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Self-organized acquisition of muscle synergy and behavior with whole body musculoskeletal infant model

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1 Introduction

The research on action acquisition through physics simulation and deep reinforcement learning has been widely conducted in order to understand the mechanisms underlying animal behavior or its development. In those researches, many agents have simple bodies and specialize in a specific task. Real animals and humans, on the other hand, have a high degree of freedom in their musculoskeletal system. While these system allow themselves to perform a wide range of tasks, their own complexity and redundancy makes it difficult for the acquisition of body control. In animals and humans, complex motor behaviour is known to involve a small set of primitive muscle control patterns, called 'muscle synergies', that provide effortless motor control. However, the establishment process of such muscle synergies is unknow. It is assumed that such synergies are acquired in early infancy through task-free spontaneous movements, which provide specific regularities in bidirectional information among muscle activities and proprioception [5]. Here, we simulated the acquisition process of muscle synergies based on simple Hebbian learning through task-free movement. Furthermore, we demonstrated that acquired muscle synergies contribute to behavior learning based on reinforcement learning.

2 Infant simulator

In this study, we used an infant musculoskeletal simulator based on real data assuming an developing model [1]. We added four abdominal muscles to the original model and created a musculoskeletal model with 190 muscles, allowing for a greater range of motion in the pelvis. The following points are unique features of this model:

1. The original model has 15 joints, and a 31-degree-of-freedom rigid link model, and 186 muscles.
2. This model defines coordinated joints that move in unison, such as the scapulohumeral rhythm, as linked joints.
3. Each muscle belongs to a spinal circuit, which has neural oscillators(Eq.(1)(2)), α and γ motor neurons, and sensory interneurons [3] [1], producing chaotic muscle actiivity.
4. The contraction force of the muscle is based on He [4]'s model.
5. The model has muscle spindles and Golgi tendon organs as proprioceptors, which provide sensory feedback based on muscle length and tension [2].
6. Based on chaotic muscle activities produced by spinal circuit, the baby model exhibit random motor babbling without any specific motor command.

$$\tau\frac{dx}{dt} = c(x-\frac{1}{3}x^3-y+I_c)+\delta(I_s-x), \tag{1}$$

$$\tau\frac{dy}{dt} = \frac{1}{c}(x-by+a)+\varepsilon I_c, \tag{2}$$

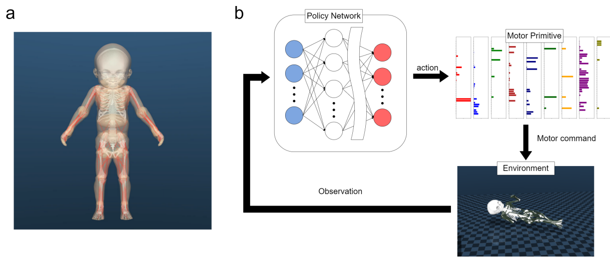

Figure 1: (a)Infant simulator [1](b)This figure shows how muscle synergies works in RL. Policy network outputs a compressed acton vector. Then, muscle synergies convert it into motor commands.

where I_c and I_s are sensory feedback. The constant parameters were set as $\tau = 5.0, a = 0.7, b = 0.675, c = 1.75, \delta = 0.013, \varepsilon = 0.022$.

3 Method

3.1 Muscle synergies

It is believed that coordinated muscle activations can be represented by a combination of weights and temporal patterns among multiple muscle pairs. In this research, we verified whether muscle synergies can be self-organized by simple co-occurence learning, so-called Hebbian plasticity. We used Non-negative Matrix Factorization(NMF) as Hebbian learning based on using muscular proprioceptive inputs obtained from random whole body movements.

NMF is widely used in the study of muscle synergy due to its interpretability as it handles non-negative values. Therefore, in this study, following previous studies, it was used to extract the weight values between muscles.

Using NMF for tendon data, the obtained matrix W represents the weights between muscles and the matrix H represents the patterns that activate W. The matrix W is used as a muscle synergy.

$$Y \simeq WH \tag{3}$$

$$w_{mk} \leftarrow w_{mk}\frac{(YH)_{mn}}{(WHH^T)_{mk}} \tag{4}$$

$$h_{kn} \leftarrow h_{kn}\frac{(W^TY)_{mn}}{(W^TWH)_{mn}} \tag{5}$$

Based on the NMF rules during random motor bubbling, weights between muscles were updated. We observed and analysed them as developmental changes and confirmed whether muscle synergies were acquired by task-free spontaneous movements.

3.2 Reinforcement learning and motor primitves

In reinforcement learning, the policy network outputs action vectors that have an action space compressed by muscle synergies. The action vectors are then converted into motor commands through muscle synergies and become inputs to the muscles.

In this research, we used Soft Actor-Critic as RL algorithm. The objective function is the expected reward and policy entropy. The entropy term allows for more random exploration compared to conventional methods.

$$J(\pi) = \mathbb{E}_{(s_t,a_t)\sim\pi}[\Sigma(R(s_t,a_t) + \alpha H(\pi(\cdot|s_t)))], \qquad (6)$$

$$H(\pi(\cdot|s_t)) = -\log \pi(a_t|s_t), \qquad (7)$$

We conducted experiments on whole body reinforcement learning to make the model learn how to roll over with acquired muscle synergies. The reward is calculated based on the orientation of the chest. In the initial state, the model is prone. The observation used in this RL experiments include the length and velocity of tendons and the orientation of the chest.

4 Results

We found that certain weight matrix consist of muscles that are functionally coherent with each other, indicating the development of specific synergies from task-free spontaneous movement. This observation is supported by the acquired weights of muscles, as shown in Fig.2.

The result of action acquisition through reinforcement learning was shown in Fig.3 The model with acquired muscle synergies achieved baby roll-like behavior(Fig.4), whereas the model without muscle synergy did not.

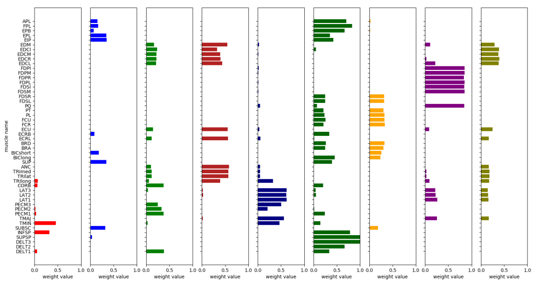

Figure 2: Acquired weights in arm

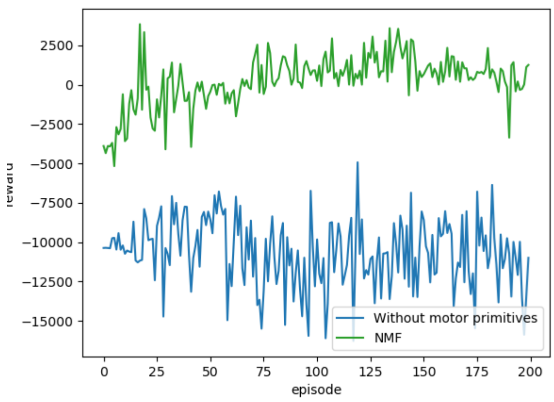

Figure 3: Rewards of roll-over task. The model with muscle synergies learned roll over-like behavior because it can easily move their body. The model without muscle synergies could not

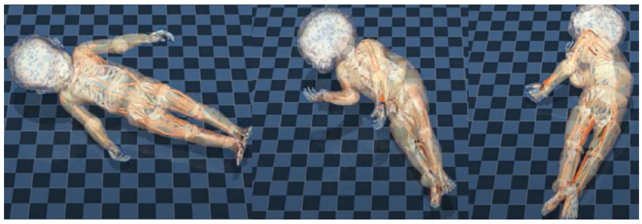

Figure 4: Example of roll over-like behavior after learning by the model with muscle synergies

5 Conclusion

In this study, we demonstrated that redundant musculoskeletal model without explicit motor commands or specified muscle coordination can obtain muscle synergies through spontaneous whole body movement. We also demonstrated that the model can learn behavior through reinforcement learning using muscle synergies although the model without muscle synergies cannot(Fig.3).

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