Running Motion in a Musculoskeletal Bipedal Robot using Muscle Activation Pattern Control Based on a Human Electromyogram

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Abstract: Some robots driven by muscle-type actuators have been studied based on a bio-inspired approach. However, a method of motion generation for them has not been established. We propose a control method based on a human electromyogram (EMG) for a musculoskeletal robot with mono- and bi-articular muscles. The simulation results show that the method is more effective than non-EMG-based method. In a dynamic simulator, we demonstrate that the method can generate feasible motor command for bipedal running with complex musculoskeletal system.

Keywords: Running, Bipedal Robot, Musculoskeletal System, Electromyogram, Muscle Activation Pattern

1. INTRODUCTION

In order to improve a physical ability of legged robot, musculoskeletal structure of animal is the useful reference. A musculoskeletal system has many interesting characteristics, such as the free control of stiffness through antagonistic actuation and bi-articular muscles contributes to the isotropy of the force distribution.

On the other hand, because running is acknowledged to be an especially challenging task, many robots have been developed that can run. Despite having this ability, these robots have not used the findings of animals enough. Therefore, musculoskeletal robots have been developed. Lucy [1] has pneumatic muscles and is capable of planar walking. However, with only mono-articular muscles and control similar to angle control, this robot cannot make the best use of the characteristics of the musculoskeletal system. Although musculoskeletal robots with bi-articular pneumatic muscles are able to run [2], this is manually tuned. Briefly, the control method of musculoskeletal robot has not been established.

Thus, we propose a bio-inspired control method. We demonstrate the bipedal running with musculoskeletal robot with bi-articular muscles in a dynamic simulator.

2. ATHLETE ROBOT

We used a model of the Athlete Robot [2](Fig. 1), which weighs about 10 kg and has a body height, thigh length, and shank length of 1.2 m, 0.3 m, and 0.36 m, respectively. This robot is driven with pneumatic artificial muscles. We used OpenHRP3 [3] as the dynamic simulator. The kinetic data for the robot were taken from 3D-CAD data. We used the theoretical equation of tension of the pneumatic muscle shown in (1) [4].

$$F = p\{A(1-\epsilon)^2 - B\}, \quad (1)$$

where F, p, and ϵ denote the contraction force, inner pressure, and contracting ratio, respectively, and A and B are constants.

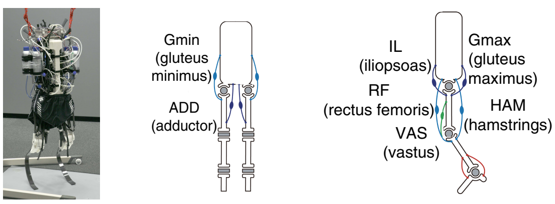

Fig. 1 Athlete Robot with layouts of its muscles.

3. CONTROL

In the legged locomotion, contact force control is more important than angle control. Contact force distribution is determined according to which combination of muscles is chosen. Therefore, an appropriate control of muscle activation strength is required. In deciding muscle activation strength, it is valid to use electromyogram (EMG), corresponding to muscle activation strength of humans.

Thus, we propose muscle activation pattern control based on a human EMG. This control consists of muscle activation patterns using a simple step function as the basis function and the learning thereof. To make learning efficient, we use a human EMG data (Fig. 2). In addition, we estimate the switching time since timing is especially important for dynamic movement.

We divide a period of running into two phases because of the difference of dynamics, namely, the thrust phase and the swing phase. Setting the threshold to half the maximum strength of the EMG, we can divide the swing phase into two phases, namely the recovery swing phase and the foot descent phase, and determine simplified patterns (an example of IL is shown in Fig. 2). Details of the muscle activation patterns for each phase and certain parameters concerning switching time are decided by a combination of constrained random sampling and hill-

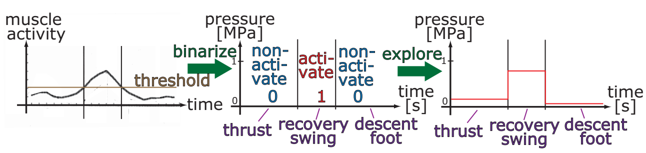

Fig. 2 EMG [5] and muscle activation pattern.

climbing optimization. In constrained random sampling, we fix the pressure of decided non-activation muscles to zero, and randomly explore the pressures of decided activation muscles and a few parameters for switching time. In hill-climbung optimization, we optimize all the parameters. Additionally, we decide the switching time of the next cycle using information from the previous cycle and the prediction at liftoff time. The duration of each phase is decided at the moment of liftoff.

4. SIMULATION EXPERIMENTS

4.1 Experimental Settings

We performed a bipedal running in a simulator. To make the robot learn a steady running motion, we provided an initial velocity. To begin, we issued the initial commands for 3.7 s to bring the robot to its starting posture. Next, we applied force from behind for 0.3 s to give the robot an initial velocity of 2.0 m/s. The evaluation metric used is the distance before falling down. The parameters of the control are the muscle activation strength of seven muscles shown in Fig. 1 in the three phases, the ending time of the initial posture (t_{init}), and the ratio of the foot descent phase to the whole swing phase (τ).

4.2 Comparison between EMG-based Sampling and Non EMG-based Sampling

We conducted constrained random sampling based on a human EMG to determine general parameters of the control. The numbers of learning parameters were 11 or 12 (excluding Gmin and ADD of all phases and non-activated muscles decided by a human EMG). Having conducted 300 trials by four ways (using EMG of [5] or [6] or [7] with IL of [5] or [7] with IL of [6]), respectively, we obtained several combinations of parameters that realized several steps of running.

We also experimented with non EMG-based sampling to verify the effect of EMG-based sampling. The numbers of learning parameters were 10 or 11 or 12 (excluding Gmin, ADD, and 5 or 6 or 7 randomly-selected parameters). We have conducted 300 trials by four different parameters, respectively. From the results, the average distances were 2.24 m and 1.99 m, with variances of 1.38 and 0.07, for the experiments with EMG-based sampling and non EMG-based method, respectively (Fig. 3). Thus, EMG-based sampling is more advantageous to find general parameters of the running motion.

4.3 Optimization of Running Motion

We conducted hill-climbing optimization of five high ranking parameters obtained from each constrained random samplings. The number of learning parameters is 23 (all the parameters). Based on the results of 150 trials, the evaluation metric increased greatly and the robot successfully realized a running motion from EMG-based samplings (Fig. 3). Thus, EMG-based sampling is effective to achieve a running motion. The optimal parameters are shown in Fig. 4. The mean velocity of the robot was 2.1 m/s, and it took 13 steps in 12.5 m (Fig. 4). As can be seen from the graph, the running pace is steady.

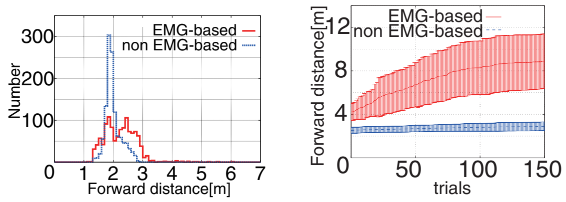

Fig. 3 Distribution of evaluation metric for random sampling (left) and the mean learning curve with standard deviation for hill-climbing optimization (right).

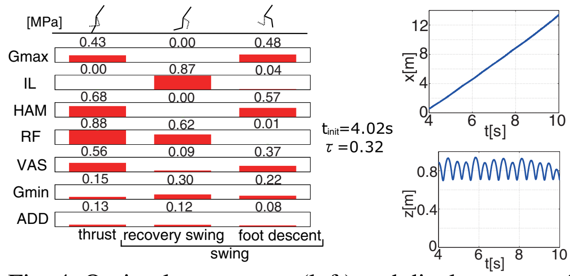

Fig. 4 Optimal parameters (left) and displacement of the robot during running (right).

5. CONCLUSION

In this study, we proposed a method to implement running in a musculoskeletal bipedal robot, and examined the running motion of a robot in a dynamic simulator. We used muscle activation pattern control in the learning based on a human EMG. Using hill-climbing optimization after EMG-based constrained random sampling, the robot model achieved 13 steps running. The mean distance before falling down in EMG-based method is about three times greater than that in non-EMG-based method. This result shows that an EMG-based search is efficient for finding appropriate patterns. Future works include the use of posture feedback for infinite running and application of this method to a real robot.

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