Estimating the Body Stiffness during Quadrupedal Locomotion using the Flexible Shoulder as a Physical Reservoir

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1 Introduction

Animals have a sophisticated morphology to move faster and adaptively. In cursorial mammals, such as cheetahs and horses, flexible connections between the forelimb and trunk are one of the most attractive characteristics. Recently, our robotic studies explored the functionality of these flexible shoulders during locomotion tasks [1].

In addition to the mechanical contribution to the motion of soft bodies, this study examines the potential of quadruped robots with flexible shoulders as computational resources. In physical reservoir computing (PRC) [2], various computational tasks can be implemented by integrating sensor information from a physical system and using its rich dynamics (e.g., soft robot). We expect that the implementation of PRC on the flexible-shouldered quadruped robot will further extend its adaptability.

First, this study attempts to estimate the control gain of the actuators that achieve shoulder flexibility while walking and running (corresponding to shoulder stiffness) based on the sensor information (Fig. 1). Specifically, a method for estimating the control parameters of the leg base from the sensor information obtained during locomotion is proposed in this study, and the results of validating the method for the quadruped robot walk, trot, and gallop in a physics simulation are reported.

2 Model

2.1 Robot system

The proposed robotic platform is comprised of a rigid trunk unit and four limb units. Each limb unit includes a prismatic limb actuator and a rotary limb actuator to generate striding limb motions. The limb and trunk units are connected through a flexible base unit, which contains two prismatic actuators for vertical and horizontal motions. This allows the limb base to move translationally in the sagittal plane.

The actuators in the proposed robotic platform are controlled using a proportional derivative (PD) control as follows:

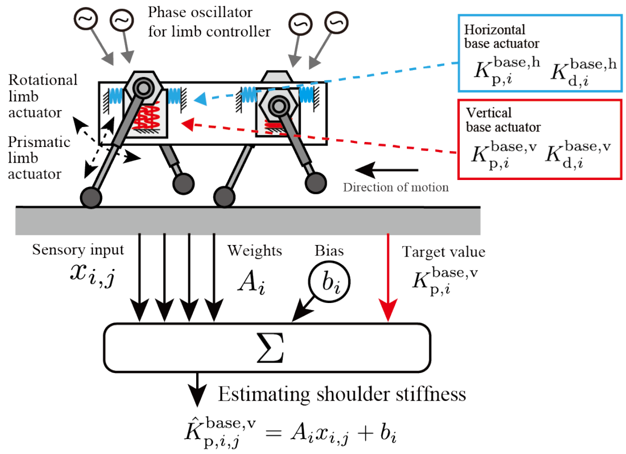

Figure 1: Estimation of the stiffness of the shoulder region using the body dynamics of the robot with flexible shoulder units.

$$F_i = -K_{\mathrm{p}}^{\mathrm{pri}}(L_i - \bar{L}_i) - K_{\mathrm{d}}^{\mathrm{pri}}\dot{L}_i, \quad (1)$$

$$\tau_i = -K_{\mathrm{p}}^{\mathrm{rot}}(\theta_i - \bar{\theta}_i) - K_{\mathrm{d}}^{\mathrm{rot}}\dot{\theta}_i, \quad (2)$$

$$F_i^{\mathrm{base,v}} = -K_{\mathrm{p},i}^{\mathrm{base,v}}(L_i^{\mathrm{base,v}} - \bar{L}_i^{\mathrm{base,v}}) - K_{\mathrm{d},i}^{\mathrm{pri}}\dot{L}_i^{\mathrm{base,v}}, \quad (3)$$

$$F_i^{\mathrm{base,h}} = -K_{\mathrm{p},i}^{\mathrm{base,h}}(L_i^{\mathrm{base,h}} - \bar{L}_i^{\mathrm{base,h}}) - K_{\mathrm{d},i}^{\mathrm{pri}}\dot{L}_i^{\mathrm{base,h}}, \quad (4)$$

where i is a suffix of the limb index ($i = \mathrm{RF, LF, RH, LH}$ representing the right forelimb, left forelimb, right hindlimb, and left hindlimb), F_i, τ_i, $F_i^{\mathrm{base,v}}$, $F_i^{\mathrm{base,h}}$ are the output force and torque of the limb prismatic and rotary actuators and the vertical and horizontal actuators, $K_{\mathrm{p(d)}}^{\mathrm{pri}}$, $K_{\mathrm{p(d)}}^{\mathrm{rot}}$, $K_{\mathrm{p(d)}}^{\mathrm{base,v}}$, $K_{\mathrm{p(d)}}^{\mathrm{base,h}}$ are the proportional (derivative) gain values of these actuators, and L_i, θ_i, $L_i^{\mathrm{base,v}}$, $L_i^{\mathrm{base,h}}$ and their bar or dot accents are the current, target, and velocity values of these actuators.

The typical gait patterns that animals exhibit (e.g., walk, trot, gallop) are implemented by setting specific phase differences between the limbs and adjusting the locomotor frequency.

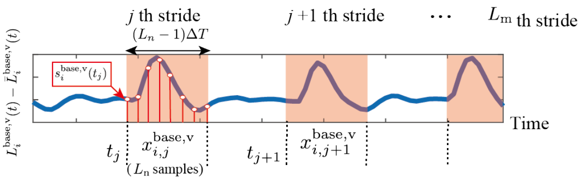

Figure 2: Sampling sensor values from the simulations of the robot simulation. The sensor values $x_{i,j}$ are corrected as L_n points during the j th stride cycle.

2.2 Estimation of shoulder stiffness by PRC

As a first step in evaluating the potential of morphological computing in the quadruped robot with flexible shoulders, we aim to estimate the shoulder stiffness using the sensor input during locomotion. The shoulder stiffness can be described as a function based on physical reservoir computing as follow:

$$\hat{K}_{\mathrm{p},i,j}^{\mathrm{base,v}} = A_i x_{i,j} + b_i, \tag{5}$$

where $\hat{K}_{\mathrm{p},i,j}^{\mathrm{base,v}}$ indicates the estimated values of the stiffness, A_i is the weight matrix for the sensor inputs, $x_{I,j}$ is a vector containing the sensor values of the ith limb during the j th stride cycle, and b_i is a bias.

In this study, we employ four sensor values from the vertical and horizontal actuators in the base unit, and the prismatic and rotary actuators in the ith limb unit is as follows:

$$x_{i,j} = [x_{i,j}^{\mathrm{base,v}}\ x_{i,j}^{\mathrm{base,h}}\ x_{i,j}^{\mathrm{pri}}\ x_{i,j}^{\mathrm{rot}}]^T. \tag{6}$$

During each stride cycle, the sensor inputs are sampled with a time resolution L_n and specific periods, as shown in Fig. 2. For example, the sensor input of the vertical actuator of the base unit is described as follows:

$$x_{i,j}^{\mathrm{base,v}} = [s_i^{\mathrm{base,v}}(t_j)\ s \cdots\ s_i^{\mathrm{base,v}}(t_j + \Delta T(L_n - 1))], \tag{7}$$

where $s_i^{\mathrm{base,v}}(t)$ is a sampled sensory input at t, t_j indicates the time of the beginning of the jth stride cycle, L_n is the time resolution, and ΔT indicates the discrete time periods. In this study, we sampled the differences between the target and present positions of the actuator (e.g., $s_i^{\mathrm{base,v}}(t) = L_i^{\mathrm{base,v}}(t) - \bar{L}_i^{\mathrm{base,v}}(t)$).

To learn A_i and b_i, we minimized the objective function O_i. The objective function is defined as the sum of the norm of errors of the estimation as follows:

$$\min_{A_i,b_i} O_i = \min_{A_i,b_i} \sum_j (\hat{K}_{\mathrm{p},i,j}^{\mathrm{base,v}} - K_{\mathrm{p},i,j}^{\mathrm{base,v}})^2. \tag{8}$$

We extracted L_m datasets from each gait pattern, that is, $3L_\mathrm{m}$ datasets were prepared for training and testing, respectively (Fig.3). The objective function O_i is minimized by a genetic algorithm (GA).

3 Results

We aim to estimate the shoulder stiffness during the walking, trotting, and galloping gaits in this study. To obtain the sensor inputs, we simulated robot walking and running using the Open Dynamics Engine (ODE), which was based on the size and gait patterns of a house cat [3]. For each type of gait pattern, we heuristically set the target shoulder stiffness value $K_{\mathrm{p,RF},j}^{\mathrm{base,v}}$ to 1000, 10000, and 2818 N/m for walking, trotting, and galloping, respectively. To investigate the effects of the data set size and time resolution, we conducted estimations with various combinations of L_m and L_n.

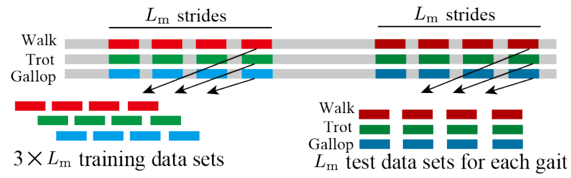

Figure 3: Training and test setup for A_i and the bias b_i.

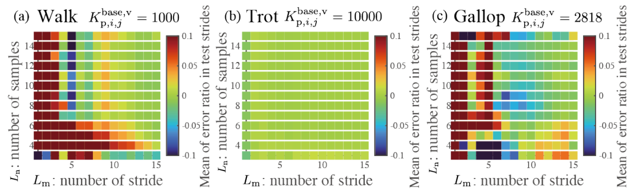

Figure 4: Error ratio of the estimation $R_\mathrm{error} = (\hat{K}_{\mathrm{p},i,j}^{\mathrm{base,v}} - K_{\mathrm{p},i,j}^{\mathrm{base,v}})/K_{\mathrm{p},i,j}^{\mathrm{base,v}}$ with altered values L_m and L_n for the tests of (a) walking, (b) trotting, and (c) galloping gaits.

The optimized A_i and b_i are sufficient estimates of the shoulder stiffness for each gait pattern. When $(L_\mathrm{m}, L_\mathrm{n}) = (15, 15)$, the average values of $\hat{K}_{\mathrm{p,RF},j}^{\mathrm{base,v}}$ in the 15 test trials were evaluated to be 1006.83, 9987.51, 2880.22 N/m for the walking, trotting, and galloping gaits, respectively. As shown in Fig. 4, when $L_\mathrm{n} > 7$ and $L_\mathrm{m} > 7$, the error ratio ($R_\mathrm{error} = (\hat{K}_{\mathrm{p},i,j}^{\mathrm{base,v}} - K_{\mathrm{p},i,j}^{\mathrm{base,v}})/K_{\mathrm{p},i,j}^{\mathrm{base,v}}$) becomes smaller than 10%.

4 Conclusion

To evaluate the morphological computation aspect of the proposed method, we demonstrated the estimation of the shoulder stiffness in a quadruped robot with a flexible shoulder during various gait patterns. As a next step, we plan to extend the proposed method to control the body stiffness based on locomotor situations.

Acknowledgments

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References

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