Constructing Constraint Force Field in Musculoskeletal Robot by Co-optimizing Muscle Arrangements and Constant Activations

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***Abstract*—Robots with high-precision motion and operation ability are of great application significance. By referring to the biomechanical structure and neural control mechanism of human motion system, the research of musculoskeletal robot system with rigid-flexible coupling characteristics is one of the important ways to improve the operation flexibility and control robustness of robot. Inspired by the equilibrium point hypothesis proposed in neuroscience, this paper proposes a co-optimization algorithm of muscle arrangement and activation to construct constraint force field in the workspace of musculoskeletal robot. When the muscle arrangement is rough due to the insufficient precision of the mechanical structure, the musculoskeletal robot can maintain accurate motion with the help of constraint force field by adopting the optimized constant activation. Experiments are carried out on a musculoskeletal robot model with human-mimetic muscle to demonstrate the effectiveness of the proposed algorithm in movement accuracy, noise robustness and generalization. This work may be of great significance for the further introduction of constraint force field into hardware system of musculoskeletal robot.**

***Index Terms*—Musculoskeletal robot, Constraint Force Field, High precision, Control Schemes of robot**

I. Introduction

REPLACING human beings by robots to carry out task in extreme environments, such as space and polar region, has become the focus of research in the field of robotics. In these extreme environments, the robot is faced with problems such as extreme temperature deviation, strong noise disturbance and fragile operation objects, which put forward high requirements for robot in robustness and accuracy. Although the robotic system has made great progress in intelligence, it still has many shortcomings in dealing with unstructured environment, dynamic situation and high-precision task.

As a long-term reference for the development of robots, the structure and mechanism of human body has provided plenty of inspiration for the design and improvement of robotic system. Although the absolute precision of the sensing and control of human is not high, it can make full use of the information which is fused across different brain regions and flexibility of its own structure to achieve high-precision, high-reliability and high-intelligence behavior. Therefore, referring to the information processing mode of human brain and the mechanism of human motion system will provide an important scientific basis for the research and development of a new generation of robots.

However, it is not easy to integrate the structure and mechanism of human in intelligence and dexterous operation into the robot system, due to the essential differences between the existing robot system and human in the morphological structure, control mechanism and functional characteristics. Many research teams have carried out plenty of preliminary exploratory research works. Embodied Cognition in a Compliantly Engineered Robot (ECCE Robot) is a series of highly anthropomorphic musculoskeletal robot developed with Human Brain Project funding [1]. Although the appearance of ECCE robot is very different from that of human beings, it has a highly similar human structures such as artificial skeleton, spine, scapular joint and tendon, which enable it to complete some human-like movements initially. Jouhou System Kougaku Laboratory (JSK Laboratory) at the University of Tokyo has been developing a series of bio-inspired musculoskeletal humanoid robots since 2000, including Kenta [2], Kojiro [3], and Kengoro [4]. In order to simulate human more accurately, they had optimized the arrangement of joints, and proposed a new kind of water cooling technology to make the drive motor of system maintain high output power continuously, so as to complete complex body movements such as push-ups and sit-ups.

In terms of control algorithm, researchers also proposed effective control methods to solve the control problems of humanoid robot system caused by the increase of joint complexity and the number of actuators by referring to the control mechanism of human motion system. Inspired by the hierarchical control architecture composed of the human brain, brainstem and spinal cord neural circuits, the research team of ECCE robot proposed a hierarchical software architecture to solve the computing and control problems caused by the large number of actuators and sensors of humanoid robots [1], [5]. Inspired by the mechanism of human body interaction innervating neural circuit, Kawaharazuka et al. proposed an Antagonist Inhibition Control (AIC) algorithm for humanoid musculoskeletal robot Kengoro to realize large-scale limb movement [6]. Chen et al. proposed a neural control framework based on the mechanism of muscle synergy in human body to solve the problem of motion control in highly redundant musculoskeletal system [7]. Aiming at the practical needs of humanoid robot to maintain stable and robust motion control under external interference, a cerebellar like control network is proposed by Capolei et al. to deal with the complex nonlinear

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characteristics of humanoid robot, which enables the robot to have dynamic adaptability in uncertain environment with disturbance [8].

This paper mainly focuses on the control algorithm inspired by biological mechanism for musculoskeletal robot. A force field with convergence property will be leveraged to assist musculoskeletal robot to complete accurate movements. Related biological theories, such as equilibrium point hypothesis, have been widely verified in the researches of neuroscience. In the research work of neuroscience, the research of convergence field originated from the research of the spinal nervous system of frogs. Neuroscientists applied constant micro-electric stimulation to specific neurons in frog spinal cord, and measured the direction and amplitude of the force generated by muscle system at different locations in a plane. Then they found that muscle forces can form a regular force field with a equilibrium point in the working space, which is called Convergent Force Field [9]. It has been demonstrated that the Convergent Force Field is significant for realizing voluntary movements of organisms [10], [11].

Inspired by the concept of Convergent Force Field in neuroscience, a recent study introduce a concept called Constraint Force Field for controlling the movement of musculoskeletal system [12]. The constraint force field is helpful for realizing high-precision movements of musculoskeletal robots with limited control accuracy. It can be constructed at the target positions by optimizing the arrangement of muscles. When the target position is the center of the constraint force field and the starting position is in its range, the robot can complete precise and robust movement with constant control signals, which is benificial for reducing the requirement of sensing feedback during the motion control of the robot. However, the optimal muscle arrangement for constructing constraint force field in [12] requires the hardware device for adjusting position of muscle attachment points has high precision, but existing mechanical equipment is difficult to meet its requirements. When the adjustment accuracy of the muscle attachment point is insufficient, the equilibrium center of the constraint field will drift away from the target position, resulting in the decrease of accuracy.

In this paper, aiming at the problem that the motion accuracy of the system decreases due to the insufficient accuracy of mechanical structure, we propose a method of co-optimization of structure and muscle activation signal. By using the optimized constant activation signal, a constraint force field can be constructed in the musculoskeletal robot system to help the system achieve accurate motion, under the condition that the muscle arrangement is rough due to the insufficient precision of the mechanical structure.

The rest of this paper will be organized as follows. Section II will first establish the dynamics model of musculoskeletal system with variable structure and activation. Section III will introduce the co-optimization algorithm of structure and activation to construct the constraint force field. Section IV will illustrate the experiment results to demonstrate the effectiveness of the proposed method. Section V is the summary and conclusion of this paper.

II. Dynamics Model of Musculoskeletal System

Muscle is the core actuator for human to realize different movements. It can receive motor command from brain and spinal cord to generate driving force for movement of the skeletal system by contraction. According to the research results of physiology [13], muscle fiber is the basic structural units of muscle. Muscle fiber is mainly composed of two kinds of proteins, namely contractile protein and non-contractile protein. The contractile protein, such as actin and myosin, can contract in response to the nerve activation signals to produce the active force for body movement. The non-contractile protein, such as connectin, not only plays an important role in supporting the fibrous structure of the muscle, but also generates tension and stores elastic potential energy when the muscle is stretched, thus improving the energy efficiency of the body movement.

In order to investigate the biomechanical characteristic of muscle, researchers have constructed many biological plausible mathematical model of muscle based on the work in physiology [14]–[16]. Hill-type model [14], [17] is one of the classical models that has been widely used in fields such as medical, biomechanics and sports science due to its advantages in biological similarity and computational convenience. This model employs a contraction element CE to mimic the contractile protein of muscle fiber, and a passive elastic element PE to mimic the non-contractile protein. In this paper, the dynamics model of musculoskeletal system is established by applying Hill-type model as actuators.

We first introduce the modeling process of musculoskeletal system with variable arrangement. The musculoskeletal model is shown in Figure 1. The arrangement of muscles in the system is depends on the attachment positions of muscles on the skeleton. Suppose there are N muscles in the musculoskeletal system. A muscle is attached to the skeleton via attachment points. In the reference coordinates of the skeleton, we use s_{ij} to represent the coordinate value of the jth attachment point of muscle i on the skeleton. Then we denote $\boldsymbol{S} = \{s_{11}, ..., s_{1P_1}, ..., s_{i,1}, ..., s_{iP_i}, ..., s_{NP_N}\}$ as the coordinate set of all attachment points, where P_i is the total number of attachment points of muscle i.

Muscle fiber length can be calculated according to the coordinate set of muscle arrangement. The length of muscle fiber is an important parameter that affecting muscle force. When the muscle fiber is at the optimal length, the muscle can produce the maximum isometric force. In consideration of the variation of the muscle arrangement, the length of muscle fiber can be calculated by the following equation [12]:

$$l_i(\boldsymbol{S}) = \sum_{j=1}^{P_{i-1}} \sqrt{(s_{ij}^w - s_{i(j+1)}^w)^T (s_{ij}^w - s_{i(j+1)}^w)} \qquad (1)$$

where s_{ij}^w represents the coordinate value of s_{ij} in the world frame of the musculoskeletal system, which can be reckoned by the kinematic relationship between joints.

According to the Hill-type model, the force generated by a muscle is composed of active force $\boldsymbol{F}^a$ and passive force $\boldsymbol{F}^p$, which can be formulated as follow:

$$\boldsymbol{F}^m(\boldsymbol{S}, \boldsymbol{a}) = \boldsymbol{F}^a + \boldsymbol{F}^p = \boldsymbol{f}^a(\boldsymbol{S}) \cdot \boldsymbol{a} + \boldsymbol{f}^p(\boldsymbol{S}). \qquad (2)$$

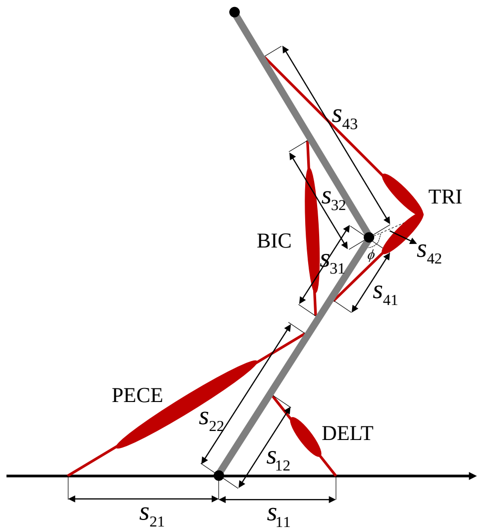

Fig. 1. The model of the musculoskeletal robot, whose muscle arrangements and activation is variable for constructing the constraint force field.

In this equation, $\boldsymbol{a}$ is a muscle activation vector, which contains dimensionless quantity between 0 and 1 that corresponding to the activation of each muscle. $\boldsymbol{f}^a(\boldsymbol{S}) = diag(f_1^a(\tilde{l}_1(\boldsymbol{S})), ..., f_N^a(\tilde{l}_N(\boldsymbol{S}))$ is a diagonal matrix composed of active muscle force, whose element is given by an exponential function to mimic the characteristics of active muscle fiber force [12], [17]:

$$f_i^a(\tilde{l}_i(\boldsymbol{S})) = f_i^o \cdot exp(-2(\tilde{l}_i(\boldsymbol{S}) - 1)^2) \tag{3}$$

where f_i^o is the maximum isometric force of muscle i, and $\tilde{l}_i(\boldsymbol{S})$ is the normalized muscle fiber length by its optimal fiber length l_i^o [12]. The values of f_i^o and l_i^o are aquired by biomechanical experiments [18]. $\boldsymbol{f}^p(\boldsymbol{S}) = [f_1^p(\tilde{l}_1(\boldsymbol{S})), ..., f_N^p(\tilde{l}_N(\boldsymbol{S}))]^T$ is a vector composed of passive muscle force, whose element is given by a piecewise function to mimic the tension of muscle fiber [12], [17]:

$$f_i^p(\tilde{l}_i(\boldsymbol{S})) = \begin{cases} f_i^o \cdot [1 + \frac{k^p[\tilde{l}_i(\boldsymbol{S}) - (1+\varepsilon_0^m)]}{\varepsilon_0^m}], & \tilde{l}_i(\boldsymbol{S}) > 1 + \varepsilon_0^m \\ f_i^o \cdot \frac{\exp(k^p(\tilde{l}_i(\boldsymbol{S})-1)/\varepsilon_0^m)}{\exp(k^p)}, & \tilde{l}_i(\boldsymbol{S}) \leq 1 + \varepsilon_0^m \end{cases} \tag{4}$$

where k^p and ε_0^m are constants that represent the exponential shape factor and the passive muscle strain factor respectively.

The rotational torques that drive the movement of musculoskeletal system are calculated from the muscle forces and their moment arms. It is important to note that the moment arm of muscle is related to the arrangement of muscles and the angle of joints. Based on the algorithm to calculate the moment arm of muscle provided in [19], we define $r_{ji}(\boldsymbol{S}, q_j)$ as the moment arm of muscle i to joint j when the joint angle is q_j. Thus the torque vector generated by muscles can be solved by the following equation:

$$\begin{aligned} \boldsymbol{T}(\boldsymbol{S}, \boldsymbol{a}, \boldsymbol{q}) &= \boldsymbol{R}(\boldsymbol{S}, \boldsymbol{q}) \cdot \boldsymbol{F}^m(\boldsymbol{S}, \boldsymbol{a}) \\ &= \begin{pmatrix} \sum_{i=1}^N r_{1i}(\boldsymbol{S}, q_1)\boldsymbol{F}_i^m(\boldsymbol{S}, \boldsymbol{a}) \\ \vdots \\ \sum_{i=1}^N r_{Hi}(\boldsymbol{S}, q_H)\boldsymbol{F}_i^m(\boldsymbol{S}, \boldsymbol{a}) \end{pmatrix} \end{aligned} \tag{5}$$

where $\boldsymbol{R}(\boldsymbol{S}, \boldsymbol{q})$ is matrix of moment arm which is composed of $r_{ji}(\boldsymbol{S}, q_j)$. H is the total number of joints. So, the dynamic equation of musculoskeletal system, with respect to the variable $\boldsymbol{S}$ and $\boldsymbol{a}$, can be formulated as follows:

$$\boldsymbol{T}(\boldsymbol{S}, \boldsymbol{a}, \boldsymbol{q}) = \boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}_c(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{b}(\dot{\boldsymbol{q}}) + \boldsymbol{G}(\boldsymbol{q}) + \boldsymbol{\tau}_f \tag{6}$$

where $\dot{\boldsymbol{q}}$ is angular velocity of joint and $\ddot{\boldsymbol{q}}$ is acceleration. $\boldsymbol{M}(\boldsymbol{q})$, $\boldsymbol{C}_c(\boldsymbol{q}, \dot{\boldsymbol{q}})$, $\boldsymbol{b}(\dot{\boldsymbol{q}})$, $\boldsymbol{G}(\boldsymbol{q})$ and $\boldsymbol{\tau}_f$ are the mass matrix of skeleton model, the Coriolis force matrix, the damping term, the gravity vector and the friction torque of the joints, respectively.

III. Constructing constraint force Field with Optimized Activation

The significance of force field with convergent characteristics for complex motion has been verified in neuroscience. The study of force field in muscle system originated from the research of the spinal nervous system of frogs. Neuroscientists has found that the terminal force of limb can form a regular equilibrium force field in the working space by measuring the direction and amplitude of the force at different positions in the space when applying a constant micro-electric current to a specific neuron cluster in the spinal cord [9]. Although there are only a few such force fields in the range of body movement, they are closely related to the diversity and rapidity of movement of organisms [10], [20], [21].

Inspired by work about force field in neuroscience, previous work [12] have introduced the concept of constraint force field into robotic system. Different from the convergent force field found in organisms, [12] proposed an optimization algorithm to optimize the muscle arrangement so as to construct constrain force field with equilibrium point at different desired position of robotic work space, which expands the application possibility of convergent force field in robotic system effectively. With the help of constraint force field, the musculoskeletal robot is able to reach the desired position accurately using constant control signal, which dramatically reduces the reliance on sensors during the movement.

However, there are some deficiencies in the work of [12]. From the view of practical application, the optimal structure obtained from the optimization algorithm in [12] requires high precision of hardware adjustment in muscle arrangement position. When the adjustment accuracy of muscle arrangement is low, the equilibrium center of the constraint force field will drift away from the target position, resulting in the reduction of motion accuracy of the system. Therefore, in this paper, based on the previous research work [12], we propose that under the condition of rough implementation of optimal structure, the constant activation signal can be optimized to compensate for the drift from the equilibrium center to the target point, so that the equilibrium center can coincide with the target point again.

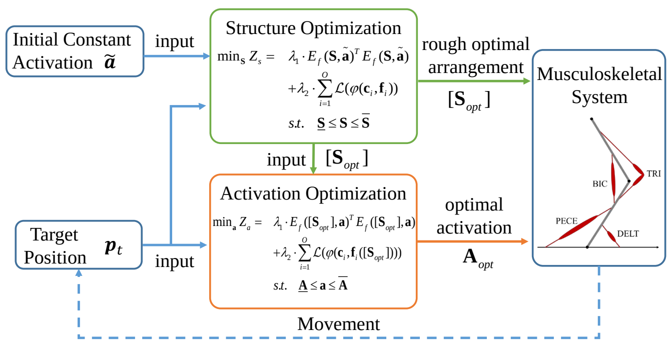

Fig. 2. The schematic diagram of the algorithm with two steps of optimization.

This improvement, on the one hand, is beneficial to adjust the muscle distribution by using the hardware system with low precision, and on the other hand, it can keep the advantage of the constraint force field to achieve precise motion by using the constant control signal.

The representation of force field will be introduced first, since it is the basis of the optimization algorithm for constructing the constraint force field. In neuroscience experiments, the force vectors of force field were measured by a force transducer which was attached to the extremity of the subject frog. Similarly, in a robotic system, when the torques of each joint are known, the equivalent terminal force of the system can be calculated by using the kinematic relationship between rigid bodies. Therefore, based on equation (5), we can derive the equivalent terminal force of the musculoskeletal system under the actuation of muscle forces:

$$\begin{aligned} E_f(\boldsymbol{S},\boldsymbol{p},\boldsymbol{a}) &= \boldsymbol{K}(\boldsymbol{p})\boldsymbol{T}(\boldsymbol{S},\boldsymbol{a},\hat{\boldsymbol{q}}(\boldsymbol{p})) \\ &= \begin{pmatrix} \sum_{j=1}^{H} K_{1j}(\boldsymbol{p})\tau_j(\boldsymbol{S},\boldsymbol{a},\hat{\boldsymbol{q}}(\boldsymbol{p})) \\ \vdots \\ \sum_{j=1}^{H} K_{Dj}(\boldsymbol{p})\tau_j(\boldsymbol{S},\boldsymbol{a},\hat{\boldsymbol{q}}(\boldsymbol{p})) \end{pmatrix} \end{aligned} \tag{7}$$

where $\boldsymbol{K}(\boldsymbol{p}) = \boldsymbol{J}(\hat{\boldsymbol{q}}(\boldsymbol{p}))^{-T}$ is the inverse matrix of transpose Jacobian matrix and $K_{ij}(\boldsymbol{p})$ is its element. $\hat{\boldsymbol{q}}(\boldsymbol{p})$ represents the joint vector of position $\boldsymbol{p}$ which is solved by inverse kinematics. $\tau_j(\boldsymbol{S},\boldsymbol{a},\hat{\boldsymbol{q}}(\boldsymbol{p}))$ is the resultant torque generated by all muscles for joint j. When the target position $\boldsymbol{p}_t$ is determined by the movement task, it can be omitted in (7). So, a constraint force field with $\boldsymbol{p}_t$ as the equilibrium center can be constructed by optimizing the muscle arrangement $\boldsymbol{S}$ and the constant activation $\boldsymbol{a}$. As introduced in [12], with fixed constant activation $\tilde{\boldsymbol{a}}$, the optimal muscle arrangement $\boldsymbol{S}_{opt}$ can be reckoned by solving a constrained optimization problem:

$$\begin{aligned} \min_{\boldsymbol{S}} Z_s =& \lambda_1 \cdot E_f(\boldsymbol{S},\tilde{\boldsymbol{a}})^T E_f(\boldsymbol{S},\tilde{\boldsymbol{a}}) \\ &+ \lambda_2 \cdot \sum_{i=1}^{O} \mathcal{L}(\varphi(\boldsymbol{c}_i(\boldsymbol{p}_t,\boldsymbol{p}_i),\boldsymbol{f}_i(\boldsymbol{S},\boldsymbol{p}_i,\tilde{\boldsymbol{a}}))) \\ &s.t. \quad \underline{\boldsymbol{S}} \leq \boldsymbol{S} \leq \overline{\boldsymbol{S}} \end{aligned} \tag{8}$$

where λ_1 and λ_2 are hyperparameters. $[\underline{\boldsymbol{S}},\overline{\boldsymbol{S}}]$ is the adjustable range of muscle arrangement. O is the number of position in ϵ-neighborhood of the target position $\boldsymbol{p}_t$. $\boldsymbol{c}_i(\boldsymbol{p}_t,\boldsymbol{p}_i)$ is the unit centripetal vector of neighborhood point $\boldsymbol{p}_i$, and $\boldsymbol{f}_i(\boldsymbol{S},\boldsymbol{p}_i,\tilde{\boldsymbol{a}})$ is the unit vector of the equivalent terminal force at the neighborhood point $\boldsymbol{p}_i$. They can be abbreviated as $\boldsymbol{c}_i$ and $\boldsymbol{f}_i$ respectively. $\varphi(\boldsymbol{c}_i,\boldsymbol{f}_i)$ is vetorial angle between $\boldsymbol{c}_i$ and $\boldsymbol{f}_i$.

In equation (8), $\mathcal{L}(\cdot)$ is the penalty function to help constructing a force filed with convergent characteristics, which is defined as a hyperbolic cosine function as follows [12]:

$$\mathcal{L}(\varphi(\boldsymbol{c}_i,\boldsymbol{f}_i)) = \lambda_3^2(cosh(\frac{cos(\varphi(\boldsymbol{c}_i,\boldsymbol{f}_i))-1}{\lambda_3})-1). \tag{9}$$

This penalty term is helpful to ensure the convergence of the constraint force field since it requires that the equivalent terminal force at the neighborhood point has a force component pointing to the target position $\boldsymbol{p}_t$ [12].

The optimal structure $\boldsymbol{S}_{opt}$ of the constrained optimization problem (8) solved by interior point method usually contains multiple decimal places. For example, in previous work [12], the precision of optimal muscle arrangement reaches $10^{-3}mm$. When the adjustment precision is rough, such as $1mm$, the motion accuracy will decrease. It means that a high adjustment accuracy of muscle arrangement is required, which brings in tremendous difficulty for practical implementation.

In this paper, in order to solve the problem of motion accuracy caused by rough structural adjustment, an optimization algorithm for constant muscle activation is proposed. Based on the optimal structure, when the structure adjustment accuracy is insufficient, this method will optimize the constant muscle activation to make the equilibrium center of the constraint force field coincide with the target position again, so that the musculoskeletal system can accurately move to the target position with the new constant activation signal.

We assume that the integer part of optimal structure $\boldsymbol{S}_{opt}$ is the adjustment precision. Let $[\boldsymbol{S}_{opt}]$ represent the rough muscle arrangement. Similar to the equation (8), the optimization problem for constant muscle activation can be defined as follows:

$$\begin{aligned} \min_{\boldsymbol{a}} Z_a =& \lambda_1 \cdot E_f([\boldsymbol{S}_{opt}],\boldsymbol{a})^T E_f([\boldsymbol{S}_{opt}],\boldsymbol{a}) \\ &+ \lambda_2 \cdot \sum_{i=1}^{O} \mathcal{L}(\varphi(\boldsymbol{c}_i(\boldsymbol{p}_t,\boldsymbol{p}_i),\boldsymbol{f}_i([\boldsymbol{S}_{opt}],\boldsymbol{p}_i,\boldsymbol{a}))) \\ &s.t. \quad \underline{\boldsymbol{A}} \leq \boldsymbol{a} \leq \overline{\boldsymbol{A}} \end{aligned} \tag{10}$$

where $[\underline{\boldsymbol{A}},\overline{\boldsymbol{A}}] = [0,1]$ is the value range of muscle activation [17], [18]. Let $\boldsymbol{A}_{opt}$ represent the optimal constant activation. By optimizing the muscle activation, this method can effectively overcome the problem caused by the insufficient structural adjustment accuracy. Meanwhile, it retains the key characteristics of the constraint force field, that is, the system can move to the target point accurately under the new constant activation signal, thus reducing the requirement for precise sensing feedback of the control signal. The schematic diagram of the whole process can be found in Figure 2.

IV. Experiments

In order to evaluate the effectiveness of the constraint force field formed by optimizing the muscle activations, a

TABLE I
OPTIMAL MUSCLE ARRANGEMENTS

$\boldsymbol{p}_t$	$\boldsymbol{S}_{opt}$ (mm)								$\boldsymbol{A}_{opt}$			
	s_{11}	s_{12}	s_{21}	s_{22}	s_{31}	s_{32}	s_{41}	s_{43}	a_1	a_2	a_3	a_4
(-25,9)	56	139	131	168	36	238	0	145	0.9557	0.9445	0.0217	0.6665
(5,33)	121	84	83	209	20	207	33	34	0.9845	0.1017	0.0649	0.849
(-9,43)	182	168	157	208	203	48	3	216	1	0.89	0.8795	0

TABLE II
EVALUATION INDEX OF MOVEMENT ACCURACY

$\boldsymbol{p}_t$	Min PE (mm)	Max PE (mm)	Mean PE (mm)	Std PE (mm)
(-25,9)	0.0013	0.0232	0.0133	6.7e-4
(5,33)	0.0024	0.0121	0.0063	3.4e-4
(-9,43)	0.0046	0.035	0.0173	8.4e-4

TABLE III
EVALUATION INDEX OF NOISE ROBUSTNESS

Noise Amplitude	Ratio	Min PE (mm)	Max PE (mm)	Mean PE (mm)	Std PE (mm)
$\zeta = 0.1$	10%	0.005	0.091	0.037	0.028
$\zeta = 0.2$	20%	0.021	0.155	0.067	0.042
$\zeta = 0.3$	30%	0.016	0.203	0.099	0.061

two-link robot with 4 Hill-type muscle units is applied in our experiments, including Pectoralis Major (PECM), Deltoid (DELT), Biceps (BIC) and Triceps (TRI). Every muscle has bionic properties by setting parameters from biomechnical experiments [12], [18]. The musculoskeletal model is shown in Figure 1. s_{ij} represents the coordinate of the jth attachment point of muscle i, whose value range is set as $[\underline{\boldsymbol{S}}, \overline{\boldsymbol{S}}] = [0, 300]$. An additional point is added in TRI to prevent penetration of bone, where $s_{42} = 4$ and $\phi = 2/3\pi$. The link length is set as $L_1 = L_2 =$300 mm, and their mass is 1 kg. For the dynamical parameters of the system, the damping coefficient is set as 500 and the joint friction is set as 0.001.

The parameters used in the optimization algorithm of (10) are the same as that in (8). The hyper-parameters λ_1, λ_2 and λ_3 are set as 10, 1000 and 0.2 respectively. The number of position O in ϵ-neighborhood of the target position is set as 8 while the radius of the neighborhood ϵ is 0.5. $10,000$ steps of simulation are conducted with the step size is set as 0.001. When solving the optimization problem of (8), the constant activation $\tilde{\boldsymbol{a}}$ is fixed in $\mathbf{1}$.

In the following part, we will discuss the feature of constraint force field with optimized activation by evaluating the motion performance in movement accuracy, noise robustness and generalization to new target. To illustrate the experiment results better, a $2\times$ 2 cm rectangle with the target position as the center is drawn. For each force field, we randomly select 100 positions as starting point to validate the motion performance of the system.

(1) Movement Accuracy. The most attractive feature of the constraint force field is that the musculoskeletal system can reach the desired position with high precision using constant activations, so that the reliance on sensors in control procedure can be released. In this work, this property is well retained because the optimized activation keep constant during the whole control procedure.

In the case of low structural accuracy (millimeter level), the constraint force field formed by optimizing the constant muscle activations is depicted in Figure 3(a1). We define the position error between the target point and the end-effector position of the robot at the end of the movement as Positioning Error (PE), which is adopted to evaluate the movement accuracy. The standard deviations (Std) of PE are recorded. The optimization and experiment results are listed in Table I and Table II, respectively.

Compared with the results from previous work [12] in Figure 3(a1), the equilibrium center of the constraint force field coincides with the target position again via optimizing the constant activations, so that the musculoskeletal system is able to reach the target point with high precision. As shown in Figure 3(a2)-(a3), 10 groups of trajectories starting from randomly selected positions in different constraint force field are illustrated. These results represent that optimizing activation can compensate the lack of precision in structure adjustment, keeping the characteristics of constraint force field in helping robotic system to achieve high precision movement.

(2) Noise Robustness. In order to compensate for the problem caused by the lack of precision in structure adjustment, the constraint force field is constructed by optimizing the constant muscle activation in this paper. So, when the optimized muscle activation signal is influenced by a random noise, whether the system can maintain robustness and accurate motion in the constraint field becomes a key factor that needs to be taken into consideration.In this part, we will verify the influence of control signal noise on the constraint force field through experiments.

We use the constraint force field whose equilibrium center is $\boldsymbol{p}_t = (-25, 9)$ as example to illustrate the experimental results. During the movement tasks that starting from the same position, random noises obeying uniform distribution are added to activation of each muscle respectively, which can be formulated as follows [12]:

$$a^i_{opt}(t) = a^i_{opt} + \zeta \cdot U(-1, 1) \tag{11}$$

where $a^i_{opt}(t)$ represents the activation of muscle i at time step

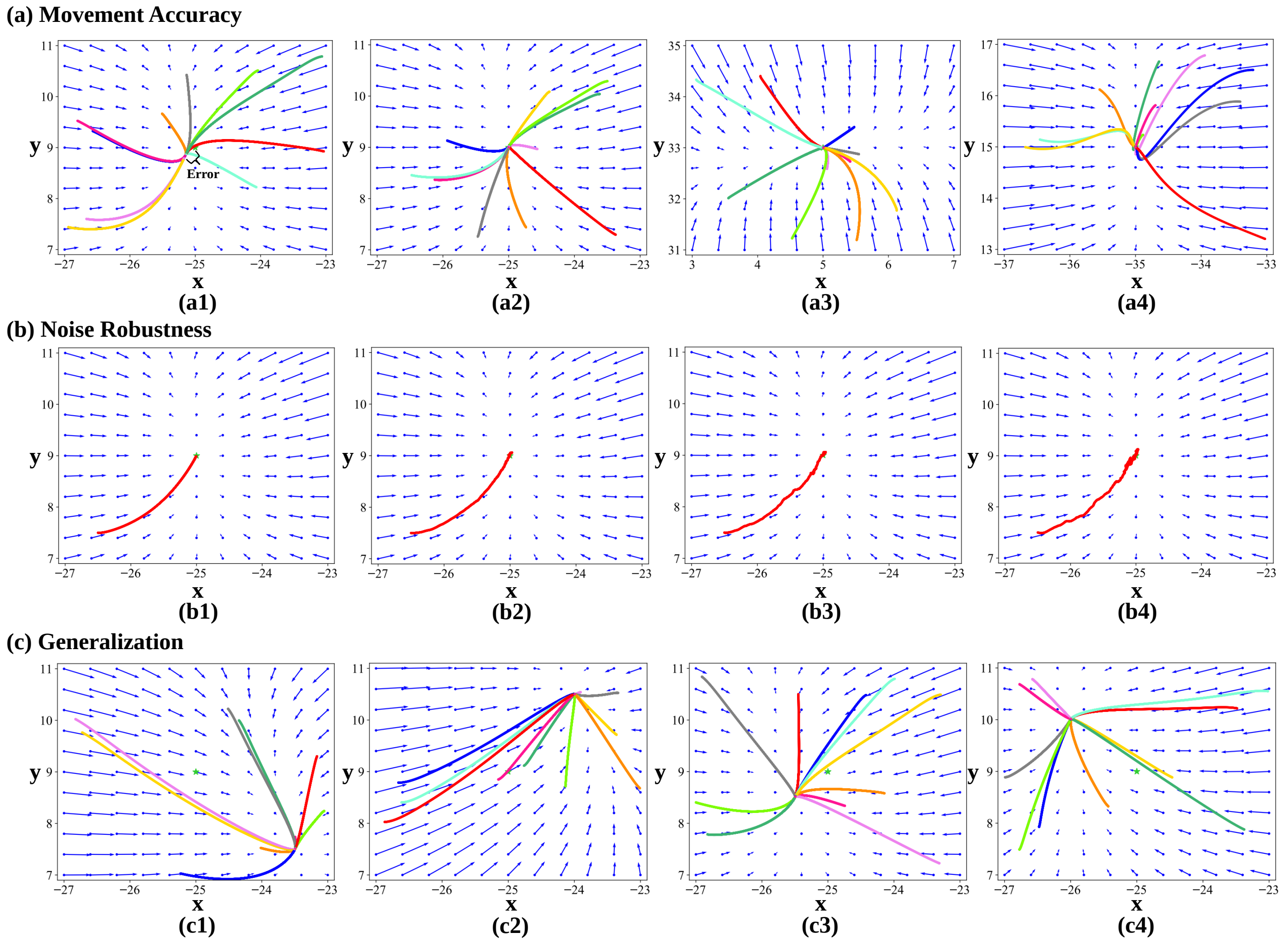

Fig. 3. The experiment results to demonstrate the effectiveness of the proposed algorithm. (a1)-(a4) Movement accuracy. (b1)-(b4) Noise robustness. (c1)-(c4) Generalization.

t, and $a^i_{opt} \in \boldsymbol{A}_{opt}$ is the optimal activation of muscle i. ζ is the maximum amplitude of the noise. For each noise amplitude, 100 motion experiments are conducted. The statistic results is provided in Table III and the movement trajectory is illustrated in Figure 3(b1)-(b4), whose $\zeta = 0, 0.1, 0.2, 0.3$ respectively.

According to the experimental results, the constraint force field becomes more sensitive to the disturbance of the activation compared with the results in [12]. When the amplitude of noise to the optimal constant activations increases, the movement trajectory of the system becomes unsmooth, but the motion trend is maintained and the mean value of PE is increasing slightly. Therefore, the constraint force field is robust to the noise disturbance of the control signal to some extent.

(3) Generalization. The construction of a constraint force field only by optimizing the muscle arrangement may result in additional time consumption for the actual control of the hardware system. In musculoskeletal model, each muscle actuator has two attachment point on the skeleton, some complex situation may contains much more attachment point in one muscle in order to provide force for multiple joint [18], [22]. Therefore, the dimension of the optimization variables are often more than twice the number of muscle actuators. In addition, the delay caused by the adjustment of muscle arrangement structure makes it difficult for the system to ensure rapid response.

In this paper, by optimizing the constant muscle activations, we can construct a new constraint force field in a certain range of the previous target position, with the optimal structure keep fixed. As shown in Figure 3(c1)-(c4), under the condition that the optimal structure $\boldsymbol{S}_{opt}$ of target position $(-25, 9)$ is kept fixed, when a new movement task with target position at $(-23.5, 7.5)$, $(-24, 10)$, $(-25.5, 8.5)$ or $(-26, 10)$, we can construct the constraint force field whose equilibrium point is the new target position by optimizing the constant activation. 10 groups of trajectories are displayed and the reaching accuracy is 0.0067 ± 0.0022mm.

The experimental results demonstrate that when the movement target is modified to a neighborhood point of the original target position, we can construct a constraint force field at the new target by optimizing the constant muscle activation without changing the optimal structure again, so that the musculoskeletal system can move to the new target accurately. This feature simplifies the steps of hardware adjustment, which is of great significance to the online construction of constraint force field and is beneficial for effectively completing continuous motion of robot system.

However, we also found that there are some limitations of this method. Only in a certain range around the original target position can the constraint force field be constructed by optimizing the activation signal. For a new position that far from the original target position, it is still necessary to optimize the structure to form the constraint force field first, and it is difficult to obtain the constraint force field by optimizing the activation signal directly. The reason for this phenomenon may be related to the influence of muscle fiber length on system dynamics and the limited range of muscle activation. In the future research work, we will carry out more in-depth exploration on this issue.

V. Conclusion

Based on the equilibrium point hypothesis proposed in neuroscience and the concept of constraint force field proposed in previous research [12], this paper mainly focuses on how to construct a constraint force field when the precision of the mechanical structure is insufficient. We propose a co-optimization algorithm of muscle arrangement and activation. This algorithm will optimize the constant muscle activation to make the equilibrium center of the constraint force field coinciding with the target position again, so that the musculoskeletal system can move to the target position with high precision. Experiments results have demonstrated the effectiveness of the proposed algorithm in movement accuracy, noise robustness and generalization. In the future, we will further explore the online construction method of constraint force field, so that it can be helpful for applications of hardware system.

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