

## **A proposed name for aperiodic brain activity: stochastic chaos**

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Even casual inspection of time series derived by sampling and recording from the fields of electroencephalographic (EEG) and magnetoencephalographic (MEG) potential generated by active brains reveals continuous widespread oscillations. These waves suggest the overlap of multiple rhythms embedded in broad spectrum noise. In dynamical terms they might be ascribed to limit cycle attractors, because spectral analysis of short segments reveals peaks in the classical frequency ranges of the alpha (8-12 Hz), theta (3-7 Hz), beta (13-30 Hz) and gamma (30-100 Hz) bands of the EEG and MEG. However, autocorrelation functions go rapidly to zero, and the basic form to which spectra converge, as the duration of segments chosen for analysis increases, is a linear decrease in log power with increasing log frequency at a slope near 2 (" $1/f^2$ ").

This form is consistent with Brownian motion and telegraph noise. The unpredictability of brain oscillations suggests that EEGs and MEGs manifest either multiple limit cycle attractors with time variance by continuous modulation, or multiple chaotic attractors with repetitive state transitions, or time-varying colored noise, or all of the above. In all likelihood these fields of potential are epiphenomenal, probably equivalent to the sounds of internal combustion engines at work, or to antique computers in science fiction movies, or to the roars of crowds at football games. In fact, most neuroscientists reject EEG and MEG evidence, in the beliefs that the real work of brains is done by action potentials in neural networks, and that recording wave activity is equivalent to observing an engine with a stethoscope or a computer with a D'Arsonval galvanometer. However, one can learn a lot about a system by listening and watching, if one knows what to seek and find.

Numerous recent studies of the behavioral correlates of so-called "unit activity" of single neurons in sensory and motor systems have shown that the carrier of behaviorally significant information is not the pulse train of the single neuron, but instead the organized activity of arrays of neurons (see review in Note 3.7 in Freeman 1995). How many neurons are needed to make an array? Does the number exceed the number that can be accessed by current methods of recording pulse trains (on the order of 100)? Where do they form, what fractions of neurons in local neighborhoods suffice, and how are their outputs selectively read by their targets of transmission?

In my view these questions have no answers, because the objects of their inquiry do not exist. Brains work with large masses of neurons having low shared variance, on the order of 0.1%, not with selected small numbers in networks with high covariance. It is the techniques of unit analysis that give a distorted view of brain function. The neural network concept is classically derived from the Golgi studies of cerebral cortical neurons by Lorente de Nó (1934), who provided the anatomical basis for the concepts of computational neural nets (McCulloch 1969), programmable computers (von Neumann 1958), and nerve cell assemblies (Hebb 1949). The problem is that, when properly used, the Golgi technique stains less than 1% of the neurons in sections of cortex. Moreover, unit recording isolates the pulses generated by local axons of only a small fraction of neurons near the electrode tip, and extracellular recording is seldom designed to observe the dendritic field potentials.

Each neuron typically receives synaptic input from thousands of other neurons within the radius of its dendritic arbor, and it gives synaptic output to thousands of others within the radius of its axon, and not the same thousands because each neuron connects with less than 1% of the neurons within its arbors, owing to the exceedingly high packing density of cortical neurons. These properties of dense but sparse interconnection of immense numbers of otherwise autonomously active nonlinear neurons provide the conditions needed for the emergence of mesoscopic masses, ensembles, and populations, which have properties related to but transcending the capacities of the neurons that create them. The most significant property of ensembles is the capacity for undergoing rapid and repeated global state changes. Examples are the abrupt reorganizations manifested in the patterns of neural activity in the brain and spinal cord by the transitions between walking and running, speaking and swallowing, sleeping and waking, and more generally the staccato flow of thoughts and mental images. These pattern changes on a massive scale appear to be incompatible with systems that are dominated by noise, such as hot plates, decaying vegetation, and unruly crowds. Neural networks have come nowhere near to explaining them.

The development of the theory of chaos in the past two decades has suggested a resolution of the discrepancy between mesoscopic global order and aperiodic seemingly random activity at microscopic levels. In particular, models of deterministic chaos have been proposed, such as twist-flip maps and the Lorenz, Rössler, and Chua attractors, which are capable of dramatic and yet fully reversible changes in their aperiodic outputs with small changes in their bifurcation parameters. However, these models are low-dimensional, stationary, autonomous, and essentially noise-free, so they are ill-formed to model brains, which fail to conform to any of these conditions. Attempts to measure correlation dimensions, Lyapunov exponents, and related numeric features of brain subsystems have failed to yield normative results and have fallen into disrepute (Rapp 1993).

However, deterministic chaos governs only a small subset of chaotic systems. Another large class is opened by reaction-diffusion equations, which includes chemical morphogenesis (Turing 1952) and irreversible thermodynamics Prigogine (1980) giving "order from disorder". These models also fail, primarily because the axon with its propagated action potential is an early phylogenetic adaptation in multicellular animals that surmounts the limitations of transmission by diffusion. At the price of a delay, an axon distributes the resultant of dendritic integration by a neuron not only without attenuation but commonly with amplification in proportion to the number of branches. The diffusion term is appropriate for modeling axodendritic cables and synapses over transmission distances  $< 1$  mm, but it is not appropriate in models of the interactions within neural networks and populations. For similar reasons, models based in hydrodynamics and turbulence are unsatisfactory; there is nothing equivalent to viscosity or to molar convection in neurodynamics. Terminal chaos (Zak 1993) is implemented in digital models of dynamical systems by randomization of the terminal bits of rational numbers in difference equations (representing real numbers in differential equations), where it lessens some of the rigidity of digital embodiments that impairs their utility for representing chaotic systems (Freeman et al. 1997). The best available models are those from synergetics, including the laser of Haken (1991), who described microscopic particles as being "enslaved" by a macroscopic "order parameter" in a relationship of "circular causality".

What distinguishes brain chaos from other kinds is the filamentous texture of neural tissue called neuropil, which is unlike any other substance in the known universe (Freeman 1995). Neural populations stem ontogenetically in embryos from aggregates of neurons that grow axons and dendrites and form synaptic connections of steadily increasing density. At some threshold the density allows neurons to transmit more pulses than they

receive, so that an aggregate undergoes a state transition from a zero point attractor to a non-zero point attractor, thereby becoming a population. Such a property has been described mathematically in random graphs, where the connectivity density is an order parameter that can instantiate state transitions (Erdos and Renyi, 1960). Accordingly, state transitions in neuronal populations can be interpreted as a kind of percolation phenomenon progressing in the neuropil medium.

The dendritic currents of single neurons that govern pulse frequencies sum their potential fields in passing across the extracellular resistance, giving rise to extraneuronal potential differences manifested in the EEG, which correspond to the local mean fields of pulse densities in neighborhoods of neurons contributing to the local field potentials. In early stages of development these fields appear as direct current "d.c." fields with erratic fluctuations in the so-called "delta" range  $< 1$  Hz. The neurons are excitatory, and their mutual excitation provides the sustained aperiodic activity that neurons require to stay alive and grow. Unlike transistors, neurons have a short shelf life if they are isolated and left inactive. The activity of an excitatory population is self-stabilized by a non-zero point attractor (Freeman 1975), giving rise to a field of nearly white noise, up to a frequency limit determined by the duration of the action potentials. The feedback can be modeled as a one-dimensional diffusion process, which randomizes the input of each neuron with respect to others' output and its own output. At some later stage, typically in humans after birth, cortical inhibitory neurons develop or transform from excitatory neurons, which contribute negative feedback, leading to the appearance of oscillations in the gamma spectrum of the EEG. The mutual excitation persists, and, in fact, is essential for the maintenance of the near-linear range of cortical oscillations through a depolarizing bias.

This self-sustaining, randomized, steady state background activity is the source from which ordered states of macroscopic neural activity emerge, like the patterns of waves at the surfaces of deep bodies of water. Neural tissues, however, are not passive media, through which effects propagate like waves in water (Freeman and Kozma 1999). The brain medium has an intimate relationship with the dynamics through a generally weak, subthreshold interaction of neurons. The synaptic interactions of neurons provide weak constraints on the participants, and the resulting covariance appears in the form of spatiotemporal patterns of EEG and MEG. The degree of covariance is low, and the shared patterns would be inaccessible by other parts of the forebrain and brainstem, if the output pathways from self-organizing cortices conformed to the topographic order of the input pathways to most primary sensory cortices. This is not the case for the output path of the olfactory bulb, which is a divergent-convergent projection that performs a spatial integral transformation on bulbar activity before it is delivered to the targets of bulbar transmission, and the broad receptor fields in the targets of neocortical outputs give reason to believe that they undergo comparable integral transforms through similarly divergent pathways. If this proves to be the case, then it follows that unit activity is the best measure of cortical inputs, and that EEG and MEG potentials provide the best measure of cortical outputs, because the volume conductor performs a similar spatial integration on the dendritic potentials of local neural neighborhoods.

Mesoscopic brain states are still too little known to have acquired an accepted terminology, and the same condition applies to the naming of their carrier waves. The names of noise, deterministic chaos, terminal chaos, chemical reaction-diffusion patterns, and turbulence are not applicable. I suggest that for the interim that it be called "stochastic chaos", because it arises from and feeds on the randomized activity of myriads of neurons, and it provides the basis for self-organization.

Whatever it be named, this type of activity provides certain advantages, including continuous aperiodic activity needed by neurons to stay fit, rapid state transitions without

the "ringing" attending departures from limit cycle attractors, broad spectrum carrier waves, minimization of tendencies to parasitic phase locking, and a source of unstructured activity for driving Hebbian synapses during learning, so as to create new basins of attraction instead of reinforcing existing attractors in complex landscapes (Freeman 1995, 1999).

### References

- Erdos, P. and Renyi A. (1960) On the evolution of random graphs. *Publ. Math. Inst. Hung. Acad. Sci.* 5: 17-61.
- Freeman WJ (1975) *Mass Action in the Nervous System*. New York: Academic Press.
- Freeman WJ (1995) *Societies of Brains*. Mahwah NJ: Lawrence Erlbaum Associates.
- Freeman WJ (1999) *How Brains Make Up Their Minds*. London UK: Weidenfeld and Nicolson.
- Freeman WJ, Chang H-J, Burke BC, Rose PA, Badler J (1997) Taming chaos: Stabilization of aperiodic attractors by noise. *IEEE Transactions on Circuits and Systems* 44: 989-996.
- Freeman WJ and R. Kozma (1999) Local-global interactions and the role of mesoscopic (intermediate-range) elements in brain dynamics. *Behavioral and Brain Sciences* (in press).
- Haken H (1991) *Synergetic Computers and Cognition*. Berlin: Springer-Verlag.
- Hebb DO (1949) *The Organization of Behavior*. New York: Wiley.
- Lorente de Nó R (1934) Studies in the structure of the cerebral cortex: I. The area entorhinalis. *Journal von Psychologie und Neurologie* 45: 381-438.
- McCulloch WS (1969) *Embodiments of Mind*. Cambridge MA: MIT Press.
- Prigogine I (1980) *From Being to Becoming: Time and Complexity in the Physical Sciences*. San Francisco: Freeman.
- Rapp P (1993) Chaos in the neurosciences: Cautionary tales from the frontier. *Biologist* 40: 89-94.
- Turing AM (1952) The chemical basis of morphogenesis. *Philosophical Transactions of the Royal Society* 237B: 37-72.
- von Neumann J (1958) *The Computer and the Brain*. New Haven CT: Yale University Press.
- Zak M (1993) Terminal model of Newtonian dynamics. *International Journal of Theoretical Physics* 32: 159-190.