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Chaotic itinerancy and its roles in cognitive neurodynamics

Ichiro Tsuda

Chaotic itinerancy is an autonomously excited trajectory through high-dimensional state space of cortical neural activity that causes the appearance of a temporal sequence of quasi-attractors. A quasi-attractor is a local region of weakly convergent flows that represent ordered activity, yet connected to divergent flows representing disordered, chaotic activity between the regions. In a cognitive neurodynamic aspect, quasi-attractors represent perceptions, thoughts and memories, chaotic trajectories between them with intelligent searches, such as history-dependent trial-and-error via exploration, and itinerancy with history-dependent sequences in thinking, speaking and writing.

Addresses
Research Institute for Electronic Science, Hokkaido University, Kita-12, Nishi-7, Kita-ku, Sapporo, Hokkaido 060-0012, Japan

Corresponding author: Tsuda, Ichiro (tsuda@math.sci.hokudai.ac.jp)

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Introduction

Motivated by studies for the elucidation of the dynamical mechanism of the complex transitions observed in brain activity, many researchers have proposed conceptual frameworks for understanding such a mechanism. Among others, we proposed a neural chaotic itinerancy [1–3,4••,5], where typical cortical transitions are not merely random but are transitory and chaotic dynamics (see, e.g., [6]). Chaotic itinerancy is a prerequisite for the persistence of memories during learning. In a neural network model, with recurrent connections of excitatory units under the presence of inhibitory units, the appearance of chaotic itinerancy among quasi-attractors as memories allows the network to learn new input patterns while maintaining memories. The significance of chaotic itinerancy becomes clearer in the situation of human communication. Indeed, to communicate, each person needs rapidly to construct and reconstruct history-dependent memory structures, which must not be disturbed by others' actions. One can construct coupled-neural networks to account for this situation [7], and extend them further to more realistic and biologically oriented neural networks consisting of a neuron model by Pinsky and Rinzel [8] for excitatory neurons, and another one by Wang and Buzsáki [9] for inhibitory neurons [10].

Hierarchical structure of memory

Memory is constructed in a hierarchical manner. The first step, a stage of *simple memory*, according to Marr [11], is realized via embedding of input patterns as attractors by means of, for example, a Hebbian learning algorithm. Auto-associative memory models are typical for the neural realization of such algorithms (see, e.g., [12]). The realization of a critical state of the attractors through multiple-metastable states can produce chaotic itinerancy. Hebbian learning then strengthens the paths connecting such quasi-attractors rather than any one attractor, because of the development of dynamical trajectories via chaotic itinerancy. This is the second stage of memory, *memory of the association process*; namely *episodic memory*. The third stage was studied recently by Kurikawa and Kaneko [13], and suggests that the input–output relation is embedded as memory, thus describing the stage of *relational memory* between sensation and action. Such memory is dynamically represented by bifurcations of dynamical states until action is output when information of sensation is input; chaotic itinerancy appears in this bifurcating process. This stage of memory formation can be considered to be a precursor of higher-order memory formed through communication, because output-driven information processing is more effective than input-driven processing when people are communicating to produce reafference via preafference (see, e.g., [14••]).

Communicating brains

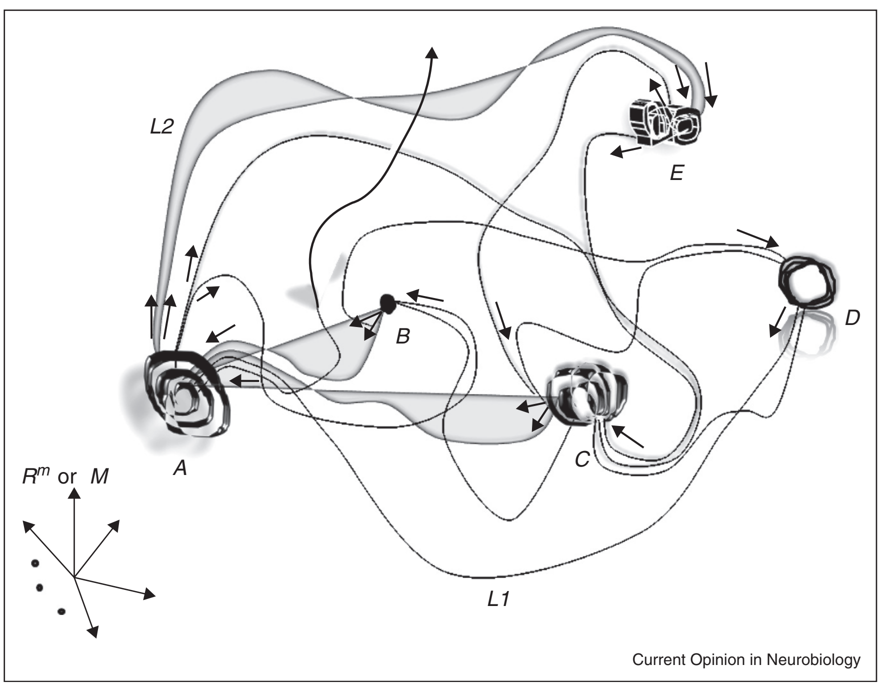
Chaotic itinerancy also appears in interacting systems, typically appearing in the brain activity of communicating people in the form of chaotic transition between synchronization and desynchronization (see, e.g., [15,16•,17]). Furthermore, an atmosphere generated by cooperative actions forms the basis for the creation of meaning when people are communicating. In relation to this situation, recent studies with mathematical models of neural networks that are based on a variational principle providing a constraint to the system showed the generation of functional units, that is, functional differentiation with the help of chaotic itinerancy [18,19].

The appearance of chaotic itinerancy in this communication paradigm is realized via the generation of metastable states [20,21•] or via critical states (see, e.g., [16•]). Metastable states have also been proposed as the transient states of ongoing coordination dynamics in neural systems, which are linked to intermittency, chaotic itinerancy and self-organized criticality in dynamical systems [20]. In a similar way to acquisition of the robustness of critical states via synaptic learning [16•], metastable states can appear in a robust manner via interacting brains in communication paradigm [21•]. Thus, the appearance of metastable states or critical states is a necessary condition for chaotic itinerancy but not a sufficient condition (see [22] for mathematical conditions for the production of chaotic itinerancy). Let us see the dynamical development in a neighborhood of such states.

Neutral stability and criticality

A quasi-attractor in chaotic itinerancy is an attractor because it possesses a positive measure of attracting regions. Thus, a quasi-attractor is different from a saddle in cases without symmetry, where symmetry restricts dynamical trajectories to some subspace of a whole state space, providing the reduction of space dimension. Nevertheless, dynamical trajectories leave a quasi-attractor and become chaotic until they reach another quasi-attractor (Figure 1). In this respect, a quasi-attractor is a Milnor attractor [23] but not a conventional attractor. However, the dynamical trajectories are trapped in a basin of attraction when a quasi-attractor as a Milnor attractor exists; thus, no chaotic wandering appears unless a basin is riddled. Therefore, to obtain chaotic transitions, a quasi-attractor should not be stabilized, at least, in the sense of linear stability. Then, in a neighborhood of a quasi-attractor, the dynamics begin from at least the second order, because of the linear term vanishing; $dx/dt = bx^2 + O(x^3)$, where x denotes a state variable and b denotes a parameter. In relation to this structure of neutral stability, Kozma *et al.* [16•] showed, with a hierarchical model of neuropercolation, that higher moments than the second order in critical states act in giving the indices for the appearance of perception and cognition. Compared with the exponential convergence in time of dynamical trajectories to a conventional attractor, caused by the presence of a linear term, the convergence to a quasi-attractor is much slower in an algebraic manner. This type of slow convergence is a realization of neutral stable states. Usually, this critical state is yielded via bifurcations, so that the dynamical system is structurally

Figure 1



Schematic drawing of quasi-attractors and dynamical trajectories in chaotic itinerancy. The dynamics develops on a smooth m-dimensional manifold M or an m-dimensional Euclidean space R^m, where $m \geq 4$. Different types of quasi-attractors are denoted by symbols, A, B, C, D, and E as one possible realization of ordered motion. Each quasi-attractor possesses the inlet and the outlet chaotic trajectories, which connect such a quasi-attractor with other quasi-attractors, thereby realizing a critical state of such a quasi-attractor. Here, a narrow bundle of trajectories such as $L1$ indicates a low-dimensional chaotic trajectory, and a broad bundle such as $L2$ indicates a high-dimensional chaotic trajectory. Arrows show the directions of dynamical development of trajectories. Transitions between quasi-attractors are chaotic and history-dependent. In particular, when quasi-attractors represent various synchronization states, chaotic itinerancy describes intermittent transitions between synchronization and desynchronization.