

The Roles Played by External Input and Synaptic Modulations in the Dynamics of Neuronal Systems

BBS commentary on Tsuda, “Towards an interpretation of dynamic
neural activity in terms of chaotic dynamical systems”.

Arunava Banerjee
Department of Computer Science
Rutgers, The State University of New Jersey
110 Frelinghuysen Road
Piscataway, NJ 08854
arunava@cs.rutgers.edu

Abstract

The framework within which Tsuda proposes his solution for transitory dynamics between attractor states is flawed from a neurological perspective. We present a more genuine framework and discuss the roles that external input and synaptic modulations play in the evolution of the dynamics of neuronal systems. Chaotic itinerancy, it is argued, is not necessary for transitory dynamics.

The dynamics of Hopfield Networks (Hopfield, 1982) are a far cry from that of systems of neurons in the brain. The existence of the energy function ensures that under the guidance of an asynchronous update rule, such networks relax to fixed point attractors. This behavior is not in conformance with that observed in systems of neurons in the brain where limit cycles, let alone stable fixed points, are not encountered. Tsuda’s efforts at introducing complex dynamics into such model networks are commendable. His solution, however, is suspect.

Tsuda’s system (Tsuda, 1991, 1994) is an otherwise standard Hopfield Network without the symmetric coupling constraint, endowed with an additional class of specialized nodes that by his own account, is primarily responsible for the system’s unconventional dynamics. It therefore stands to reason that we take a closer look at these nodes.

Roughly speaking, the nodes in the noted class stay dynamically inactive (imparting a constant bias) as the remainder of the system approaches an attractor. If the remainder of the system settles on

a fixed point, these nodes spring into action and attempt to dislodge it from that state. The dynamics of the overall system is itinerant when this attempt meets success. Although this constitutes an elegant example of an artificial neural network, the claim of biological relevance seems contrived.

The specialized nodes, in essence, maintain a record of the activity of the system from the most recent instance when it attained a state of equilibrium (however long ago this might have been), and persistently relay this information to the remainder of the network for as long as it takes for it to attain its next state of equilibrium. These are exceptional qualities that cannot be ascribed to any class of neurons in the brain, axonal tuft cells or otherwise.

These observations also throw doubt on the second category of systems that Tsuda proposes (systems that manifest SCND attractors). Both the unstable "driving" network that displays chaotic itinerancy, as well as the multistable "receiving" network that admits multiple fixed point attractors, are untenable from a neurological perspective.

The above arguments are not intended to make a case against chaos in systems of neurons in the brain. On the contrary, our own investigations into the dynamics of systems of spiking neurons (Banerjee, 2001a, 2001b) indicate that under normal operational conditions (the state of sparse activity typically observed in the brain), the behavior of such systems is almost surely chaotic; stable periodic, stable quasiperiodic, and stable fixed point behavior almost surely do not occur. Furthermore, analysis of the phase-space structure of these systems has revealed that attractors in such systems are potentially anisotropic (in our framework several Milnor attractors are combined to form one generalized topological attractor, hence the anisotropy).

Our views are, however, diametrically opposed when it comes to the question of *the role of chaos* in neuronal systems. Ingrained in this question is the position that chaos is a likely *remedy* for any of a number of difficult situations that the brain might face during its regular course of activity. This outlook is harmful for it presumes other modes of behavior (such as stable periodic or fixed point behavior) in the brain, all of which remain unsubstantiated after several decades of intensive experimental research (in this regard, the revised views in (Freeman & Skarda, 1990) are noteworthy). An unfortunate consequence of this outlook has been the creation of several spurious issues with regard to the dynamic aspects of memory. The physical realization of semantic memory is considered different from that of episodic memory based on the erroneous assumption that the former is represented as a fixed point attractor. Although their physical realizations might indeed be different, if such is the case the differences will be found elsewhere.

In what follows, we highlight the profound difficulties that lie before us on the road to a clearer understanding of the dynamics of neuronal systems.

First, any analysis is inherently incomplete should the impact of external input on the neuronal system not be considered. Neuronal systems do not operate in isolation. Whereas the study of an isolated system (or one that receives an initial input following which the dynamics evolves in

isolation) does provide insight into the general tendencies of its dynamics, the interplay between the dynamics and the input remains obscure. To illustrate, any cortical column is incessantly bombarded by input from neighboring cortical columns as well as the thalamus. When the impact of this input is taken into consideration, the problem takes on an added dimension of complexity. What was heretofore dynamics in a domain of static attractors, is transformed, at the very least, into dynamics in a domain of evolving attractors. This follows from the observation that input into the system can be regarded as a bifurcation parameter. In this perpetually changing domain, attractors drift, new ones originate, some coalesce, and some disappear. Transition between attractors is effected either by the catastrophic birth of a new attractor around the dynamic state of the system, or by the smooth, albeit relatively fast, drift of an attractor in a manner such that the dynamic state of the system is overtaken by its realm of attraction.

Second, the impact of synaptic modulations on a neuronal system complements the impact of the external input, since it too can be regarded as a bifurcation parameter. The deliberations in the previous paragraph, therefore, apply equally well here. Even if the rules that govern synaptic modulations prove to be simple, the corresponding impact on the structures in the phase-space of the neuronal system will, in all likelihood, be non-trivial.

The resultant scenario is therefore one of profound complexity.

References

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