

Chaotic itinerancy, temporal segmentation and spatio-temporal combinatorial codes

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Abstract

We study a deterministic dynamics with two time scales in a continuous state attractor network. To the usual (fast) relaxation dynamics towards point attractors (“patterns”) we add a slow coupling dynamics that makes the visited patterns lose stability, leading to an itinerant behavior in the form of punctuated equilibria. One finds that the transition frequency matrix for transitions between patterns shows non-trivial statistical properties in the chaotic itinerant regime. We show that mixture input patterns can be temporally segmented by the itinerant dynamics. The viability of a combinatorial spatio-temporal neural code is also demonstrated.

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Several complex systems present a non-uniform rate of change, where stationary states (“patterns”) suddenly lose their stability and are substituted by new ones. Such punctuated behavior has been observed on a wide range of time scales from evolutionary, economic, social and weather dynamics, to brain behavior and laboratory devices such as laser cavities [1–3]. Usually this “itinerancy” between states is thought of as “thermal” transitions between deep valleys in a rugged landscape, possibly in the glassy dynamics regime. Such a process, by definition, is stochastic, so that times of transition and the choice of the next pattern are random. In this work, we consider the opposite spectrum, of systems where the loss of the pattern stability is due to internal deterministic mechanisms [4–7]. Of course, natural systems certainly fall between these two descriptions.

The specific model studied here is a multistable system where the relevant transitions occur when a stationary state (a point attractor) loses stability so that the system falls into a new

point attractor, and so on, forming an itinerant trajectory (see Fig. 1). The more general case of itinerancy between several kinds of attractors (limit cycles, torus and low dimensional chaotic attractors) has also been studied (see, for example, the special issue [3]).

Our model consists of a continuous state attractor network [8] storing P patterns with an added slow anti-Hebbian dynamics [9–11] (which may represent some coupling self-regulation by negative feedback). The model has a discrete time parallel dynamics with a full connected network, that is, it is a mean field coupled maps model:

$$S_i(t + 1) = \tanh[\gamma(h_i(t) + I_i(t))], \quad (1)$$

where S_i , the state of neuron $i = 1, \dots, N$, is a real variable in the interval $[-1, 1]$, h_i is the local field $h_i(t) = \sum_{j=1}^N J_{ij} S_j(t)$, and $I_i(t)$ is an (eventual) external input. The parameter γ is the transfer function gain (in this paper, $\gamma = 10$). Notice that we have called the units “neurons” only by convention, since they could be better interpreted as neural populations or basic units in a network (like glomeruli in the olfactory system, species in ecological systems, population of agents in social systems etc.). With this interpretations, the mean field character present in the model is more plausible.

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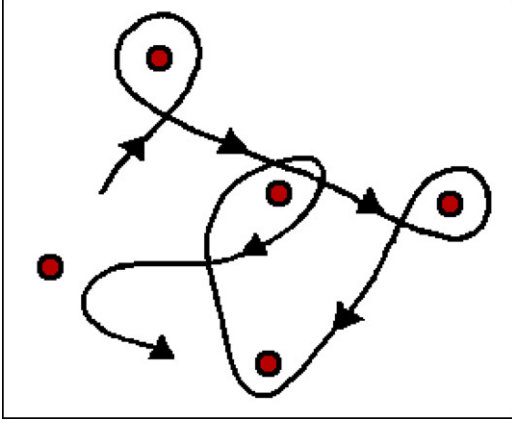


Fig. 1. Schematic phase space showing an itinerant walk between point attractors.

Eq. (1) defines the dynamics for the fast variables $S_i(t)$ given the coupling matrix J_{ij} . In our model, this matrix is slowly time dependent:

$$J_{ij}(t) = J_{ij}^H + J_{ij}^A(t), \quad (2)$$

where there is a constant Hebbian (“correlational”) component J_{ij}^H that stores P patterns, defining a basic attractor landscape, and a time dependent anti-Hebbian part $J_{ij}^A(t)$ that modulates this landscape and produces the escape events.

The Hebbian component has the usual form:

$$J_{ij}^H = \frac{1}{N} \sum_{\mu} \xi_i^{\mu} \xi_j^{\mu}, \quad (3)$$

where $\xi^{\mu} = \{\xi_i^{\mu}\}$, $i = 1, \dots, N$; $\mu = 1, \dots, P$, are random patterns to be stored. For convenience, we use binary random variables $\xi_i^{\mu} = \pm 1$. As usual, we set $J_{ii} = 0$.

The present state $\mathbf{S}(t)$ of the system modulates the “energy” landscape (defined by slow variables $J_{ij}(t)$), so that if the system is visiting a local minimum, that minimum slowly loses its stability until it turns into a saddle or a maximum and an escape event occurs. The change in the attractor landscape, however, is transient, having only an exponentially decreasing memory of the past visited states. So, the anti-Hebbian component has the form

$$J_{ij}^A(t+1) = \left(1 - \frac{1}{\tau}\right) J_{ij}^A(t) - \frac{\epsilon}{N} S_i(t) S_j(t). \quad (4)$$

The initial condition is $J_{ij}^A(0) = 0$. The first term (the “coupling memory decay”) guarantees that any change produced by visiting some state vanishes with characteristic time τ after the escape from that state. The second term is the anti-Hebbian contribution, parametrized by a step size ϵ and scaled by $1/N$ to preserve compatibility with Eq. (3). So, the rate of transitions between patterns (or even the possibility of such transitions) depends on the two parameters τ and ϵ .

The matrix J_{ij}^H defines a permanent landscape of attractor basins that is reversibly modulated but not destroyed by the anti-Hebbian term. We notice that a similar dynamics has been studied by Kawamoto and Anderson for the particular

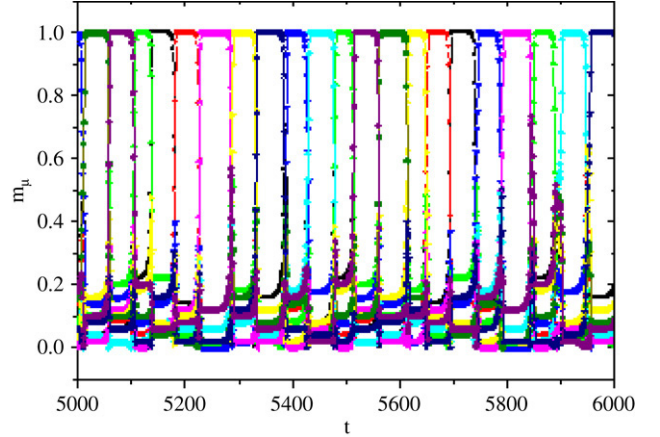


Fig. 2. Time series of overlap moduli $|m^{\mu}|$ for $P = 10$, with $\epsilon = 0.009$, $\tau = 600$ and $N = 100$.

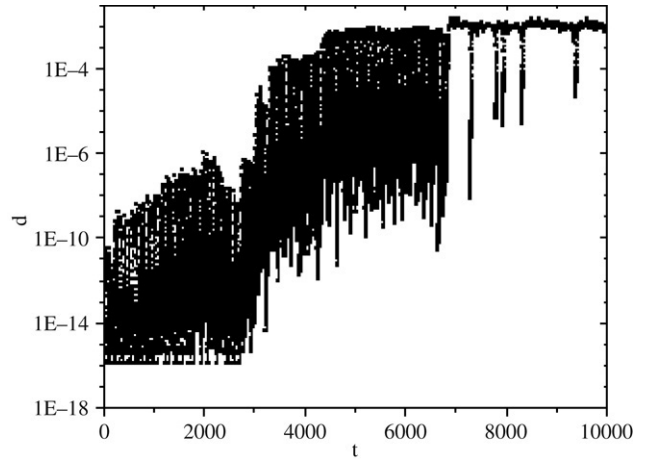


Fig. 3. Distance between trajectories $d(t)$ as a function of time. The two systems have identical initial coupling matrices and differ only in the first neuron, $|S_1(0) - S'_1(0)| = 10^{-15}$.

case $P = 2$, intending to model visual pattern reversion in the Necker cube [10]. Here we extend that study to general number of patterns P . Also Hoshino et al. [11] used a similar anti-Hebbian dynamics with an asymmetric coupling matrix to study transitions between fixed points and cycles. Here we are interested in the chaotic itinerancy phase that already appears with the simpler Hebbian matrix.

Our results are presented in terms of low dimensional order parameters (“overlaps”) that measure the correlation (cosine) between the state vector of the network and the stored patterns, $m_{\mu}(t) \equiv \sum_{j=1}^N S_j(t) \xi_j^{\mu} / (|\mathbf{S}(t)| |\xi^{\mu}|)$, where $|\xi^{\mu}| = \sqrt{N}$ and $|\mathbf{S}(t)|$ are the vector Euclidean norms. In Fig. 2 we show an example of time series of the overlaps for $P = 10$ patterns. We define an (arbitrary but not crucial) threshold $\lambda = 0.8$ so that we consider that a pattern (or its anti-pattern) is being visited if $|m^{\mu}| > \lambda$. The $S(t)$ trajectory is indeed chaotic, as can be verified by observing the distance $d(t) = \sum_i^N (S_i(t) - S'_i(t))^2$ between two orbits $\mathbf{S}(t)$ and $\mathbf{S}'(t)$ with very small differences in initial conditions (Fig. 3).

From the time series one gets the symbolic time series where there only appears the pattern (if any) being visited (Fig. 4).

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