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Facilitating neural dynamics for delay compensation: A road to predictive neural dynamics?

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ABSTRACT

Goal-directed behavior is a hallmark of cognition. An important prerequisite to goal-directed behavior is that of prediction. In order to establish a goal and devise a plan, one needs to see into the future and predict possible future events. Our earlier work has suggested that compensation mechanisms for neuronal transmission delay may have led to a preliminary form of prediction. In that work, facilitating neuronal dynamics was found to be effective in overcoming delay (the Facilitating Activation Network model, or FAN). The extrapolative property of the delay compensation mechanism can be considered as prediction for incoming signals (predicting the present based on the past). The previous FAN model turns out to have a limitation especially when longer delay needs to be compensated, which requires higher facilitation rates than FAN's normal range. We derived an improved facilitating dynamics at the neuronal level to overcome this limitation. In this paper, we tested our proposed approach in controllers for 2D pole balancing, where the new approach was shown to perform better than the previous FAN model. Next, 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 facilitating dynamics in delay compensation, and its potential development into prediction, a necessary condition for goal-directed behavior.

1. Introduction

Goal-directed behavior is a hallmark of intelligent cognitive systems. Therefore, understanding such behavior is not only important but also essential to scrutinize intelligence. However, it is not easy to directly investigate goal-directed behavior since there is an implied *agent* behind such behavior, and there is yet not a consensus on what constitutes an agent.

Thus, here we take a different approach to initiate a first step toward understanding goal-directed behavior. Our strategy is to focus on a precondition, or a necessary condition for goal-directed behavior, rather than trying to address the problem head-on.

The main question we will address here is how the precondition could have evolved. Once the prerequisite has evolved, it could have laid a critical stepping stone toward goal-directed behavior. We theorize that one important necessary condition of goal-directed behavior is prediction. Note that a goal is always defined as a future event. Thus, without the ability to anticipate future events, one may not be able to establish a goal. In order to anticipate, one needs to be able to predict. Consequently, by analyzing how prediction has evolved, we could shed light on a potential evolutionary pathway toward goal-directed behavior. Also, we must note that prediction is increasingly being recognized as one of the core functions of the brain (Hawkins & Blakeslee, 2004; Llinás, 2002) (see also Carpenter and Grossberg (1992) and Li and Kozma (2003) on prediction in dynamic neural network architectures).

In our previous work (Lim & Choe, 2006a, 2006b, 2006c, 2008), we hypothesized that delay in the nervous system could have led to a delay compensation mechanism, which in turn could have further developed into a predictive function. First, let us take a look at neuronal delay in detail before investigating the predictive property of the delay compensation mechanism. Strictly speaking, representations of the present in the brain may not even be precisely aligned with the present in the environment. Our sensory information would reflect the past if the higher perceptual areas in the brain register the signal at the moment the signal is received. Consider visual processing. A series of steps is required for visual stimulus information to reach higher visual processing areas: photoreceptors, bipolar cells, ganglion cells, the lateral geniculate nucleus, the primary visual cortex, and beyond (Nijhawan, 2008). It could take in the range of 100 to 130 ms for the visual signal to arrive in the prefrontal cortex (in monkeys) (Thorpe & Fabre-Thorpe, 2001). In order to make up for the neuronal transmission delay, the brain should utilize information from the past and *predict* the current state.

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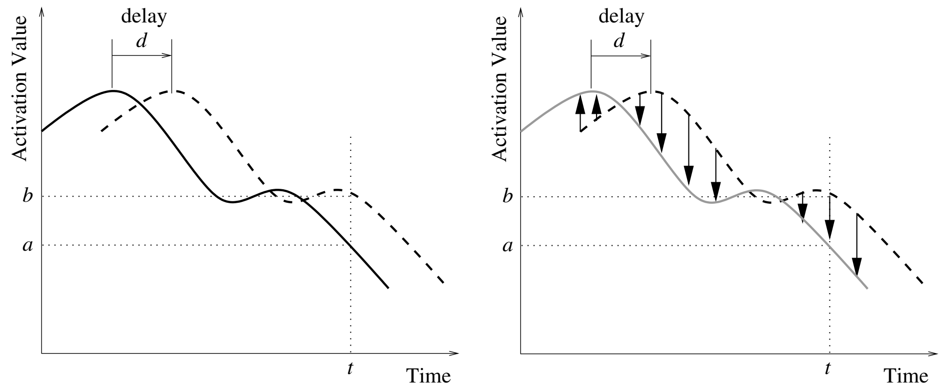
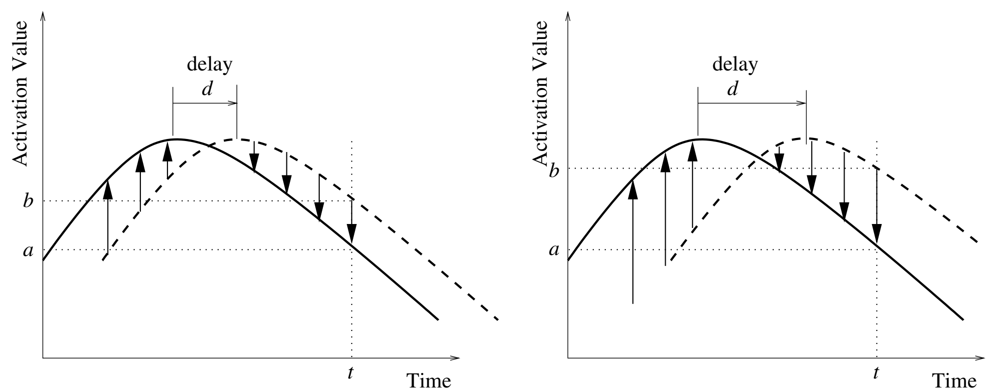


(a) Delay. (b) Facilitation.

Fig. 1. Delay and delay compensation through facilitating neural activity. (a) The solid curve represents the original signal, and the dotted curve corresponds to the delayed signal (delayed by d). (b) The original signal can be extrapolated by facilitating the neural activity (further increasing when the signal is increasing, and further decreasing when the signal is decreasing). For example, an activation value b at time t (original signal from $t-d$, delayed by d) can be modulated down to a through facilitating dynamics, where the modulated value a is an approximation of the original signal at time t.



(a) Short delay. (b) Long delay.

Fig. 2. Length of delay and required degree of facilitation for delay compensation. The solid curve represents the original signal, and the dotted curve the delayed signal (delayed by d). (a) Short delay requires only a moderate amount of facilitation to compensate for the delay. (b) More facilitation is needed as the length of delay between the original and the delayed signal becomes greater (the vertical arrows are longer in (b) than in (a)).

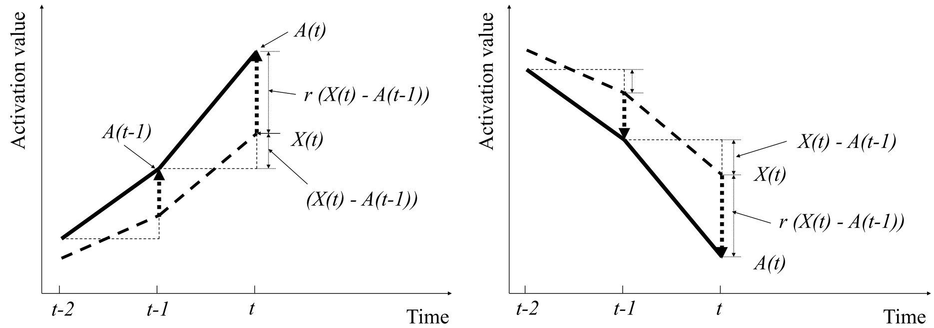
Some researchers probed this topic in terms of delay compensation (Lim, 2006; Lim & Choe, 2006b, 2006c) or prediction (Downing, 2005; Krekelberg & Lappe, 2000). Lim and Choe suggested a neural dynamic model for delay compensation using Facilitating Activity Network (FAN) based on short-term plasticity in the neuron known as *facilitating synapses* (Lim, 2006; Lim & Choe, 2006b). Facilitating synapses have been found at a single neuron level in which the membrane potential shows a dynamic sensitivity to the changing rate of the input (Liaw & Berger, 1999; Lim, 2006). As illustrated in Fig. 1, the original signal can be recovered from the delayed signal by using facilitating dynamics. According to the facilitation model, as Fig. 2 illustrates, higher facilitation rates are needed to effectively deal with longer delay. However, the FAN model turns out to have limitations, i.e., oscillation under high facilitation rate (see Section 3 for details). Furthermore, the analysis in Lim (2006) and Lim and Choe (2006c) did not consider differential utilization of facilitation among different neuron types within the context of the entire network (e.g., sensory neurons vs. motor neurons).

Here, we propose an improved dynamic model, *Neuronal Dynamics using Previous Immediate Activation value* (NDPIA) that solves the oscillation problem in FAN. In addition, we conducted experiments in less restricted conditions than in Lim (2006) and Lim and Choe (2006c): (1) input delay was applied to the system for the entire duration of each experiment, and (2) we extended the delay to twice the usual value compared to the earlier experiments with 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 employed a two degree-of-freedom (2D) pole-balancing (Gomez & Miikkulainen, 1998) agents with evolved recurrent neural networks as their controllers (cf. Gomez and Miikkulainen (2003) and Gomez (2003)). We used conventional neuroevolution to train the networks (see Section 3.2 for detailed justification, and R.G. Ward and R. Ward (2009) for successful use of such strategy in a different task domain).

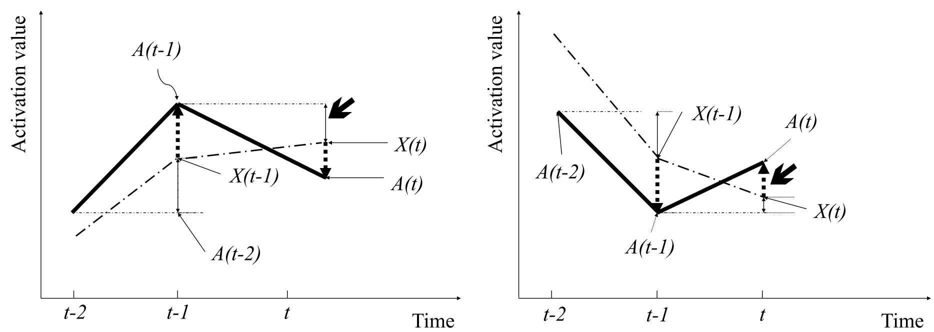
Our main findings are as follows: (1) NDPIA can solve the oscillation problem in FAN during heightened facilitation. (2) Motor neurons in a NDPIA network tend to evolve high facilitation rates, confirming similar previous results with FAN. (3) Longer delay leads to higher facilitation rates. (4) Neural network controllers using NDPIA dynamics result in better performance in pole-balancing tasks than those based on FAN. (5) NDPIA networks show robust performance under extremely high facilitation rates, especially when only the motor neurons are facilitated. These results suggest that delay and facilitation rate must be positively correlated for effective compensation of delay, and the best part in the system to introduce such dynamics is the motor system.

Below, we first look into related research, then we analyze the limitations in the FAN dynamics. Then we will propose a new facilitating dynamics (NDPIA). Next, the 2D pole-balancing problem and evolutionary neural networks will be introduced. Finally we will present and analyze the results, followed by discussion and conclusion.



(a) Increasing activation. (b) Decreasing activation.

Fig. 3. Facilitating Neural Activity. (a) The immediate activation value $X(t)$ is modulated by the difference between $X(t)$ and the modulated activation value $A(t-1)$ in the previous time step, with facilitation rate r. (b) The same principle can be applied to the decreasing activation case.



(a) Increasing activation. (b) Decreasing activation.

Fig. 4. Problems in facilitating dynamics of FAN. (a) When the activity is increasing, the immediate activation value $X(t)$ could be smaller than the modulated value $A(t-1)$ from the previous time step, so the modulated value at the present $A(t)$ becomes smaller than the immediate value $X(t)$. This property of the conventional FAN model makes the system output to become unstable. (b) Basically, the same analysis can be applied in the case of decreasing activity. When the activity is decreasing, $X(t)$ is larger than $A(t-1)$. Hence, $A(t)$ becomes even larger than $X(t)$.

2. Background

The activation level or the 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 (Fortune & Rose, 2001; Liaw & Berger, 1999). These activities occur within several hundred milliseconds from the onset of the stimulus (Liaw & Berger, 1999; Markram, 2003). Lim (2006), Lim and Choe (2006b, 2006c) investigated the relationship between these neuronal dynamics and delay compensation, and suggested that facilitating dynamics at a single neuron level may play an important role in the compensation of neuronal transmission delay.

How can such dynamics be realized in a neural network? We can begin with conventional artificial neural networks (ANNs), but ANNs lack such single neuron-level dynamics (note the adding recurrent connections can introduce a network-level dynamics). As we can see in Eq. (1), the activation values in conventional ANNs are determined by the instantaneous input value and the connection weights.

$$X(t) = g\left(\sum_{j=1}^{m} w_j X_j(t)\right) \tag{1}$$

where $g(\cdot)$ is a nonlinear activation function such as the sigmoid function, m is the number of neurons of the preceding layer, w_j is the connection weight, and X_j is an activation value from a neuron of the preceding layer (Lim, 2006; Lim & Choe, 2006b, 2006c). Eq. (1) shows that there is no room to consider the past values of X_j. Recurrent ANNs could be one simple solution for this, but the dynamics may not be fast enough to cope with input delays. Tan and Cauwenberghe (1999) proposed a neural network based Smith predictor to compensate for large time delay; Miall and Wolpert (1996) used the Kalman filter in the internal forward model to predict the next state; and Lim and Choe (2006c) showed that facilitating neuronal dynamics at a single neuron level can play an important role in compensating for input delays.

In order to overcome the issues above, the activation value needs to be directly modulated as in the Facilitating Activity Network (FAN) model (Lim, 2006; Lim & Choe, 2006b, 2006c):

$$A(t) = X(t) + r\Delta(t) \tag{2}$$

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 ($-1 \leq r \leq 1$), and $\Delta(t)$ is $X(t) - A(t-1)$.

If $r \geq 0$, and if the signal increases for a while, the activation value is augmented by the difference $\Delta(t)$ of the immediate activation value $X(t)$ and the previous modulated activation $A(t-1)$ with the rate r (see Fig. 3(a)). If $r \geq 0$, but if the signal decreases, the activation value is diminished by $\Delta(t)$, because it becomes a negative value in this case as shown in Fig. 3(b). This results in facilitation.

Suppose $r \leq 0$, and that the signal increases for a while, then the activation value is diminished by the difference $\Delta(t)$ between the immediate activation value and the previous modulated activation with the rate r. If the signal decreases for a while under the same condition, the amount of decrease becomes smaller than the immediate value by $\Delta(t)$ with the rate r, because r is a negative value and $\Delta(t)$ is a negative value as well, so $r\Delta(t)$ becomes a positive value. This makes the signal greater than the immediate signal. Furthermore it means that the signal is decreased less than what it is supposed to be. In other words, the modulated activation values can be considered within the range of $(X(t) - \Delta(t)) \leq A(t) \leq (X(t) + \Delta(t))$ (Lim, 2006) which means that the