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A novel adaptive control of a human musculoskeletal arm model☆

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ABSTRACT

The paper proposes a novel adaptive control of the human musculoskeletal arm model in order to simulate reaching movements of the human upper extremity. The controller is based on a normalized radial basis function neural network, which takes the Actor-Critic structure. The normalized radial basis function neural network simultaneously approximates the policy function of the actor network and the value function of the critic network. An adaptive adjustment mechanism is dynamically established to realize the state space constructions. The approach could effectively overcome the curse of dimensionality caused by state space division and always keep the structure in an optimal state. The human arm model adopts a Hill-type model with two joints, six muscles. As a validation, numerical simulations are performed to achieve the reaching movements of the human upper extremity. The results show that the adaptive control can well instruct the human arm model to mimic the reaching movements.

1. Introduction

It is always the common desire of robotic researchers that the robots are able to perform all kinds of delicate and complex movements as human beings do. The United States, Europe, China and the other countries have put forward "brain plan" in succession to interpret and understand the function and mechanism of the brain. One of the research branch is to simulate or mimic the human natural movements by robotics. In fulfilling the mimic of human natural arm movements, it is necessary and important to know how the human brain activates and interacts with the specific muscles of the human arm. Furthermore, it is still an active topic to simulate the reaching movements through the human musculoskeletal arm model via an appropriate control.

Taking the human upper extremity lifting movement as an example, the process can be described as follow. Firstly, the brain determines the initial position, the final position and the trajectories. It should be noted that the trajectories are not necessarily unique. The human arm model may generate a realistic path with consuming the least effort. Then, the central nervous system (CNS) sends the appropriate signals to stretch the muscles and produce forces so as to drive the upper extremity reaching to the destination. The human arm model should take into account the basic anatomical characters, involving an assemblage of the rigid bodies as well as muscles. In the process, the key problem is to deal with

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the redundancy of the muscles. Finally, the brain may control and drive the upper extremity depending on the continual information feedback [1].

More than half a century ago, researchers began to study modeling of the human arm. Yu and his colleagues had presented a neural network-based dynamics model of a digital human arm in order to simulate the reaching movements of the human upper extremity. Their model was based on a Hill-type model, regarded as an assemblage of two rigid bodies connected by joints and muscles. The musculotendon contractions were activated via a low-pass filtering operation. A recurrent neural network approach was introduced to the dynamic model with real time numerical simulations [1]. Tahara and his colleagues developed a non-linear musculoskeletal redundant arm model to simulate the reaching movements of human upper extremity [2]. They explained the non-linear muscle properties acquired from physiological understandings. Tahara's non-linear musculoskeletal arm model was also a Hill-type model on the basis of the Arimoto's research. Arimoto and his colleagues described the relationship between the convergence performance and the desired position [3]. They suggested to use the damping shaping of each joint for the human-like reaching movements. In order to understand and describe how humans modulate the viscosity of the rotational joint, Gribble and his colleagues presented their observations in [4]. They revealed that the main contribution of the modulation of the joint impedance was the co-contraction of the agonist muscles and the antagonist muscles.

Thelen and his colleagues proposed a “computed muscle control” algorithm to make the musculoskeletal model moving to the target [5] along with desired trajectory. Their controller was the static optimization with feedforward and feedback controls. De Sapio and his colleagues designed a task-oriented control strategy to simulate goal-targeted human arm movements [6]. Yu and his colleagues presented a neural network based controller for their digital human arm model. Both the model and the controller could be trained in real time to finish reaching movements[1]. Jagodnik and his colleagues proposed a proportional derivative(PD) controller for the planar human arm model [7]. Thomas and his colleagues applied a PD control based on an Actor-Critic architecture for the human upper extremity [8]. Both the actor and the critic in the control used the same neural network. Dong and his colleagues [9,10] developed an adaptive sliding mode control for the human upper extremity with real time simulation. Zadravec proposed an optimal control method based on the minimum joint torque cost function [11]. The optimal hand trajectories were planned and muscles functioning constraints were modeled. However, Zadravec's method was much relied on the exact parameters of specific human arms. As a progress, Hadi Balaghi and his colleagues proposed an “adaptive optimal multi-critic based neuro-fuzzy controller” (AOMCNFC) to accomplish the reaching movement control of the human musculoskeletal arm model [12].

In this paper, a Hill-type human musculoskeletal arm model proposed by Huijie and Ray [1] is applied to achieve the reaching movement of the human upper extremity. Taking the Actor-Critic reinforcement learning structure, the adaptive controller is designed on the basis of the normalized radial basis function (NRBF) neural network. The updating mechanism is proposed to make the NRBF neural network dynamically realizing the state space construction as well as efficiently solving the “dimensionality disaster” problem which is easy to occur in the generalization of the state space. Therefore, the adaptive controller has the advantage to deal with the redundancy of muscles. Rest of paper is organized as follow. The human musculoskeletal arm model is presented in Section 2. The adaptive controller based on the normalized radial basis function (NRBF) neural network is detailed explained in Section 3. The numerical simulations and results of the reaching movement of the human upper extremity are illustrated in Section 4. Some conclusions and future work are given in the conclusion part.

2. The arm musculoskeletal model

The musculoskeletal arm model (showed in Fig. 1) constitutes of a rigid multi-body system with two joints (shoulder and elbow joints) spanned by a set of musculotendon actuators [1]. Considering the effects of gravity, the model may move in the vertical plane. The simplified 6 muscles includes 2 antagonist shoulder muscles acting across the shoulder joint, 2 antagonist elbow muscles acting across the elbow joint and 2 antagonist double-joint muscles acting across both the shoulder joint and the elbow joint [1].

2.1. Arm musculotendon dynamics

The arm model is a constrained 2-DOF mechanical-like manipulator system. A set of generalized coordinates q are used to describe the configuration of the model. The orientation of the model is defined by the joint angles of the generalized coordinates. The dynamic motion equation is expressed as

$$M(q)\ddot{q} + H(\dot{q}, q) + G(q) = T. \tag{1}$$

In (1), M(q) is the mass inertia matrix. q indicates vectors of two joint angles ($q = [q_1, q_2]^T$). $H(\dot{q}, q)$ and $G(q)$ are respectively the viscosity matrix and gravity matrix. The values of the inertial and other parameters can be found in [1].

$M(q), H(\dot{q}, q)$ and $G(q)$ are computed as follow

$$M(q) = \begin{bmatrix} m_1 l_{g1}^2 + m_2(l_1^2 + l_{g2}^2 + 2l_1 l_{g2} c_2) + I_1 + I_2 & m_2(l_{g2}^2 + l_1 l_{g2} c_2) + I_2 \\ m_2(l_{g2}^2 + l_1 l_{g2} c_2) + I_2 & m_2 l_{g2}^2 + I_2 \end{bmatrix}, \tag{2}$$

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