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FROM MICRO-CHAOS TO MACRO-CHAOS: CHAOS CAN SURVIVE EVEN IN MACROSCOPIC STATES OF NEURAL ACTIVITIES

Commentary on Wright et al. on EEG-Chaos

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ABSTRACT: This critique of Wright et al.'s (1993) macroscopic EEG model is based on recent findings by Kaneko (1990) concerning dynamic behaviors in a globally coupled map. A coupled chaotic system does not always follow linear and equilibrium statistical mechanics. Some aspects of attractive neural networks and chaotic learning are also discussed.

KEYWORDS: chaos, EEG simulation, electroencephalogram, linear dynamics, neocortex, network symmetry, neurodynamics, pyramidal cell, wave velocity.

1. Wright et al. (1993) indicate that their new EEG model reconciles a local chaotic EEG model (Freeman, 1991) with a global near-equilibrium EEG model (Wright et al., 1990). It is worth looking closely at the plausibility of the models and assumptions adopted, as Wright et al.'s theory is attractive in its potential bearing on the question of how microscopic neural events are related to macroscopic ones and what the relationship between neural events and mind might be. Although many points in the target article could be be discussed, I focus here only on two: breakdown of linearity in macroscopic activities, and some further aspects of attractive neural networks.

2. Kaneko (1990) invented coupled map lattices and globally coupled maps as tools to describe various dynamic behaviors in complex dynamical systems. A coupled map lattice (CML) consists of chaotic maps, each with nearest neighbor interactions of diffusion type. In a globally coupled map (GCM), all chaotic elements are fully interconnected. This commentary concerns only maps of this kind.

3. I agree with the anatomical constraints noted by Wright et al., that is, asymmetric couplings at the microscopic level (of the order of a hundred micrometers) and symmetric couplings at the macroscopic level (of the order of millimeters). I also accept the theoretical and experimental validity of the presence of chaos at the microscopic level. I cannot, however, agree with the authors' conclusion that macroscopic neural events follow a linear and near-equilibrium pattern.

4. A GCM can be a model for macroscopic neural events based on microscopic chaos. Microscopic chaos can be described by a discrete one-dimensional map. The validity of a discrete map as a model of local chaos is supported by the comparatively low dimensionality (2-4) of attractors (as observed, for example, in Freeman's 1987 experiments) as well as by the direct relation between a vector field and the lower-dimensional return map of a variable such as the spike interval. In GCM, couplings among local chaotic maps are symmetric. If local elements are highly chaotic, it is natural to expect that the statistical nature of GCM will be equilibrium or near-equilibrium. Kaneko (1990), however, observed a violation of the law of large numbers. This striking statistical effect is universal in the sense that it holds irrespective of the functional form of the elementary map and the global couplings. The sole exception is a globally coupled "tent map" (a piecewise-linear map shaped like a tent). Kaneko (1992) elucidated this question in terms of invariant measures. Almost all chaotic maps, according to Kaneko, have an unstable invariant measure under the global couplings despite their stability in the case of isolated maps. In these systems, not only can the law of large numbers be violated but so can the central limit theorem.

5. The above findings show that randomness and order -- both remarkable characteristics of chaos -- still survive in a network of chaotic elements. This is not the nature of equilibrium or near-equilibrium systems, but that of far-from-equilibrium ones. There may still be grounds for invalidating this theory with respect to the cortical problem under consideration, because of the discreteness of the system (i.e., discrete time); according to this objection, this is a characteristic of maps, not of flow. However, a similar violation has been observed in computer simulations of globally coupled differential systems (Kaneko, private communication). Thus, Wright et al.'s theory is contradicted by the above arguments.

6. This contradiction may stem from Wright et al.'s analysis of the global ECoG (electrocorticogram). They analysed the ECoG filtered to the 1-30Hz band by means of the autoregression (AR) model. According to my understanding, the AR model can describe at most polynomial nonlinearity, which is not sufficient for an analysis of chaos. Furthermore, Wright et al. assume a linear response of the evoked potential in their system identification procedure, while the frequency components of ECoG they choose are limited to the low frequency range. This generates a difficulty in clearly separating deterministic and noisy components.

7. My second criticism concerns attractor neural networks. Wright et al. overlook other important aspects of cortical chaos. One can conceive of a network of pyramidal neurons surrounded by stellate neurons. If the network of pyramidal neurons has modifiable synapses of the Hebbian type, this system can subserve associative memory. If probabilities are introduced to act as a stochastic renewal of neurodynamics, the memory retrieval process becomes chaotic (Tsuda et al., 1987; Tsuda, 1992). This type of chaos occurs to link memories.

8. Let the net perform learning while retrieving memories. We conducted various computer experiments on this type of learning with and without chaos. Chaos enhanced the learning ability of the networks (Tsuda,

1994). When this additional learning is performed, basin boundaries of memory representation change in phase space and reorganization of phase space is consequently achieved. This may imply hierarchical organization and a reorganization of memory.

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