LETTER

Influence of Neural Delay in Sensorimotor Systems on the Control Performance and Mechanism in Bicycle Riding

Yusuke Azuma and Akira Hirose

Department of Electronic Engineering, The University of Tokyo
7-3-1 Hongo, Bunkyo-ku, Tokyo, 113-8656, Japan
E-mail: ahirose@ee.t.u-tokyo.ac.jp

(Submitted on December 10, 2007)

Abstract **–** Neural sensorimotor systems have unavoidable delay in the processing. In this paper, we investigate the influence of the delay on control performance in numerical experiment with simple networks. Obtained results suggest not only the fact that the delay degrades control performance of reflex motion in proportion to the amount of the delay, but also the possibility that it influences the signal generation of relevant volitional motion. The motion generation mechanism seems dependent on the amount of delay. That is, when the delay increases beyond a certain threshold, the control strategy changes from a feedback method into a predictive one. An appropriate delay can even be in favor of the volitional motion learning in total.

Keywords **–** Motion learning, Developmental learning, Reinforcement learning, Reflex motion, Volitional motion

1. Introduction

Biological sensorimotor systems have unavoidable delay when sensory signals yield motor effects because of the transmission and processing retardation as well as the mechanical inertia of objects. In the human beings, the amount of the delay is typically several tens to a few hundreds of milliseconds. When we need a quicker response, we need to overcome this delay. In this sense, we have to be adaptive in a predictive manner [1].

An interesting experiment was presented in a paper by Ishida & Sawada [2]. A test subject tracks a moving target on a computer screen with a mouse (cursor) for various periodic motions. Then there is a region of the period of the reciprocating motion of the target where the cursor precedes the target and, in this case, the manner of the preceding is such that a transient locus error is minimized when the target moves abruptly non-periodically. The fact suggests, at least, that the human being behave in a certain special way to overcome the unavoidable delay.

In this paper, we investigate the delay effect on simple sensorimotor neural networks experimentally. We assume a task to ride a bicycle to observe reflex and volitional motions, in which a feedforward network is loaded with various amount of delay. We find in the experiments that the delay degrades the reflex motion performance in proportion to the delay time up to a certain delay amount. For a larger delay, the performance is rapidly deteriorated. In addition, the delay influences the performance in learning volitional signal generation to realize a motion relevant to the previously learnt reflex motion. It is also suggested that a moderate delay sometimes results in a better performance of the learning of the volitional motion in total because the control strategy changes from a feedback method into a predictive one.

2. Modelling

2.1 Bicycle and human body

Figure 1(a) is a top view of a bicycle moving in a small time step Δt. The advance Δs is related to the distance between front and rear wheels d, handle angle ϕ, curvature radius of bicycle trajectory R, and change in

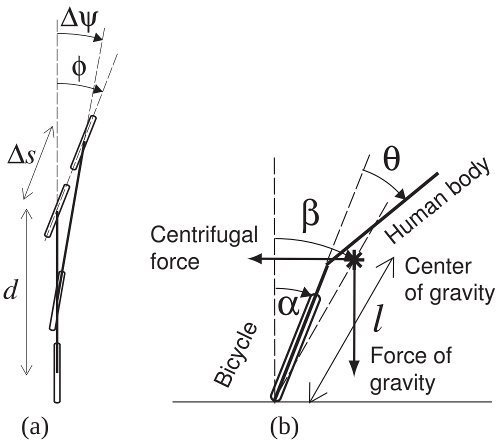


Figure 1. (a)Top view and (b)rear view of a man riding bicycle.

the forward movement direction $\Delta\psi$ as

$$\Delta s \sin\phi = d \sin\Delta\psi \approx d\Delta\psi \tag{1}$$

Since $R = \Delta s/\Delta\psi = d/\sin\phi$, we obtain

$$\Delta\psi = v\Delta t/R \tag{2}$$

Figure 1(b) is a rear view of the bicycle and human body, which is analogous to a double inverted pendulum, where α and β denote the tilt angle of bicycle to the ground and that of human to the bicycle, respectively, m is total weight of the bicycle and the human body, and l is the length from the ground contact point of the wheel to the center of gravity of the total mass. Since the rate of change in the angular momentum $ml^2\ddot{\beta}$ is equal to the torque, that is a difference between the force of gravity mg and centrifugal force mv^2/R, we have

$$ml^2\ddot{\beta} = mgl\sin\beta - lmv^2\cos\beta/R \tag{3}$$

We calculate the state evolution by (3). A falling is expressed as $\beta = \pi/2$.

The values of the physical parameters was chosen as d=1.0m, both of the heights of the bicycle and the body 0.8m, body weight 70kg, bicycle weight 10[kg], bicycle velocity constantly 3m/s for simplicity, and the calculation time step Δt=1ms.

2.2 Neural network

We model reflex motion, which is quick and simple, and volitional motion, which may be slow and complex. When we rid a bicycle, we control our sitting posture and handle direction to balance ourselves. If we feel falling to the right, for example, we quickly drive the handle to the right and tilt our body to the left. In the simulation presented below, we control the handle and the body using a network. The bicycle velocity is kept constant for simplicity.

We realize a reflex control by a simple single-layer feedforward neural network. By choosing neutral position of body and direction of handle as 0, we find spatial symmetry with respect to 0 position or direction. Therefore, we employ an activation function of hyperbolic tangent with which we represent left and right by plus and minus numbers.

Figure 2 shows the network constructions we employ in this paper to observe the influence of delay. First, as a preliminary experiment, we conduct a reflex motion experiment using Network (a) with a single input of bicycle tilt angle α. Neural delay is expressed as d. Next, using Network (b), we examine a reflex motion using both α and its changing rate (time derivative) $\dot{\alpha}$. Finally, we observe a related volitional motion using Network (c) or (d) with additional inputs of volitional signals fed to the body tilt neuron $a_{\mathrm{turn}\theta}$ and handle angle neuron $a_{\mathrm{turn}\phi}$.

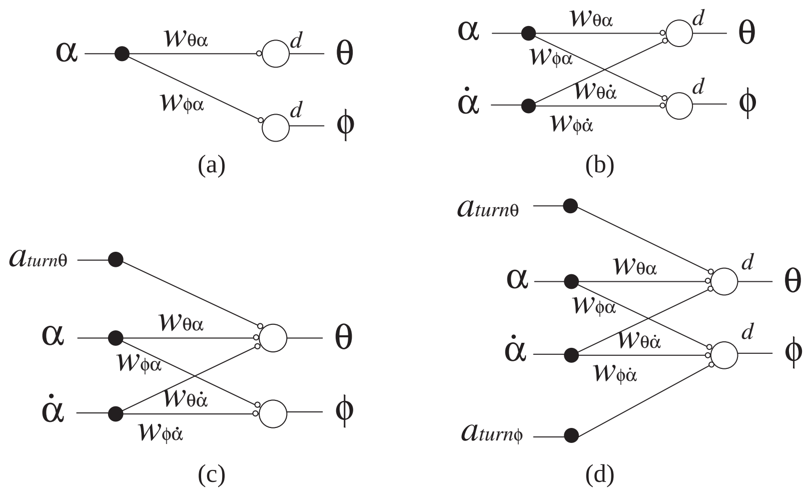


Figure 2: Neural network constructions for (a)reflex motion simulation with one input of tilt angle α, (b)that with two inputs of tilt angle α and its derivative $\dot{\alpha}$, (c)volitional motion with a volitional signal for body tilt neuron $a_{\mathrm{turn}\theta}$ only, and (d)that with volitional signals $a_{\mathrm{turn}\theta}$ and another for handle angle neuron $a_{\mathrm{turn}\phi}$ in addition. Neural delay is d for all of the neurons.

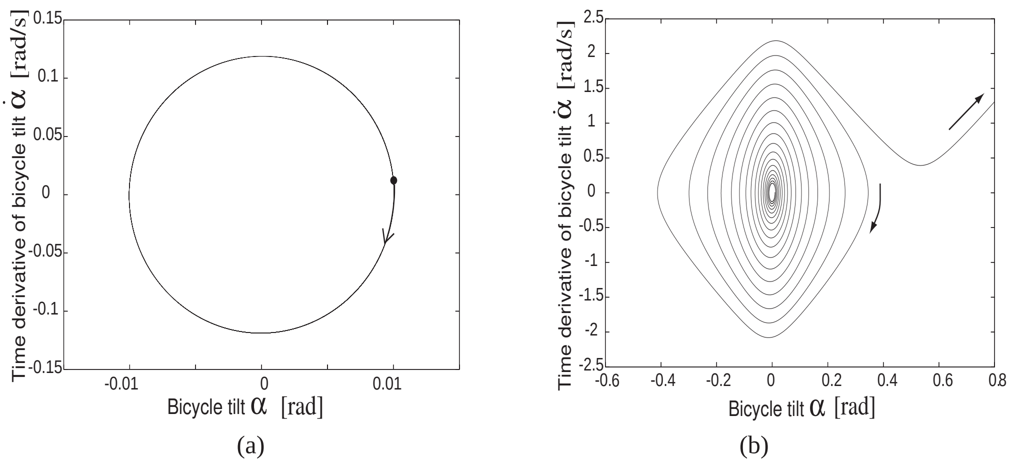


Figure 3. State trajectories of single-input system for delay of (a)d=0 and (b)d=5ms.

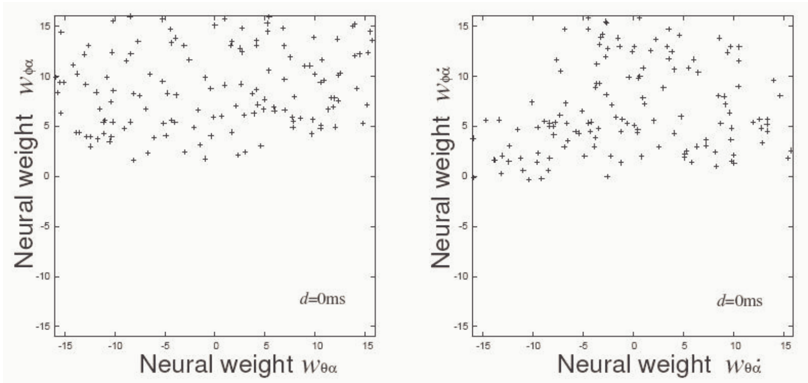
3. Reflex Motion in Bicycle Riding

3.1 Single input network (Preliminary experiment)

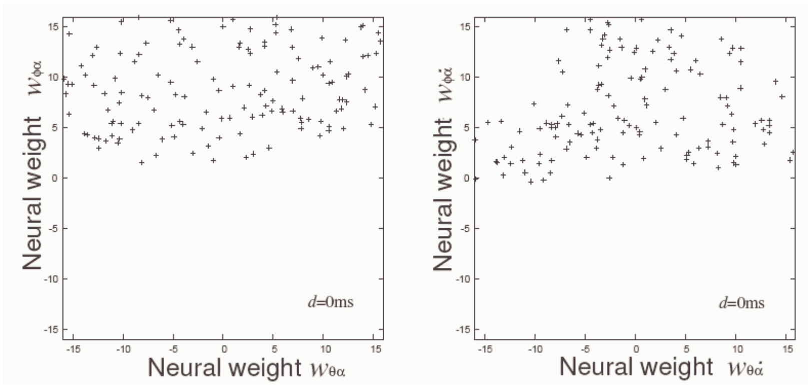
We examine the delay influence on reflex motion for Network (a) with a single input of bicycle tilt α only. We generate neural weights at random and observe the behavior of the sensorimotor system. The initial state is α=0.01rad and $\dot{\alpha}$=0.01rad/s. Typical results are illustrated in Fig.3 as state trajectory in the α–$\dot{\alpha}$ space. Figure 3(a) is a result when the network has no delay. We find a stable trajectory. On the contrary, Fig.3(b) shows a typical result when a small delay (5ms) exists. The trajectory is unstable, and the bicycle finally falls. It is obvious that even a small delay influences the behavior of a sensorimotor system.

3.2 Two input network (Bicycle tilt and its changing rate)

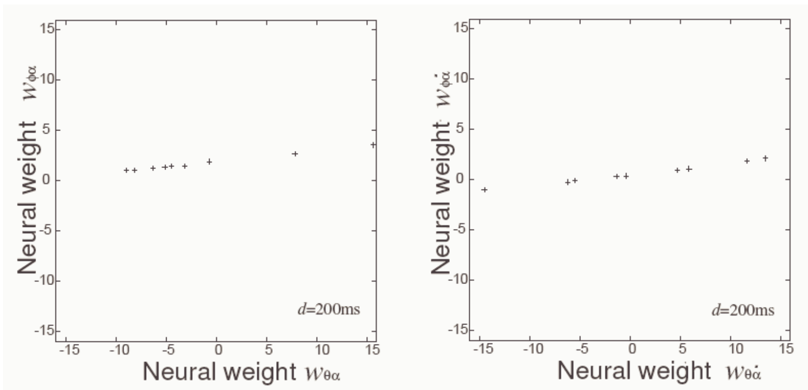
Human beings also catch outer world motion in the vision. We simplify the fact into an availability of time derivative information of tilt, $\dot{\alpha}$, in addition to α itself. The network construction is Fig.2(b).



(a)



(b)



(c)

Figure 4: Neural weight maps $w_{\theta\alpha} - w_{\phi\alpha}$ and $w_{\theta\dot{\alpha}} - w_{\phi\dot{\alpha}}$ for trials resulting in stabilization when the delay is (a)$d = 0$, (b)$d = 100$ms, and (c)$d = 200$ms, respectively.

Again we choose neural weights at random to examine if the bicycle fluctuation diminishes or not, where 'diminish' means that both α and θ remains within $\pm 10^{-3}$rad for more than 5s. In Fig.4, we plot the weights $w_{\theta\alpha}$, $w_{\phi\alpha}$, $w_{\theta\dot{\alpha}}$, and $w_{\phi\dot{\alpha}}$ *only when the fluctuation diminishes*, i.e., when the ride is successful. The weights construct four-dimensional space in total, while the chart represents them on the two planes. The area where the points exist shows the parameter region of stable control.

Figure 4(a) shows the result when there is no delay. The stable area is wide. Figure 4(b) is a result for a delay

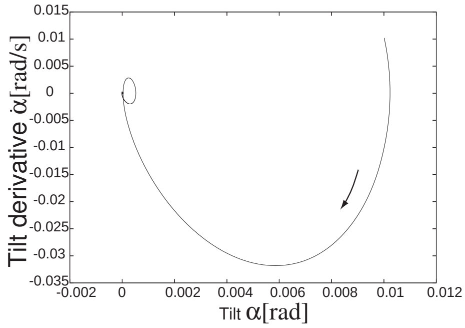
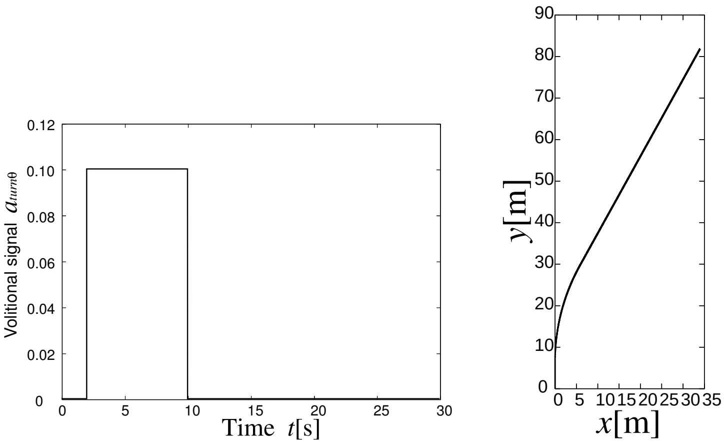


Figure 5. Stable state trajectory when the time derivative tilt angle $\dot{\alpha}$ is available as an input in reflex motion.



(a) (b)

Figure 6: Example of (a)volitional signal input to the body tilt neuron $a_{\mathrm{turn}\theta}$ and (b)obtained right-turning locus in a right turn task.

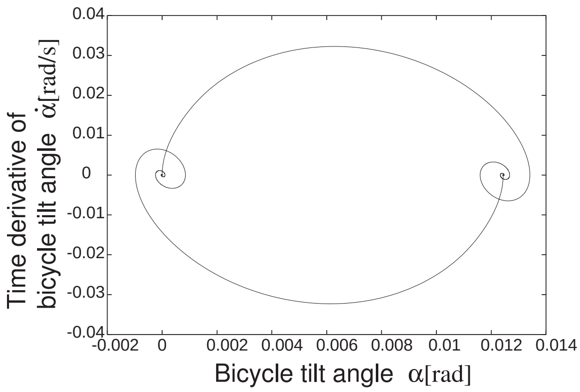
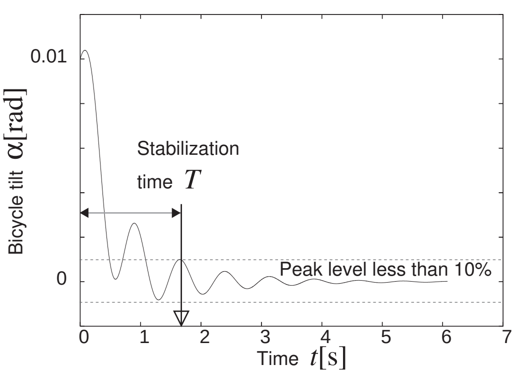
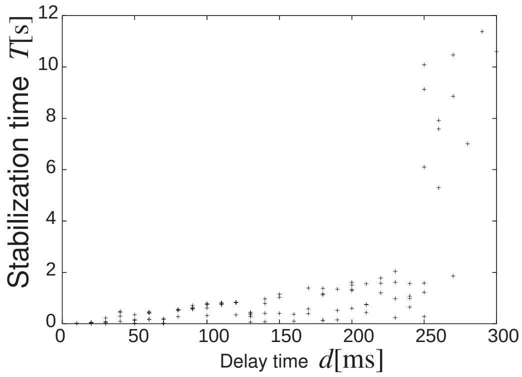


Figure 7. State trajectory obtained for the right turn behavior shown in Fig.6.

of 100ms. The stable region is limited in a belt. Figure 4(c) is for a delay of 200ms. The belt is much thinner. For a larger delay, we cannot find out stable regions any more. A larger delay obviously restricts the stable parameter area. An example of stable state trajectories is shown in Fig.5.



(a)



(b)

Figure 8: (a)Definition of stabilization time T in the waveform of bicycle tilt α versus time t, and (b)obtained stabilization time T versus delay time d after completion of reinforcement learning of four weights $w_{\theta\alpha}$, $w_{\phi\alpha}$, $w_{\theta\dot{\alpha}}$ and $w_{\phi\dot{\alpha}}$.

4. Volitional Motion Relevant to Reflex Motion Learnt Previously

4.1 Preliminary experiment to observe the relationship between reflex motion and volitional motion to turn

Action to turn is a volitional motion with consciousness, which is completely different from a reflex motion. However, in the case of a volitional motion that is relevant to a reflex motion, we assume that the reflex also works simultaneously because of its reflex nature. In other words, we deal with a turn motion not as a completely independent volitional motion but, instead, a mixture generated with a volitional control signal and a previously learnt reflex signal. A possible neural model is illustrated in Fig.2(c).

As a preliminary experiment, we conduct an experiment to see what motion the network in Fig.2(c) generates when it receives a simple input signal shown in Fig.6(a). We assume a delay of d=100ms. Figure 6(b) presents the resulting locus. When it receives the signal $a_{\mathrm{turn}\theta}$, it starts to turn, and when the signal ends, it also stops to turn, without falling down. Figure 7 shows the state trajectory. The state starts from the center of the left curl at the coordinate origin. When the volitional signal is input, the state migrates to another curl on the right-hand side, and when the signal ends, it returns to the initial state at the origin. The volitional signal shifts the initial stable state to another stable one, where the body is slightly askew, resulting in a smooth right turn. This motion is generated cooperatively by the reflex motion learnt in Section 3.2.

In an analogous way, when we applied another volitional signal $a_{\mathrm{turn}\phi}$, which modulates the handle angle ϕ, a similar reaction was observed. In reality, we can expect that both of $a_{\mathrm{turn}\theta}$ and $a_{\mathrm{turn}\phi}$ together generate a smooth turn motion. The network is shown in Fig.2(d).

4.2 Volitional Task, conditions, and preparatory reflex motion learning

We investigate the delay influence on the learning of volitional behavior to turn to the right. We employ Network (d), shown in Fig.2(d), having additional inputs of volitional signals at body tilt and handle angle neurons, $a_{\mathrm{turn}\theta}$ and $a_{\mathrm{turn}\phi}$, respectively. The learning process is as follows.

First, we conduct a preparatory experiment of reinforcement learning of reflex motion only for bicycle stabilization. It simulates unconscious daily learning to acquire the reflex reaction. In the learning, the four weights, $w_{\theta\alpha}$, $w_{\phi\alpha}$, $w_{\theta\dot{\alpha}}$ and $w_{\phi\dot{\alpha}}$, are adjusted to minimize the stabilization time T defined in Fig.8(a). This process optimizes the reflex motion. Figure 8(b) shows the stabilization time T versus neural delay time d. We find that T grows longer in proportion to d up to $d \approx$250ms. For a larger d, the stabilization time T drastically increases. The delay of 250ms is found to be a critical value in the present system.

After this reflex motion learning is completed, we go on to the following volitional motion learning where the system learns the volitional signal waveforms, while the reflex weights are fixed in this stage. The simulation schedule is similar to that in developmental learning [3]. Figure 9(a) illustrates the task in the volitional motion to

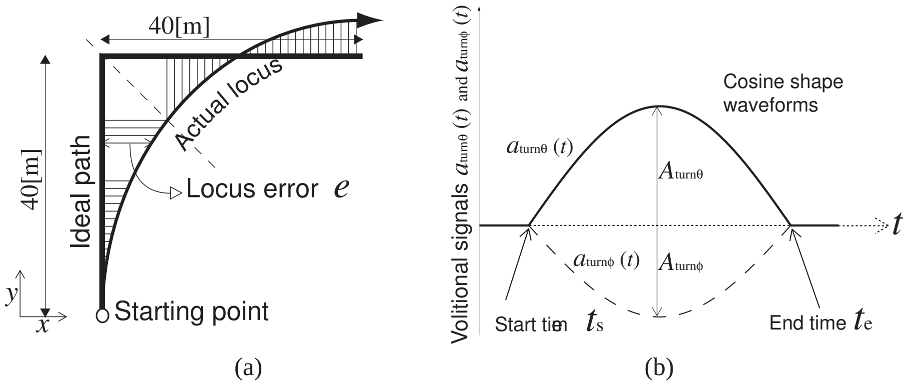


Figure 9: (a)The locus error e to be accumulated and averaged in the task to turn to the right, and (b)waveform of the volitional signals fed to body tilt neuron $a_{\mathrm{turn}\theta}$ and handle angle neuron $a_{\mathrm{turn}\phi}$. The amplitude values, $A_{\mathrm{turn}\theta}$ and $A_{\mathrm{turn}\phi}$, and their common start time t_{s}, and end time t_{e} are optimized through reinforcement learning.

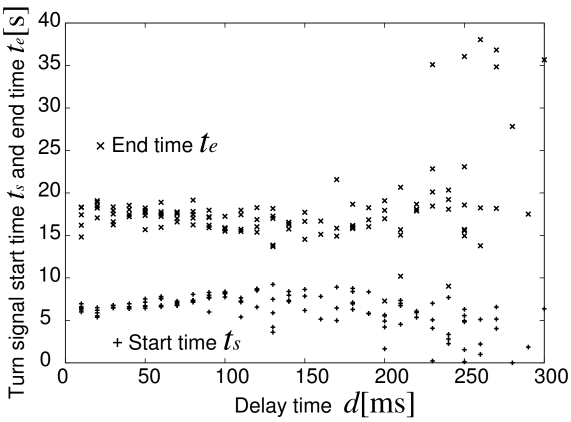


Figure 10. Turn signal start time t_{s} and end time t_{e} versus delay time d.

turn to the right. The deviation of the actual locus from the ideal path is accumulated step by step to yield average locus error e, which is evaluated in the reinforcement learning. To change the body tilt and the handle direction, we feed volitional signals $a_{\mathrm{turn}\theta}(t)$ and $a_{\mathrm{turn}\phi}(t)$ to the respective neurons, which are variable and optimized in the volitional-motion learning. Figure 9(b) shows the waveforms of the signals $a_{\mathrm{turn}\theta}(t)$ and $a_{\mathrm{turn}\phi}(t)$, which correspond to a half cycle of cosine waveform, with four parameters of start time t_s, end time t_e, signed (positive or negative) amplitude for body $A_{\mathrm{turn}\theta}$, and that for handle $A_{\mathrm{turn}\phi}$. The volitional signals are optimized in terms of these four parameters. That is, the system learns optimal t_s, t_e, $A_{\mathrm{turn}\theta}$, and $A_{\mathrm{turn}\phi}$ in another stage of reinforcement learning.

4.3 Results of reinforcement learning

Figure 10 shows the plots of start time t_s and end time t_e of volitional signal injection, which is optimized in reinforcement learning for various neural delay time d. Each delay value d contains several successful learning results corresponding to multiple trials. The origin of the time is the time when the bicycle starts the starting point in Fig.9(a). When d is smaller than ≈100ms, the dispersion of t_s and t_e is small. The signal duration ($t_e - t_s$) is found minimum at d ≈120ms. For a larger d, the dispersion gradually grows larger. When $d > 250$ms, the dispersion gets infinitely large, and the learning process often fails.

Figure 11 shows the average locus error E versus the neural delay d. We find that E is minimum at d ≈120ms. Figure 12 shows the obtained signed amplitude of the volitional signals, $A_{\mathrm{turn}\theta}$ and $A_{\mathrm{turn}\phi}$, versus the delay time d. Their absolute values reduces in accordance with the increase of the delay time d.

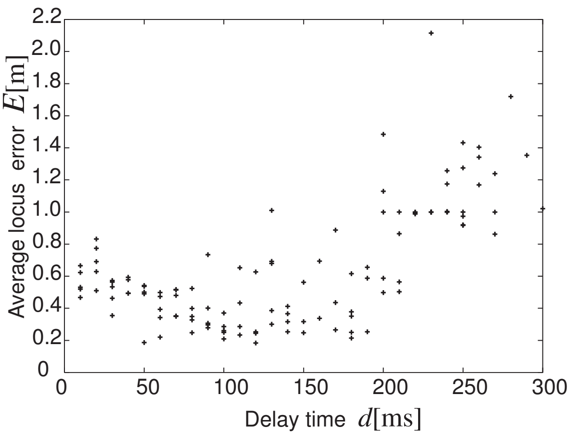


Figure 11. Average locus error E versus delay time d.

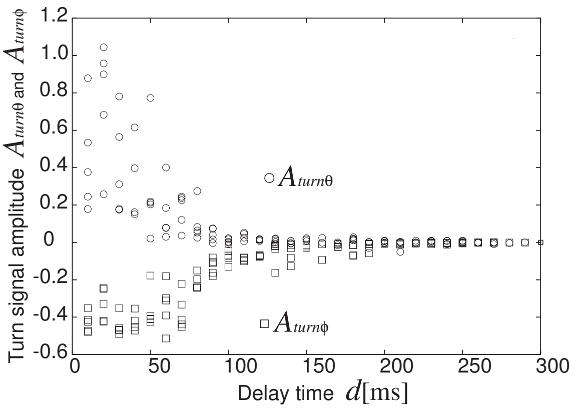


Figure 12. Optimized signed amplitudes of volitional turn signals $A_{\mathrm{turn}\theta}$ and $A_{\mathrm{turn}\phi}$ versus delay time d.

4.4 Discussion

In Fig.10, the volitional signal duration is minimum at around d=120ms. This value agrees with the minimum error delay in Fig.11. It is interesting that a moderate delay results in a better learning of volitional motion rather than a small d (< 50ms).

In Fig.12, for a larger d, the absolute values of the signed amplitudes $A_{\mathrm{turn}\theta}$ and $A_{\mathrm{turn}\phi}$ converges at 0. The reason lies in the slow feedback in reflex motion for a large d. That is, large volitional signals make the bicycle fall down because of the slow feedback. They reduce exponentially to the change in d, while the error E changes only moderately.

In the above experiment, we have found that a moderate delay leads to a better learning in the volitional motion to turn to the right in the bicycle riding. An explanation is given as follows. When the neural delay d is small, the sensorimotor system observes the state instantaneously without delay, and controls the bicycle in a feedback manner by spending a certain time. Contrarily, when d is large, the system cannot observe the effect of its control and, therefore, it cannot employ a feedback strategy. Instead, the system generates signal in a cavalier fashion, or in a predicting manner, and then just waits for the result.

Another explanation may be available, if we regard the learning as a class of search, as follows. In Fig.4, we found that the successful parameter region becomes narrower when d is larger in the reflex motion learning. If the delay is small, the reflex learning may stop cursorily before it falls a better state because the task is too easy. In contrast, if a moderate delay exists, the reflex motion learning makes progress further to a much better state. It may lead to a better learning of volitional motion. A too large delay d (>200ms) results in fatal difficulty in total.

5. Conclusion

A sensorimotor system learns how to overcome unavoidable delay to respond to environment. It has been shown that a moderate delay sometimes results in a better learning of relevant volitional motion. An explanation is as follows. When the neural delay is small, the sensorimotor system observes the state instantaneously and continuously, and controls the bicycle in a feedback manner. Contrarily, when the delay is moderately large, the system cannot observe the effect of its control output and, therefore, it cannot employ a feedback strategy. Instead, the system generates signal in a cavalier fashion, or in a predicting manner, and then just waits for the future result. It has been suggested that the amount of delay influences the neural learning strategy.

References

[1] R. Miall, D. Weir, and J. Stein, "Manual tracking of visual targets by trained monkeys," *Behavioural Brain Research*, vol.20, no.2, pp.185--201, May 1986.

[2] F. Ishida and Y. Sawada, "Human hand moves proactively to external stimulus: An evolutional strategy for minimizing transient error," *Physical Review Letters*, vol.93, no.16, p.168105, October 2004.

[3] A. Hirose, Y. Asano, and T. Hamano, "Developmental learning with behavioral mode tuning by carrier-frequency modulation in coherent neural networks," *IEEE Transactions on Neural Networks*, vol.17, no.6, pp.1532--1543, November 2006.

Yusuke Azuma received the B.E. and M.E. degrees both in electronic engineering from the University of Tokyo, Tokyo, Japan, in 2005 and 2007, respectively. He is currently with Elysium Inc. His research interest includes adaptive control and computer aided design.

Akira Hirose received the Ph.D. degree in electrical engineering from the University of Tokyo, Tokyo, Japan, in 1991. In 1987, he joined the Research Center for Advanced Science and Technology (RCAST), the University of Tokyo, as a Research Associate, where he was engaged in research on optical communications and measurement. In 1991, he was appointed an Instructor at the RCAST, and started neural network research. From 1993 to 1995, on leave of absence from the University of Tokyo, he was with the Institute for Neuroinformatics, University of Bonn, Bonn, Germany. He became an Associate Professor at the RCAST in 1995, and a Professor at the Department of Electronic Engineering, The University of Tokyo, in 2007. The main fields of his current research interest are wireless electronics and neural networks. Dr. Hirose is a member of the IEEE and the JNNS.