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Title	Nonlinear Dynamical Systems Theory and Engineering Neural Network : Can Each Afford Plausible Interpretation of 'How' and 'What'?
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In my opinion, before rejecting the possibility of interpreting how interneurons work, we must carefully investigate another process of encoding information by single neurons and by neuron assemblies: the temporal encoding of information. In area 17, neurons with dynamic orientation selectivity were recently found in addition to a conventional type of neuron known as the orientation-selective cell – the simple cell (Dinse et al. 1990). One type of neuron among these dynamic cells develops selectivity following a stage of nonselective excitation and the other changes temporally its orientation selectivity. Because of the abundance of such neurons in area 17, it is difficult to think of such a neuron being “a rogue” cell. Thus, even at the single-neuron level the intermixed information represented by a neuron in multimodal fashion may have another dimension for a code, that is, temporal dimension.

An elaborated analysis of the temporal modulation of neuron activities has been made in both cortical and subcortical areas. In particular, the temporal modulation of the spike trains of neurons not only in the inferior temporal cortex but also in the striate cortex was confirmed by evidence that cells could encode multiple parameters of the input information (Richmond et al. 1987; 1990; Richmond & Optican 1987; 1990). In this case, single-unit recording and principal component analysis were useful as experimental and mathematical tools, respectively. Further analysis of the temporal coding of data obtained in single-unit recordings might give “a very valuable piece of information” concerning how a neuron, even an interneuron, processes information at higher levels. However, even though a single neuron can encode multiple stimulus parameters in the waveform of spike train, the multiplicity of the code will not be so high at the single-neuron level, which will lead to incompleteness of encoding and hence decoding in single-neuron activities.

Thus, as Robinson points out, a complete spatiotemporal coding of information is ascribed to neural networks. Besides the oculomotor system described by Robinson, a beautiful example of the coding problem has been investigated by Freeman in measurements of collective activity in the rabbit’s olfactory bulb as well as in neural network models (Freeman 1987; Skarda & Freeman 1987; Yao & Freeman 1990). Odor information is encoded in spatial patterns of the bulb’s activities. Moreover, through the temporal chaos created in the dynamical processing of sensory information the bulb network acquires variability in the processing and learning of sensory information, depending on the animal’s internal state; here, only a collective activity of neurons in the bulb is a meaningful variable, that is, observable.

There is a non-black-box mathematical theory that can extract hidden dynamics, namely, modern nonlinear dynamical systems theory. With this theory we can analyze, for example, how interneurons enhance their computational ability in consequence of the network’s behaving in a deterministically chaotic manner (Tsuda 1992). One role of deterministic chaos is then to unravel in the temporal dimension the intermixed information over the spatial dimension, preserving the functional relevance of the overall activity of networks. This dynamic information processing can be generalized with a notion of “chaotic itinerancy” and embodied in a neural network model for dynamic associative memory (Tsuda 1991). Thus, dynamical systems theory may help explain how neural networks process information. It can also be applied to systems that cannot be “anatomically isolated,” where most “black box mathematical models” fail, since it does not treat “input-output relations” but the process of information flow.

Nevertheless, dynamical systems theory cannot directly describe what meaning is processed. Contrary to Robinson, I would like to emphasize that what seems to be the most crucial but difficult, and almost unsolved, problem concerning the brain is the problem of “what” (see also Marr 1982). In brain theory, we have to deal with a system where the observer is

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[DAR] Robinson succeeds in showing that neither “single-unit recordings” nor “black box models” alone are promising in our attempt to understand higher functions of the brain. He especially points out our inability to know “how the (information) processing is done” with single-unit recordings; nor can we describe “how real neurons do it” using mathematical black box models. His theory is persuasive because he describes it by citing his own and other neural network models and theories of the oculomotor system that he views as having succeeded in describing the system’s functions. Nevertheless, there seems to be room for commentary. I accordingly will highlight the following two points: the notion of dynamic information processing, which is set aside in the target article, and the question of the methodology for understanding brain function.

involved. It is thus a theory of an observer who tries to understand the meaning and information structure of the environment, in relation to his internal state. Here, the environment cannot be decoupled from the observer. This process of understanding is inevitably interpretative. Classical hermeneutics may serve as a methodology for the understanding of such a system (Tsuda 1984; Winograd & Flores 1986).

We must interpret what a neuron or a neural network is doing except, perhaps, the pure output unit. It is determined in advance what a computer should do, and we do know the purpose of its whole system and even its parts, whereas we do not know this about the brain. We start with an assumption about "what," which allows a plausible interpretation. In other words, any machine is straightforward in the sense that it functions as a whole in consequence of being assembled of functional parts, whereas in the brain a temporal differentiation of functions seems to progress at the neuronal level in consequence of the system's purpose. This differentiation can be found in neural events with short time scales as well as in phylogenetic and ontogenetic development.

The plausibility of an interpretation cannot be directly substantiated by experiments. An engineering approach that gives an appropriate design for the system can help strengthen the plausibility. Thus, I agree with Robinson that "applications of neural networks . . . can build a bridge between system function and hidden-unit behavior and tell us how to relate one to the other."