PERIOD ESTIMATION OF UNKNOWN PERIODIC PERTURBATION IN BIPED BALANCE CONTROL

Satoshi Ito, Tomohiro Kashima, Minoru Sasaki (Gifu University)

ABSTRACT

This paper addresses a biped balancing task in which an unknown periodic external force is exerted. In the previous paper, we described a control and learning process using the ankle strategy model of the biped balance. However, the period estimation based on the filtering process did not so effectively work for the external force with two-frequency component. In this paper, we extend this control scheme by introducing the period estimation by local correlation. The effectiveness of period estimation as well as the torque pattern learning are confirmed by computer simulations and robot experiments.

INTRODUCTION

A biped balancing task in which an unknown periodic external force is exerted is observed on the boat, as shown in Fig. 1. On the periodically tilting floor of the boat, human can maintain upright posture by changing the joint angle of the ankle: Human firstly maintains this posture carefully depend on the sensory feedback. However, if boat motion that produces perturbation is periodic, the human learns its motion resulting in that the balance is maintained unconsciously. In other words, humans can learn the movement of the ankle as a periodic motion pattern.

In our previous papers, we formulate such a balancing task by an ankle strategy model composing of two links, and then proposed a control and learning method for external force in known period condition [1], and extend it for unknown period condition with filter process to obtain its lower frequency (long-period) component from the ankle joint movements [2]. However, this method was difficult to apply to the case where the complex periodic external force such as that contains two frequency components, since the low frequency component is not so clearly filtered. In this paper, we extend it by introducing the period estimation based on the local autocorrelation.

PROBLEM FORMULATION

The control and learning problem in biped balance is treated here as the motion caused by so-called "ankle strategy" [3].

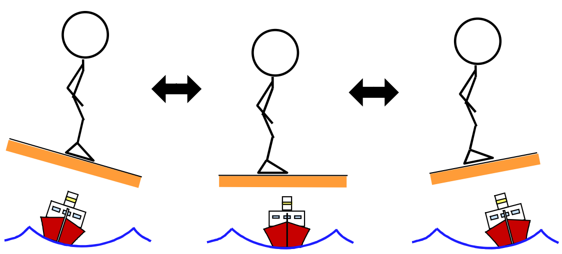

Fig.1: balancing task under periodic external force.

The link model of the biped balance in this paper is illustrated in Fig. 2: it is a two-link model in sagittal plane. The foot part contact the floor at only two points, where the vertical component of ground reaction forces F_T and F_H is detected. In addition, ankle joint angle θ and its velocity $\dot{\theta}$ are obtained as sensory information. Ankle joint torque τ is actively outputted. Unknown external force denoted by F_x and F_y is exerted. The problem is: what control law can adaptively stabilize the upright posture, and what learning low can memorize a produced motion as a motion pattern.

To describe the latter learning problem, it is here assumed that motion pattern is expressed as a torque pattern of, in this case, ankle joint. Therefore, the learning is a torque pattern memorization that is produced to cope with unknown periodic external forces. Regarding to the former control problem, we consider the sensory information of the ground reaction forces are important to stabilize the upright posture under unknown external forces. Then, the learning becomes a process that stabilizes it without crucial information on ground reaction forces.

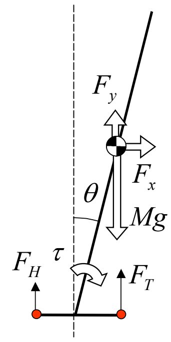

Fig.2:Biped balance model

PERIOD ESTIMATION

In the learning, the period estimation of the periodic motion caused by unknown periodic external force becomes a basic process. It is estimated from the ankle joint movements, because it usually shows the periodic motion with the same period as the external force. For the estimation, we utilize a local autocorrelation as follows:

1. The trajectory of the ankle joint angle is stored back in time to $\theta_s(t,t_0)$ during the interval T_s from t_0:

   $$\theta_s(t,t_0) = \theta(t_0+t) \quad (-T_s \le t \le 0\ )$$

2. Using this $\theta_s(t,t_0)$, the local autocorrelation is calculated by

   $$r(t) = \frac{\langle \theta_s(t,t_0), \theta(t)\rangle_{T_s}}{\langle \theta_s(t,t_0), \theta_s(t,t_0)\rangle_{T_s} \cdot \langle \theta(t), \theta(t)\rangle_{T_s}}$$

   Here,

   $$\langle a(t), b(t)\rangle_{T_s} = \int_{-T_s}^{0} a(t+\xi)\cdot b(t+\xi)d\xi$$

3. This $r(t)$ should be nearly equal to 1 with every interval T_e because of its periodicity. Thus, the time $t_{\max}(k)$ which gives the local maximal value beyond a threshold $r_0\,(<1)$ are memorized. Here, k is an integer denoting

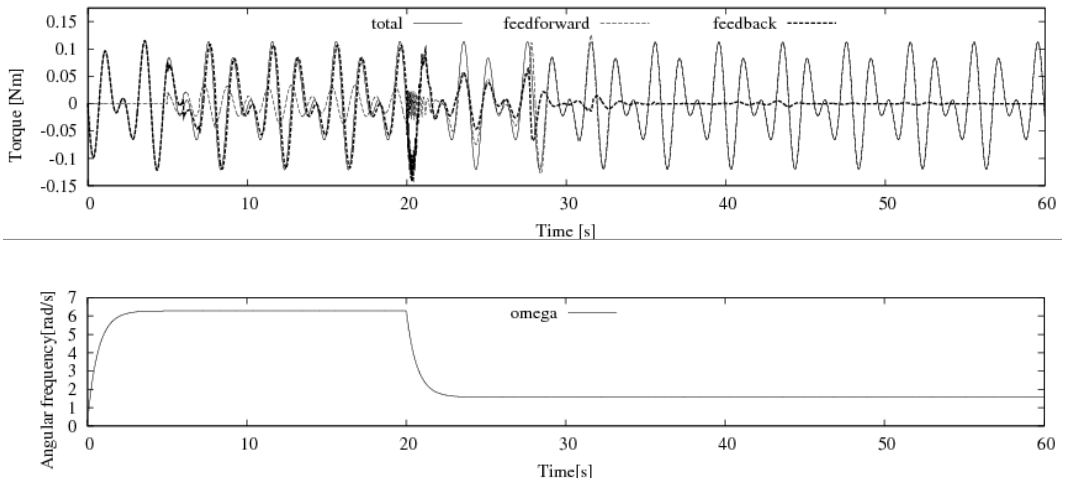

Fig.3 simulation results

the order of the maximal value.

4. $\hat{T}_e$ is calculated by averaging some $t_{\max}(k) - t_{mav}(k-1)$ with every time interval T_p. Then, The estimated value of the angular frequency $\hat{\omega}_e$ is obtained by the following equation

$$\hat{\omega}_e = 2\pi / \hat{T}_e$$

CONTROL ANS LEARNING METHOD

The control law is constructed from two term: a feedback term τ_{fb} and a feedforward term τ_{ff}: as the feedback term, we adopt a control law in our previous paper, which contains the feedback of the ground reaction forces. The feed forward term is, on the other hand, constructed by implicitly identifying the unknown external force. From the periodicity, the external force is expanded to the Fourier series using the estimated angular frequency $\hat{\omega}_e$. The Fourier coefficients are learned by use of the learning law. Specifically, the control law is:

$$\tau = \tau_{ff} + \tau_{fb}$$

$$\tau_{ff} = Y_r \cdot \hat{\phi}$$

$$\tau_{fb} = -K_d\dot{\theta} - K_p\theta + K_f\int(F_H - F_T)dt \ (= -K_d s)$$

and, learning law is:

$$\dot{\hat{\varphi}} = -\Gamma Y_r^T s$$

where

$$Y_r = [\sin\hat{\omega}_e t, \cos\hat{\omega}_e t, \cdots, \sin n\hat{\omega}_e t, \cos n\hat{\omega}_e t]$$

$\hat{\phi}$ is Fourier coefficients to estimete, Γ is a positive definite matrix that adjusts the learning rate, and K_d, K_p, K_f are feedback gains.

SIMULATIONS

The computer simulations are executed to confirm an effect of the control and learning law. The link parameters in Fig. 2 are set as M =0.50 [kg], L =0.2 [m], =0.05 [m], I =0.025 [kgm^2]. For the period estimation, parameters are set as T_s =1 [s], T_p =10 [s], and r_0 =0.99. For controller, we set: K_d =20, K_p =70, K_f =, Γ =diag[25, $\cdots$, 25] and n=20. Learning starts at 5 s. The external force is set as equation.

$$F_x = Mg\sin\alpha$$

$$F_y = Mg(1-\cos\alpha)$$

which is equivalent to the gravitational effect on the slope with the gradient α given as follows:

$$\alpha = A_1 \sin 2\pi f_1 + A_2 \sin 2\pi f_2$$

where $A_1 = A_2 = 3$ [deg], f_1=0.5 [Hz], f_2=0.75[Hz]. The 4th-order Runge Kutta method is used with the step size 1 [ms].

The torque trajectory τ with its feedforward and feedback components τ_{ff} and τ_{fb} are depicted in Fig. 3 in addition to a time course of the estimated angular frequency $\hat{\omega}_e$. The controller learns even complex periodic trajectories.

CONCLUDING REMARKS

Introducing the period estimation scheme, a biped balance control and its torque pattern learning is considered. As a result, motion pattern memorization as well as a balance control is achieved with respect to unknown periodic external forces. A robot experiment is now executed to verify the behavior of our control and learning method.

REFERENCES

[1] Satoshi Ito and Haruhisa Kawasaki, "Regularity in an environment produces an internal torque pattern for biped balance control"; *Biological Cybernetics*, Vol. **92**, 241-251 (2005)

[2] Satoshi Ito, Kohei Moriki, Minoru Sasaki, Haruhisa Kawasaki, "Robot experiment of torque learning for biped balance with respect to periodic external force"; *Procs. of 2005 12th International Conference on Advanced Robotics (CD-ROM)*, p.p. 418-423, Seattle, USA, July, 2005

[3] Horak FB, Nashner LM, "Central program of postural movements: adaptive to alerted support-surface configurations"; J Neurophysiol. **55**, p.p. 1369- 1382 (1986)