Incorporating Real-Time Random Time Effects in Neural Networks: A Temporal Summation Mechanism

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Abstract

Implementing random time effects in neural networks has been a challenge for neural network researchers. In this paper, we propose a neurophysiologically inspired temporal summation mechanism to reflect real-time random dynamic processing in neural networks. According to the physiology of neuronal firing, a presynaptic neuron sends out a burst of random spikes to a postsynaptic neuron. In the postsynaptic neuron, spikes arriving at different points in time are summed until the postsynaptic membrane potential exceeds a threshold, thus initiating postsynaptic firing. This temporal summation process can be used as a metric for deriving time predictions in neural networks. To demonstrate potential applications of temporal summation, we have employed a feedforward, two-layer network featuring a Hebbian learning rule to perform simulations using the semantic priming experimental paradigm. We are able to successfully reproduce not only the basic patterns of observed response time data (e.g., positively skewed response time distributions and speed-accuracy trade-offs) but also the semantic priming effect and the time-course of priming as a function of stimulus-onset-asynchrony. These results suggest that the proposed temporal summation mechanism may be a promising candidate for incorporating real-time, random time effects into neural network modeling of human cognition.

1. Introduction

Neural network modeling of human cognition represents an attempt to combine two of the three levels of analysis proposed by Marr (1982), viz., the psychological (algorithmic) and the neurophysiological (implementation) levels. While considering the role of the real-time dimension in neural network modeling, two perspectives are relevant. From the neurophysiological perspective, the firing pattern of neurons, a basic building block of neural information processing, is usually described as a real-time random process (Bialek, Rieke, de Ruyter van Steveninck, & Warland, 1991; Gerstner, Ritz, & van Hemmen, 1993). From a psychological perspective, the response time variable has been an important source of information for understanding human cognition (Luce, 1986). These perspectives have motivated us to consider the incorporation of the temporal dimension into neural network modeling. Moreover, it can be argued that incorporating real-time dynamics into neural networks represents an essential step in specifying the linking rules between psychological and neurophysiological levels, which is critical to understanding cognition.

Although some doubt has been raised about the ability of extant feedforward neural networks to predict the time course of information processing (Massaro & Cowman, 1993), some noteworthy mechanisms have been proposed, including: (1) gradual propagation of activation in time (Cascade model, McClelland, 1979; GRAIN model, McClelland, 1993; Cohen, Dunbar, & McClelland, 1990; Seidenberg & McClelland, 1989[1] ; Kawamoto, 1993), (2) an independent decision module having linear integrator with threshold (see, e.g., Lacouture & Marley, 1991, 1994), (3) number of iterations required to get from initial state to stabilized state (e.g., Anderson, Silverstein, Ritz, & Jones, 1977; Masson, 1991, 1995), and (4) vector distance between initial- and stable states (Sharkey, 1989). In particular, gradual propagation (McClelland, 1979, 1993) seems to come closest to implementing real-time dynamics. McClelland's models predict mean response times by assuming a non-linear pattern of the time course of gradual activation through neural network layers. However, it is not clear how *random* time effects can be simulated using gradual activation, nor what aspect of neurophysiological mechanisms is responsible for the assumed non-linear function for the time pattern, particularly if one is to deem the neurophysiological plausibility as being important.

This research seeks to provide a neurophysiologically motivated foundation for incorporating real-time random dynamic processing in neural networks. Many neural network models have utilized the mean firing rate (which contains information about the activation level of a neuron) as the basic metric of communication between neurons. The mean firing rate is, however, an unsatisfactory metric because it averages out the information related to the temporal pattern of firing (Gerstner et al., 1993; Palm, Aertsen, & Gerstein, 1988). Accordingly, when

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[1] Seidenberg & McClelland (1989) used mean square error as an indicator of mean response time based on the cascade model.

incorporating real-time dynamics into neural networks, it may be advisable to identify and utilize those firing mechanisms and metrics which are capable of reflecting temporal processing patterns.

2. Temporal Summation of Neural Information Processing

Neural firing results from the operation of two independent mechanisms: a spatial summation mechanism and a temporal summation mechanism (see Levitt, 1981; Arbib, 1989). A presynaptic neuron, once excited, sends out a train of random spikes to a postsynaptic neuron. The postsynaptic neuron accumulates spikes from different pre-synaptic neurons (i.e., spatial summation) over time (i.e., temporal summation) until activation from the presynaptic neurons exceeds a predetermined threshold, triggering a postsynaptic firing (see Figure 1).

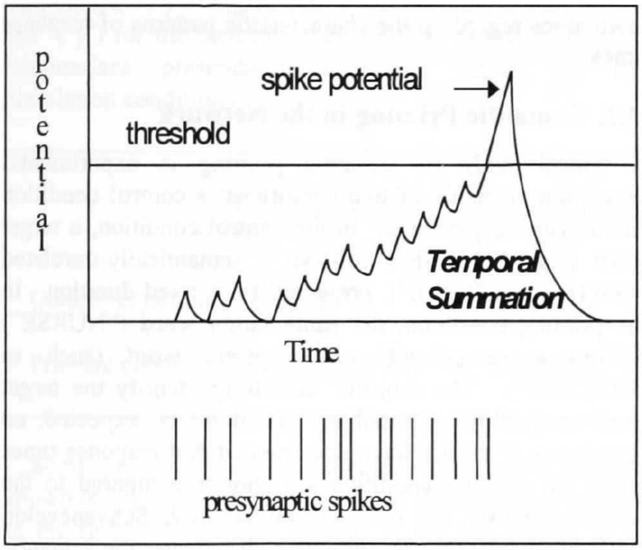

Figure 1. Pictorial depiction of temporal summation mechanism

Spatial summation constitutes one of the basic building blocks in almost all neural network models, and has been widely utilized (Rumelhart & McClelland, 1986; Hopfield, 1982). Although the existence of the temporal summation mechanism is equally well-known and established in neurophysiology, surprisingly little attention has been paid toward incorporating this mechanism in past neural network modeling. Accordingly, we contend that the temporal summation mechanism may provide one way of implementing real-time dynamics into neural networks.

We will now review and summarize the formal description of temporal summation at the postsynaptic neuron as it relates to neural network modeling (for more details, see Ricciardi, 1977; Sato, 1978). An input unit, once excited, sends out a time-series of all-or-none spikes to the output units of a network. Let us assume that spikes, denoted by $S_i(t) = 0$ or 1, are generated in input unit i via a Poisson process with parameter λ (i.e., the mean number of spikes during a given time interval is proportional to the time interval itself). An output unit accumulates trains of spikes from different input units, weighted by the connection strength (W_{ij}) between input unit i and output unit j. Specifically, leaky integration in temporal summation weakens the activation of an output unit when no spikes arrive--such a leaky integration is commonly assumed in simulating a single neuron's activity (see, for instance, McKenna, Davis, & Zornetzer, 1992).

Formally, the change of activation in output unit j at time t ($\Delta net_j(t)$) can be written as the following stochastic equation:

$$\Delta net_j(t) = \underbrace{\sum_{i=1}^{m} W_{ij} a_i}_{\textit{Spatial Summation}} \underbrace{\left[\int_{t}^{t+\Delta t} S_i(h)dh \right]}_{\textit{Temporal Summation}} - \underbrace{\xi \bullet net_j(t) \bullet \Delta t}_{\textit{Leakage Term}} \qquad (1)$$

where W_{ij} (≥ 0) is the connection weight between input unit i and output unit j, a_i represents the activity of input unit i, and ξ (≥ 0) is a leakage parameter.

In principle, temporal summation can be applied to the modeling of any psychological phenomenon that involves the time course of processing. In the present study, with the view of exploring the psychological plausibility of the temporal summation mechanism, we have applied it to the semantic priming phenomenon.

3. Simulating the Semantic Priming Effect

3.1. The Neural Network

To implement temporal summation, we constructed a feedforward, two-layer network with all input units (semantic feature units) being fully connected to output units (concept units). We use a binary vector $\mathbf{a} = (a_1, ..., a_m)$, where $a_i = 1$ (on) or 0 (off) to indicate the presence or absence of the i-th semantic feature in an input stimulus (e.g., "has-a-wing" for concept "BIRD"). The output of the network is described by another binary vector $\mathbf{b} = (b_1, ..., b_n)$ where $b_j = 1$ (on) or 0 (off) indicates the concept-triggering response of the j-th output unit (e.g., "BIRD"). The output b_j, corresponding to concept j, is produced using the non-linear threshold function $b_j = f\left[net_j(t) - \theta\right]$, where $net_j(t)$ is the activation of unit j at time t, θ is a threshold, and $f(x) = 1$ if $x \geq 0$ and 0 otherwise. As described in equation (1) above, $net_j(t)$ is a random variable that changes over time according to the nonlinear stochastic process.

The following form of Hebb's learning rule was employed (cf. Hebb, 1949; Grossberg, 1987; Levy, 1982):

$$\Delta W_{ij} = \alpha \bullet a_i \bullet b_j - \delta \bullet W_{ij} \qquad \textbf{(2)}$$

where α (>0) is the learning rate and δ (>0) is a decay constant. The network was trained to learn concepts; each concept was defined by the corresponding prototype vector: $\mathbf{y}^j = (y_1^j,\ldots,y_m^j)$, where $y_i^j \equiv P(a_i = 1|\, b_j = 1)$, $(j = 1,\ldots,n)$. For the purpose of the simulations, these prototype vectors were artificially generated. On each training trial for a particular concept (say concept j), a binary vector is randomly generated from the prototype vector $\mathbf{y}^j$ and presented to the network as an input while output unit b_j remains turned on. Under these modeling assumptions, it can be readily shown that at equilibrium (i.e., when $E[\Delta W_{ij}] = 0$), we have:

$$E[W_{ij}] = \frac{\alpha}{\delta} P(b_j = 1)P(a_i = 1|b_j = 1)$$

(see Clark & Ravishankar, 1990). In other words, a connection weight is determined by the product of the base rate of concept j (the prior probability of the output unit firing) and the conditional probability of existence of feature i given concept j. The network was trained for six randomly presented concepts over 12,000 training trials. The resulting weights were then used for subsequent simulations.

3.2. Response Time

Response time in the network is defined as the time lag between presentation of an input vector and the earliest firing of an output unit. From the characteristics of the temporal summation mechanism, four basic properties of the simulated response time patterns can be predicted for the network.

First, response time will be probabilistic rather than deterministic owing to the random Poisson process assumption of temporal summation. Consequently, the network produces a response time distribution instead of simply the mean response time. In particular, the shape of the response time distribution will be positively skewed, a consequence of the accumulation of activation over time in the presence of a fixed threshold (Ratcliff, 1978).

Second, note that leaky integration in the accumulation of activation in the network gives rise to non-linearity in temporal summation. Although this non-linearity is a common assumption of some random walk models (Ratcliff, 1980; Smith, 1994), it may, in fact, be attributable to temporal summation of neural firing. This insight points to the benefit of giving due consideration to neurophysiological mechanisms in conjunction with mathematical modeling (e.g., Link, 1992).

Third, exploiting the properties of the Hebbian learning rule, it can be formally shown that the response time is determined by similarity between an input feature vector and a prototype concept vector. Defining similarity, $s(\mathbf{a}, \mathbf{y})$, as a dot product between an input feature vector $\mathbf{a}$ and a prototype concept vector $\mathbf{y}$, we derived the mean drift rate of activation of the corresponding output unit given the input vector. The mean drift rate is proportional to the similarity between the two vectors. This implies that greater similarity of an input vector to a stored prototype vector will elicit a faster response in the corresponding output unit. This relation between similarity and response time will be demonstrated in the following section which reports our simulation results of semantic priming effects.

Finally, as the threshold (θ) of the network is varied, the response time changes. Manipulating this threshold will lead to speed-accuracy trade-offs (i.e., reciprocity between response time and error rate). Speed-accuracy trade-offs have been a common empirical finding in cognitive studies (see, Wickelgren, 1977, for a review).

Simulations of our network have confirmed all four predictions regarding the characteristic patterns of response times.

3.3. Semantic Priming in the Network

A typical study of semantic priming in experimental psychology consists of two conditions: a control condition and a priming condition. In the control condition, a target word (e.g., "NURSE") follows a semantically-unrelated word (such as "TREE"), presented for a fixed duration. In the priming condition, the same target word ("NURSE") follows a semantically-related prime word (such as "DOCTOR"). The subjects' task is to identify the target word as quickly as possible. As might be expected, an abundance of studies have documented that response times under the priming condition are shorter compared to the control condition (for reviews, see Meyer & Schvaneveldt, 1971; Neely, 1991). In particular, the greater the semantic similarity between the prime and target, the greater the priming effect. Another important finding is that as the stimulus-onset-asynchrony (denoted by T_{SOA}) between prime and target increases, the semantic priming effect increases and eventually reaches an asymptote level, which depends on semantic similarity between prime and target (Lorch, 1982; Ratcliff & McKoon, 1981).

In the present network, simulation of the semantic priming effect was carried out by successively presenting two input vectors (one pertaining to the prime and another to the target) and recording the response time of the output unit corresponding to the target vector. All the data acquired from the following simulations are based on 1,000 simulation trials. Specifically, let the three input vectors $\mathbf{a}^{CT}$, $\mathbf{a}^{PM}$, and $\mathbf{a}^{TG}$ denote the control-, prime-, and target vectors, respectively. As mentioned earlier, each element of the binary "target" vector $\mathbf{a}^{TG}$ is generated probabilistically from a prototype vector, say $\mathbf{y}^s$. By defining the control and

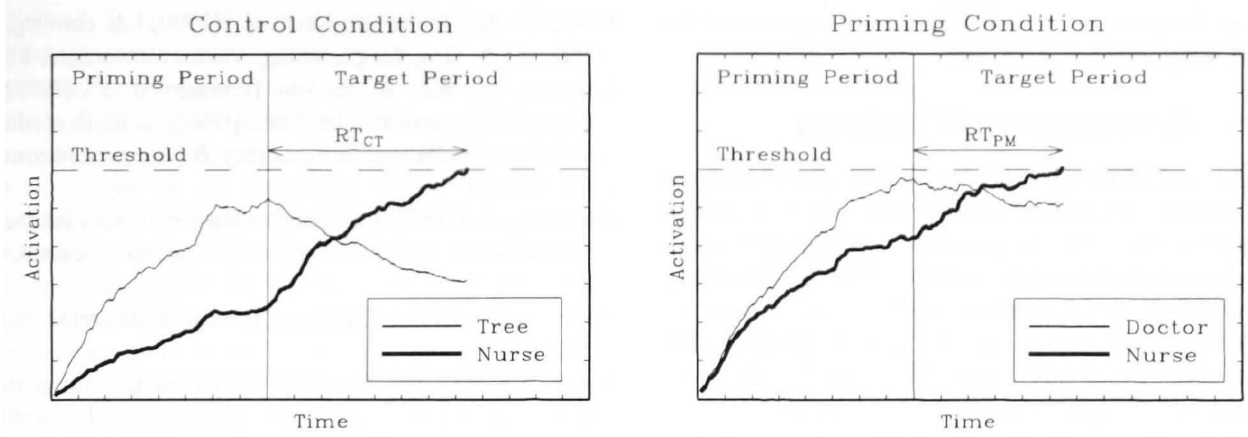

Figure 2. The time course of activation for the control and priming conditions

priming conditions as above, the similarity between a prime vector and the prototype vector corresponding to a target output, $s(\mathbf{a}^{PM}, \mathbf{y}^{s})$ is greater for the priming condition than $s(\mathbf{a}^{CT}, \mathbf{y}^{s})$ for the control condition. The following diagram summarizes presentation sequences under the two simulation conditions:

	Priming period ($0 \leq t \leq T_{SOA}$)		**Target period** ($t > T_{SOA}$)
Control condition:	TREE ($\mathbf{a}^{CT}$)	→	NURSE ($\mathbf{a}^{TG}$)
Priming condition:	DOCTOR($\mathbf{a}^{PM}$)	→	NURSE ($\mathbf{a}^{TG}$)

Some typical patterns of activation in the output units are shown in Figure 2. A comparison of the activation patterns in the first part (priming period) of the two panels in the figure reveals different levels of pre-activation of the target output unit ("NURSE") between control and priming conditions. During the priming period, owing to greater similarity, the pre-activation of a target output unit in the priming condition increases faster than in the control condition. Next, in the target period, when the target word $\mathbf{a}^{TG}$ is presented to the network at time $t=T_{SOA}$, the activation starts to increase from the pre-activated level. Because a target output unit has a higher pre-activation level in the priming condition than in the control condition, the target output unit activation in the priming condition reaches the threshold faster, thus producing a shorter response time. Further, the size of the semantic priming effect is directly related to the semantic similarity between a prime and target. Formally, one can readily derive the following equation for RT_q describing the relation between response time and similarity for both simulation conditions [q = CT (control) or PM (priming)]:

$$RT_{\mathbf{q}} = \frac{1}{\xi} \ln \left[\frac{\beta\, E[b_s][s(\mathbf{a}^{TG}, \mathbf{y}^{s}) - s(\mathbf{a}^{\mathbf{q}}, \mathbf{y}^{s})\,(1 - e^{-\xi\, T_{SOA}})]}{\beta\, E[b_s]\, s(\mathbf{a}^{TG}, \mathbf{y}^{s}) - \theta + \varepsilon} \right] \tag{3}$$

where β is equal to λα/ξδ, θ is the response threshold, and ε is time-dependent random noise with zero mean. Note that from the above equation, we have mean $RT_{CT} >$ mean RT_{PM} since $s(\mathbf{a}^{CT}, \mathbf{y}^{s}) < s(\mathbf{a}^{PM}, \mathbf{y}^{s})$.

Figure 3 shows the influence of varying the SOA on the semantic priming effect. That is, as the SOA increases, the priming effect initially increases and then approaches an asymptote level. This pattern of our results closely approximates empirical findings (Lorch, 1982; Ratcliff & McKoon, 1981). It is noteworthy that this asymptotic

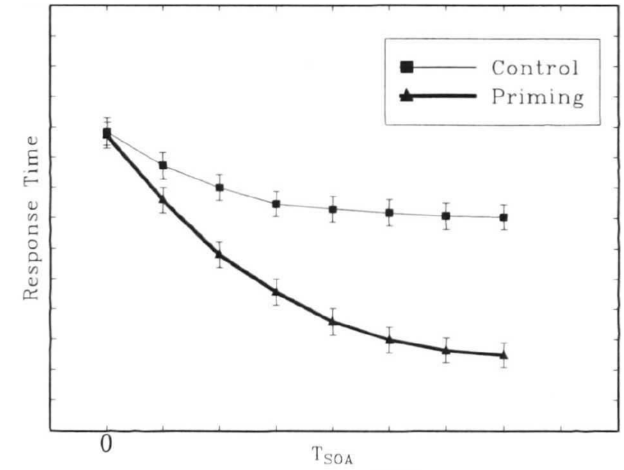

Figure 3. Priming effects as a function of Stimulus-Onset Asynchrony (vertical error bars depict 99% confidence intervals)

pattern of the priming effect is a direct consequence of the assumed leaky integration process.

4. Summary and Conclusion

The main goal of the present investigation was to design a neural network that reflects random time effects in human information processing. In particular, we have proposed a temporal summation mechanism inspired by the physiology of neural firing. As an application of this mechanism, we have demonstrated that a neural network implementing temporal summation can successfully simulate response time data, in particular, the "semantic priming effect" in human cognition. These results suggest that the temporal summation mechanism may be a promising candidate for implementing real-time dynamics into neural networks.

By producing temporal activation patterns that are similar to those produced by gradual activation, the present study further develops and extends McClelland's cascade and GRAIN models (McClelland, 1979, 1993). However, this extension is accomplished, not by resorting to further mathematical sophistication, but by making use of the neurophysiologically grounded temporal summation mechanism. We believe that this implementation is an important advance because it represents a natural and logical extension to current modeling of real-time random dynamics in neural networks.

In conclusion, by featuring the proposed temporal summation mechanism, the present study has opened up a new avenue for simulating random time effects in neural networks. Introducing this mechanism into neural network modeling is likely to enhance our understanding of human cognition by permitting both a psychological and neurophysiological treatment of the time dimension.

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