbance. This implies that the schemes are most influenced by harmonic disturbance.

The biped succeeds to follow the prescribed trajectory (with small tracking errors), and provides excellent trajectory tracking performance. The tracking performance of both of the control schemes is compared from the aspect of mean tracking error. The mean tracking error (MTE) is defined as the mean tracking error generated by four of the joints of the biped at each simulation instant. The MTE curves generated by the biped with the AFC schemes, for the cases of without disturbance and in the existence of harmonic disturbance, are illustrated in Figure 6. It is noticed that the error margin of the EAFC control schemes is significantly smaller than that of the AFCCA control model. From Figure 6(b), it is shown evidently that the performance of the biped under AFCCA control scheme degrades considerably in the presence of the harmonic disturbance. However, for the AFCCA scheme, the error margin is kept below 0.008 rad after 0.17 s, which is comparable to the case of without disturbance (0.005 rad).

Table II. Results summary obtained from the AFC schemes for steady walking trajectory.

<table>
<thead>
<tr>
<th>Schemes</th>
<th>Disturbances</th>
<th>$K_p$ (s)</th>
<th>$K_q$ (s^2)</th>
<th>$K_m$</th>
<th>ATE (rad)</th>
<th>Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFCCA</td>
<td>No disturbance Q_o</td>
<td>900</td>
<td>60</td>
<td>8.0</td>
<td>0.0127</td>
<td>0.9896</td>
</tr>
<tr>
<td></td>
<td>Constant torque Q_c</td>
<td>900</td>
<td>60</td>
<td>8.0</td>
<td>0.0127</td>
<td>0.9896</td>
</tr>
<tr>
<td></td>
<td>Harmonic torque Q_h</td>
<td>900</td>
<td>60</td>
<td>8.0</td>
<td>0.0254</td>
<td>0.9531</td>
</tr>
<tr>
<td></td>
<td>Pulsating torque Q_p</td>
<td>900</td>
<td>60</td>
<td>8.0</td>
<td>0.0141</td>
<td>0.9874</td>
</tr>
<tr>
<td>EAFC</td>
<td>No disturbance Q_o</td>
<td>999.9968</td>
<td>319.0535</td>
<td>6.1120</td>
<td>0.0087</td>
<td>0.9960</td>
</tr>
<tr>
<td></td>
<td>Constant torque Q_c</td>
<td>999.9465</td>
<td>331.0203</td>
<td>5.4174</td>
<td>0.0086</td>
<td>0.9960</td>
</tr>
<tr>
<td></td>
<td>Harmonic torque Q_h</td>
<td>999.7722</td>
<td>395.1400</td>
<td>7.9839</td>
<td>0.0099</td>
<td>0.9944</td>
</tr>
<tr>
<td></td>
<td>Pulsating torque Q_p</td>
<td>999.8762</td>
<td>334.8606</td>
<td>6.9561</td>
<td>0.0087</td>
<td>0.9960</td>
</tr>
</tbody>
</table>
6. CONCLUSIONS

The AFC methods demonstrate high accuracy and robustness in the biped-tracking problem, even in the presence of various disturbances. It is concluded that the proposed AFC schemes succeed in compensating the nonlinear terms and external disturbances that act on the biped system.

The AFCCA scheme succeeds in giving excellent trajectory tracking performance using a simple algorithm. However, the tracking performance could be further improved by using the proposed evolutionary method – the EAFC scheme. The simulation results reveal that EAFC outperforms AFCCA in all cases. With the EAFC scheme, the tuning of the optimum controller parameters becomes easier and automatic based on the tracking errors generated.

The effectiveness of the proposed control scheme should be further investigated by considering various disturbances model, different prescribed reference input, and various ground conditions. In addition, an experimental biped model should be developed to validate the effectiveness and feasibility of the proposed control schemes. This will be the focus of our future study.

REFERENCES


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