

Modeling and Online Learning of Musculoskeletal Intersensory Networks for Static Controls of Tendon-driven Humanoids

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1 Introduction

While the musculoskeletal humanoid has various benefits that human beings have, applying conventional control methods is challenging due to the difficulty in modeling its complex body. To solve this problem, we need to modelize the body not as an accurate geometric model but as a variable structure such as the neural network, and update it using the actual robot sensor information (Fig. 1). So far, methods that represent the relationship between joint angles and muscle lengths by data table [1], polynomials [2], and neural networks [3] have been developed. In these studies, data of joint angles and muscle lengths are obtained from motion capture, etc., and each data structure is constructed offline. In this study, we represent the intersensory network of the musculoskeletal structure (musculoskeletal intersensory network, MISN) by the variable structure of neural networks, update it online, and control the musculoskeletal humanoid using it.

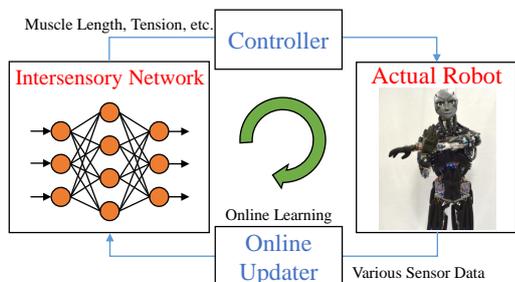


Figure 1: Overview of this study.

2 Musculoskeletal Intersensory Networks

2.1 Sensors of Musculoskeletal Humanoids

The type of musculoskeletal humanoid we handle in this study has tendons wound by electric motors, and the moment arms of muscles to joints are not constant like in human beings. We show the basic musculoskeletal structure and sensors in Fig. 2. We can measure muscle lengths l and muscle tensions T from the muscles antagonistically arranged to joints. Although we can measure joint angles θ depending on the robot, measuring θ of ball joints is difficult. Also, musculoskeletal humanoids have vision sensors and are sometimes equipped with tactile sensors. For MISN, we use l and T which almost certainly exist, and θ which

sometimes does not exist but can be estimated by using vision [4].

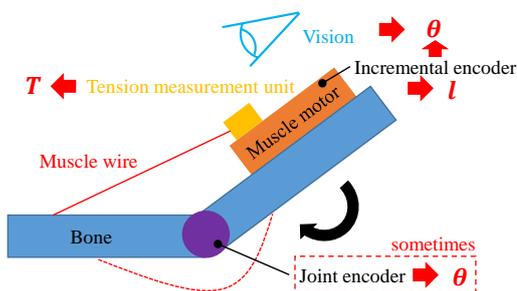


Figure 2: Basic musculoskeletal structure and sensors.

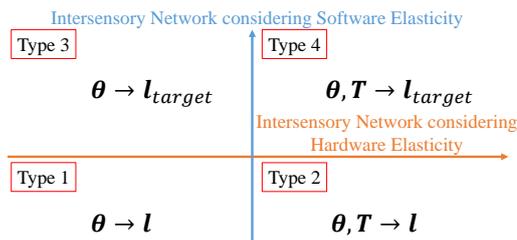


Figure 3: Classification of musculoskeletal intersensory networks, regarding the hardware and software elasticity.

2.2 Classification of Musculoskeletal Intersensory Networks

We construct MISNs of the relationship among l , T , and θ . These networks are the mappings of certain sensor values a to b ($a \rightarrow b$), and b must be calculated from a . We can classify them in terms of the hardware and software elasticity as shown in Fig. 3.

First, we classify MISNs by the hardware elasticity. The studies [1–3] stated in Sec. 1 construct the network of $\theta \rightarrow l$. However, these studies assume that muscles do not elongate as the hardware. In actuality, the body tissue of the musculoskeletal humanoid is flexible, and there exist various hardware elasticities such as nonlinear springs and muscle wire elongations. Thus, we construct MISN as $\theta \rightarrow l$ with low hardware elasticity and as $(\theta, T) \rightarrow l$ with high hardware elasticity. The simplest network when adding the effect of T to $\theta \rightarrow l$ is $(\theta, T) \rightarrow l$.

Second, we classify MISNs by the software elasticity. One of the reasons why we derive l from θ or (θ, T) is to

calculate the target muscle length realizing the target sensor values of θ and \mathbf{T} . However, when sending the target muscle length, if we accurately realize the muscle length by feedback control, a robot with closed structures may break. Therefore, we use muscle stiffness control as shown below,

$$\mathbf{T}_{target} = \mathbf{T}_{bias} + \max(\mathbf{0}, K_{stiff}(\mathbf{l} - \mathbf{l}_{target})) \quad (1)$$

where \mathbf{l}_{target} is the target muscle length, \mathbf{T}_{target} is the target muscle tension, \mathbf{T}_{bias} is the bias term, and K_{stiff} is the muscle stiffness matrix. This control can permit the error between \mathbf{l} and \mathbf{l}_{target} . From this control, we can consider two network types outputting \mathbf{l} or \mathbf{l}_{target} .

So, we can consider four MISNs of Type 1: $\theta \rightarrow \mathbf{l}$, Type 2: $(\theta, \mathbf{T}) \rightarrow \mathbf{l}$, Type 3: $\theta \rightarrow \mathbf{l}_{target}$, and Type 4: $(\theta, \mathbf{T}) \rightarrow \mathbf{l}_{target}$. These four each have merits and demerits. First, $(\theta, \mathbf{T}) \rightarrow \mathbf{l}$ is more difficult to construct than $\theta \rightarrow \mathbf{l}$, due to the necessity of searching in the space of not only joint angles but also muscle tensions. Also, we can calculate more accurate muscle lengths by using the network outputting \mathbf{l}_{target} than by using the network outputting \mathbf{l} . On the other hand, considering the effect of \mathbf{l} in the network outputting \mathbf{l}_{target} is difficult, and this causes problems when updating the network online [5].

3 Experiments

First, the position control gradually becomes accurate by updating MISN of Type 3, as shown in Fig. 4. The robot could not grasp the object in the beginning, but could grasp it finally by updating the network online. Second, by using MISN of Type 4 considering the hardware elasticity, we can estimate the robot posture under external forces, as shown in Fig. 5. Compared to the network of Type 3 without the hardware elasticity, the network of Type 4 can estimate the change in posture affected by external forces. Third, by using MISN of Type 2, we can control the impact force with variable stiffness control, as shown in Fig. 6. By simulating the body stiffness from MISN and using a hill-climbing method, we can change the body stiffness and parry the impact by setting the body stiffness low.

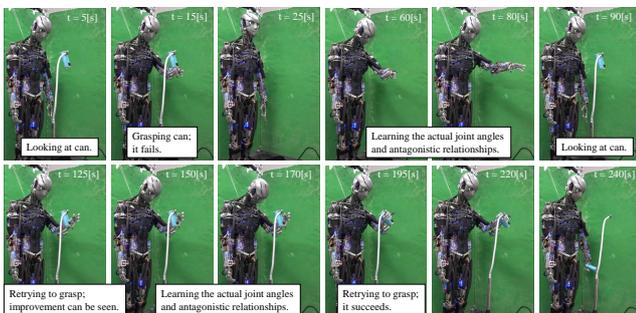


Figure 4: Position control experiment using MISN of Type 3, while updating the network online.

4 Conclusions

We can classify the intersensory networks of complex musculoskeletal structures into four types, in terms of the

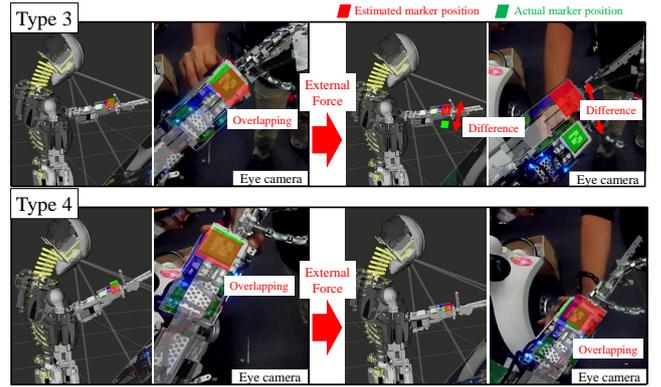


Figure 5: Comparison of joint angle estimations between MISNs of Type 3 and 4.

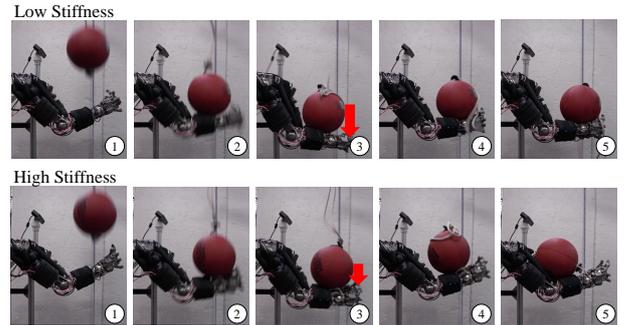


Figure 6: Impact correspondence experiment by variable stiffness control using MISN of Type 2.

hardware and software elasticity. By considering the software elasticity, we can conduct position control accurately, but the online learning becomes difficult. By considering the hardware elasticity, controls considering external forces are enabled, but the construction of the network becomes difficult. Also, the robot can conduct position, torque, and variable stiffness control more accurately, while moving the body and updating the musculoskeletal intersensory network. In future works, we would like to modelize dynamic sensor relationships and conduct dynamic body controls.

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