Spontaneous generation of anti-gravitational arm motion based on anatomical constraints of the human body

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Abstract

A neuro-musculo-skeletal model of human upper limb is constructed that can spontaneously generate natural reaching motion without prior formation of an optimal trajectory. Given a goal position, the model immediately generates muscular activation signals that tend to move the hand to the goal, utilizing the anatomical constraints of the body motion. The simulated motions agree with those of humans, suggesting that such mechanism may be incorporated in actual human motor control.

1. Introduction

It is generally accepted that human well-practiced movement is generated along a priorly planned trajectory that minimizes a certain objective function such as hand position jerk or rate of change of joint torque[1,2]. In order to generate appropriate muscle stimulation signals for an optimally planned hand trajectory, an inverse-dynamics problem of the musculo-skeletal system should be solved in the brain[3]. Humans, however, can also generate reasonable motions, even for natural unconcerned gesture or inexperienced motion, in which we can not assume formation of an optimal trajectory based on an objective function.

Human motion seems to be generated not to resist against the anatomical constraints of the human body, such as limb kinematics, inertial properties of limbs, range of joint motion, muscle size and attachment and so on. Such body constraints may be utilized so as to spontaneously induce casual movement. Based on this hypothesis, in this study, we attempt to develop a neural network model that can spontaneously generate natural reaching motion toward a target. An inexperienced targeted reaching movement can be regarded as an example of natural, casual motion.

2. Model

2.1 Musculo-skeletal model

Human mimetic musculo-skeletal model is constructed as two-dimensional three rigid links representing upper arm, fore arm and hand in a sagittal plane as shown in Figure 1. The equations of motion of the three rigid-link system are derived as

$$\mathbf{M(q)\ddot{q}} + \mathbf{h(\dot{q},q)} + \mathbf{g(q)} - \alpha\mathbf{(q)} + \beta\mathbf{(\dot{q})} = \mathbf{T} \tag{1}$$

where $\mathbf{q}$ is a (3 × 1) vector of joint angles, $\mathbf{T}$ is a (3 × 1) vector of joint torques caused by contraction of muscles, $\mathbf{M(q)}$ is a (3 × 3) inertia matrix, $\mathbf{h(\dot{q},q)}$ is a (3 × 1) vector of torque component depending on Coriolis and centrifugal force, and $\mathbf{g(q)}$ is a (3 × 1) vector of torque component depending on the gravity respectively, elements of which are functions of parenthesized variables. $\alpha\mathbf{(q)}$ and $\beta\mathbf{(\dot{q})}$ are (3 × 1) vectors of the torques exerted by the joint elastic and viscous elements, which defines the passive resistive torques due to joint capsules and ligaments, restricting ranges of joint motions. The inertial parameters of each segment are determined so as to be equivalent to those of actual human. The joint elastic and viscous elements are represented by the following double-exponential function[4] and the linear viscous elements:

$$\alpha_j = k_1 \exp(-k_2(q_j - k_3)) - k_4 \exp(-k_5(k_6 - q_j)) \tag{2}$$
$$\beta_j = c_j \dot{q}_j \tag{3}$$

where α_j and β_j are the torques exerted by elastic and viscous elements around the j th joint (the j th element of $\alpha\mathbf{(q)}$ and $\beta\mathbf{(\dot{q})}$), q_j is the j th joint angle, and $k_{1\sim6}$ and c_j are coefficients (see Table 1), respectively.

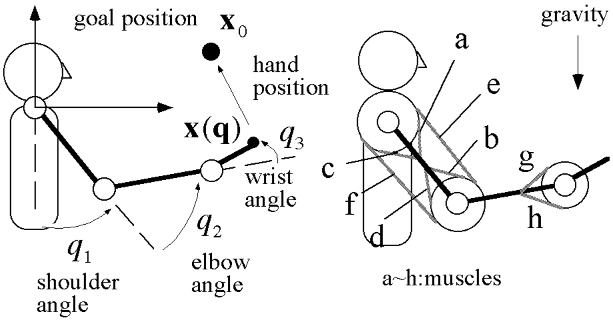

Figure 1. Musculo-skeletal model

Table1. Joint parameters

Joint	k_1	k_2	k_3	k_4	k_5	k_6	c
Shoulder	1.	2.16	-0.12	1.	3.35	2.02	1.6
Elbow	1.	3.96	0.70	1.	3.14	1.73	0.8
Wrist	1.	2.04	-0.76	1.	2.40	0.83	0.5

On each upper extremity, total of 8 muscles are considered including biarticular muscles as shown in Figure 1. Moment arms of the muscles are assumed to be constant irrespective of joint angles. The joint torque vector $\mathbf{T}$ can be expressed as

$$\mathbf{T} = -\mathbf{G}^T \cdot \mathbf{F} \tag{4}$$

where $\mathbf{F}$ is a (8 × 1) vector of muscle forces, and $\mathbf{G}$ is a (8 × 3) matrix of the moment arms. Each muscle generate force according to muscle activation a_m by the following muscle model[5]:

$$\begin{aligned} f_m &= \bar{f}_m \cdot k(\xi_m) \cdot h(\eta_m) \cdot a_m \\ k(\xi_m) &= 0.32 + 0.71\exp\{-1.11(\xi_m - 1)\}\sin\{3.72(\xi_m - 0.66)\} \\ h(\eta_m) &= \{1 + \tanh(3.0\eta_m)\} \end{aligned} \tag{5}$$

where m is muscle number, f_m is muscle force, $\bar{f}_m$ is the maximum muscle force, L_m is muscle length, $\bar{L}_m$ is the optimal muscle length, $\dot{L}_m$ is muscle shortening velocity (positive for stretching), $\bar{\dot{L}}_m$ is the maximum muscle velocity (=3.0m/s), ξ_m is the normalized muscle length $L_m / \bar{L}_m$, η_m is the normalized muscle velocity $\dot{L}_m / \bar{\dot{L}}_m$, $k(\xi_m)$ is the force-length relationship, and $h(\eta_m)$ is the force-velocity relationship, respectively. Muscle activation dynamics are modeled by the following equation:

$$\tau(da_m / dt) = -a_m + y_m \tag{6}$$

where y_m is a motor command to the muscle from the nervous system, τ is the muscle activation time constant (=0.07sec). Musculo-skeletal parameters, such as moment arms and maximum muscle forces are determined by literature so as to be equivalent to those of actual human.

2.2 Nervous model

2.2.1 Motion generating principle

In this study, motion is generated based on the following pseudo-potential P, the minimum point of which is the goal position, $\mathbf{x}_0$, represented in the spatial coordinate.

$$P = (\mathbf{q} - \mathbf{q}_0)^T \mathbf{W}(\mathbf{q} - \mathbf{q}_0) \tag{7}$$

where $\mathbf{q}_0$ is the joint angles of the limb when the goal position $\mathbf{x}_0$ is reached, $\mathbf{W}$ is a (3 × 3) positive definite weight matrix. In order to generate motion based on this potential, the muscles need to generate joint torques satisfying the following equation:

$$\mathbf{T} = \mathbf{W}(\mathbf{q}_0 - \mathbf{q}) - \alpha(\mathbf{q}) + g(\mathbf{q}) \tag{8}$$

It is theoretically confirmed that such system is stable because of the viscous property of the joints[6].

2.2.2 Recurrent neural network model

In order to generate joint torques by Equation (8), $\mathbf{q}_0$ has to be estimated from the goal position $\mathbf{x}_0$, which is represented in the spatial coordinate provided by the visual system. However, because the number of degrees of freedom of joint angles exceeds that of the two-dimensional spatial coordinate system, there are infinitely many combinations of joint angles to point the same position. Here we consider to utilize the dynamics of a recurrent neural network[7] to spontaneously transform spatial position into joint angles. In order to construct a recurrent neural network that can autonomously estimate the joint angles from present hand position, the following potential function $I_\mathbf{u}$ is defined:

$$\begin{aligned} I_\mathbf{u} &= \delta\Big(\sum_j \int_{\bar{q}_j}^{u_j} -\alpha_j(\theta)d\theta + \sum_i -m_i \bar{\mathbf{g}}^T \cdot \mathbf{r}_i^g(\mathbf{u})\Big) \\ &+ \frac{\kappa}{2}\{\mathbf{J}(\mathbf{u})(\mathbf{u}-\mathbf{q}) - (\mathbf{x}_0 - \mathbf{x})\}^T \{\mathbf{J}(\mathbf{u})(\mathbf{u}-\mathbf{q}) - (\mathbf{x}_0 - \mathbf{x})\} \end{aligned} \tag{9}$$

where $\mathbf{u}$ is the neural representation of joint angles, u_j is the j th element of $\mathbf{u}$, $\bar{q}_j$ is the angle when $\alpha_j = 0$ (neutral posture), m_i is the mass of the i th segment, $\mathbf{r}_i^g$ is a (2 × 1) vector of center of gravity of the i th segment, $\bar{\mathbf{g}}$ is the gravitational acceleration vector, $\mathbf{J}(\mathbf{u})$ is the Jacobian matrix at $\mathbf{u}$, and δ and κ are coefficients. The first and second terms represent total potential energy stored in the musculo-skeletal system of the upper limb. The third term denotes a penalty for not satisfying a constraint $\mathbf{J}(\mathbf{u})(\mathbf{u}-\mathbf{q}) - (\mathbf{x}_0 - \mathbf{x}) = \mathbf{0}$, which decreases as the hand position $\mathbf{x}(\mathbf{u})$ approaches to $\mathbf{x}_0$. The recurrent neural network which autonomously decrease the potential $I_\mathbf{u}$ can be expressed as

$$\begin{aligned} d\mathbf{u}/dt &= -\mu(\nabla_\mathbf{u} I_\mathbf{u}) \\ &= -\mu\Big\{\delta(-\alpha(\mathbf{u}) + \mathbf{g}(\mathbf{u})) + \kappa\mathbf{J}^T\{\mathbf{J}(\mathbf{u})(\mathbf{u}-\mathbf{q}) - (\mathbf{x}_0 - \mathbf{x})\}\Big\} \end{aligned} \tag{10}$$

where μ is a coefficient. According to the change in $\mathbf{u}$ represented in the nervous system, the nervous system then calculates neural representation of joint torques, $\mathbf{N}$, according to Equation (8) as

$$\mathbf{N} = \mathbf{W}(\mathbf{u}-\mathbf{q}) - \alpha(\mathbf{q}) + \mathbf{g}(\mathbf{q}) \tag{11}$$

In this study, it is assumed $\mathbf{W} = w\mathbf{I}$, where $\mathbf{I}$ is a (3 × 3) unit matrix, and w is a coefficient.

Since number of muscles exceeds number of joint degrees of freedom, another layer of recurrent neural network is constructed for estimation of appropriate muscle activation signals from $\mathbf{N}$, assuming the following potential function:

$$I_{\mathrm{v}} = \xi \mathbf{v}^T\mathbf{v} + \frac{\kappa'}{2}(-\mathbf{G}^T\mathbf{F}-\mathbf{N})^T(-\mathbf{G}^T\mathbf{F}-\mathbf{N}) \tag{12}$$

where $\mathbf{v}$ is the (8 × 1) vector of the inner states of motoneurons, and ξ and κ' are coefficients. The first term represents the sum of square of v_m, and the second term denotes a constraint that $\mathbf{N}$ is equal to the summation of the muscular forces. The recurrent neural network which autonomously decrease the potential I_{v} can be expressed as

$$\begin{aligned} d\mathbf{v}/dt &= -\mu'(\nabla_{\mathrm{v}} I_{\mathrm{v}}) \\ &= -\mu'\left\{2\xi\mathbf{v} - \kappa'(\mathbf{G}^T\overline{\mathbf{F}})^T(-\mathbf{G}^T\mathbf{F}-\mathbf{N})\right\} \end{aligned} \tag{13}$$

$$y_m = \max(2/(1+\exp(-3v_m)-1, 0) \tag{14}$$

where $\overline{\mathbf{F}} = diag[\bar{f}_1, \bar{f}_2, \bar{f}_3, \bar{f}_4, \bar{f}_5, \bar{f}_6, \bar{f}_7, \bar{f}_8]$, y_m is the motor command to the mth muscle, value of which is restricted from 0 to 1 by the output function (14), and μ' is a coefficient.

By incorporating the potential described by Equation (12), Equation (10) can be rewritten as

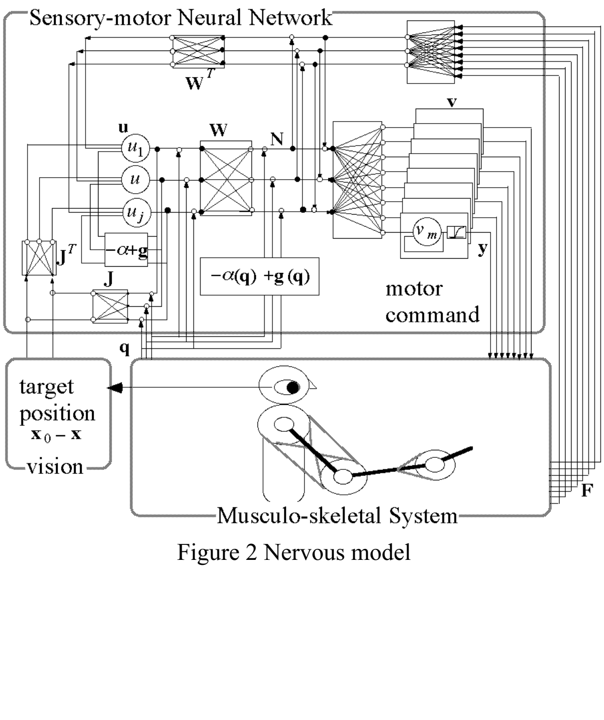

Figure 2 Nervous model

$$\begin{aligned} d\mathbf{u}/dt = -\mu\{&\delta(-\alpha(\mathbf{u})+\mathbf{g}(\mathbf{u})) \\ &+\kappa\mathbf{J}^T\left\{\mathbf{J}(\mathbf{u})(\mathbf{u}-\mathbf{q})-(\mathbf{x}_0-\mathbf{x})\right\} - \lambda\mathbf{W}^T(-\mathbf{G}^T\mathbf{F}-\mathbf{N})\} \end{aligned} \tag{10*}$$

where λ is a coefficient.

Figure 2 shows a schematic diagram of the neural network model. Given the visual information regarding a goal position, $\mathbf{x}_0 - \mathbf{x}$, the neural network model produces muscle activation signals that tends to minimize the potential defined by Equation (9) and (12), and motion is generated. Then the resultant motion (joint angles $\mathbf{q}$ and muscle forces $\mathbf{F}$) is returned back continuously to the nervous system through proprioceptors. Thus the entire neuro-musculo-skeletal systems are mutually integrated, and motion that is naturally affected by the structure and properties of the musculo-skeletal system can be generated.

In this model, the joint torques due to the joint elasticity and the gravity seems to be compensated as Equation (11), but because of the time lag or delay in the neuro-dynamics, generated motions are actually affected by them passively.

3. Simulation Method

Motion towards a given goal position $\mathbf{x}_0$ from an initial posture at $t = 0$ can be calculated by numerically integrating Equations (1,6,10*,13), which are expressed as 25 simultaneous differential equations. In order to solve this initial-value problem, we use the fourth-order Runge-Kutta method for numerical integration, for a time interval of 0.005sec. All programs are written in C language on an engineering workstation (HP C160).

The coefficients, $\mu, \delta, \kappa, w, \mu', \gamma, \kappa', \lambda$, are determined as 0.01, $500/(t+1)^2$, $800(t+1)^2$, 10 (4 for downward motion), 0.02, 25, 5, and 100, respectively, so that the human-like motion can be generated. The values of δ and κ are represented as functions of time, because $d\mathbf{u}/dt$ (Equation(10*)) becomes zero before the hand reaches to the goal, especially when motion opposes the joint property and/or the gravity.

4. Results

Figure 3 shows the stick figures of the simulated reaching motions for two different combinations of initial and goal positions. A dot in each stick diagram represents a goal position, and an arrow indicates direction of motion. The generated trajectories are compared with the actually measured trajectories, represented by series of white circles in the figure. The attached graphs compare the joint angles (JA) and tangential speed of hand (tan sp) for each simulated and actually

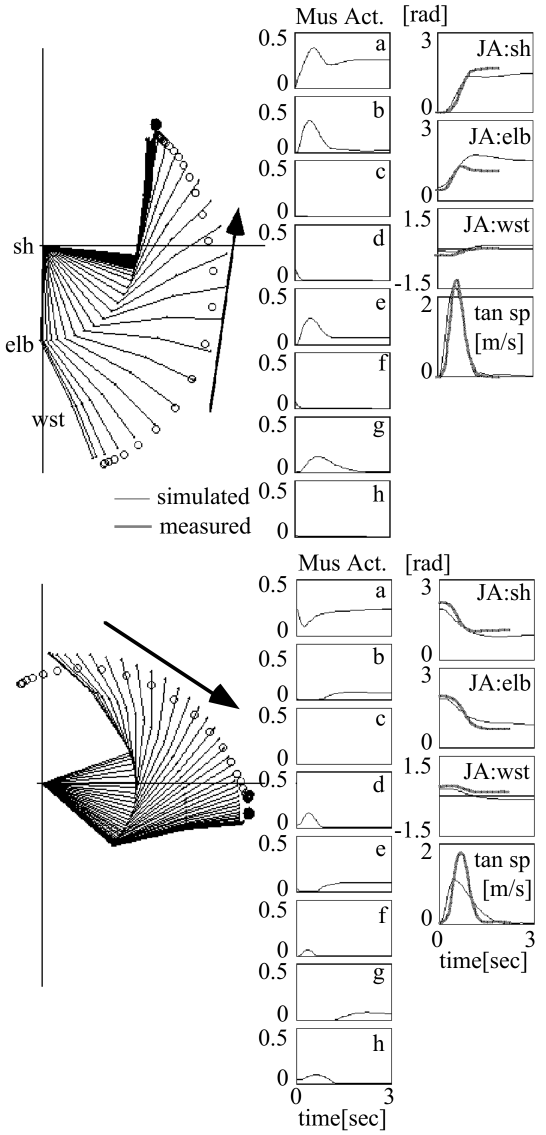

Figure 3. Generated anti-gravitational motions

measured motions. The muscle activations a_m (Mus Act) are also presented.

Figure 3 demonstrates that the proposed model can successfully generate anti-gravitational reaching motions similar to those of actual humans. The minimum hand jark model[1] predicts linear trajectories for these motions, but the proposed model could successfully generate curved paths, not going against structural restrictions of the body due to the passive joint properties and the gravitational effect. The tangential speed profile also becomes a bell-shaped curve. The muscle activation profiles are smooth and not contradicting to the motions, indicating that muscles are reasonably utilized.

5. Discussions

In this study, anatomical constraints of the musculo-skeletal system are assumed to be represented as potential functions; by utilizing the neural dynamics of the proposed network, the redundancy problem in motor coordination is solved and structurally reasonable motions are spontaneously generated. Complex musculo-skeletal structure of the human body is often regarded as constraints or perturbations which must be technically compensated for intended motion control. This study implies that the anatomical constraints can be turned into advantage, and may be utilized for inducing structurally reasonable motion. Such structurally adapted motion may be energetically reasonable as well. Optimality of human movement seems to be collaterally emerged as a consequence of motion generation based on the body structure.

In this study, the structurally adapted motions are not generated by explicit control based on a priorly planned optimal trajectories, but continuously emerged due to attractor dynamics. Because of the mutual interactions among the entire neuro-musculo-skeletal systems, the integrated system becomes a gradient system, attractor of which is an equilibrium point defining a goal position and all state variables behave autonomously as if a ball slides down a valley to its bottom. Therefore, reasonable motion can be spontaneously generated without explicit optimization.

Synthesis of human motion generally requires massive computational power for solving an optimization problem. This model, however, can generate almost real time movement by using an engineering workstation, indicating its possible future application in motion synthesis of a computerized mannequin for evaluation of human interaction with system or environment.

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