A Novel Muscle Coordination Method for Musculoskeletal Humanoid Systems and Its Application in Bionic Arm Control

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Abstract. The muscle force control of musculoskeletal humanoid system has been considered for years in motor control, biomechanics and robotics disciplines. In this paper, we consider the muscle force control as a problem of muscle coordination. We give a general muscle coordination method for mechanical systems driven by agonist and antagonist muscles. Specifically, the muscle force is computed by two steps. First, the initial muscle force is computed by pseudo-inverse. Here, the pseudo-inverse solution naturally satisfies the minimum total muscle force in the least squares sense. Second, the initial optimized muscle force is optimized by taking the optimization criteria of distributing muscle force in the middle of its output force range. The two steps provide an even-distributed muscle force. The proposed method is validated by a movement tracking of a bionic arm which has 5 degrees of freedom and 22 muscles. The force distribution property, tracking accuracy and efficiency are also tested.

Keywords: Muscle Force Computation, Arm Movement Control, Redundancy Solution.

1 Introduction

Several research works in different disciplines have been distributed in order to understand the muscle control of the musculoskeletal humanoid systems. The initial scientific works in human motor control consider the muscle control as coordination of sensor input and motor output. The sensor-motor coordination is explained by modeled central nervous system [1]. Later, the muscle control is dealt with in biomechanics. Here, the basic idea is building an accurate muscle model, setting all the constraints in muscle space and joint space (such as force limit, motion boundary, time delay etc.) and using global optimization to solve the problem as a whole [2][3]. As the global optimization is computationally very exhaustive task, parallel computation is introduced to reduce the computational time [4]. There have been two successful commercial software packages to simulate human movement: AnyBody Modeling System by AnyBody Technology and SIMM by MusculoGraphics. Recently, with the development of artificial muscle

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technology, many muscle-like actuators are available, such as cable-driven actuator, pneumatic actuator, and so on. By using these new actuators, robotic researchers built a number of musculoskeletal humanoid robots, such as ECCE from University of Zurich, Kenshiro from University of Tokyo, Lucy from Vrije Universiteit Brussel, etc. These robots provide physical platforms to emulate muscle force control of musculoskeletal systems. However, the control of these musculoskeletal humanoid system is still under development. Regarding the coincidence with electromyogram (EMG) measurement, there has been one paper written by Anderson and Pandy, stating that the muscle force curve computed by the global optimization looks similar with the real EMG measurement when doing extreme movement of high jumping [4].

Actually, the muscle force control can be considered as muscle coordination. As there exists redundancy in joint space, muscle space and impedance space, the solution of the muscle coordination is not unique [5]. Based on different criteria, the muscle coordination solutions are different. For example, Pandy considered the criterion of the minimum of the overall energy-consuming of muscles[3]. Dong et al. chose the criterion to be “anti-fatigue”, i.e., the load was distributed evenly among muscles [6]. If we only focus on the control performance without considering energy-consuming or force distribution, the problem is easier. In Tahara et al.’s research, the muscle force is distributed from computed joint torque. PD control is then used for each muscle’s control [7]. Actually, from the neuroscience research, the muscle force control is also influenced by the body movement patterns. The dynamics of the musculoskeletal system has order parameter which can determine the phase transition of movements. These scenarios are found in finger movement and limb movement patterns [8].

In this paper, we give a general muscle coordination method for mechanical systems driven by agonist and antagonist muscles. Specifically, the muscle force is computed by two steps. First, the initial muscle force is computed by pseudo-inverse. Here, the pseudo-inverse solution naturally satisfies the minimum total muscle force in the least squares sense. Second, the initial optimized muscle force is optimized by taking the optimization criteria of distributing muscle force in the middle of its output force range. The two steps provide an even-distributed muscle force. The proposed method is validated by a movement tracking of a bionic arm which has 5 degrees of freedom and 22 muscles. The force distribution property, tracking accuracy and efficiency are also tested.

2 Muscle Coordination

2.1 Pseudo-inverse in Initial Muscle Force Computation

In this subsection, we use pseudo-inverse to compute the initial muscle force. The input is the desired joint trajectory and muscle force boundary. The output is the minimum muscle force under the sense of least-squares. The basic idea is firstly creating a linear equation based on the description of the acceleration contribution in joint space and muscle space, respectively. Then the muscle activation level is calculated by solving the above linear equation. Finally, the muscle force is computed by scaling the muscle activation level with its corresponding maximum muscle force.

The general dynamic equation of the musculoskeletal systems can be written in the general form

$$H(q,t)\ddot{q} + C(q,t)\dot{q} + G(t) = f(F_m) \tag{1}$$

where $f(F_m)$ maps muscle force F_m to joint torque. Here, we transform it into the following form

$$\ddot{q} = \underbrace{H(q,t)^{-1} f(F_m)}_{\ddot{q}_\Gamma} + \underbrace{\left(-H(q,t)^{-1}(C(q,t) + G(t))\right)}_{\ddot{q}_{\Lambda\Xi}} \tag{2}$$

The above equations indicate that in the joint space, the acceleration contribution comes from 1): joint torque Γ, 2): centripetal, coriolis and gravity torque $\Lambda + \Xi$. Hence, we can compute the acceleration contribution from joint torque $\ddot{q}_\Gamma$ by Eq.2. Whereas, from another viewpoint, in the muscle space, each muscle has its acceleration contribution. Here, we assume the total muscle number is n_{muscle}. For the j-th $(1 \leq j \leq n_{muscle})$ muscle, its maximum acceleration contribution can be written as

$$\ddot{q}_{m,j,max} = H(q,t)^{-1} \Gamma_{j,max} \quad (1 \leq j \leq n_{muscle}) \tag{3}$$

where

$$\begin{aligned}
\Gamma_{1,max} &= J_m^T \left[F_{m,1,max}\ 0\ 0 \cdots\ 0\ 0\right]^T \\
\Gamma_{2,max} &= J_m^T \left[0\ F_{m,2,max}\ 0 \cdots\ 0\ 0\right]^T \\
&\cdots \\
\Gamma_{n_{muscle},max} &= J_m^T \left[0\ 0\ 0 \cdots\ 0\ F_{m,n_{muscle},max}\right]^T
\end{aligned}$$

By combining the above two computational ways of acceleration contribution in joint space and muscle space, we can build a linear equation

$$\left[\ddot{q}_{m,1,max}\ \ddot{q}_{m,2,max} \cdots \ddot{q}_{m,n_{muscle},max}\right]\left[\sigma_1\ \sigma_2 \cdots \sigma_{n_{muscle}}\right]^T = \ddot{q_\Gamma} \tag{4}$$

where $\left[\sigma_1\ \sigma_2 \cdots \sigma_{n_{muscle}}\right]^T$ is a vector of muscle activation levels. The muscle activation level is a scalar in the interval $[0,1]$, representing the percentage of maximum contraction force of muscle. It is noted that $\ddot{q}_{m,j,max}$ $(1 \leq j \leq n_{muscle})$ and $\ddot{q_\Gamma}$ are vectors. The dimensions of $\ddot{q}_{m,j,max}$ and $\ddot{q_\Gamma}$ are the same equaling to the joint number. Supposing the total joint number is n_{joint}, $\ddot{q}_{m,j,max}$ and $\ddot{q_\Gamma}$ can be written in the form

$$\ddot{q}_{m,j,max} = \begin{bmatrix} \ddot{q}_{m,j,1} \\ \ddot{q}_{m,j,2} \\ \vdots \\ \ddot{q}_{m,j,n_{joint}} \end{bmatrix}_{n_{joint}\times 1}, \quad \ddot{q}_\Gamma = \begin{bmatrix} \ddot{q}_{\Gamma,1} \\ \ddot{q}_{\Gamma,2} \\ \vdots \\ \ddot{q}_{\Gamma,n_{joint}} \end{bmatrix}_{n_{joint}\times 1} \tag{5}$$

Considering Eq.4, we can use pseudo-inverse to compute muscle activation level

$$\left[\sigma_1\ \sigma_2\ \cdots\ \sigma_{n_{muscle}}\right]^T = \left(\left[\ddot{q}_{m,1,max}\ \ddot{q}_{m,2,max}\ \cdots\ \ddot{q}_{m,n_{muscle},max}\right]\right)^+ \ddot{q}_\Gamma \tag{6}$$

where $(\cdot)^+$ is the pseudo-inverse of $(\cdot)$. Therefore, the muscle force can be calculated as a product of maximum contraction force and activation level

$$F_{m,ini} = \left[F_{m,1,max}\cdot\sigma_1\ \cdots\ F_{m,n_{muscle},max}\cdot\sigma_{n_{muscle}}\right]^T \tag{7}$$

2.2 Gradient Descent in Muscle Force Optimization

The computed initial muscle force $F_{m,ini}$ dose not consider the physical constraints of muscles, which are: 1) the maximum output force of muscle is limited; 2) muscle can only contract. Here, we use gradient descent to make muscle force satisfy the above constraints. The basic idea is to find a gradient direction in the null space of the pseudo-inverse solution obtained in Step 1 to relocate the initial muscle force $F_{m,ini}$ to an optimized state, which satisfies muscle constraints 1) and 2).

We assume each muscle force is limited in the interval from $F_{m,j,min}$ to $F_{m,j,max}$ for $1 \le j \le n_{muscle}$. Our objective is to find a gradient direction to make each muscle force $F_{m,j}$ equal or greater than $F_{m,j,min}$, and equal or less than $F_{m,j,max}$. Considering the muscle force boundary constraints, one possible way is to make the output force of each muscle be closest to the middle point between $F_{m,j,min}$ and $F_{m,j,max}$. The physical meaning of this method is to distribute overall load to all the muscles evenly where each muscle works around its proper working load. Based on this load distribution principle, the muscles can continually work for a long time. According to the above muscle force distribution principle, we choose a function h as

$$h\left(F_m\right) = \sum_{j=1}^{n_{muscle}} \left(\frac{F_{m,j} - F_{m,j,mid}}{F_{m,j,mid} - F_{m,j,max}}\right)^2 \tag{8}$$

where

$$0 \le F_{m,j,min} \le F_{m,j} \le F_{m,j,max},\ F_{m,j,mid} = \frac{F_{m,j,min} + F_{m,j,max}}{2}$$
$$j = 1, 2, \cdots, n_{muscle}$$

We define F_{in} as a vector representing the internal force of muscles generated by redundant muscles which has the same dimension with F_m. We calculate F_{in} as the gradient of the function h, i.e.,

$$F_{in} = K_{in}\ \nabla_h|_{F_{m,ini}} = K_{in} \begin{bmatrix} 2\frac{F_{m,ini,1}-F_{m,1,mid}}{F_{m,1,mid}-F_{m,1,max}} \\ 2\frac{F_{m,ini,2}-F_{m,2,mid}}{F_{m,2,mid}-F_{m,2,max}} \\ \vdots \\ 2\frac{F_{m,ini,n_{muscle}}-F_{m,n_{muscle},mid}}{F_{m,n_{muscle},mid}-F_{m,n_{muscle},max}} \end{bmatrix} \tag{9}$$

where K_{in} is a scalar matrix controlling the optimization speed. It is easy to prove that the direction of F_{in} points to $F_{m,i,mid}$. We map the internal force F_{in} into F_m space (i.e., pseudo-inverse solution's null space) as

$$g(F_{in}) = \left(I - \left(J_m^T\right)^+ J_m^T\right) F_{in} \tag{10}$$

where I is an identity matrix having the same dimension with muscle space. According to Moore-Penrose pseudo-inverse, $g(F_{in})$ is orthogonal with the space of $F_{m,ini}$. Finally, the optimized muscle force is calculated as

$$F_m = F_{m,ini} + g(F_{in}) \tag{11}$$

3 Evaluation

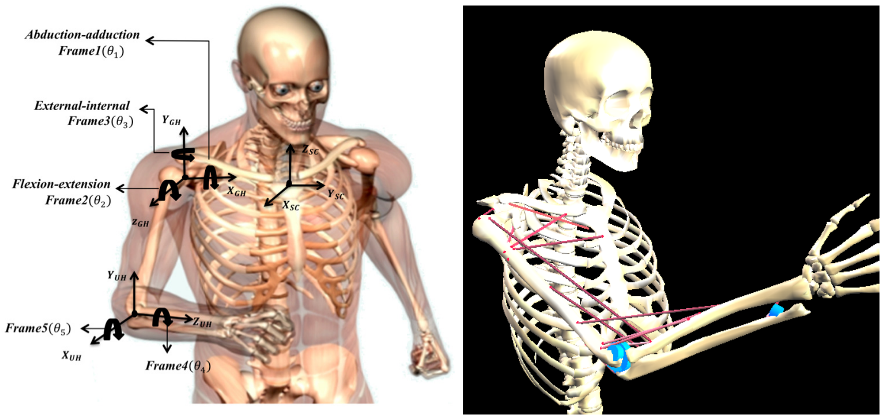
3.1 Bionic Arm Modeling

First of all, we define symbols for the convenience of derivation. $Rot(\theta, x)$, $Rot(\theta, y)$ and $Rot(\theta, z)$ are rotation matrices between different frames x, y, and z axis where θ is the rotation angle. $Trans(d_x, d_y, d_z)$ is transition matrix within a frame where d_x, d_y, and d_z are the transition distances in x, y, and z directions, respectively. T_i^j is the transfer matrix from frame i to frame j. In this simulation, we defined the frame 1 to 5 as shown in Fig.1 (a). Joint angles $[\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T$ are the rotational angles corresponding to Frame 1 to Frame 5, respectively. The range of shoulder angle is set as from -20 to 100 degrees, and the range of the elbow is set as from 0 to 170 degrees. Here, we use Muscular Skeletal Modeling Software (MSMS) [9] to create the virtual bionic arm, based on which, we make animation to evaluate the movement computed by the proposed method (Fig.1 (b)).

In the simulation, the bionic arm is composed of two parts: shoulder and elbow. In total, the model is composed of five rotational degrees of freedom (DOF) where three of them are in the shoulder joint (shoulder abduction-adduction, shoulder flexion-extension and shoulder external-internal rotation), and two are in the elbow joint (elbow flexion-extension and forearm pronation-supination). The parameters setting of the bionic arm is based on the real data of a human upper limb. The setting of length, mass, mass center position and inertia coefficients are from [10]. There are 22 muscles configured in the model. The specific configuration of the muscles, i.e., coordinate setting of the origins and insertions in the Gleno-Humeral joint coordinate system (X_{GH}, Y_{GH}, Z_{GH}), are from [11].

3.2 Performance

We used the above bionic arm model to test the proposed method. Without loss of generality, the desired trajectory of the five rotational joints is sine signal: amplitude: -1/3π; frequency: 1; phase: 0; bias: 1/3π. The maximum muscle force $F_{m,i,max}$ ($1 \leq i \leq 22$) is set as 100N. The total simulation time is set as 10s.



(a) (b)

Fig. 1. Bionic arm. (a) Frame setting of the bionic arm. (b) Snapshot of the arm movement in Muscular Skeletal Modeling Software (MSMS).

"Anti-fatigue" Force Distribution. As there are 22 muscles configured in this model, the result can provide an insight on the muscle force distribution. Fig.2 (a-b) show the computed muscle force in the initial pseudo-inverse step (Subsection 2.1) and in the optimized gradient descent step (Subsection 2.2), respectively. In each subfigure, the upper part is the muscle force distribution statistics. The horizontal axis is the muscle index and the vertical axis is the average percentage ratio of the specific muscle force amplitude to its corresponding maximum muscle force $F_{m,max}$. The lower part is the muscle force curves where the horizontal axis is, similarly, the muscle index and vertical axis is the simulation time. By comparing (a) and (b), we can see that the initial muscle force optimization provides large variance ($\sigma \doteq 0.04$) in muscle force. In contrast, the optimized muscle force gives smaller variance ($\sigma \doteq 0.02$) in muscle force.

Tracking Accuracy. We recorded the tracking error of the five joint angles. The tracking performance is shown in Fig.2 (c). The horizontal axis is the simulation time, from 0 to 10s. The vertical axis is the joint index, from q_1 to q_5 in rad. It shows that the tracking error for the five joints is within the range of 10^{-3} rad, indicating that the proposed method has a good tracking property.

Efficiency. The simulation environment is MacBook Air laptop. The basic configuration of the computer is listed below: processor: 1.7GHz Intel Core i5; memory: 4GB 1333 MHz DDR3; startup disk: Macintosh HD 200GB; operation system: Mac OS X Lion 10.7.4 (11E53). The computational time is shown in Fig.2 (d) where the horizontal axis is the time index representing simulation time (from 0 to 10s). Vertical axis is the accumulative computational time in s. It shows that the computational time is nearly linear which means the proposed method approximately consumes equal time to compute muscle force for different arm postures.

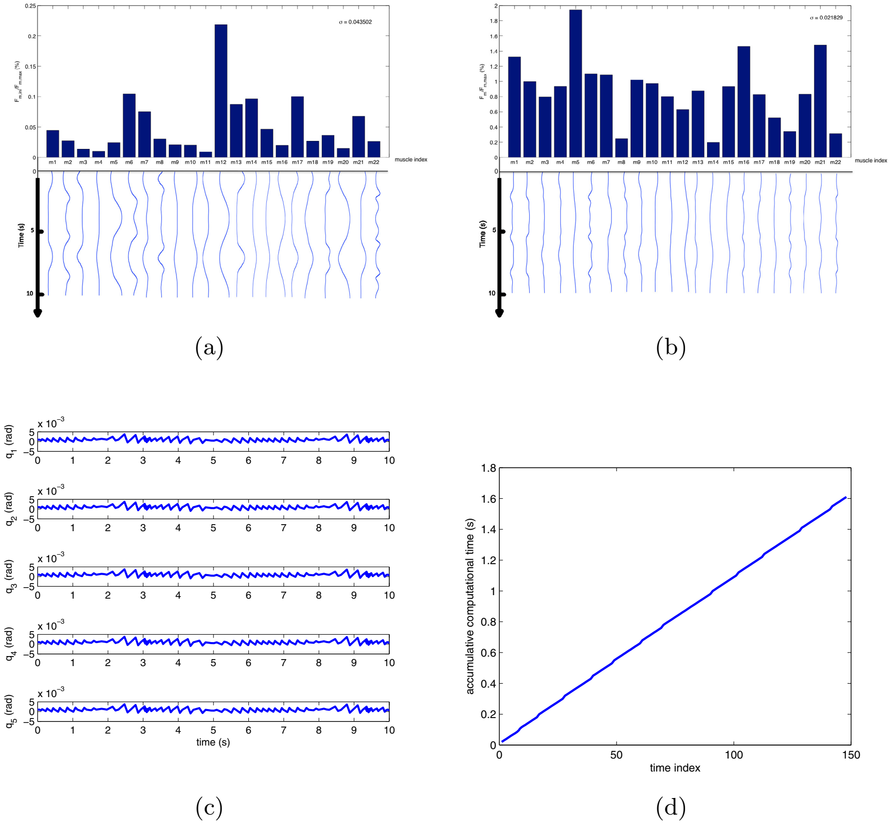


Fig. 2. Performance evaluation in force distribution, tracking accuracy and efficiency. (a)Initial muscle force distribution. (b) Optimized muscle force distribution. (c) Tracking error of the joints. (d) Accumulative computational time.

4 Conclusion

This paper gives a general solution for muscle force control of the musculoskeletal humanoid systems. The two steps of muscle force coordination compute the muscle force satisfying the muscle force constraints. The proposed method is tested by a bionic arm with 5 degrees of freedom and 22 muscles. The results show that the proposed method provides an evenly-distributed muscle forces efficiently.

References

1. Wise, S., Shadmehr, R.: Motor Control. In: Encyclopedia of the Human Brain, pp. 137–157 (2002)
2. Garner, B.A., Pandy, M.G.: A kenematic model of the upper limb based on the visible human project (vhp) image dataset. Computer Methods in Biomechanics and Biomedical Engineering 2, 107–124 (1999)
3. Pandy, M.: Computer modeling and simulation of human movement. Annual Review of Biomedical Engineering 3, 245–273 (2001)
4. Anderson, F., Pandy, M.: A dynamic optimization solution for vertical jumping in three dimensions. Computer Methods in Biomechanics and Biomedical Engineering 2, 201–231 (1999)
5. Yamaguchi, G.: Dynamic Modeling of Musculoskeletal Motion: A Vectorized Appoach for Biomechanical Analysis in Three Dimensions. Springer (2005)
6. Dong, H., Mavridis, N.: Muscle force distribution for adaptive control of a humanoid robot arm with redundant bi-articular and mono-articular muscle mechanism. Artificial Life and Robotics (2013)
7. Tahara, K., Luo, Z., Arimoto, S., Kino, H.: Sensory-motor control mechanism for reaching movements of a redundant musculo-skeletal arm. Journal of Robotic Systems 22, 639–651 (2005)
8. Kelso, J.A.: Dynamic Patterns. MIT Press (1995)
9. Khachani, M., Davoodi, R., Loeb, G.: Musculo-skeletal modeling software (msms) for biomechanics and virtual rehabilitation. In: Proceeding of American Society of Biomechanics Conference (2007)
10. Nagano, A., Yoshioka, S., Komura, T., Himeno, R., Fukashiro, S.: A three-dimensional linked segment model of the whole human body. International Journal of Sport and Health Science 3, 311–325 (2005)
11. Maurel, W., Thalmann, D., Hoffmeyer, P., Beylot, P., Gingins, P., Kalra, P., Magnenat, N., Hoffmeyer, P.: A biomechanical musculoskeletal model of human upper limb for dynamic simulation. In: Proceedings of the Eurographics Computer Animation and Simulation Workshop (1996)