33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Control of Human Spine in Repetitive Sagittal Plane Flexion and Extension Motion Using a CPG based ANN Approach

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Abstract— **The complexity associated with musculoskeletal modeling, simulation, and neural control of the human spine is a challenging problem in the field of biomechanics. This paper presents a novel method for simulation of a 3D trunk model under control of 48 muscle actuators. Central pattern generators (CPG) and artificial neural network (ANN) are used simultaneously to generate muscles activation patterns. The parameters of the ANN are updated based on a novel learning method used to address the kinetic redundancy due to presence of 48 muscles driving the trunk. We demonstrated the feasibility of the proposed method with numerical simulation of experiments involving rhythmic motion between upright standing and 55 degrees of flexion. The tracking performance of the model is accurate to within 2° while reciprocal muscle activation patterns were similar to the observed experimental coordination patterns in normal subjects. The suggested method can be used to map high-level control strategies to low-level control signals in complex biomechanical and biorobotic systems. This will also provide insight about underlying neural control mechanisms.**

I. Introduction

Low back pain is a widespread disorder in industrialized countries. Based on epidemiological reports, 80% of the population faces this activity limitation at least once in their lifetime [1] which places tremendous human and economic costs to individuals and societies. Handling heavy loads, with fast trunk motions (i.e. movements with extreme trunk angular position, velocity and acceleration), repetitive movements, and awkward postures are some of the risk factors related to low back injuries. Hence, better understanding of the neuro-musculo-skeletal system performance would help us to recognize various abnormalities in spine behavior and assist us in a way to design the workplace to reduce the risk of injuries. For this purpose, we can use biomechanical models to investigate the consequences of various movement strategies for estimation of muscle forces and joint reaction forces affecting the spine [2].

The complexity of spinal models is partly due to kinematic and kinetic redundancies in the multi-link spinal system driven by multiple-muscles. In the literature, various optimization methods are often used to solve the kinematic and kinetic redundancies [3-5]. However, the difficulty with optimal control methods is the selection of an appropriate cost function used for solving the optimization problem. Different cost functions will produce significantly different results [6]. Recently, Nasseroleslami et al. [7] used a neuro-fuzzy network, and a special reward function which depends on the muscle moment arm to update its weights. In this approach, they could solve the kinetic redundancy problem while the error between actual and desired trajectories drives the neuro-fuzzy system. A yet unanswered question is the relative role of the feedback system and the optimization process which determines the muscle recruitment and human movement planning. Full-state feedback is not only unrealistic from neurophysiological viewpoint, but may also cause instability in presence of short and long delays. Therefore, a combination of feed-forward and feedback control using an internal model of the system may be closer to reality [4].

To answer these questions, we remark that there are evidences that the central pattern generators (CPGs) in spinal cord can produce rhythmic motion in vertebrate animals. In robotics literatures, the CPG is sometimes used to produce the desired trajectories for motion planning [2], [8-11]. In other applications, the CPG has been used to generate the control commands in functional electrical stimulation (FES) systems. In particular, Stites and Abbas [12] employed pattern generators and pattern shapers to drive a swinging leg. However, they did not use position or velocity feedback errors in the pattern generator system. Zhang [6] also used CPGs and neural networks in an FES application. In simulated experiments, he achieved normal walking patterns, but he did not deal with muscle redundancy.

The primary aim in this paper is to simulate the spine as a 3D pendulum driven by 48 muscle actuators during flexion and extension tasks in the sagittal plane. For this aim, we use CPG as it used in FES studies to activate muscles. Furthermore, based on reference [6], we will use artificial neural network (ANN) between muscle's model and CPG.

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This ANN plays the role of spinal interneurons. We also use a novel learning method to train the ANN for solving the kinetic redundancy problem. In next sections we will describe the details of the model, present the simulation results of oscillatory maneuvers and briefly discuss the results.

II. METHODS

A. Trunk model

A 3D inverted pendulum is considered to model the trunk. The model is constrained at L5-S1 with a ball and socket joint and controlled with 48 muscles actuators [13]. The dynamic equation of the trunk is as follows:

$$J_1\dot{W} = -WWJ_1W + N_{input} - G(\theta) \tag{1}$$

where $J_1, WW, W, N_{input}, \theta$ and $G(\theta)$ are inertia matrix, skew symmetric matrix corresponding to W, angular velocity in the body coordinate system, net muscular torque around L5-S1, angular position vector and the moment vector from gravity, respectively [13].

B. Muscle model

We use the popular Hill-type muscle model, as described by:

$$f = f_{\max}(a.f_l(l).f_v(\dot{l}) + f_p(l)) \tag{2}$$

where a is the muscle activation, l is muscle length, $\dot{l}$ is contraction velocity, f_l is force-length relationship, f_v is force-velocity relationship, f_p is muscle passive force function, and $f_{\max}$ is the maximum muscle force which can be calculated by multiplying Physiological Cross Section Area (PCSA) with maximum muscle stress.

C. CPG model

Experimental observations have shown that there are neural circuits in the spinal cord known as central pattern generators (CPGs) [8]. CPGs can generate motor primitives from high level commands that lead to a high dimensional muscle recruitment pattern. When a CPG is utilized as part of an FES control, it provides phase, frequency, and amplitude which are necessary for generating a desired motion [6].

In the literature, we can find various mathematical models of the CPG [14-16]. Among them, Matsouka's model [16] is widely used [6], [17], [18]. For our purpose Matsouka's model is adopted due to its simple structure to facilitate implementation. The model consists of two neurons: one drives the flexor and the other drives the extensor; these neurons have a self and mutual inhibitory interaction. Mathematically, the model can be written as follows:

$$\begin{aligned}
\tau_1\dot{x}_1 &= -x_1 - \beta v_1 - hy_2 + c + Le \\
\tau_2\dot{v}_i &= -v_1 + y_1 \\
\tau_1\dot{x}_2 &= -x_2 - \beta v_2 - hy_1 + c - Le \\
\tau_2\dot{v}_2 &= -v_2 + y_2
\end{aligned} \tag{3}$$

where

$$\boldsymbol{y}_1 = \max(\boldsymbol{x}_1, 0)$$
$$\boldsymbol{y}_2 = \max(\boldsymbol{x}_2, 0)$$
$$\boldsymbol{y}_{out} = \boldsymbol{y}_1 - \boldsymbol{y}_2$$

In the above equations, x_1, v_1, x_2, and v_2 are the internal states of the oscillators and $\boldsymbol{y}_{out}$ is the CPG output. τ_1 and τ_2 are the time constants, c is tonic input, L is feedback gain, e is sensory feedback, and finally h and β represent the mutual and self inhibitory parameters, respectively. To have a rhythmic oscillation, the ratio between τ_1 and τ_2 must be in the range of 0.1-0.5 [19]. If we choose L large enough, it will guarantee that the oscillator frequency will entrain with sensory feedback [6]. We should pre-set the CPG frequency according to the motion frequency. Moreover, its frequency can be calculated using the following equation [20]:

$$f = \frac{1}{2\pi}\sqrt{\frac{1 + (\frac{\beta}{h} - 1)(\frac{\tau_1}{\tau_2} + 1)}{\tau_1\tau_2}} \tag{4}$$

Based on reference [10], one oscillator is used per degree of freedom. In our work, since the desired motion is in the sagittal plane, we designed an oscillator for the flexion angle. For the other two DOFs, we set zeros as the CPG output.

D. Artificial neural networks

There are complicated circuitries and interneurononal connections between the CPG and motoneurons [6] that can be simulated by ANN's [6]. A radial basis function (RBF) neural network is proposed for this purpose [6], with a different learning method inspired form Nasseroleslami's formulation [7] to deal with redundancy problem.

To accomplish our aim, for each muscle we consider an RBF neural network. As a result, we have 48 sub networks in total. CPG output is fed to each sub network, and we calculate the outputs according to the following equation:

$$\alpha_i = \sum_{j=1}^{m} w_{ij}\phi_{ij} \tag{5}$$

where

$$\phi_{ij} = \exp(-\frac{(yout - c_{ij})^2}{2\sigma_{ij}^2})$$

α_i represents the muscle activation, ϕ_{ij} is the membership function of the hidden neurons, w_{ij} is the weight of membership functions, $yout$ is the CPG output, c_{ij} is the center of the Gaussian functions, σ_{ij} represent the variances, i is the muscle index, and j represents the number of hidden neurons in the second layer.

Now ANN must be trained to achieve a satisfactory control. So we consider the following cost function:

$$E = E_e + E_\alpha = \frac{1}{2}k_e(r_e)^2 + \frac{1}{2}k_\alpha(r_\alpha)^2 \tag{6}$$
$$E = \frac{1}{2}k_e(h_1 e + h_2 \dot{e})^2 + \frac{1}{2}k_\alpha(\alpha)^2$$

where e is the error between desired and actual trajectory, $\dot{e}$ is the rate of error, α is the muscle activation, and finally k_e, and k_α are selected to normalize the values.

Selection of the center values is the vital first step in RBF neural networks. The Gaussian function's center and variance, as well as their weights will be updated. Updating the parameters are done as follows:

$$W_i(k+1) = W_i(k) - \eta\frac{\partial E}{\partial W_i} \tag{7}$$
$$\sigma_i(k+1) = \sigma_i(k) - \eta\frac{\partial E}{\partial \sigma_i}$$
$$u_i(k+1) = u_i(k) - \eta\frac{\partial E}{\partial u_i}$$

On the other hand, because J is a function of muscles moment arm, it can be used to resolve the redundancy in musculoskeletal system, based on muscles configuration. J can be calculated as follows [9]:

$$J_{iK} = \frac{\partial\theta_K}{\partial\alpha_i} = \frac{\partial\theta_K}{\partial M_K}\cdot\frac{\partial M_K}{\partial f_i^{active}}\cdot\frac{\partial f_i^{active}}{\partial\alpha_i} \propto d_{iK}.PCSA_i \tag{8}$$

where d_{ik} is the moment arm of the i^{th} muscle around the k^{th} direction, and $PCSA_i$ is the muscle physiological cross sectional area.

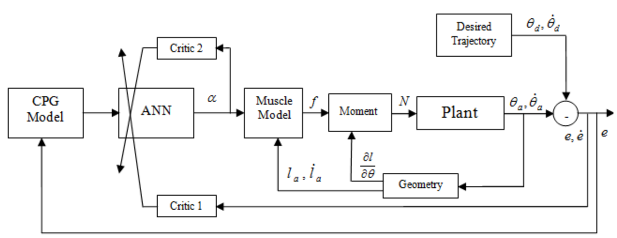

Fig. 1. Schematic diagram of the control algorithm.

E. Computational algorithm

Muscle length can be calculated based on its insertion and origin, while its insertion changes instantaneously according to angular position. Muscle velocity is computed by derivative of the muscle length with respect to time. Consequently, muscle moment arm can be described by the following equation:

$$\frac{\partial l}{\partial\Theta} = \begin{bmatrix}\frac{\partial l}{\partial\psi} & \frac{\partial l}{\partial\varphi} & \frac{\partial l}{\partial\theta}\end{bmatrix}^T = \begin{bmatrix}\frac{\partial l}{\partial\theta_1} & \frac{\partial l}{\partial\theta_2} & \frac{\partial l}{\partial\theta_3}\end{bmatrix}^T \tag{9}$$

Control algorithm, as depicted in Fig. 1, consists of two parts: feed-forward and feed-back paths.

Feed-forward path: CPG produces basic information like amplitude, phase, and motion frequency. Its output feeds ANN. Then, muscle dynamics is driven with ANN's output. Finally, muscles output act as actuators to control the trunk motion.

Feed-back path: in this stage, error between desired and actual trajectories is fed to CPG to adjust its frequency based on the error frequency. In fact, CPG entrains with error which is the main CPG's characteristic. In addition, combination of the error feedback and muscle's activation are used in the cost function. In this strategy, we can obtain the updating rule for Gaussian function parameters.

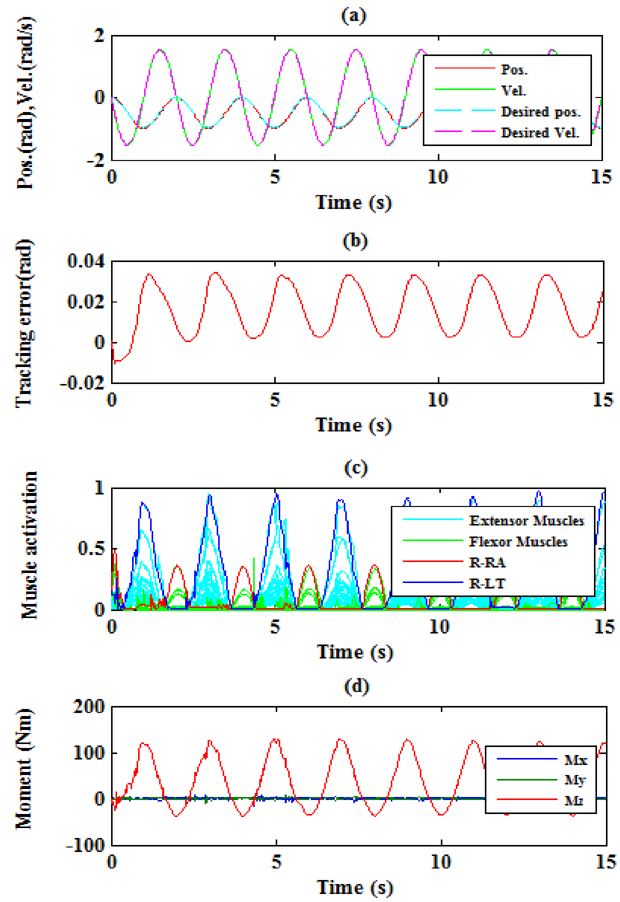

Fig. 2. (a) Desired and actual position and velocity profiles, (b) muscles activation profile: R-RA and R-LT are abbreviations for right Rectus Abdominus and right Longissimus Thoracis, respectively, (c) moment profile around joint, (d) and profile for flexion and extension motion in sagittal plane.

III. Results and Discussion

We have simulated an oscillatory movement between 0 to 55° with a frequency of 2 Hz. The activations of flexor and extensor muscles are shown in Fig. 2c. As we can see in this figure, the amplitude of extensor muscle activations is much larger than the flexor muscle activations because we have modeled gravity in our simulation. Furthermore, the flexor and extensor activations are in phase while they are anti phase with each other; indeed, when the flexor muscles are active, the extensor muscle must be inactive, and vice versa. Fig. 2a illustrates a very good tracking performance of the system. The maximum error between the simulated and desired angular position is 0.035 rad (see Fig. 2b). Therefore, our system has accomplished a satisfactory performance which can be further optimized by adjusting the free parameters.

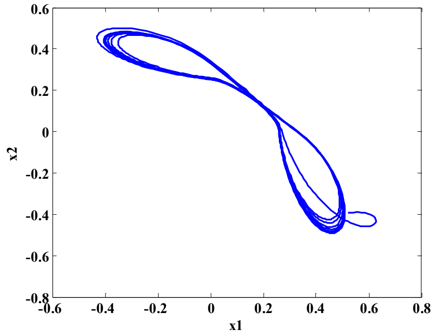

Fig. 3. Limit cycle of oscillator in phase space.

The oscillator limit cycle has been depicted in Fig. 3. It shows that the CPG has a stable limit cycle. Furthermore, it means motor primitives and the stability of the patterns contribute to tracking performance of the controller while kinetic redundancy has been resolved as well.

Previous methods, which consider CPG in their models [6], [12], [17] must separate the flexor and extensor muscles from each other. The CPG model sends the signal to each of them separately. However, in our model, the CPG sends a signal for all muscles. Furthermore, we do not need to separate the flexors and extensors from each others because our learning method can predict the relative activities of the muscles. In addition, the system keeps the flexor muscles in phase with each other and out of phase with the extensor muscles. It is possible to include the stability constraints to promote co-activation to satisfy the required joint impedance in light of possible perturbation in the system. Since learning methods are dependent on muscle moment arms and their cross sectional area, muscles activation levels were different among agonist muscle groups and it is confirmed with the observed normal behavior of the muscles [3].

Although we have provided the preliminary results of a mathematical model that entails setting of a large number of parameters, we see promising similarity in comparison to experimental findings in the literatures [21-22]. We have designed additional experiments that tests the muscle recruitment patterns and movement profiles for point to point and repetitive trunk planar and complex movements with different cycle time, range of motion and directions. The similarity of predictions under similar boundary conditions gives additional confidence about feasibility of the complex mathematical model.

Some of the limitations of our model emerge from the simplifications. We have ignored some DOFs of the trunk model and further assumed that the whole system acts as an inverted pendulum. Passive tissues were not considered in the model and the joint was considered as ball and socket while in real systems, the translational degrees of freedom should be considered as well. These limitations shall be eliminated in future to yield a more realistic model.

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