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Chapter 13

Thermodynamics of Cerebral Cortex Assayed by Measures of Mass Action

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The term *criticality* has multiple meanings in different contexts. For interpretation of recordings of electroencephalographic (EEG) and electrocorticographic (ECoG) potentials from sensory cortices of humans and animals we adopt the convention established in thermodynamics for the critical point that terminates the boundary between gaseous and liquid states, and the region beyond the point. Our recordings reveal intermittent bursts of beta and gamma oscillations. In doing so we define state variables to replace the conventional variables of pressure, volume and temperature with measures of ECoG power, entropy, and feedback gain. Each burst of oscillation has a narrow distribution of frequencies that carries a spatial pattern of amplitude modulation (AM), but only when the subjects hold themselves in a stance of expectancy, waiting for one of multiple conditioned stimuli (CS) that will direct them into one of several actions (CR), and then only when they receive an expected CS. Local $1/f$ fluctuations have the form of phase modulation (PM) patterns that resemble fog in vapor. Large-scale, spatially coherent AM patterns emerge from and dissolve into this random background activity but only on receiving a CS. They do so by spontaneous symmetry breaking in a phase transition that resembles the condensation of a raindrop, in that it requires a large distribution of components, a source of transition energy, a singularity in the dynamics, and a connectivity that can sustain interaction over relatively immense correlation distances with respect to particle size. We conclude that the background activity at the pseudo-equilibrium state conforms to fractal distributions of phase patterns corresponding to a phase transition from a gas-like, disorganized, low-density phase to a liquid-like high-density, more organized phase, that the activation of a Hebbian assembly is required for the phase transition,

that a singularity is required to initiate and terminate a phase transition, and that the high-density phase can help to explain the richness of perceptual experience on recall and recognition of a stimulus.

1. Introduction

John Nicolis devoted his life and career to the application of concepts and techniques from the mathematical and physical sciences to explain the workings of hierarchical dynamical systems in biology, and to apply his deep understanding of the theory of chaos to the creation and processing of information by the cognitive functions of the human brain. Among the important organizing principles is that of criticality. A biological system such as the brain can hold itself in a state of readiness to transit from constrained immobility in expectancy to an active, evolving goal directed action and back again (Capolupo *et al.*, 2012). The cerebral cortex does this by maintaining itself at the edge of chaos (Nicolis, 1987) in a state of criticality (Kozma *et al.*, 2013). This essay is dedicated to the memory of Nicolis and his contributions.

The term originated in clinical medicine in the 17th century in reference to the resolution of an infectious disease by a crisis followed by death or recovery. The meaning in mathematics and physics has evolved to denote a transition from one state to another under the influence of control parameters. In thermodynamics the term may denote proximity to a phase boundary between solid, liquid and gas phases in a diagram of phase space. Phase transitions describe drastic changes in the material on crossing a boundary. Of particular interest is the existence of the critical point that terminates the upper end of the gas-liquid phase boundary for water. Beyond the critical point there lies a domain of criticality in which gas and liquid coexist as vapor. Within the domain there are no boundaries. The case of water provides of course only a useful example of phase transitions. A similar behavior is observed in other physical systems. Others besides us have hypothesized that cortex holds itself in such a region of *metastability* (Bressler and Kelso, 2001; Tsuda, 2001; Freeman and Holmes, 2005; Kelso and Tognoli, 2006; Vitiello, 2009). In this review we explore the possibility that cortex can transit from criticality into unequivocal phases (Kozma *et al.*, 2005; Freeman, 2008; Freeman, Livi *et al.*, 2012).

The salient question is how does cortex maintain criticality? How does an exceedingly large population of neurons maintain itself by interactions on the knife-edge of chaos between multiple adjacent basins of chaotic

attractors? Nuclear physicists have used the concept of criticality to denote the threshold for ignition of a sustained nuclear chain reaction, i.e., fission. The critical state of nuclear chain reaction is achieved by a delicate balance between the material composition of the reactor and its geometrical properties. The criticality condition is expressed as the identity of geometrical curvature (buckling) and material curvature. Chain reactions in nuclear processes are designed to satisfy strong linear operational regime conditions, in order to assure stability of the underlying chain reaction. That usage fails to include the self-regulatory processes in systems with nonlinear homeostatic feedback that characterize cerebral cortices.

Recently the concept of self-organized criticality has captured the attention of neuroscientists (Beggs and Plenz, 2003). Despite the empirical evidence of cortex conforming to the self-stabilized, scale-free dynamics of the sand pile during the existence of quasi-stable states (Bak, 1996; Plenz and Thiagarajan, 2007; Beggs, 2008; Petermann *et al.*, 2009), the model fails to exhibit the emergence of orderly patterns within a domain of criticality (Kozma *et al.*, 2005, Freeman and Zhai, 2009). Bonachela *et al.* (2010) describe SOC (Self-Organized Criticality) as “pseudo-critical” and suggest that we should “...look for more elaborated (adaptive/evolutionary) explanations, beyond simple self-organization, to account for this.” Our answer to the question is that cortical neurons sustain this metastable state by mutual excitation, and that its stability is guaranteed by the neural refractory periods. Numerous experimental observations of power-law and scale-free distributions in brain structures (Breitenberg and Schüz, 1998; Breakspear, 2004) and functions displayed in the log-log plots (Linkenkaer-Hansen *et al.*, 2001; Harrison *et al.*, 2002; Hwa and Ferree, 2002; Freeman, 2004b; Freeman and Breakspear, 2007) imply self-similarity over long spatial distances underlying dynamical formation of coherent domains of excitations. One of several objectives of future studies is to clarify how self-similarity and criticality in brains may be related to coherent states in the many-body theories in physics (Vitiello, 2009, 2012).

The next question is how does cortex transit within this critical state between gas-like randomness on the one hand and liquid-like order on the other hand? In this review we postulate that within the broad domain of cortex variously sized populations of neurons emerge and transit between the two extremes, with intermittent condensation of activity into spatiotemporal patterns that soon evaporate. We have developed thermodynamic models of the cortex, which are expressed in control theory using differential equations (Freeman, 1975), random graph theory

(neuropercolation: Kozma, 2007), and many-body physics (Freeman and Vitiello, 2006, 2008; Freeman, Livi *et al.*, 2012). The model has two phases of neural activity: gas-like and liquid-like. In the gas-like phase the neurons are uncoupled and maximally individuated, which is the optimal condition for processing microscopic sensory information at low density. In the liquid-like phase the neurons are strongly coupled and thereby locked into briefly stable macroscopic activity patterns at high density, such that every neuron transmits to and receives from all other neurons by virtue of divergent-convergent transmission, by which each transmitting neuron sends its output to $\sim 10^4$ neurons, and each receiving neuron gets input from $\sim 10^4$ neurons. In effect the divergent-convergent tract performs a Gabor transform on the output (Freeman, 2001), which distributes the output so that each fraction of the whole, given to different targets, contains the same global information albeit at reduced resolution.

Our answer to the question of how phase transitions occur is that reinforcement learning sensitizes the cortex selectively to learned input denoted conditional stimuli. The CS triggers a regenerative exponential increase in amplitude-dependent synaptic gain that results in an explosive increase in cortical activity in a narrow spectral band. Experimental observations show that the cortical impulse response conforms to a cosine with an exponential envelope (Freeman, 1975; Freeman and Quiñero, 2013). The increase in gain reverses the sign of the exponent from negative to positive, hence the regenerative increase. The amplitude of neural output is strictly limited by refractory periods. It is the density that increases by geometric increase in steps of 10^4 to saturation of the neuropil in under a quarter cycle of the carrier frequency.

Our basis for adopting phase transitions to model cortical dynamics is our speculation that what distinguishes the sensation of a stimulus from the perceptual experience of the memory of the stimulus by recall and recognition is the massive and immediate mobilization of information stored in masses of cortical synapses. The suddenness of the experience dictates that the recall must occur by a nearly instantaneous phase transition in the cortex from randomness to order. We have found the mechanism of spontaneous breakdown of symmetry in many-body physics to be of great utility, since it predicts the insurgence of long range correlations among the system constituents and therefore the dynamical transition from randomness to order (Freeman and Vitiello, 2006, 2008). In prior publications we have described in painstaking detail the properties of the cortical neuropil in the low-density state of random noise (Freeman, 1975),

and the spatial patterns in the electrocorticogram (ECoG, Freeman, 2000) that emerge in the high-intensity engagement of the cortex in intentional behaviors (Freeman and Kozma, 2010). In this brief review we address two further questions. How does cortex condense a pattern, and how does it terminate it by evaporation? Just as important as the recall of a memory by a stimulus is the exit strategy by which the cortex ends it and makes way for the next.

2. The Properties of the Background Phase and of the Active Phase

The critical state revealed by the ECoG is shown in Fig. 1. A hungry cat with electrodes fixed across the dipole generator of the olfactory cortex was placed in a box and allowed to settle into watchfulness. Introduction of a faint odor of fish in the airstream aroused the cat into search by sniffing, as shown by the gamma bursts. An hour later the same stimulus failed to arouse the cat from postprandial torpor. The example shows the ubiquity of background activity, the state-dependence of the cortex on responses to stimuli, and the intermittency of the bursts of oscillation.

Figure 1. We illustrate the olfactory ECoG from a cat in aroused and torpid states in response to a brief odor of fish at the arrow (Fig. 7.1, p. 404, Freeman, 1975).

Figure 2. AM patterns in response to conditioned stimuli are compared during training (vertical differences) and after consolidation (horizontal differences) are displayed as contour plots of electric potential (Freeman and Schneider, 1982).

Each burst carries a spatial pattern of amplitude modulation (AM) (Fig. 2). The pattern is revealed by a 64-channel recording followed by filtering in the gamma range to extract the carrier frequency of the transmitted pattern. The background activity conforms to random noise with no convergence to patterns, so the AM pattern formation is by the spontaneous breaking of symmetry. Each AM pattern consists of 64 measurements of the amplitude at each time step, forming a 64×1 feature vector that defines a point in 64-space. The AM patterns fall into clusters, one for each CS that the subject can categorize, including the background (control) smell. Each cluster has a center of gravity. Classification of each new AM pattern is by determining the shortest Euclidean distance to a nearby center. The classificatory information is spatially uniform; both high and low amplitudes are of equal value. All these features have been described in the theoretical model whose main ingredient is the spontaneous breakdown of symmetry, which can be modeled either by neuropercolation or by the many-body formalism. The formation of AM patterns is there described to be the process characterized by the system internal dynamics, which is in crucial agreement with the experimental

observation that the AM patterns lack invariance with respect to fixed stimuli. They change with overnight consolidation of the learning in each day, and with new learning upon experimental changes in the context and significance of a CS.

AM patterns depend on two stages of learning: the acquisition of a new category, and the integration of that category into the fabric of memory (consolidation). We infer this from analysis of the pattern change in the cortical evoked potential (impulse response) from training subjects to respond to the evoking stimulus as a CS. In the naïve state the response is oscillation with an exponential decay (Fig. 2, upper left). With training the response changes due to an increase in excitatory synaptic strength between excitatory neurons (Emery and Freeman, 1969), creating a Hebbian cell assembly (Fig. 3a). Any subset of receptors that receives sensory input ignites the entire assembly, thereby amplifying, abstracting, and generalizing the input information. Simulations show that the increase in strength of the Hebbian synapse greatly enhances gamma oscillation, so that the sign of the exponent of the ECoG response reverses from negative to positive. We conclude that the formation and activation of a

Figure 3. (a) Topographic mapping characterizes the bulbar input pathway. Convergent-divergent connections characterize the internal connectivity of the olfactory system. Hebbian learning forms an assembly (black dots) that ignites with stimulation of any subset. (b) The increased strength, K_{ee} , of the Hebbian synapse (bold arrows), strongly enhances gamma oscillations in response to learned stimuli (CS) (Freeman, 1979).

Hebbian assembly are necessary for phase transitions, thereby restricting emergence of gamma bursts only in response to behaviorally significant stimuli. However, the latency of the bursts is not locked to the stimulus arrival times, so the assembly is not sufficient to initiate a phase transition. Some endogenous factor is at work between bursts.

3. Initiation of a Phase Transition Leading to Burst Formation

The high resolution provided by the Hilbert transform is required to reveal the details of the ECoG between bursts. Band pass filtering is necessary for effective use of the Hilbert transform with the center frequency set at a peak value of the power spectral density of the spatial ensemble average (of the 64 ECoGs). The superimposed ECoGs are highly correlated for the duration of each burst (Fig. 4a). They wax and wane together in nearly synchronized beats. At down beats the signals often reveal a discontinuity in the phase, seen as a sudden shift to a different frequency and position on the ensuing cycle.

The Hilbert transform converts each of the 64 ECoGs to analytic signals, which we express in two time series: the analytic phase, $\phi_{ij}(t)$, and the analytic amplitude, $A_{ij}(t)$. The rate of change in the analytic phase is the analytic frequency, $\omega_{ij}(t)$, from the change in phase with each step in radians, $\Delta\phi_{ij}(t)$, divided by the digitizing step in s, Δt (Fig. 4b). The flat segments during a burst show the stationarity of the frequency of the carrier wave. The arrows point to the minima of the spatial standard deviation, $SD_X(t)$, which gives the pass band of the analytic signal. The analytic amplitude, $A_{ij}(t)$, is used to calculate the spatial ensemble average power, $A^2(t)$ (Fig. 4c), and the feature vector, $\mathbf{A}(t)$, which is calculated by dividing each amplitude by the spatial ensemble average.

Taking the $\log_{10}$ of the analytic power revealed the fine structure during downbeats (Fig. 4d). ECoG power did not go to zero, but in short intervals it could decrease by as much as 10^{-6} from the prevailing level of power during the beat (Fig. 5a, b). These null spikes often occur alone but more commonly in clusters. They appeared rather dramatically in cinematic displays of the analytic power (Freeman and Vitiello, 2008) (<http://soma.berkeley.edu>). The variances in spike location and especially in power were very high, because the locations of the spikes seldom closely coincided with the locations of an electrode in space or of a digitizing step in time. The width of the null spikes with deep minima conformed to the

Figure 4. Hilbert analysis of data from ECoG arrays of size 8×8 , as shown in Fig. 2; (a) signal values of all 64 channels filtered 20 Hz–28 Hz; (b) instantaneous frequencies $\omega_{ij}(t)$ with plateau regions marked by arrows at minima of $SD_X(t)$; (c) analytic power, $A_{ij}^2(t)$, showing the beats; (d) analytic power in $\log_{10}$ amplitude emphasizing the null spikes when analytic power drops as low as 10^{-6} of the nominal level.

point spread function of the cortical generator calculated from anatomical and physiological depth measurements (Freeman, 2006), implying that the event was at a point in time and space.

What made the null spike a focus of interest was the convergence of theory and experiment in predicting a *singularity* as essential for the onset of a phase transition (Freeman and Vitiello, 2006, 2008). In the formation of a droplet in the condensation of water vapor some microscopic defect in the medium such as a grain of dust starts the process, so the drop grows by radial expansion. We postulate that in the cortex a similar node was required to initiate a burst of oscillation, the spread of which caused a conic phase gradient in the analytic phase and Fourier phase of

Figure 5. (a,b) The interburst analytic power illustrated in 2D and 3D was compared with the point spread function of the ECoG of a cortical column (c). The null spike collocated with the maximum of phase, $\phi_{ij}(t)$, in the conic phase gradient that accompanied the AM pattern after a null spike. From Freeman (2006 and 2009).

the carrier frequency. The spatial pattern of each phase cone had a fixed apex with a sign and location that varied randomly from each burst to the next (Freeman and Baird, 1987; Freeman and Barrie, 2000; Freeman, 2004b). The carrier frequency in radians/s divided by the slope of the cone in radians/mm gave the phase velocity in m/s, which was equal to the conduction velocity of the intracortical axons running parallel to the cortical surface. The properties of the cone had no relation to the CS. The random variation of the sign indicated that the phase transition was comparable to a subcritical Hopf bifurcation and could not manifest the location of a pacemaker. Instead the burst resembled the properties of

a virtual particle, which carried the energy of interaction through the population and sustained the coherence (Freeman and Vitiello, 2008). The conic apex was in itself a singularity, and there was preliminary evidence that it collocated with the preceding null spike (Fig. 5d). New data will be required for confirmation, taken with closer electrode spacing, much faster digitizing rates (e.g., 5000/s rather than 500/s), and better design of basis functions for digital decomposition of overlapping phase cones.

4. The Mechanism of Termination of a Burst

With each act of observation (a sniff, saccade or whisk) a subject was testing the environment with a set of Bayesian prior probabilities that was expressed in a landscape of attractors (Skarda and Freeman, 1987). The attractors were elicited in every sensory cortex by the limbic system. Ignition of a Hebbian assembly placed the trajectory of cortical dynamics in the appropriate basin of a limit cycle attractor. Convergence to the attractor gave the corresponding AM pattern. The transfer of cortical control from the background chaotic attractor to a limit cycle attractor was the key step. We postulate that the null spike enabled the transfer by suppressing the dense interactions at some point that decohered the activity and *created a discontinuity*. The spread thereafter was revealed by the conic phase gradient that accompanied each AM pattern (Freeman and Barrie, 2000). Upon uncoupling of the neurons any existing AM pattern was obliterated.

In other words, during the coherent oscillation at the center frequency of a burst, the microscopic activity of neurons was entrained into the population by the strength of the synaptic feedback gain, so in dynamical terms the ECoG served as an order parameter (Haken, 1983). But the characteristic frequencies of the millions of feedback loops were distributed in the pass band of the carrier (Fig. 4b). As the oscillators drifted apart in phase around the center frequency, there came times when excitation and inhibition cancelled, giving beats resembling those of Rayleigh noise (Rice, 1950). The interval between beats was solely determined by the pass band (Rice, 1950; Freeman, 2009; Ruiz *et al.*, 2010). Paradoxically the rates of firing of neurons at the microscopic level would not reveal the macroscopic event, by which an AM pattern was terminated when the order parameter approached zero. It was the instantaneous coherence that vanished.

Further experimental evidence for the role of singularity was provided by cinematic display of the filtered ECoG, which revealed vortices for which the center of rotation constituted another form of singularity (Kozma

and Freeman, 2008; Freeman and Vitiello, 2010). The existence of these dynamical patterns can be modeled with dissipative field theory in many-body physics (Freeman and Vitiello, 2008; Freeman, Livi *et al.*, 2012).

5. The Idealized Carnot Cycle

The Carnot formalism was originally represented by isoclines of pressure vs. volume at fixed temperatures. Following Clausius the coordinates were replaced by energy and entropy, as illustrated in a temperature-entropy diagram (Fig. 6). Starting the cycle at minimal temperature and maximal disorder (1), free energy is dissipated as matter is compressed (A) into a highly ordered state (2) with decreased entropy and without increase in temperature. Then (B) temperature is increased by adiabatic compression to maximal energy without change in order (3). Upon release from compression the matter undergoes isothermal expansion (C) to a disordered state (4), and it returns to its initial state (1) by cooling with adiabatic expansion and without further change in energy (D).

Considering that the cortex is an open thermodynamic system operating far from equilibrium (Freeman, 2008; Freeman, Livi *et al.*, 2012), we adapted the Carnot cycle into neural terms by replacing the static variable of temperature with a measure of the rate of energy dissipation and the static variable of entropy with the rate of loss of order (Fig. 7). We used the mean power, $\underline{A}^2(t)$, as an indirect measure of pulse density, which varied in proportion to mean firing rates, the numbers of neurons firing, and the degree of synchronization imposed by synaptic binding. We used the magnitude of the Euclidean distance, $D_e(t)$, between feature vectors on successive digitizing steps to estimate the degree of disorder hence entropy, on the premise that small steps characterizing classifiable AM patterns gave greater certainty about structure, while large steps between AM patterns indicated low information. We conceived the cycle as beginning (1) with minimum of power, $\underline{A}^2(t)$, when pre-existing structure was terminated by a null spike (Fig. 5b) and maximum disorder supervened. In step (A) a basin of attraction was selected by the ignition of a Hebbian assembly formed by prior learning. Both $\underline{A}^2(t)$ and $D_e(t)$ were derived from the ECoG. They differed in that $\underline{A}^2(t)$ was the spatial mean of the analytic power at each step, while $D_e(t)$ was the step-wise temporal difference of the feature vector after the normalization of each frame (subtracting the frame mean and dividing by the spatial standard deviation). $\underline{A}^2(t)$ indexed the rate of consumption of free energy, and $D_e(t)$ indexed the rate of decrease in

Figure 6. (a) The signals are plotted of mean analytic power, $A^2(t)$ (black), and the Euclidean distance between successive digitizing steps, $D_e(t)$ (gray), in the 20–80 Hz pass band of the ECoG of a single trial. (b) The pragmatic information, $H_e(t) = \underline{A}^2(t)/D_e(t)$, served as a scalar index of the order parameter revealing brief peaks especially following onset of a conditioned stimulus (CS) at $t = 0$. (c) The distribution of the scalar index had a long tail of infrequent high values. (d) Classifiable AM patterns were found in the segments following the CS where $H_e(t) > 5$ (black dashes show the durations of the classified segments and the time intervals between them on successive trials). From Figs. 1.03–1.04 in Freeman (2004a).

order (increase in entropy). In other words, the smaller was the step size, the greater was the certainty of knowing the AM pattern and therefore the amount of information the pattern gave.

In step (A) the ignition of the assembly triggers a global change in activity, which is ideally expressed not by an increase in the number of pulses per unit volume but by an increase in the coherence of neural firing at the carrier frequency. This means that the released energy is not distributed

Figure 7. (a) The idealized Carnot cycle shown in the entropy versus temperature diagram during the analytic power beating cycle. Notations: 1 – isothermal compression; 2 – adiabatic heating; 3 – isothermal expansion; 4 – adiabatic cooling. From Freeman, Kozma and Vitiello (2012) (b) The modified Carnot cycle is displayed as the degree of disorder (entropy) versus pulse density (temperature). Notations are: 1 – down beat containing a null spike (start of cycle); 2 – emergence of AM pattern by condensation through a Hebbian assembly; 3 – maximum cognitive information (pulse density); 4 – evaporation of AM pattern by gain reduction; 1 – return to the next down beat by phase dispersion. From Freeman, Kozma and Vitiello (2012).

among the system's degrees of freedom in the form of kinetic energy driving ions across membranes (Freeman, Livi *et al.*, 2012). Instead it is used to enhance the collective long-range correlation modes among the interacting neurons constituting a virtual particle. Each cortical neuron connects with 10^4 others, then 10^8 , 10^{12} , and so on, leading in very few serial synaptic steps to the condensed state (2), in which every neuron contributes directly to cortical output, whether its firing rate is low or high. It is the recruitment of all neurons into the dense phase that provides the richness of context required to express and experience knowledge.

In step (B) the output rises to maximum output and maximum classification (3). In step (C) to (4) the AM pattern evaporates, owing to the refractory periods of the neurons, leading to the unbinding and the loss of coherence into noise. In step (4) to (1) (D) the pulse density returns to the background level (adiabatic cooling) not by diminished firing rates but by interference as the local oscillations, lacking binding, go out of phase. All these steps dissipate substantial metabolic free energy and incur what biologists refer to as an oxygen debt, meaning an expenditure

of free energy that must be repaid by oxidative metabolism. In other words, neurons immediately converge to an attractor by dissipating free energy in condensing and later replenishing it by burning glucose to make ATP that is used to restore depleted transmembrane ionic gradients. The restoration is observed by brain imaging with BOLD (blood oxygen level depletion) using fMRI (Freeman, Ahlfors and Menon, 2009).

6. The Generalized Carnot Cycle: The Rankine Cycle

In the idealized Carnot cycle with a homogeneous medium there was no phase transition. Generalization to include the two phases was by embedding the cycle in the domain of criticality, the Rankine cycle (Fig. 8).

Figure 8. (a) The phase diagram shows the Rankine cycle, a generalization of the Carnot cycle, with the cycle embedded in a domain of criticality. 1 – mainly gas phase with maximal disorder; 2 – condensation into order in mainly liquid phase; 3 – rise to maximal pressure and minimal volume; 4 – loss of order by expansion into gas (evaporation); 1 – relaxation to disorder by reduction of pressure. Adapted from Baratuci (2011) (b) The phase diagram is re-labeled to describe the four steps of the cycle as isoclines in an abstraction to assist further experimental exploration and modeling. 1 – symmetry of random background activity; 2 – reduction in entropy by emergence of an AM pattern after spontaneous breaking of symmetry by a Hebbian assembly; 3 – increase in interaction to maximal power and order by nonlinear amplitude-dependent negative feedback gain (Freeman, 1979); 4 – attenuation of AM patterns by refractory periods with disintegration into background noise (evaporation); 1 – return to symmetry by reduction of feedback gain and decoherence without change in firing rates. From Freeman and Quiñan Quiroga (2012)

Figure 9. The phase diagram is re-labeled to describe the four steps of the cycle as isoclines in an abstraction to assist further experimental exploration and modeling. 1 – symmetry of random background activity; 2 – reduction in entropy by emergence of an AM pattern after spontaneous breaking of symmetry by a Hebbian assembly; 3 – increase in interaction to maximal power and order by nonlinear amplitude-dependent negative feedback gain (Freeman, 1979); 4 – attenuation of AM patterns by refractory periods with disintegration into background noise (evaporation); 1 – return to symmetry by reduction of feedback gain and decoherence without change in firing rates. From Freeman and Quiroga (2012).

The adapted Carnot cycle is transferred to the domain of criticality beyond the critical point that terminates the phase boundary between gas and liquid (Baratuci, 2011). In this domain the density shifts between mainly gas and mainly liquid without boundaries with changes in temperature, pressure and volume. We again adapted the four stages around the cycle (Fig. 9). We used the rate of change in the AM pattern as a measure of the disorder (and conversely its reciprocal as a measure of the rate of increase in information). We used the ECoG power to replace pressure. We measured the normalized pulse probability to calculate the nonlinear negative feedback gain, $G(v) = dp/dv$, as an index of the intensity of synaptic interaction producing the ECoG, where p was pulse density and v was wave density (Freeman, 1979; Freeman and Erwin, 2008).

In stage (1) the cortical population was in a gas-like phase of maximal disorder with sparse firing and no coherence. We attributed the initial

rise in power, $\underline{A}^2(t)$ (A in Fig. 6) to the release of cortical neurons from prior binding and firing in response to a broad range of centrifugal and sensory input. Sensory input carrying a CS ignited a Hebbian assembly that initiated a burst of narrow band oscillation and selected a basin of attraction (1–2). The onset at (1) was by a null spike accompanied by a discontinuity in the analytic phase, $\phi(t)$. During the initial increase in $\underline{A}^2(t)$ the AM pattern emerged (2) with the accompanying spatial pattern of phase, $\phi(t)$. The spontaneous breaking of symmetry decreased the entropy. The energy taken by the system from transmembrane ionic gradients was given to collective modes responsible for the long-range coherent oscillations among the neurons. In the field model this was depicted as the isothermal increase in the mutual excitation of neurons leading to the coherence of firing in the condensed phase (Eq. B.7 in Freeman and Vitiello (2006); Eq. 9 in Freeman and Vitiello (2008); Eq. 33 in Freeman *et al.* (2012)). The energy sequestration into coherence gave the lower energy state of the basin that ‘attracted’ the cortex.

Adaptation of the Carnot and Rankine models of cortical activity enabled us to define a measure of the amount of work done, which was firmly based on the 1st and 2nd laws of thermodynamics. Carnot estimated the amount of work done in each cycle by calculating the area enclosed in the cycle. We devised an equivalent index to estimate the amount of knowledge created by each cycle. We calculated an index called the *pragmatic information* after Atmanspacher and Scheingraber (1990). They described the ratio of the rate of energy dissipation to the rate of order formation (rate of reduction in entropy) as a “fundamental extension of Shannonian information” (pp. 731–732). We used the ratio of the rate of energy dissipation to the rate of entropy increase, hence $H_e(t) = \underline{A}^2(t)/D_e(t)$ (Freeman, 2005). $H_e(t)$ was the ratio rather than the product in calculating the area, because the size of the step change in the Euclidean distance was inversely related to information. A large step meant lack of information, and a small step meant reduced uncertainty. $H_e(t)$ proved to be the optimal index for locating and classifying AM patterns (Fig. 10) once the carrier frequencies were identified.

Carnot defined the efficiency of a steam engine generically as the ratio of useful work done to the energy expended. His engineering definition was $1 - T_C/T_H$, where T_H and T_C were respectively the input and output temperatures. We devised a comparable measure of cortical efficiency, $R_e(t)$, by calculating the ratio of the coherent activity to the total activity that included fluctuations dispersed in phase and frequency. Overlapping

Figure 10. (a) The pragmatic information, $H_e(t) = \Delta^2(t)/D_e(t)$ served as a scalar index of the order parameter in the 20–80 Hz pass band of the ECoG of a single trial. (b) The longer time scale showed brief peaks of high order following onset of a conditioned stimulus (CS) at 0. (c) The distribution of the scalar index had a long tail of infrequent high values. (d) Classifiable AM patterns were found in the segments following the CS where $H_e(t) > 5$ (black dashes showing the durations of the classified segments and their time intervals on successive trials). From Fig. 1.04 in Freeman (2004a).

excitatory and inhibitory potentials canceled but not their metabolic energy costs, leading to the phrase “dark energy” (Raichle and Mintun, 2006). We evaluated $R_e(t)$ by applying a moving window to an array of 64 filtered ECoGs (Freeman, 2004a). The window duration was twice the wavelength of the center frequency of the pass band. We divided the temporal standard deviation, $SD_T(t)$, of the spatial ensemble average of 64 ECoGs by the mean $\overline{SD_T}(t)$ of the 64 ECoG. For perfect synchrony $R_e(t) = 1$ with no cancellation; for the summation of random ECoGs $R_e(t)$ approached

$(1/64)^{0.5}$, the square root of the number of channels. $R_e(t)$ was highly correlated with $1/D_e(t)$ (Freeman, 2004a) and proved useful for finding bursts for which the carrier frequency was not known beforehand.

7. Discussion and Conclusions

Clearly the concept of criticality is multifaceted, and clearly its multiple aspects are required for describing the dynamics of the cortex in perception. Measurement of spatiotemporal patterns in the ECoG and EEG is also necessary, because there is no other extant means of evaluating the spatial patterns of phase and amplitude of narrow band oscillations than large arrays of electrodes having spacing in the mm and sub-mm range. The dynamics revealed by the electric field potentials are readily modeled by far-from-equilibrium, dissipative thermodynamics (Freeman, Livi *et al.*, 2012), which is all the more appropriate seeing that brains use metabolic energy at rates far above all other organs. Knowledge and intelligence are very expensive.

The concept of *self-organized criticality* (Plenz and Thiagarajan, 2007; Beggs, 2008; Petermann *et al.*, 2009; Freeman and Zhai, 2009) describes the background state, in which we observed myriad phase cones having power-law distributions of durations (Freeman, 2004b) but with no classifiable AM patterns, which corresponded to *neural avalanches* that maintained the critical state (Beggs and Plenz 2003; Peterman, 2009; Bonchela *et al.*, 2010). These observations of self-similar scale-free brain functional activity (Figs. 1a and 1b) are consistent with the formation of coherent domains ruled by many-body dynamics (Vitiello, 2009).

It is important to note that in contrast to the repetitive cycles of a steam engine, the cortical cycle is actually a spiral or helix in time (Vitiello, 2009, 2012; Freeman, 2008), because with each cycle of constructing knowledge from information the cortex changes itself by learning.

We have described the operation of the Carnot and Rankine cycles in primary sensory cortices where percepts are initiated from sensory input. We predict that the cycles will be found operating in the entorhinal cortex in conjunction with the formation of gestalts (multisensory percepts) and in locations performing other higher-level cognitive tasks (Freeman and Quian Quiroga, 2013) as a general-purpose algorithm. What we have is a beachhead of understanding that opens the cortex more broadly to modeling with non-equilibrium thermodynamics. In our view the most important new insight is the formulation of evidence for condensation into an extreme

density of neural activity in the cortical neuropil followed by evaporation. No other neural mechanism can come as close to repetitively integrating the massive quantity of information that appears in sequential recall of memories and the recognition of a stimulus in a flash of insight (Yufik, 1998; Baars *et al.*, 2003; Majumdar, Pribram and Barrett, 2006; Tononi, 2008; Seth, 2009; Tallon-Baudry, 2009). Equally important is the discovery of the mechanisms that terminate the AM patterns by decoherence, which we characterize as evaporation leading to the singularity of the null spike. We propose that these events are essential to the mechanisms that constitute and control the intermittent stream of consciousness (Ruiz *et al.*, 2011; Panagiotides *et al.*, 2010), providing the shutter for the cinematic flow.

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