Research Article

Humanoid Lower Limb: Design, Analysis, Observer-Based Fuzzy Adaptive Control and Experiment

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With flexibility similar to human muscles, pneumatic artificial muscles (PAMs) are widely used in bionic robots. They have a high power-mass ratio and are only affected by single-acting pneumatic pressure. Some robots are actuated by a pair of PAMs in the form of antagonistic muscles or joints through a parallel mechanism. The pneumatic pressure and length of PAMs should be measured simultaneously for feedback using a pressure transducer and draw-wire displacement sensor. The PAM designed by the FESTO (10 mm diameter) is too small to install a draw-wire displacement sensor coaxially and cannot measure muscle length change directly. To solve this problem, an angular transducer is adopted to measure joint angles as a whole. Then, the inertia of the lower limb is identified, and observer-based fuzzy adaptive control is introduced to combine with integrated control of the angular transducer. The parameters of the fuzzy control are optimized by the Gaussian basis neural network function, and an observer is developed to estimate the unmeasured angular accelerations. Finally, two experiments are conducted to confirm the effectiveness of the method. It is demonstrated that piriformis and musculus obturator internus act as agonistic muscle and antagonistic muscles alternatively, and iliopsoas is mainly responsible for strengthening because of the constant output force. Piriformis has a greater influence on yaw and roll angles, while musculus obturator internus is the one that influences the pitch angle the most. Due to joint friction, the dead zone of the high-speed on-off valve, lag of compressed air in the trachea, and coupling among angles are very difficult to realize precise trajectory tracking of the pitch, yaw, and roll angles simultaneously.

1. Introduction

Humanoid robot joint actuated by electric motor plays an important role in the robot industry. Researches have been done and most of them are focused on the control algorithm, such as fuzzy model-based nonlinear networked control, [1] adaptive back stepping control, [2] adaptive sliding-mode control [3], and adaptive fuzzy sliding mode controller with a nonlinear observer [4]. Hydraulic with the advantage of high torque at low speed has been applied in the humanoid robot joint design [5, 6].

The human body has an extremely complex muscular skeleton. Pneumatic artificial muscles (PAMs) of which are high power-to-weight, adapt to complex environments, and endowed with similar properties to human muscles [7, 8].

During the past several years, humanoid robot joints designed with PAMs have been used to investigate the contribution of muscles. Adaptive back stepping fast terminal sliding mode control is applied in a 2-link robot actuated by PAMs [9]. The relationship between electric motor and PAMs is investigated when two of them are employed in parallel at the joint simultaneously [10]. Advanced nonlinear PID is implemented in the humanoid robotic leg for compliance and posture control [11]. Research on this topic is restricted to antagonist muscles, which is not consistent with the actual distribution of human muscle.

The musculoskeletal humanoid body structure consists of complicated bones and redundant flexible muscles; however, the design has a basic mechanical structure without

mentioning how to simplify and control the system [12]. It is similar to the case with a musculoskeletal lower-limb robot driven by multifilament muscles [13]. An anthropomorphic musculoskeletal upper limb with a strain gauge as a feedback transducer cannot be controlled precisely [14]. Nevertheless, it cannot be simplified as a parallel mechanism, for which further steps need to be taken to investigate pneumatic servo nonlinear feedback control and the muscle properties of different postures.

Parallel mechanisms driven PAMs are controlled by adaptive robust controller [15], adaptive fuzzy cerebellar model articulation controller [16], and fuzzy torque control [17]. However, existing studies are limited to control a single PAM using draw-wire displacement sensors and pressure transducers.

Therefore, a spatial humanoid lower limb with simplified irregular distribution driven by PAMs was proposed. PAMs are too small to install draw-wire displacement sensors coaxially, and they cannot measure muscle length change directly. Piriformis, musculus obturator internus, and iliopsoas are taken as a muscle group, and we adopt angular transducer to measure joint angles as a whole, then observer-based fuzzy adaptive (OBFA) control is introduced, instead of controlling every single actuator. Muscles of the human lower limb are simplified according to function and position; the musculoskeletal humanoid lower limb is designed based on the result in Section 2. Section 3 presents inertia identification with the Newton–Euler and structure matrix. Section 4 illustrates an adaptive observer designed to estimate the unmeasured variables and optimization parameters with Gaussian basis neural network function. In Section 5, the experimental verification of the proposed algorithm is presented.

2. Nonlinear System

The human lower limb muscle consists of the pelvic girdle, thigh muscle, and calf muscle. The pelvic girdle includes the iliopsoas, tensor fasciae latae, gluteus maximus, gluteus medius, piriformis, obturator internus, quadratus femoris, gluteus minimus, and obturator externus. Thigh muscles include the rectus femoris, vastus intermedius, vastus lateralis, vastus medialis, pectineus, adductor longus, gracilis, breviductor, adductor magnus, semitendinosus, semimembranosus, biceps femoris, and biceps flexor cruris. The calf muscle consists of the extensor longus pollicis, extensor longus digitorum, musculus tibialis anterior, soleus, gastrocnemius, musculus tibialis posterior, musculus flexor digitorum longus, musculus flexor pollicis longus, popliteus, peroneus longus, peroneus brevis, and hamstring. By combining the position and function of muscles with its structure matrix eigenvalue of the joints, we can simplify the hip joint actuated by piriformis, obturator internus, and iliopsoas and the knee joint actuated by rectus femoris, gracilis, biceps flexor cruris, and hamstring, [18] as shown in Figure 1.

Based on the analysis of a human musculoskeletal, we design a humanoid lower limb with PAMs, Figures 2(a) and 2(b), to substitute human muscle. Fixing the pelvis to

the frame, we divide the femur into two parts: the first part of the femur is connected to the pelvis by a spherical hinge, and the second part is connected to the first part by the hip platform in the upside and to the knee platform using a spherical hinge in the downside. Musculi obturator internus and piriformis are distributed in the front and rear of the femur, respectively, and iliopsoas has the outward of the pelvis in the upside and front of the hip platform in the downside. The rectus femoris, gracilis, hamstring, and biceps flexor cruris evenly lay between the pelvis and knee platform in the front and rear separately. PAMs are connected to the pelvis, hip platform, and knee platform by a thread, and an angular transducer is mounted on the hip platform to measure the hip joint angle in real-time.

Mechanism schematics of the hip joint can be seen in Figure 2(c) [19]. Fixing points in the pelvis are A_1 , A_2 , and A_3 . The center of the bearing sphere that connects the thigh bone and pelvic is A_0 , and the reference coordinate systems in the pelvic and body-fixed coordinate system in the bearing sphere are $A_X A_Y A_Z$, and $A_X' A_Y' A_Z'$, respectively, with the forward, inward, and upward defined as positive. Pitch, yaw, and roll angle in the hip joint are α_1 , β_1 , and γ_1 . The center of the hip platform is B_0 , and the reference coordinate system in B_0 is $B_X B_Y B_Z$, with the fixed points in the hip platform being B_1 and B_2 .

For the hip joint, the input and output are the muscle length and joint angle changes. With time derivation taken into consideration, the following relationship can be obtained as follows:

$$\Delta l_h = J_h \Delta \theta_h = \begin{pmatrix} J_{11} & J_{12} & J_{13} \\ J_{21} & J_{22} & J_{23} \\ J_{31} & J_{32} & J_{33} \end{pmatrix} \begin{pmatrix} \Delta \alpha_1 \\ \Delta \beta_1 \\ \Delta \gamma_1 \end{pmatrix}, \quad (1)$$

where Δl_h and $\Delta \theta_h$ are the muscle length and joint angle change, respectively. Term J_h is used to depict the relationship between input and output and is called the structure matrix.

3. Inertia Identification

Human bones are complex in shape, and the muscles are irregularly distributed; hence, we combine the Newton–Euler with structure matrix. Two different methods are used (with similar results) to analyze the hip joint torque; the detailed experimental procedure is given in Section 5. The moment equation is given as

$$I_B \dot{\omega}_h + \omega_h \times (I_B \omega_h) = J_h^T f_h, \quad (2)$$

where $I_B = \begin{bmatrix} I_{11} & I_{12} & I_{13} \\ I_{21} & I_{22} & I_{23} \\ I_{31} & I_{32} & I_{33} \end{bmatrix}$ is inertia matrix of the humanoid

lower limb, $\omega_h = \begin{bmatrix} \dot{\alpha}_1 \\ \dot{\beta}_1 \\ \dot{\gamma}_1 \end{bmatrix}$, and $\dot{\omega}_h = \begin{bmatrix} \ddot{\alpha}_1 \\ \ddot{\beta}_1 \\ \ddot{\gamma}_1 \end{bmatrix}$ are the angular velocities and angular accelerations, respectively.

Equation (2) can be expressed in matrix form as

FIGURE 1: Simplified skeletal and muscle of the human thigh.

FIGURE 2: Prototype of the humanoid lower limb. (a) Photograph of the humanoid lower limb. (b) Thigh diagram. (c) Schematic diagram of the hip joint.

$$\begin{bmatrix} I_{11} & I_{12} & I_{13} \\ I_{21} & I_{22} & I_{23} \\ I_{31} & I_{32} & I_{33} \end{bmatrix} \begin{bmatrix} \ddot{\alpha}_1 \\ \ddot{\beta}_1 \\ \ddot{\gamma}_1 \end{bmatrix} + \begin{bmatrix} \dot{\alpha}_1 \\ \dot{\beta}_1 \\ \dot{\gamma}_1 \end{bmatrix} \times \left(\begin{bmatrix} I_{11} & I_{12} & I_{13} \\ I_{21} & I_{22} & I_{23} \\ I_{31} & I_{32} & I_{33} \end{bmatrix} \begin{bmatrix} \dot{\alpha}_1 \\ \dot{\beta}_1 \\ \dot{\gamma}_1 \end{bmatrix} \right) = J_h^T f_h. \quad (3)$$

Following mathematical computation, the equation is reduced as

$$\begin{bmatrix} I_{11}\ddot{\alpha}_1 + I_{12}\ddot{\beta}_1 + I_{13}\ddot{\gamma}_1 \\ I_{21}\ddot{\alpha}_1 + I_{22}\ddot{\beta}_1 + I_{23}\ddot{\gamma}_1 \\ I_{31}\ddot{\alpha}_1 + I_{32}\ddot{\beta}_1 + I_{33}\ddot{\gamma}_1 \end{bmatrix} + \begin{bmatrix} I_{31}\dot{\alpha}_1\dot{\beta}_1 + I_{32}\dot{\beta}_1^2 + I_{33}\dot{\beta}_1\dot{\gamma}_1 - I_{21}\dot{\alpha}_1\dot{\gamma}_1 - I_{22}\dot{\beta}_1\dot{\gamma}_1 - I_{23}\dot{\gamma}_1^2 \\ I_{11}\dot{\alpha}_1\dot{\gamma}_1 + I_{12}\dot{\beta}_1\dot{\gamma}_1 + I_{13}\dot{\gamma}_1^2 - I_{31}\dot{\alpha}_1^2 - I_{32}\dot{\alpha}_1\dot{\beta}_1 - I_{33}\dot{\alpha}_1\dot{\gamma}_1 \\ I_{21}\dot{\alpha}_1^2 + I_{22}\dot{\alpha}_1\dot{\beta}_1 + I_{23}\dot{\alpha}_1\dot{\gamma}_1 - I_{11}\dot{\alpha}_1\dot{\beta}_1 - I_{12}\dot{\beta}_1^2 - I_{13}\dot{\beta}_1\dot{\gamma}_1 \end{bmatrix} = J_h^T f_h. \quad (4)$$

By extracting the unknown inertia variables to form a matrix, equation (4) can be simplified as a linear algebra equation in the form $Ax = b$ as follows:

$$\begin{bmatrix} \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1\dot{\gamma}_1 & -\dot{\beta}_1\dot{\gamma}_1 & -\dot{\gamma}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\beta}_1^2 & \dot{\beta}_1\dot{\gamma}_1 \\ \dot{\gamma}_1 & \dot{\beta}_1\dot{\gamma}_1 & \dot{\gamma}_1^2 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1^2 & -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\alpha}_1\dot{\gamma}_1 \\ -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\beta}_1^2 & -\dot{\beta}_1\dot{\gamma}_1 & \dot{\alpha}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\alpha}_1\dot{\gamma}_1 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 \end{bmatrix} \begin{bmatrix} I_{11} \\ I_{12} \\ I_{13} \\ I_{21} \\ I_{22} \\ I_{23} \\ I_{31} \\ I_{32} \\ I_{33} \end{bmatrix} = J_h^T f_h, \quad (5)$$

where $A = \begin{bmatrix} \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1\dot{\gamma}_1 & -\dot{\beta}_1\dot{\gamma}_1 & -\dot{\gamma}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\beta}_1^2 & \dot{\beta}_1\dot{\gamma}_1 \\ \dot{\gamma}_1 & \dot{\beta}_1\dot{\gamma}_1 & \dot{\gamma}_1^2 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1^2 & -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\alpha}_1\dot{\gamma}_1 \\ -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\beta}_1^2 & -\dot{\beta}_1\dot{\gamma}_1 & \dot{\alpha}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\alpha}_1\dot{\gamma}_1 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 \end{bmatrix}$ is coefficient, $x = [I_{11} \ I_{12} \ I_{13} \ I_{21} \ I_{22} \ I_{23} \ I_{31} \ I_{32} \ I_{33}]^T$ is the unknown inertia variables, and $b = J_h^T f_h$ is the moment of the limb with structure matrix method.

The solution of linear algebra equation $Ax = b$ is written as

$$x = A^{-1}b. \quad (6)$$

Hence,

$$\begin{bmatrix} I_{11} \\ I_{12} \\ I_{13} \\ I_{21} \\ I_{22} \\ I_{23} \\ I_{31} \\ I_{32} \\ I_{33} \end{bmatrix} = \begin{bmatrix} \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1\dot{\gamma}_1 & -\dot{\beta}_1\dot{\gamma}_1 & -\dot{\gamma}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\beta}_1^2 & \dot{\beta}_1\dot{\gamma}_1 \\ \dot{\gamma}_1 & \dot{\beta}_1\dot{\gamma}_1 & \dot{\gamma}_1^2 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 & -\dot{\alpha}_1^2 & -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\alpha}_1\dot{\gamma}_1 \\ -\dot{\alpha}_1\dot{\beta}_1 & -\dot{\beta}_1^2 & -\dot{\beta}_1\dot{\gamma}_1 & \dot{\alpha}_1^2 & \dot{\alpha}_1\dot{\beta}_1 & \dot{\alpha}_1\dot{\gamma}_1 & \ddot{\alpha}_1 & \ddot{\beta}_1 & \ddot{\gamma}_1 \end{bmatrix}^{-1} (J_h^T f_h). \quad (7)$$

4. State Equation and Control Algorithm

4.1. State Equation. PAMs are modeled as single rigid blocks, based on the Jacobian matrix and virtual work principles. [20] Kinetics of the limb can be expressed as

$$\tau_h = -J_b^{-T} \left[F_B + \sum_{i=1}^3 {}^i J_{hi}^T F_{hi} \right], \quad (8)$$

where τ_h is the torque in the hip joint, J_b and ${}^i J_{hi}$ are structure and coefficient matrices in which the PAMs displacements and linear velocities, respectively, are transferred to the generalized coordinates, and F_{hi} is the external coupling force between the PAMs.

Nonlinear SISO system of the joint is expressed as

$$\begin{cases} \dot{x} = f_m(x) + g_{mn}(x)u_i + d_i, \\ y = x, \end{cases} \quad (9)$$

where $x = (x_1 \ x_2)^T$, $x_1 = (\alpha_1 \ \beta_1 \ \gamma_1)$ is the angle, and $x_2 = (\dot{\alpha}_1 \ \dot{\beta}_1 \ \dot{\gamma}_1)$ is the angular velocities, angle and angular velocities are the input $f_m(x) = -M_h^{-1}(q)C_h(\dot{q}, q) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix}$, and $g_{mn}(x) = -M_h^{-1}(q) = \begin{bmatrix} g_{11}(x) & g_{12}(x) & g_{13}(x) \\ g_{21}(x) & g_{22}(x) & g_{23}(x) \\ g_{31}(x) & g_{32}(x) & g_{33}(x) \end{bmatrix}$ are nonlinear functions, while $M_h(q_1) = J_b^{-T} I_B$ is inertia matrix and $C_h(\dot{q}, q) = J_b^{-T} [\omega_h \times (I_B \omega_h)]$ are the centrifugal force and Coriolis force acting on the dynamic model. Moreover, $u_i = [u_1 \ u_2 \ u_3]^T$ is the control law while $d_i = M_h^{-1}(q)\tau_d$ is deemed as the external interference.

4.2. Fuzzy Adaptive Control. If $f_m(x)$ and $g_{mn}(x)$ are known and $d_h = [d_1 \ d_2 \ d_3]^T = 0$, the control law of hip joint can be written as

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} g_{11}(x) & g_{12}(x) & g_{13}(x) \\ g_{21}(x) & g_{22}(x) & g_{23}(x) \\ g_{31}(x) & g_{32}(x) & g_{33}(x) \end{bmatrix}^{-1} \left(\begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix} - \begin{bmatrix} \ddot{\alpha}_1 \\ \ddot{\beta}_1 \\ \ddot{\gamma}_1 \end{bmatrix} \right). \quad (10)$$

With the appropriate $K_c = [k_0 \ k_1 \ k_2]^T$, polynomial $k_2\ddot{e} + k_1\dot{e} + k_0e$ has all its roots in the left half plane, and the control law can be defined as

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} g_{11}(x) & g_{12}(x) & g_{13}(x) \\ g_{21}(x) & g_{22}(x) & g_{23}(x) \\ g_{31}(x) & g_{32}(x) & g_{33}(x) \end{bmatrix}^{-1} \cdot \left(-\begin{bmatrix} f_1(x) \\ f_2(x) \\ f_3(x) \end{bmatrix} + \begin{bmatrix} \ddot{\alpha}_1 \\ \ddot{\beta}_1 \\ \ddot{\gamma}_1 \end{bmatrix} + \begin{bmatrix} k_0 \\ k_1 \\ k_2 \end{bmatrix} [e \ \dot{e} \ \ddot{e}]^T \right), \quad (11)$$

where e , $\dot{e}$, and $\ddot{e}$ are the angle errors, angular velocity errors and angular acceleration errors. k_0 , k_1 , and k_2 are the coefficients.

Then, equation (11) can be derived from $k_2\ddot{e} + k_1\dot{e} + k_0e = 0$, which shows its inability to be realized.

Through the use of produce inference, singleton fuzzifier, and center-average defuzzifier, the output of the fuzzy system is given as

$$y_l = \frac{\sum_{i=1}^3 y_l \left(\prod_{i=1}^3 \mu_{F_i^l}(x_i) \right)}{\sum_{i=1}^3 \left(\prod_{i=1}^3 \mu_{F_i^l}(x_i) \right)}. \quad (12)$$

Equation (12) can be expressed as [21–27]

$$y(x) = \theta^T \xi(x), \quad (13)$$

where $\xi(x) = [\xi_1(x) \ \xi_2(x) \ \xi_3(x)]^T$ is the fuzzy basis function, and $\theta = [\gamma_1 \ \gamma_2 \ \gamma_3]^T$ is a vector of adjustable parameters.

4.3. Neural Network Parameter Optimization. For replicating human thinking that follows a structured pattern, the Gaussian membership function is selected as the membership function as follows:

$$\mu_{F_i^l}(x_i) = \exp \left[-\left(\frac{x_i - \bar{x}_i^l}{\sigma_i^l} \right)^2 \right], \quad i = 1, \dots, 3, \quad (14)$$

where x_i is the input, $\bar{x}_i^l$ is the center of the Gaussian membership function, and σ_i^l is the width of the Gaussian membership function.

The fuzzy basis function is defined as

$$\xi_i(x) = \frac{\mu_{F_1^l}(x_1) \mu_{F_2^l}(x_2) \mu_{F_3^l}(x_3)}{\sum_{l=1}^3 \left(\mu_{F_1^l}(x_1) \mu_{F_2^l}(x_2) \mu_{F_3^l}(x_3) \right)}, \quad (15)$$

where Gaussian membership function are $\mu_{F_1^1}(x_1) = \exp[-(x_1 - \bar{x}_1^1/\sigma_1^1)^2]$, $\mu_{F_2^1}(x_2) = \exp[-(x_2 - \bar{x}_2^1/\sigma_2^1)^2]$, $\mu_{F_3^1}(x_3) = \exp[-(x_3 - \bar{x}_3^1/\sigma_3^1)^2]$, and fuzzy basis function are $\xi_1(x) = (\mu_{F_1^1}(x_1) \cdot \mu_{F_2^1}(x_2) \cdot \mu_{F_3^1}(x_3)) / (\mu_{F_1^1}(x_1) \cdot \mu_{F_2^1}(x_2) \cdot \mu_{F_3^1}(x_3) + \mu_{F_1^2}(x_1) \cdot \mu_{F_2^2}(x_2) \cdot \mu_{F_3^2}(x_3) + \mu_{F_1^3}(x_1) \cdot \mu_{F_2^3}(x_2) \cdot \mu_{F_3^3}(x_3))$, $\xi_2(x) = (\mu_{F_2^1}(x_1) \cdot \mu_{F_2^2}(x_2) \cdot \mu_{F_3^3}(x_3)) / (\mu_{F_1^1}(x_1) \cdot \mu_{F_2^1}(x_2) \cdot \mu_{F_3^1}(x_3) + \mu_{F_1^2}(x_1) \cdot \mu_{F_2^2}(x_2) \cdot \mu_{F_3^2}(x_3) + \mu_{F_1^3}(x_1) \cdot \mu_{F_2^3}(x_2) \cdot \mu_{F_3^3}(x_3))$, $\xi_3(x) = (\mu_{F_3^1}(x_1) \cdot \mu_{F_2^3}(x_2) \cdot \mu_{F_3^3}(x_3)) / (\mu_{F_1^1}(x_1) \cdot \mu_{F_2^1}(x_2) \cdot \mu_{F_3^1}(x_3) + \mu_{F_1^2}(x_1) \cdot \mu_{F_2^2}(x_2) \cdot \mu_{F_3^2}(x_3) + \mu_{F_1^3}(x_1) \cdot \mu_{F_2^3}(x_2) \cdot \mu_{F_3^3}(x_3))$, respectively.

The essential part of the Gaussian basis neural network function is an error back-propagation algorithm for adjusting the weights of each layer to obtain the minimal value of mean-square error between the actual output and the expected output of the network. The input and output are the air pressure in the PAMs and hip joint angles in the three directions. The distributed Gaussian basis function is shown in Figure 3.

Based on the fuzzy control with universal approximation property, the nonlinear functions $f_m(x)$ and $g_{mn}(x)$ are approximated by fuzzy systems $\hat{f}_m(x)$ and $\hat{g}_{mn}(x)$, respectively.

Denote

FIGURE 3: Gaussian basis functions.

$$\begin{aligned} f_m(x) &= [\hat{f}_1(x) \ \hat{f}_2(x) \ \hat{f}_3(x)]^T \\ &= [\theta_{f1}^T \ \theta_{f2}^T \ \theta_{f3}^T]^T \xi(x) \\ &= \Theta_f^T \Phi_f(x), \end{aligned}$$

$$\begin{aligned} \hat{g}_{mn}(x) &= [\hat{g}_1(x) \ \hat{g}_2(x) \ \hat{g}_3(x)] = \begin{bmatrix} \hat{g}_{11}(x) & \hat{g}_{12}(x) & \hat{g}_{13}(x) \\ \hat{g}_{21}(x) & \hat{g}_{22}(x) & \hat{g}_{23}(x) \\ \hat{g}_{31}(x) & \hat{g}_{32}(x) & \hat{g}_{33}(x) \end{bmatrix} \\ &= \begin{bmatrix} \hat{g}_{11}(x) & \hat{g}_{21}(x) & \hat{g}_{31}(x) \\ \hat{g}_{12}(x) & \hat{g}_{22}(x) & \hat{g}_{32}(x) \\ \hat{g}_{13}(x) & \hat{g}_{23}(x) & \hat{g}_{33}(x) \end{bmatrix}^T \\ &= \begin{bmatrix} \theta_{g11}^T & \theta_{g21}^T & \theta_{g31}^T \\ \theta_{g12}^T & \theta_{g22}^T & \theta_{g32}^T \\ \theta_{g13}^T & \theta_{g23}^T & \theta_{g33}^T \end{bmatrix}^T \cdot \text{diag}[\Phi_{g1}(x) \ \Phi_{g2}(x) \ \Phi_{g3}(x)] \\ &= \begin{bmatrix} \theta_{g11} & \theta_{g21} & \theta_{g31} \\ \theta_{g12} & \theta_{g22} & \theta_{g32} \\ \theta_{g13} & \theta_{g23} & \theta_{g33} \end{bmatrix} \cdot \text{diag}[\Phi_{g1}(x) \ \Phi_{g2}(x) \ \Phi_{g3}(x)] \\ &= \Theta_g^T \Phi_g(x). \end{aligned} \quad (16)$$

where θ_{fm}^T and θ_{gmn}^T are vectors of adjustable parameters of $\hat{f}_m(x)$ and $\hat{g}_{mn}(x)$, respectively. $\hat{f}_1(x)$, $\hat{f}_2(x)$, $\hat{f}_3(x)$ and

$\hat{g}_1(x)$, $\hat{g}_2(x)$, $\hat{g}_3(x)$ are subentries of $f_m(x)$ and $g_{mn}(x)$, respectively, and θ_{f1} , θ_{f2} , θ_{f3} and θ_{g11} , θ_{g21} , θ_{g31} , θ_{g12} , θ_{g22} , θ_{g32} , θ_{g13} , θ_{g23} , θ_{g33} are corresponding adjustable parameters of $\hat{f}_m(x)$ and $g_{mn}(x)$, respectively. Θ_f and Θ_g are compact adjustable parameters of $f_m(x)$ and $g_m(x)$, respectively, while $\Phi_f(x)$ and $\Phi_g(x)$ are fuzzy basis functions of $\hat{f}_m(x)$ and $\hat{g}_m(x)$, respectively.

4.4. Observer-Based Fuzzy Adaptive Control. In the state variable $x = (\dot{x}_1 \ \dot{x}_2)^T$, $\dot{x}_1$ and $\dot{x}_2$ are angular velocities, and angular accelerations, respectively, which are not measured directly. $\hat{x}$ and $\hat{y}$ are introduced to estimate x and y , and the fuzzy adaptive observer is given as follows:

$$\begin{cases} \dot{\hat{x}} = A\hat{x} + B(\hat{f}_m(\hat{x}) + \hat{g}_{mn}(\hat{x})u_i + d_i) + K_0(y - C^T\hat{x}), \\ \hat{y} = C^T\hat{x}. \end{cases} \quad (17)$$

The observation error is defined as $\tilde{e} = x - \hat{x}$ and $\tilde{y} = y - \hat{y}$. Combining equation (11) with equation (17), we obtain the following:

$$\begin{cases} \dot{\tilde{e}} = A\tilde{e} - K_0\tilde{y} + Bu_r + B[(f_m(x) - \hat{f}_m(\hat{x})) + (g_{mn}(x) - \hat{g}_{mn}(\hat{x}))u_i], \\ \tilde{y} = C^T\tilde{e}. \end{cases} \quad (18)$$

The control law in equation (11) can be rewritten as

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} \hat{g}_{11}(\hat{x}) & \hat{g}_{12}(\hat{x}) & \hat{g}_{13}(\hat{x}) \\ \hat{g}_{21}(\hat{x}) & \hat{g}_{22}(\hat{x}) & \hat{g}_{23}(\hat{x}) \\ \hat{g}_{31}(\hat{x}) & \hat{g}_{32}(\hat{x}) & \hat{g}_{33}(\hat{x}) \end{bmatrix}^{-1} \left[- \begin{bmatrix} \hat{f}_1(\hat{x}) \\ \hat{f}_2(\hat{x}) \\ \hat{f}_3(\hat{x}) \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \ddot{\beta}_1 \\ \ddot{\gamma}_1 \end{bmatrix} + \begin{bmatrix} k_0 \\ k_1 \\ k_2 \end{bmatrix} \begin{bmatrix} \ddot{\tilde{e}} & \dot{\tilde{e}} & \tilde{e} \end{bmatrix}^T - \begin{bmatrix} u_{r1} \\ u_{r2} \\ u_{r3} \end{bmatrix} \right], \quad (19)$$

where fuzzy control with universal approximation and related parameters x is replaced with $\hat{x}$.

The dynamic observer error is given as

$$\begin{aligned}\dot{\tilde{e}} &= (A - K_0 C^T) \tilde{e} + B u_r + B \left[(\hat{f}_m(\hat{x} | \Theta_{fm}^*) - \hat{f}_m(\hat{x})) + (\hat{g}_{mn}(\hat{x} | \Theta_{gmn}^*) - \hat{g}_{mn}(\hat{x})) u_i \right] \\ &\quad + B \left[(f_m(x) - \hat{f}_m(\hat{x} | \Theta_{fm}^*)) + (g_{mn}(x) - \hat{g}_{mn}(\hat{x} | \Theta_{gmn}^*)) u_i \right] \\ &= (A - K_0 C^T) \tilde{e} + B u_r + B \tilde{\Theta}_{fm} \Phi_{fm}(\hat{x}) + B \tilde{\Theta}_{gmn} \Phi_{gmn}(\hat{x}) u_i + B w,\end{aligned}\quad (20)$$

where

$$\begin{cases} \Theta_{fm} = \Theta_{fm}^* - \Theta_{fm}, \\ \tilde{\Theta}_{gmn} = \Theta_{gmn}^* - \Theta_{gmn}, \end{cases}$$

$$w = (f_m(x) - \hat{f}_m(\hat{x} | \Theta_{fm}^*)) + (g_{mn}(x) - \hat{g}_{mn}(\hat{x} | \Theta_{gmn}^*)) u_i, \quad (21)$$

and $\dot{\tilde{\Theta}}_{fm} = \dot{\Theta}_{fm}$, $\dot{\tilde{\Theta}}_{gmn} = \dot{\Theta}_{gmn}$. One can deduce that the tracking error converges asymptotically to zero by the Lyapunov function, which simultaneously proves system stability. The structure of the humanoid lower limb control system and the structure of the humanoid lower limb with OBFA control system are illustrated in Figures 4 and 5.

5. Experiment Results

The experiment process operates as described below. Control algorithm, kinematics, and kinetics are programmed with visual studio is the controller and is taken as a superior machine, which is characterized by flexible program and massive calculation. We adopt Field Programmable Gate Array (FPGA) as a lower computer of which is stable and fast operation. The controller continuously sent out signals such as 001, 010, 011, 100, 101, and 110 in sequence to FPGA with Windows timer. FPGA outputs PWM waveform, which is amplified by driver circuit to actuate valve open and close in a high speed, inflating, and deflating the PAMs. Current signal of which to resist disturbance is weak, not suitable for feedback. Resistance is 250 ohm which can transfer 4–20 milliamper current signal to 0–5 voltage signal. Pressures of PAMs are measured by a pressure transducer and then transferred to a voltage signal, combining with angles of joint (angular transducer) which are taken as feedback to the controller. Main factors that limit the whole system are mechanical part. Valve is applied as high-speed on-off valve and its frequency is 120–135HZ, which meets the requirements of PAMs. Flow chart of experiment can be seen in Figure 6.

Experiments were carried out with two cases of input trajectory tracking of which ramp signal is speed signal and sine-like is humanoid movement.

In neural network parameter optimization process, parameters are set as $\eta_w = 1$, $\eta_m = 1$, $\eta_\sigma = 1$ and they represent learning rate from input layer to hidden layer, mean value of Gauss function, and learning rate of standard value, respectively.

Control parameters of the OBFA controller can be set as $\gamma_f = \gamma_1 = \gamma_2 = \gamma_3 = 2$. The coefficient of row vector in the Θ_f is γ_f . Column vector in the Θ_g are γ_1 , γ_2 , and γ_3 . k_1 , k_2 , and k_3 are the parameters in equation (19), the most desirable coefficient are 1.2. r_1 , r_2 , and r_3 are the coefficients of u_{r1} , u_{r2} , and u_{r3} , and the parameters can be determined as 1. In the Kalman–Yakubovich Lemma Q_{11} and Q_{22} are the variables of diagonal matrix Q and they are taken as $Q_{11} = Q_{22} = 6$.

5.1. Ramp Signal Trajectory Tracking. The hip joint muscle and joint characteristics with ramp signal trajectories of the pitch, yaw, and roll angles are shown in Figures 7–11.

Figure 7 shows ramp signal trajectory tracking using OBFA control. Solid lines represent the desired trajectory, which is tracked by the dashed lines representing the measured trajectory of the hip joint with time. Figure 8 shows the ramp signal trajectory tracking error. The error between the desired and measured pitch, yaw, and roll angles remain within acceptable limits. At 1.92 s, the ramp signal trajectory tracking reaches the maximum error value at 0.48° , 0.46° , and 0.61° for pitch, yaw, and roll angles, respectively, which shows that friction in the ball hinge affects joint trajectory tracking.

Figure 9 represents length change of muscles in ramp signal trajectory tracking. The muscili obturator internus is an agonistic muscle and is stretched initially and then contract actively until 1.16 s, with the contraction length being 27 mm. Piriformis begin to contract at 1.12 s and have a maximum contraction length of 15 mm at 1.84 s. During the trajectory tracking process, the muscili obturator internus and piriformis are alternatively taken as agonistic and antagonistic muscles.

Figure 10 represents the force change of muscles in ramp signal trajectory tracking. The muscili obturator internus output force is 228 N, and joint moment 1 achieves its local maximum of 26 N·m at approximately 1.1 s, which proves that the muscili obturator internus plays an important role in hip adduction and abduction.

Figure 11 describes joint torque change in ramp signal trajectory tracking. The piriformis raises from -712 N to -191 N at 1.84 s; joint moments 1 and 3 are maximum at 50 N·m and 55 N·m, respectively, which further proves that the piriformis has a great influence on flexion and revolution. The iliopsoas acts as a strengthening muscle with constant output force.

FIGURE 4: The structure of the humanoid lower limb control system.

5.2. Sine-like Signal Trajectory Tracking. As pitch, yaw, and roll angles of a humanoid lower limb joint are sine-like, we choose a sine-like signal to study hip joint muscle and joint characteristics during trajectory tracking.

Figure 12 shows sine-like signal trajectory tracking with the OBFA control. Solid lines represent the desired trajectory, which is tracked by the dashed lines representing the measured trajectory. Amplitude of pitch, yaw, and roll angles are 7.16° , 15.6147° , and 6.30° at 0.16 s, 1.28 s, and 0.16 s with the maximum error separately.

Figure 13 shows the sine-like signal trajectory tracking error with the OBFA control. The error and lag between the desired and measured pitch, yaw, and roll angles are acceptable. The sine-like trajectory tracking is found to reach maximum error value at 0.12° , 0.0467° , and 0.36° for pitch, yaw, and roll angles, respectively. The musculi obturator internus, piriformis, and iliopsoas are inflated, implying that pitch, yaw, and roll angles are not zero in their primary stage.

Because of coupling among angles and muscles, the trajectory tracking error of pitch angle is similar to that of yaw angle in the first half, while in the latter half, yaw and roll angles have similar tracking error. Due to friction at the joints, dead zone of the high-speed-on-off valve, lag of compressed air in the trachea, and coupling among angles, it is difficult to realize precise trajectory tracking of the pitch, yaw, and roll angles simultaneously. Hence, most researches are restricted to yaw angle trajectory tracking, while a few simultaneously consider pitch and yaw angles; however, research on roll angle is negligible at present.

Length and force changes of muscles in sine-like signal trajectory tracking are shown in Figure 14 and Figure 15. PAMs are only affected by air pressure, and the two curves show similar trends, thereby validating our conclusions. The musculi obturator internus acts as an agonistic muscle, and piriformis is an antagonistic muscle which is negative and stretched from -55 N to -378 N and

FIGURE 5: The structure of the humanoid lower limb with OBFA control system.

FIGURE 6: Flow chart of experiment.

FIGURE 7: Ramp signal trajectory tracking curves of (a) pitch angle, (b) yaw angle, and (c) roll angle.

FIGURE 8: Ramp signal trajectory tracking error curves of (a) pitch angle, (b) yaw angle, and (c) roll angle.

FIGURE 9: Length changes of muscles in ramp signal trajectory tracking curves.

FIGURE 10: Force changes of muscles in ramp signal trajectory tracking curves.

then back to -69 N. The iliopsoas exhibits isotonic contraction keeping a constant output force regardless of changes in length.

Figure 16 shows joint torque change in sine-like signal trajectory tracking. The joint moment 1 reaches the maximum value of 27.3 N·m, when pitch and yaw angles slope

FIGURE 11: Joint torque changes in ramp signal trajectory tracking curves.

FIGURE 12: Sine-like signal trajectory tracking curves of (a) pitch angle, (b) yaw angle, and (c) roll angle.

FIGURE 13: Sine-like signal trajectory tracking error curves of (a) pitch angle, (b) yaw angle, and (c) roll angle.

FIGURE 14: Length changes of muscles in sine-like signal trajectory tracking curves.

FIGURE 15: Force changes of muscles in sine-like signal trajectory tracking curves.

FIGURE 16: Joint torque changes in sine-like signal trajectory tracking curves.

upwards. Joint moment 1 is smaller than the other two moments (mostly), which demonstrates that circumduction occurs with minimum torque and is one of the reasons for the difficulty in precise control.

6. Conclusions

We designed a simplified parallel mechanism spatial humanoid lower limb driven by PAMs with cross sagittal, sagittal, and coronal sections. Since changes in muscle length cannot be measured directly, we controlled the hip joint as a whole with OBFA. The effectiveness of the proposed method was verified experimentally. The piriformis and musculus obturator internus act as agonistic and antagonistic muscle alternatively, while iliopsoas is responsible for strengthening the muscles with constant output force. The lower limb was made to control the knee joint, consisting of the rectus femoris, gracilis, hamstring, and biceps flexor cruris. Furthermore, the crack for hip and knee joint was made to work simultaneously with coupling.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to research, authorship, and/or publication of this article.

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