Enhanced Facilitatory Neuronal Dynamics for Delay Compensation

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***Abstract*— Our earlier work has suggested that neuronal transmission delay may cause serious problems unless a compensation mechanism exists. In that work, facilitating neuronal dynamics was found to be effective in battling delay (the Facilitating Activation Network model, or FAN). A systematic analysis showed that the previous FAN model has a subtle problem especially when high facilitation rates are used. We derived an improved facilitating dynamics at the neuronal level to overcome this limitation. In this paper, we tested our proposed approach in 2D pole balancing controllers, where it was shown to perform better than the previous FAN model. We also systematically tested the correlation between delay duration on the one hand and facilitation rate that effectively overcome the increasing delay on the other hand. Finally, we investigated the differential utilization of facilitating dynamics in sensory vs. motor neurons and found that motor neurons utilize the facilitating dynamics more than the sensory neurons. These findings are expected to help us better understand the role of facilitation in natural and artificial agents.**

I. INTRODUCTION

What we see at any given moment is actually an event occurred in the past. We are able to perceive the environment only after sensory signals arrive at the central nervous system (CNS). It takes about a hundred to a couple of hundred milliseconds for sensory inputs to travel from the peripheral sensors to the CNS [1]. Moreover, in many cases we need to react according to the sensory inputs as soon as possible. In order to move a set of muscles, CNS generates and sends appropriate motor commands to the corresponding muscle (Figure 1(a)). During this process, there are additional neuronal signal transmissions from CNS to the muscle, and we have further neuronal delays.

These hundreds of milliseconds of neuronal delays may not be a problem in many cases, but suppose an object is flying toward us. As soon as we perceive the moving object, we need to decide whether to evade or to catch it within a fraction of a second. In either case, we need to move our muscles. If the object is moving fast enough, we have to consider that the position of the ball right now is not the same as that registered in the CNS. Suppose the ball is moving along the x axis as shown in the bottom of figure 1(b). The moving object was located at x_1 when visual sensors receive the information from the environment at time t_1. Then actual motor output is generated at time t_6 at which time the object has moved to the position x_3. Our visual input was about the information at time t_1 and location x_1 but the real position of the object would be x_3 when we react to the input. In other words we saw the moving object at location x_1, and when we are about to move our muscles, the object is not there (location x_1) anymore.

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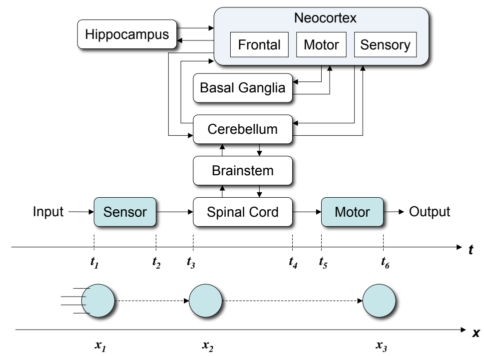


Fig. 1. Neural transmission delay and a moving object. Upper part was adapted from [2].

How do we cope with such a circumstance? There have been some researchers who probed this topic in terms of delay compensation [3],[4],[5] or prediction [2],[6],[7]. Lim and Choe [3],[4] suggested a neural dynamic model for delay compensation using facilitating activity network (FAN) based on short term plasticity in a neuron. Facilitating synapses have been found at a single neuron level in which membrane action potential shows a dynamic sensitivity to the changing rate of inputs [3],[8]. Although FANs have better performance than neuronal networks without facilitating neural dynamics, they have not shown analytically why FANs are more robust in an input delay condition. Moreover, they have not probed how these neuronal dynamics affect the entire network, and what will happen under longer delays.

In this paper, we propose Neuronal Dynamics using the Previous Immediate Activation value (NDPIA) at a single neuron level and show how neurons are facilitated or depressed in a neuronal network level. Input delay was applied to the system for the entire duration of each experiment. We extended the delay to twice the usual value (in FAN), and analyzed the results from the increased delay.

To test NDPIA and to investigate the properties of the neuronal networks with the suggested neuronal dynamics, we developed 2 degree-of-freedom (2D) pole-balancing [9] agents with recurrent neural networks as their controllers. Evolutionary neural networks have shown promise in evolving non-linear controllers [10],[11]. So, we used a conventional genetic algorithm (GA) to train the networks (see Experiments section A for detailed justification).

Our results suggest the following: First of all, NDPIA can solve subtle problems of FAN during facilitation. Second, facilitating only motor output neurons is better in compensating for delay at a neuronal network level than facilitating either the sensory input neurons or both the sensory input and the motor output neurons. In addition, facilitation rate should be increased as delay is increased given the same inputs.

Below, we first look into single neuron dynamics and the problems of conventional dynamics in [3],[4],[5]. Then we will suggest a new neuron-level facilitating dynamics (NDPIA), and analyze neuronal network-level dynamics. 2D pole-balancing problem and evolutionary neural networks will be introduced to test our model. Finally we will analyze the results, followed by discussion and conclusion.

II. Neural Dynamics and Delay

In this section, we will review facilitating and depressing dynamics in a single neuron level. Then subtle problems with the FAN model will be pointed out and a new neuronal dynamics proposed. We will also investigate the relationship between neuronal delays and facilitating dynamics; and network-level neuronal dynamics.

A. Facilitating and Depressing Dynamics

Neurophysiologists have found that there are two different synaptic dynamics: depressing and facilitating [8],[12]. The activation level, or membrane potential of the postsynaptic neuron is modulated by the change in the rate of past activation. These dynamic synapses generate short-term plasticity, which shows activity-dependent decrease (depression) or increase (facilitation) in synaptic transmission [8]. These activities occur within several hundred milliseconds from the onset of the activity [8],[13]. Lim and Choe [3],[4],[5] investigated the relationship between these neuronal dynamics and delay compensation, and suggested that facilitating neuronal dynamics in a single neuron level may play an important role in compensation of neuronal transmission delay.

These two neuronal dynamics should be implemented in different ways from conventional artificial neural networks (ANNs). As we can see in (1), the activation values in conventional ANNs are determined by the instantaneous input value and the connection weights.

$$X_i(t) = g\left(\sum_{j=1}^{m} w_{ij} X_j(t)\right) \quad (1)$$

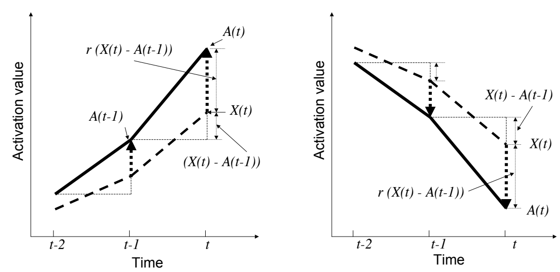
where $g(\cdot)$ is a nonlinear activation function such as the sigmoid function, m is the number of neurons of the preceding layer, and w_{ij} is the connection weight [3],[4],[5]. Equation (1) shows there is no room to consider the past X_i. Recurrent ANNs could be one simple solution for this, but they have only limited information of neural activations in the past. Recurrent ANNs themselves may not be enough to cope with input delays: Tan and Cauwenberghe[14] proposed a neural network based Smith predictor to compensate for large time delay; Miall and Wolpert[15] used the Kalman filter in the internal forward model to predict the next state; Lim and Choe[5] showed that facilitating neuronal dynamics may have an important role in compensating for input delays.

The activation value of a single neuron with neuronal dynamics can be defined as either facilitating or depressing:

$$A(t) = X(t) + r\Delta x_a(t) \quad (2)$$

where $A(t)$ is a modulated (facilitated or depressed) activation value at time t, $X(t)$ is the immediate activation value, r is a dynamic rate ($-1 \leq r \leq 1$), and $\Delta x_a(t)$ is $X(t) - A(t-1)$. The dynamic rate r can be either that of facilitation or depression (the above is due to [3],[4],[5]).

If $r \geq 0$, and if the signal increases for a while, the activation value is augmented by the difference ($\Delta x_a(t)$) of the immediate activation value $X(t)$ and the previous modulated one $A(t-1)$ with the rate r (see figure 2(a)). If $r \geq 0$, but if the signal decreases, the activation value is diminished by $\Delta x_a(t)$, because it becomes negative value in this case as you can see figure 2(b). These are called facilitating dynamics in a single neuron.



(a) Increasing activation (b) Decreasing activation

Fig. 2. Facilitating neural activity

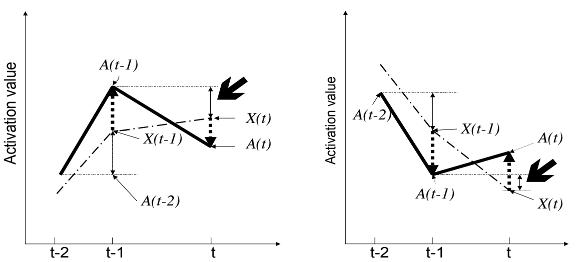
Suppose $r \leq 0$, and signal increases for a while, then the activation value is diminished by the difference ($\Delta x_a(t)$) between the immediate activation value and the previous modulated one with the rate r. If the signal decreases for a while under the same condition, the amount of decease became smaller than the immediate value by $\Delta x_a(t)$ with the rate r, because r is negative value and $\Delta x_a(t)$ is negative value as well, so conclusively $r\Delta x_a(t)$ becomes a positive value. It makes the signal greater than the immediate signal. Further it means the signal is less decreased than what it is supposed to be. In other words, modulated activation values can be considered within the range of $(X(t) - \Delta x_a(t)) \leq A(t) \leq (X(t) + \Delta x_a(t))$ [3] which means the present activation value could be diminished by $\Delta x_a(t)$ (depressing dynamics) or augmented by $\Delta x_a(t)$ (facilitating dynamics). Lim and Choe [3] suggested that these neuronal dynamics may play an important role in compensating delays.

But the neuronal dynamics by (2) has potential problems since $A(t)$ has a recursive component.

$$A(t) = \left(\sum_{n=0}^{k-1} (-1)^n r^n (1+r) X(t-n)\right) + (-1)^k r^k A(t-k) \quad (3)$$

Equation (2) can be expanded into (3). Now we can more clearly see that the current modulated activation value $A(t)$ is a function of $X(t-1), X(t-2), X(t-3)$ and so on. The problem is that, given $r > 0$, $X(t-1)$, $X(t-3)$, etc. contribute negatively while $X(t-2)$, $X(t-4)$, etc. positively. These positive and negative components can give rise to abrupt fluctuations in $A(t)$ that original do not exist in the input signal.

To better illustrate the problem, let us take an example in the case of facilitating dynamics. As we can see in figure 3(a), even if $X(t)$ keeps increasing from $X(t-1)$, the immediate activation value $X(t)$ could be smaller than the previous one $A(t-1)$ which is not desirable since $A(\cdot)$ will fluctuate unlike $X(\cdot)$. Same phenomenon happens when the activity is deceasing as in figure 3(b). This problem appears in case of depressing dynamics in a similar manner.



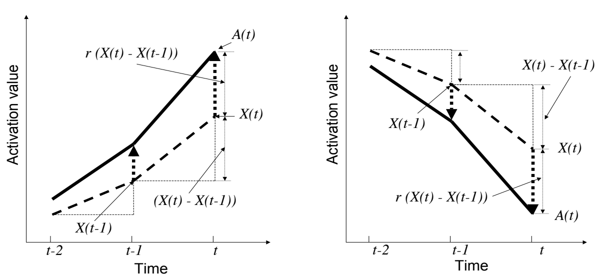
(a) Increase case (b) Decrease case

Fig. 3. Problems in Facilitating Dynamics

In order to address this issue, we propose an improved neuronal dynamics model, NDPIA which considers only the previous immediate activation value.

$$A(t) = X(t) + r\Delta x(t) \tag{4}$$

where $A(t)$ is the modulated (facilitated or depressed) activation value at time t, $X(t)$ is the immediate activation value, r is a dynamic rate, and $\Delta x(t)$ is $X(t)-X(t-1)$. The dynamic rate r can be either facilitation or depression, and it is not limited to $-1 \leq r \leq 1$, so that we can either facilitate or depress the immediate activation values as highly as we want. But practically, this value would not be to high.



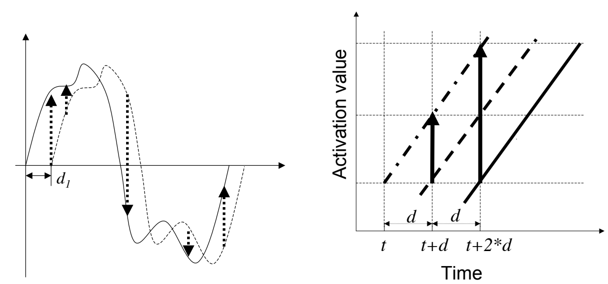
(a) Increasing activation (b) Decreasing activation

Fig. 4. Proposed facilitation neural activity

As we have shown in (3), the effect of $X(t-(n+1))$ disappears very quickly as n increases and r is less than 1. NDPIA accounts for the current and the previous immediate activation values. So in order to consider the previous activation values prior to the immediate one, we used recurrent neural networks, and the context inputs from the hidden layer could make up for the effect of older past activation values.

B. Facilitating Dynamics and Neuronal Delay

Short-term synaptic plasticity, especially facilitating synapses may play an important role in compensating for neuronal transmission delay [3],[4],[5], and the facilitating activity dynamics improves the ability of the neural networks in compensating for delays [3],[4],[5]. Figure 5(a) illustrates why facilitating activity can be an effective method to compensate for delays. Suppose the solid line is an original signal, and the dashed line is a delayed signal by d time units. If a delayed signal is facilitated by an amount of the change rate of the signal with fixed facilitation rate r, then the delayed signal approaches the original signal in either increasing or decreasing case. If the delay increases more the delayed signal should be facilitated more to approximate the original signal as shown in figure 5(b).



(a) Facilitating activation values (b) More facilitation for longer delay

Fig. 5. (a) Facilitating neural activity in a delay condition. The solid line represents the original signal, and dotted line is the delayed signal. Up and down arrows mean facilitation. (b) 2-step delay (solid line) needs more facilitation than the 1-step delay (dashed line) to line up with the original signal (dash-dotted line).

C. Network Level Neuronal Dynamics

Although it is clear that facilitating neuronal activity in a single neuron can be effective in compensating for neuronal transmission delays, it was not clearly analyzed which neurons in the network should be facilitated. A network consists of several neurons and layers. Then a question may arise: Which neuron in the network should be facilitated or depressed to compensate for delays? The relationship and coordination between neurons in a network will be investigated in the Experiments section below.

III. Experiments

First, we made sure that the proposed neuronal dynamics, NDPIA can address the problems of the conventional one. To investigate the network-level dynamics in a network, we evolved agents having recurrent neural network with neuronal dynamics. The dynamic rates could make the system be either facilitating or depressing. We could see which neurons tend to have high facilitation rates. Based on this idea, to test whether these network-level dynamics can be applied to real world applications, we used 2D pole balancing problem with sensory delays.

A. 2D Pole-Balancing Problem with Delayed Inputs

We tested our new facilitating dynamics in a single neuron level and neuronal network-level dynamics in a 2D pole-balancing system (figure 6).

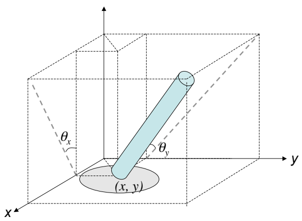


Fig. 6. 2 degree-of-freedom pole-balancing system

The state of the cart (the gray circle on the bottom figure 6) with a pole on top is characterized by the following physical parameters: The cart position in the plane (x, y), the velocity of the cart $(\dot{x}, \dot{y})$, the angle of the pole from the vertical in the x and the y directions (θ_x, θ_y), and their angular velocities $(\dot{\theta_x}, \dot{\theta_y})$ [9].

To test our facilitation dynamics, we modified the 2D pole-balancing problem with delayed sensory inputs [5]. The differences from [5] are as follows. First, we tested this with delays in all inputs during the entire test period in all experiments (reference [5] applied delay to all the inputs only for a specific time period). Second, we evolved the agents under no delay condition and tested the cases up to two-step delay. Longer delay may not be acceptable because of the high possibility of phase difference (see details in the Discussion section). In [5] only one step delay was investigated for measuring the performance of networks. Third, we used the conventional GA to evolve the agents' controller instead of Enforced SubPopulation algorithm (ESP) [9],[11]. In ESP in contrast to other GAs, a neuron in the network has its own population and a network is constructed by neurons from subpopulations. By using subpopulation, ESP can evolve a network to conduct a task rapidly, but neurons in a subpopulation tend to become homogeneous quickly. This tendency somehow interfered with the evolution of dynamic rates in our experiments, so we used the conventional GA.

B. Experimental Setup

1) Proposed Dynamics: A signal $2\exp(-t) \times \sin(t)$ (t is time) was used to verify whether NDPIA can solve the fluctuation problem in FAN. Additional experiments will be provided in the next experiment section to see whether this works in a real world application.

2) Neural Dynamics in a Network Level: Lim and Choe [5], [3] investigated dynamic activation rates in a single neuron level, but as far as we know, they have not tested the effect of facilitation in different parts of the network.

We evolved agents having recurrent neural networks with dynamics neuronal activities. These activity rates were evolved to ranging across $-1 \leq r \leq 1$ which means it could be facilitating or depressing.

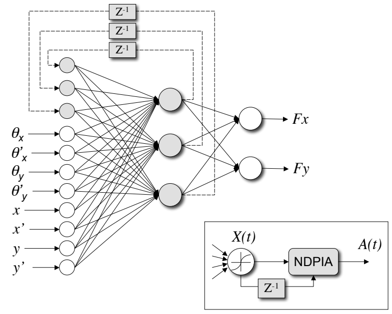


Fig. 7. Recurrent neural network for 2D pole-balancing. The signal flow inside each neuron is shown in the box. Z^{-1} means unit delay.

We used a recurrent neural network with eight input nodes, three context input nodes, three hidden neurons, and two output neurons in order to control the cart in the plane ($3\text{m} \times 3\text{m}$). Figure 7 shows the recurrent network that we used in the experiments. Output neurons F_x and F_y represent the force in the x and the y direction, respectively.

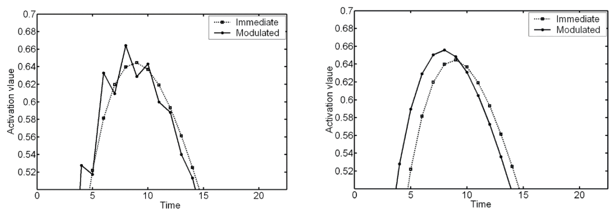
3) Neuroevolution: In training these non-linear controllers, neuroevolution methods were proved efficient [10],[11]. Contrary to [10],[11], we used a conventional neuroevolution method instead of ESP. Our purpose was not to develop controllers quickly, but to get most optimal controllers regardless of the training time. The chromosome encoded the connection weights between input nodes and hidden layer neurons, and between hidden layer neurons and output neurons. In the experiment of the evolution of dynamic activation rates, we additionally included a dynamic rate parameter in the chromosome. Crossover occurred with probability 0.7 and the chromosome was mutated by ± 0.3 (perturbation rate) with probability 0.2.

4) 2D Pole-Balancing Problem: Our evolved agents apply force to the cart in a flat surface to balance the pole (within $\pm 15^\circ$ angle of the pole from the vertical in the x and y directions). The force was applied in both the x and y directions at 0.1 second intervals. If an agent balances the pole more than 5,000 steps (1 step = 100 milliseconds), we consider it as a success. Fitness function returned the number of steps which means the agent balanced the pole within $\pm 15^\circ$ from the vertical and stayed inside a 3 meter area (-1.5m to 1.5m in x and y axes). 50 recurrent networks were evaluated in each generation, and to avoid situations where some neurons evolve to have accidentally good fitness values, we used the roulette wheel sampling method [16],[17],[18]. We used 0.5m length pole tilted 1 degree from the vertical towards the $+y$ direction with a 0 velocity at the initial state. The force in the range [-10 to 10] N was applied to the cart at a time step of 0.1 second.

We investigated (1) the effect of dynamic rates in a single neuron level by evolving the rates from depressing to facilitating property, (2) compared the performance between FAN and NDPIA, and (3) showed that facilitating motor neurons are better at coping with longer delays than facilitating sensory inputs or both sensory and motor neurons.

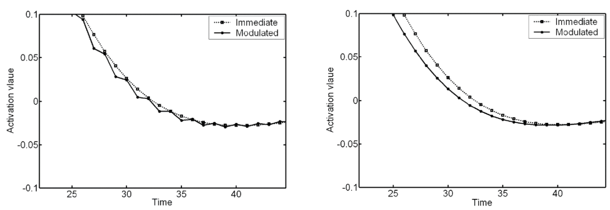
IV. Results

A. Single Neuron Dynamics



(a) FAN (b) Proposed NDPIA

Fig. 8. Fast signal change. This graph is a part of $2\exp(-t) \times \sin(t)$. $r = 0.8$ was used as the facilitation rate. (a) When the signal changes quickly, the dynamics in [3],[4],[5] give fluctuated activation value. (b) The proposed method eliminates the fluctuation problem.



(a) FAN (b) Proposed NDPIA

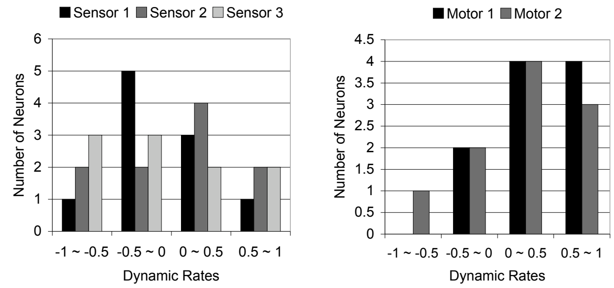
Fig. 9. Slow Signal Change. This graph is a part of $2\exp(-t) \times \sin(t)$. $r = 0.9$ was used as the facilitation rate. (a) Even when signal changes slowly, if r is high, the dynamics in [3],[4],[5] give fluctuated activation values. (b) The proposed one again eliminates the fluctuation problem.

When NDPIA is applied to the delay tasks, we were able to solve the fluctuating activation problem that we mentioned in Section II. Figure 8(a) shows a part of $2\exp(-t) \times \sin(t)$. We used 0.8 as the facilitation rate. As we can see, when the immediate activation value cannot keep up with the modulated one in FAN, some fluctuation occurs in the modulated activation values. In other words, facilitation did not occur properly in this case. Using NDPIA, these subtle fluctuation can be removed as shown in figure 9. Even when the activation values change slowly as in figure 9(b), if the facilitation activation rate is high enough (0.9 was used in this case), the fluctuation would occur again. 0.9 might seem too high, but as we examined in Section II-B, high facilitation rates can come up. As before, NDPIA removed the fluctuations (figure 9(b)).

B. Evolved Dynamic Activation Rate

Considering that agents balance the pole on the cart, and the agents have neural network controllers, we may think of the hidden layer of the neural network as a sensory input module, and the output layer as a motor module (figure 7). One question here is if neurons in these modules evolve different dynamics.

We evolved dynamic activation rates in sensory neurons (hidden) and motor neurons (output) as well as the synaptic weights of the neural networks.



(a) Dynamic rates in sensory neurons (b) Dynamic rates in motor neurons

Fig. 10. Distribution of dynamic rates in sensory and motor neurons

Figure 10(a) shows that dynamic rates are quite evenly distributed in the range of -1 to 1 for the sensory neurons. On the other hand, figure 10(b) shows that high dynamic rates are dominant in motor neurons. That is, motor neurons have evolved clearly higher dynamic rates than sensory neurons.

Based on this, we can conclude that non-linear controllers that balance the 2D pole have a tendency to facilitate the motor neurons' activation values more than sensory neurons.

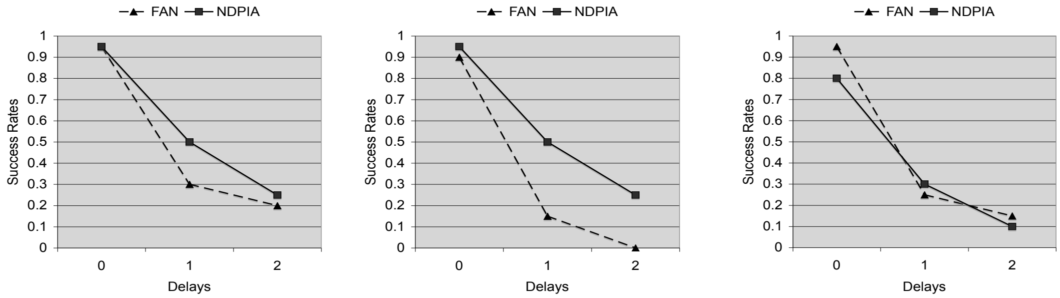
C. Performance Comparison between FAN and NDPIA

To compare the performance of FAN against NDPIA, we evolved 60 FAN networks and 60 NDPIA networks under no delay. Among the 60, 20 networks were evolved with facilitating motor outputs, 20 networks were evolved with facilitating sensory inputs, and 20 remaining networks were evolved with facilitation of both sensory neurons and motor neurons for each model (FAN and NDPIA respectively). We tested the evolved networks under no delay, 1-step delay, and 2-step delay environment to see the effect of dynamic activation rates. A fixed dynamic rate 0.7 was used for all the cases. Figure 11 shows that NDPIA has better performance than FAN in all cases. There was not much difference when delays were not introduce to the networks (see delay 0 cases in figure 11(a), (b), and(c)), but the difference of performance becomes clear as delay increases as we can see in figure 11.

D. Dynamics in Single Neuron and Network Level

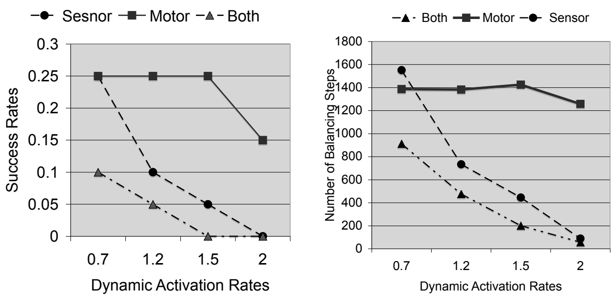
In this experiment, we investigated the effect of changing dynamic activation rates under longer delay. Networks showed lower performance in longer delay as shown in figure 11 when we used a fixed dynamic rate. As we examined in Section II, If we increase the fixed dynamic rate value, then the performance of networks can be improved.

The performances of the networks are degraded as delays increase. Then as we investigated in the previous section II-B, increasing the facilitation rates can be one way to cope with the increase in delay. Facilitating either sensory inputs or both the sensory neurons and the motor neurons showed a degradation in performance. Facilitation of only the motor output maintained stable performance. We considered it as a success when a network kept the pole balanced for a shorter duration in the longer delay condition (75% of that under no delay condition) (figure 12(a)). Figure 12(b) shows that the



(a) Facilitating sensor neurons (b) Facilitating motor neurons (c) Facilitating both sensory and motor neurons

Fig. 11. NDPIA has better performance than FAN under longer delays.



(a) Success rates (b) Average balancing steps

Fig. 12. The performance of facilitation dynamics in 2-step delay

change of performance as facilitation rates increase in two-step delay experiments. Even though more delay is applied to the networks, increasing dynamic rates is not effective when sensory neurons were facilitated. It was effective when only motor neurons were facilitated.

V. Discussion and Conclusions

The main contribution of our work is that we have improved the previous facilitation model [3],[4],[5] so that higher facilitation rates can be used without side effects (periodic fluctuation). As a consequence, our new approach allowed our model to deal with longer delays. However, our approach is not free of limitations. For example, our approach may not work well if the signal changes more rapidly than the delay duration (or equivalently if the delay duration is longer than the time scale of signal change). In order to deal with such situations, sensorimotor anticipation [19] or sensory prediction [2],[19] may be needed.

We will further investigate the case where different neurons have different delays due to noise. The role of the depressing neurons in a network needs to be probed because it is still unclear, even though facilitating dynamics in a single neuron clearly affect to the compensation for delay.

In this paper, we proposed an improved facilitating dynamics, NDPIA, to address subtle shortcomings in the previous FAN model by [3],[4],[5]. We showed that our approach overcomes the limitations and results in higher performance in a standard 2D pole-balancing task. Our extensive analysis also revealed an intimate relationship between higher facilitation rates and longer delays the controller can tolerate. Finally, we have found that facilitating dynamics is most effective in motor neurons. Our findings are expected to help us better understand the role of facilitating dynamics in brain function.

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