

# Nonlinear brain dynamics as macroscopic manifestation of underlying many-body field dynamics

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## Abstract

Neural activity patterns related to behavior occur at many scales in time and space from the atomic and molecular to the whole brain. Patterns form through interactions in both directions, so that the impact of transmitter molecule release can be analyzed to larger scales through synapses, dendrites, neurons, populations and brain systems to behavior, and control of that release can be described step-wise through transforms to smaller scales. Here we explore the feasibility of interpreting neurophysiological data in the context of many-body physics by using tools that physicists have devised to analyze comparable hierarchies in other fields of science. We focus on a mesoscopic level that offers a multi-step pathway between the microscopic functions of neurons and the macroscopic functions of brain systems revealed by hemodynamic imaging. We use electroencephalographic (EEG) records collected from high-density electrode arrays fixed on the epidural surfaces of primary sensory and limbic areas in rabbits and cats trained to discriminate conditioned stimuli (CS) in the various modalities. High temporal resolution of EEG signals with the Hilbert transform gives evidence for diverse intermittent spatial patterns of amplitude (AM) and phase modulations (PM) of carrier waves that repeatedly re-synchronize in the beta and gamma ranges in very short time lags over very long distances. The dominant mechanism for neural interactions by axodendritic synaptic transmission should impose distance-dependent delays on the EEG oscillations owing to finite propagation velocities and sequential synaptic delays. It does not. EEGs show evidence for anomalous dispersion: neural populations have a low velocity range of information and energy transfers, and a high velocity range of the spread of phase transitions. This distinction labels the phenomenon but does not explain it. In this report we analyze these phenomena using concepts of energy dissipation, the maintenance by cortex of multiple ground states corresponding to AM patterns, and the exclusive selection by spontaneous breakdown of symmetry (SBS) of single states in sequential phase transitions.

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## 1. Introduction

### 1.1. Overview: Phenomena observed in brain dynamics and explained using tools of physics

Classical physics has provided a strong foundation for understanding brain function through measuring brain activity, modeling the functional connectivity of networks of neurons with algebraic matrices, and modeling the dynamics of neurons and neural populations with sets of coupled differential equations [1,2], Appendix A. The areas of physics that have been most fruitful have been Newtonian mechanics, the theory of the potential, optics, thermodynamics, and statistical mechanics. These tools enabled recognition and documentation of the physical states of brains; the structures and dynamics of neurons; the operations of membranes and organelles that generate and channel electric currents; and the molecular and ionic carriers that implement the neural machineries of electrogenesis and learning. They support description of brain functions at several levels of complexity through measuring neural activity in the brains of animal and human subjects engaged in behavioral exchanges with their environments. In these brain states a salient property has been the coordinated oscillations of populations of neurons that were changing rapidly in concert with changes in the environment—more specifically, with the evolution of the meaningful relationships between each subject and its environment that were established and maintained by the action-perception cycle [3,4].

Most experimental neurobiologists and neural theorists have focused on sensorimotor functions and their adaptations through various forms of learning and memory (e.g., [5–7]). Reliance has been placed on measurements of the rates and intervals of trains of action potentials of small numbers of neurons that are tuned to perceptual invariances (e.g., [8]) and modeling neural interactions with discrete networks of simulated neurons. These and related studies have given a vivid picture of cortex as a mosaic of modules [9], each of which performs a sensory or motor function; they have not given a picture of comparable clarity of the integration of modules. In our experimental work aiming

to understand global cooperation among modules we have focused on the fields of potential established by dendritic currents of populations of neurons, which are often called local field potentials (LFP) when recorded in the brain, electrocorticograms (ECoG) when taken from the cortical surface, and electroencephalograms (EEG) when at the scalp. Here we use “EEG” irrespective of recording site. Models for these oscillations have included linear filters of noise, either white [10–12] or  $1/f$  [13–16]. Mechanisms have been modeled by negative feedback among local populations [17], thalamocortical loops [18–21], subcortical loops [22], electrochemical reactions based in membrane permeabilities [23,24], and resonant modes of wave mechanics [25]. Here we depend on models with multiple types of nonlinear distributed feedback among diverse populations [1].

The types of behavior we address included high-level generalization, abstraction, and contextualization effected late in the action-perception cycle of Piaget [26], Merleau-Ponty [27], and Maturana and Varela [28]. Our experimental designs and modeling are based on the neuropsychological field theories of Lashley [29], Köhler [30] and Pribram [31]. Karl Lashley wrote: “Generalization [stimulus equivalence] is one of the primitive basic functions of organized nervous tissue. . . . Here is the dilemma. Nerve impulses are transmitted from cell to cell through definite intercellular connections. Yet all behavior seems to be determined by masses of excitation. . . . What sort of nervous organization might be capable of responding to a pattern of excitation without limited specialized paths of conduction? The problem is almost universal in the activities of the nervous system” [32, p. 306]. Wolfgang Köhler wrote: “Our present knowledge of human perception leaves no doubt as to the general form of any theory which is to do justice to such knowledge: a theory of perception must be a field theory. By this we mean that the neural functions and processes with which the perceptual facts are associated in each case are located in a continuous medium” [30, p. 55]. Pribram [31] proposed a holographic model to explain psychological field data. Bartlett [33] wrote: “. . . some widely held views [of memory] have to be completely discarded, and none more completely than that which treats recall as the re-excitement in some way of fixed and changeless ‘traces’ ” (p. vi). On empirical grounds John [34] inferred: “. . . consciousness is a property of quantum-like processes, within a brain field resonating within a core of structures . . .”. We therefore sought to devise a neurodynamics of dendritic potentials by which to synthesize contemporary unit and EEG data with classical mid-20th century perceptual field theory into a new framework.

Our analysis of electroencephalographic activity (EEG) has shown that cortical activity does not change continuously with time but by multiple spatial patterns in sequences during each perceptual action that resemble cinematographic frames on multiple screens [35–38]. We identify the source of these patterns with regions in the embedding medium of neurons that is provided by the neocortical neuropil: the dense felt-work of axons, dendrites, cell bodies, glia and capillaries forming a superficial continuum 1–3 mm in thickness over the entire extent of each cerebral hemisphere in mammals. The carrier waves of the patterned activity in frames come in at least two ranges that we identify with beta (12–30 Hz) and gamma (30–80 Hz) oscillations in animal EEG [16,39,40]. The abrupt change in dynamical state with each new frame is not readily amenable to description either with classic integrodifferential equations (e.g., [17,41]) or the algebras of neural networks. We propose that each frame is formed by a *phase transition* [38].

The initiation and maintenance of shared oscillations by this phase transition requires rapid communication among neurons. Several alternative mechanisms have been proposed as the agency for widespread synchrony. These are based in the dendritic loop current as the chief agent for *intracellular* communication and the axonal action potential as the chief agent for *intercellular* communication. The propagating action potential is the mechanism by which multicellular organisms greater in size than about a millimeter overcome the limitations of diffusion by providing for rapid communication over long distances without attenuation. Diffusion of chemical transmitters substances remains the agent in synaptic clefts and extracellular channels with lengths on the order of hundreds of microns. Indeed the cable equation used to describe passive loop currents also describes a 1-dimensional diffusion process. Passive conduction suffices for distances less than 1 mm; neurons exceeding that range are well known to have dendritic spike mechanisms that complement diffusion. Fuxe and Agnati [42] and Bach-y-Rita [43] have compiled extensive evidence for what they call *nonsynaptic diffusion neurotransmission (NDN)* to explain *volume transmission*, which appears to be related to John’s [34] “ionic clouds”. We believe that the temporal precision and fineness of spatial texture of synchronized cortical activity that we have documented (see above) and modeled [16] over distances of mm to cm are incompatible with the mechanism of long-range ionic diffusion.

Communication by propagating action potentials imposes distance-dependent delays in the onset of resynchronization during a phase transition over an area of cortex. The delays are measurable as brief but distance-dependent phase lags at the various frequencies of oscillation [38]. However, the length of most axons in cortex is a small fraction of observed distances of long-range correlation, with the requirement for synaptic renewal at each successive relay. Even

the presence of relatively sparse long axons, which provide for high velocity jumps to seed areas over long distances creating *small-world* effects [44,45], cannot easily explain the observed long-range correlations, which are maintained despite continuous variations in transmission frequencies that are apparent in aperiodic “chaotic” oscillations. Several groups have proposed that zero-lag correlation between oscillations at distant sites might be explained by reciprocal transmission at equal velocities [46–48]. We believe that the evidence points instead to the classical physical description of *anomalous dispersion* [49] at finite velocities, by which the rate of propagation of phase transitions through cortex might exceed the rates of propagation of energy and information. Use of averaging over extended time periods can readily account for zero-lag correlation [50], but the observed phase gradients emerge over distances of many cm in less than 1/4 cycle (3–7 ms) of oscillations in the beta and gamma ranges (12–80+ Hz) in neocortex.

Some researchers have sought to explain zero-lag correlations with processes other than axodendritic synaptic transmission. Both electric fields and magnetic fields accompany neural loop currents. Bullock [10] showed *in vitro* that weak electric fields modulate neural firing. However, the intensities of the extracellular electric forces are 3 orders of magnitude smaller than the transmembrane potential differences. The electric potential gradients of the EEG have been shown [51] to be inadequate *in vivo* to account for the long-range of the observed coherent activity, largely owing to the shunting action of glia that reduce the fraction of extracellular dendritic current penetrating adjacent neurons and minimize ephaptic cross-talk among cortical neurons. Like the decay in diffusion potential the fall of electric potential with distance is too rapid, and the intensity of the Coulomb forces is too weak to explain either the abruptness of phase transitions manifested in EEGs or the entry of beta and gamma oscillations into synchrony within the observed time windows of a few ms over distances of 1–19 cm [36,50,52–54]. Regarding the agency of magnetic fields, the search in cortex for magnetic field receptors like those in bees and birds serving navigation remains inconclusive [55]. Moreover, there are no significant electromagnetic fields (radio waves) in brains; EEG oscillations are too slow and excessive in wavelength, and brain electric and magnetic permeabilities differ by 80:1.

As a reasonable alternative we turn to the mathematical machinery of many-body field theory that enables us to describe phase transitions in distributed nonlinear media having innumerable co-existing and overlapping ground states, actual and potential. One might wonder about the necessity and the correctness of using many-body field theory in treating brain dynamics. The common belief is that, if physics has to be involved in the description of brain dynamics, classical tools such as non-linear dynamics and statistical mechanics should suffice. However, many-body field theory appears to us as the only existing theoretical tool capable to explain the *dynamic origin* of long-range correlations, their rapid and efficient formation and dissolution, their interim stability in ground states, the multiplicity of coexisting and possibly non-interfering ground states, their degree of ordering, and their rich textures relating to sensory and motor facets of behaviors. It is historical fact that many-body quantum field theory has been devised and constructed in past decades exactly to understand features like ordered pattern formation and phase transitions in condensed matter physics that could not be understood in classical physics, similar to those in the brain.

The notion of coherent collective modes, which are macroscopic features of quantum origin, has been used in many practical applications (in solid state physics and laser physics, for example). In a familiar crystal, a magnet, the ordered patterns observed at room temperature, without recourse to low-temperature superconductivity or superfluidity, are well known examples of *macroscopic quantum systems* [56]. The domain of validity of the ‘quantum’ is *not* restricted to the microscopic world. There are macroscopic features of classically behaving systems, like the ones just mentioned, which cannot be explained without recourse to the quantum dynamics. This does not mean that the biochemistry, neurophysiological analysis and/or any other classical tool of investigation might be superseded. Rather, it means that brain studies made by continuing use of these traditional classical tools might be enhanced by descriptions of the underlying dynamics that will enable us to understand and model the experimental data.

One final remark is that quantum field theory (QFT) differs drastically from quantum mechanics (QM) and must not be confused with it. To explain such a difference goes outside the task of the present paper. We only say that multiple, physically distinct, ground states do not exist in QM [57,58], contrarily to what happens in many-body field theory, and thus there cannot co-exist different physical phases for a system in QM. The interested reader can find more on this in Umezawa [56] and in Vitiello [4] (see also [59]).

## 1.2. *The many-body model and the macroscopic collective field of action*

Our field theoretic model leads to our view of the phase transition as a condensation that is comparable to the formation of fog and rain drops from water vapor, and that might serve to model both the gamma and beta phase

transitions. According to such a model, originally proposed by Ricciardi and Umezawa [60], developed by others [61–66], and extended to dissipative dynamics [4,67], the production of activity with long-range correlation in the brain takes place through the mechanism of spontaneous breakdown of symmetry (SBS), which has for decades been shown to describe long-range correlation in condensed matter physics. The adoption of such a field theoretic approach enables us to model the whole cerebral hemisphere and its hierarchy of components down to the atomic level as a fully integrated macroscopic quantum system, namely as a macroscopic system which is a quantum system not in the trivial sense that it is made, like all existing matter, by quantum components such as atoms and molecules, but, as already mentioned, in the sense that some of its macroscopic properties can best be described with recourse to quantum dynamics.

A central concern in our attempt to apply many-body physics is then expressed in the question: What might be the *bridge* between microscopic, atomic and molecular, units and the macroscopic neural activity as we observe it? Traditionally, the unit of neural activity is taken to be the action potential, the dendritic postsynaptic potential (PSP), the chemical packet in the synaptic vesicle, an extracellular diffusion field, or a gap junction. On the one hand, the neuron, cell body, synapse, microtubule, vesicle, or other microscopic structures *are not to be considered as quantum objects* in our analysis. The Planck constant,  $h$ , is undeniably the unit of action at the atomic scale and below, but it is not the decisive factor at the level of neuronal populations. On the other hand, what appears to emerge from our experiments is a *wave packet* [1,2] acting as a bridge from quantum dynamics at the atomic level through the microscopic pulse trains of neurons to the macroscopic properties of large populations of neurons. The wave packet we refer to is a macroscopic collective field of action that has measurable field properties: the phase, the amplitude, and their spatial and temporal rates of change (gradients and frequencies) at each point in time and space in the sustaining neuropil. Our measurements of the durations, recurrence intervals and diameters of neocortical EEG phase patterns have power-law distributions with no detectable minima. The means and standard deviations (SD) vary depending on the scale of measurement within the limits of observation. The power spectral densities in both time ( $\text{PSD}_T$ ) and space ( $\text{PSD}_X$ ) of EEGs from surface arrays likewise conform to power-law distributions,  $1/f^\alpha$ , with  $\alpha$  commonly near 2. These findings [37,38] and those of others [13,14,68] suggest that the activity patterns generated by neocortical neuropil might be scale-free [39,69] with self-similarity in EEG patterns over distances ranging from hypercolumns to an entire cerebral hemisphere, thus explaining the similarity of neocortical dynamics in mammals differing in brain size by 4 orders of magnitude, from mouse [70] to whale [71], which contrasts strikingly with the relatively small range of size of avian, reptilian and dinosaur brains lacking neocortex.

It is important again to stress that our wave packet is not to be confused with the notion of wave packet describing probability amplitudes in QM (the common denomination is only accidental). In our field-theoretic approach, the wave packet is *a collective mode that sustains a field of neural activity* [1], which gives rise to the observable fields of EEGs and action potentials we record from arrays of electrodes. We propose to explore the utility of modeling the wave packet observed in our experiments with the Nambu–Goldstone boson wave or mode in Bose–Einstein condensates in the dissipative many-body model [4,67].

Our paper is organized as follows. In Sections 2 and 3 we present analyses of EEG observations. In Sections 4 and 5 we introduce the concepts of SBS, order, and long-range correlation in the many-body model. In Sections 6 we analyze the role of dissipation in the observed phase transitions and related experimental observations. We devote Sections 7–9 to exploring the implications of our findings, and Section 10 to concluding remarks and comments. Appendix A outlines  $K$ -fields and  $K$ -sets; Appendix B summarizes the mathematical formalism of our many-body model.

Our talisman in this scientific endeavor is a human subject, who may be imagined as a bright young woman with intractable epilepsy [72]. Her complex partial seizures robbed her of consciousness and replaced intentional actions with meaningless movements. Failure of medication led to neurosurgical evaluation requiring placement of intracranial electrode arrays. Her EEG data were transmitted without personal identification from clinic to laboratory; her history and therapeutic outcome are curtained by anonymity.

## 2. Observation and measurement of multiple EEG signals at high space-time resolution

Two main features of our EEG data justify our proposal to use QFT for explanation: the textured patterns of amplitude modulation (AM) in distinct frequency bands that serve to classify EEG segments with respect to categories of conditioned stimuli (CS), and the remarkably rapid onsets of AM patterns in sequences that resemble cinemato-

graphic frames. We propose to identify each spatial AM pattern with a ground state, and its manner of onset as SBS. The high spatial resolution required to measure AM pattern textures came by using 1-D and 2-D high-density electrode arrays (typically  $8 \times 8$ ) fixed on the scalp or over the surfaces of cortical areas. We determined the optimal interelectrode intervals by using 1-D curvilinear arrays to over-sample the spatial EEG distributions with ultra-close spacing and the 1-D fast Fourier transform (FFT) to calculate the spatial spectrum and fix a spatial Nyquist frequency that would avoid both aliasing and over-sampling [36,73]. The high temporal resolution required for sequencing came by applying the Hilbert transform to EEG signals after band pass filtering [36–38]. We optimized our filter settings by constructing tuning curves resembling ROC curves with the criterion of maximal classification of spatial AM patterns with respect to CS. Unlike the Fourier transform that decomposed an extended time series into fixed frequency components, the Hilbert transform decomposed an EEG signal into the analytic amplitude,  $A(t)$ , and the analytic phase,  $\phi(t)$ , at each digitizing time step on each channel giving a point in time and space. Owing to the relative invariance of the extracellular specific impedance,  $r$  [1], the square of the analytic amplitude,  $A^2(t)$ , gave an estimate of the instantaneous power,  $i^2r$ , expended by a local neighborhood of cortex in generating the ionic current density,  $i$ , underlying the EEG, where the real part of the complex analytic signal indexed the current of excitatory neurons and the imaginary part indexed the current of inhibitory neurons forming negative feedback loops in cortex. The set of  $n$  amplitudes from an array of  $n$  electrodes (typically 64) defined a feature vector,  $\mathbf{A}^2(t)$  (boldface indicating a vector), at each time step for the set of  $n$  points on the cortical surface. The vector specified a point on a dynamic trajectory in *brain state-space*, which we conceived as the collection of all possible brain states, essentially infinite. Our measurement of  $n$  EEG signals defined a trajectory in a finite  $n$ -dimensional subspace, so the point specified by  $\mathbf{A}^2(t)$  was unique to a spatial AM pattern of the aperiodic carrier wave with mean amplitude,  $\underline{A}(t)$  (underline indicating a mean value over  $n$  signals). Similar AM patterns formed a cluster in  $n$ -space, and multiple dissimilar patterns formed either multiple clusters or trajectories with large Euclidean distances between digitizing steps through  $n$ -space. When we measured a cluster by its center of gravity and its SD radius and verified its behavioral correlate, then by any of several statistical classification techniques we assigned a category of CS to that cluster [39,74–76]. A cluster with a verified behavioral correlate was denoted an *ordered AM pattern of an ordered wave packet*.

The vector served also as our order parameter, because when the trajectory of a sequence of points entered into a cluster, that location in state space signified increased order from the perspective of an intentional state of the brain, owing to the correlation with a CS. The Euclidean distance between successive points in  $n$ -space,  $D_e(t)$ , specified the rate of change in the order parameter. We calculated  $D_e = [\mathbf{A}^2(t) - \mathbf{A}^2(t - 1)]$  after frame normalization, as distinct from  $\Delta \underline{A}^2(t) = [\underline{A}^2(t) - \underline{A}^2(t - 1)]$  without normalization, the latter being the rate of change in mean power. Typically  $D_e(t)$  took large steps between clusters, decreased to a low value when the trajectory entered a cluster, and remained low for tens of ms within a frame. Therefore  $D_e(t)$  served as a measure of the spatial AM pattern stability as a significant property of a wave packet.

The analytic phase in rad divided by the digitizing time interval in s at each step on each channel specified the *instantaneous frequency*,  $\omega(t)$  in rad/s, in the designated band. Our measurements showed that typically the rate of change in  $\omega(t)$  was low in frames that coincided with low  $D_e(t)$ , which indicated stabilization or relative invariance of frequencies accompanying the stability of AM patterns, hence stationarity within frames. Between frames  $\omega(t)$  increased often several fold or decreased even below zero in interframe breaks. The discontinuities repeated at rates in the theta or alpha range of the EEG [77]. Sudden changes in phase were designated *phase slip* [78]. In array recordings the phase slips tended to occur almost simultaneously over the entire array. A useful index of the temporal stability was the spatial standard deviation of analytic phase differences,  $SD_X(t)$ , to be distinguished from the temporal standard deviation,  $SD_T(t)$ , in temporal windows. Peaks in  $SD_X(t)$  bracketed the stationary frames and defined the beginning and end of wave packets.

The commonality of the aperiodic carrier wave demonstrated by visual inspection that the neural activity was synchronized across a designated spectral range. Commonality was confirmed by showing that the first component in principal components analysis typically contained  $>95\%$  of the total variance. The continual variation in the frequency impeded the use of phase to measure synchronization; the EEG often had featureless fluctuations with no periodic activity at which to define a frequency unequivocally. The  $1/f^\alpha$  PSD $_T$  in log–log coordinates with  $\alpha \sim 2$  tended toward the exponent in Brownian motion [36]. A quantitative index of synchrony independent of phase was devised for arrays of aperiodic oscillatory EEG signals in a moving window twice the wavelength of the center frequency of the pass band required for the Hilbert transform: the ratio,  $R_e(t)$ , of the temporal standard deviation of the mean filtered

EEG to the mean temporal standard deviation of the  $n$  EEGs,  $R_e(t) = \text{SD}_T$  of mean  $\underline{A}_T^2(t)/\text{mean } \underline{\text{SD}}_T$  of  $A_j^2(t)$ ,  $j = 1, n$ . When the oscillations were entirely synchronized,  $R_e(t) = 1$ ; when  $n$  EEGs were totally desynchronized,  $R_e(t)$  approached one over the square root of the number of digitizing steps in the moving window. Experimentally  $R_e(t)$  rose rapidly within a few ms after a phase discontinuity indexed by  $\text{SD}_X(t)$  and several ms before the onset of a marked increase in mean analytic amplitude,  $\underline{A}(t)$ . That timing showed that the increase in analytic amplitude could not be ascribed to synchronization, which had already taken place [38]. The succession of the high and low values of  $R_e(t)$  revealed episodic emergence and dissolution of synchrony; therefore  $R_e(t)$  was adopted as an index of cortical *efficiency* [79], on the premise that cortical transmission of spatial patterns was most energy-efficient when the dendritic currents were most synchronized. From this perspective the re-synchronization of cortical oscillations after a re-initialization of their phases was an energy-conserving step in a phase transition, preparatory to a major increase in transmission intensity of a wave packet after pattern stabilization, as measured by  $\underline{A}^2(t)$ .

These indices characterized four successive events comprising cortical phase transitions forming wave packets. First re-initialization of phase was marked by a rapid rise and drop in  $\text{SD}_X(t)$ . Next came re-synchronization shown by a rise in  $R_e(t)$ , followed by selection of an AM pattern,  $A^2(t)$ , and pattern stabilization indexed by  $D_e(t)$ . Lastly the mean rate of free energy dissipation,  $\underline{A}^2(t)$ , increased to a maximum in the time interval before the next phase slip. Hence during a wave packet cortex transmitted a synchronized carrier wave at high intensity with stabilized AM pattern and frequency.

The times of onset of phase slips with respect to CS varied unpredictably from trial to trial. Empirically [39] we found that the best predictor of the onset times of ordered AM patterns was the ratio of the rate of free energy dissipation to the rate of change in the order parameter,  $H_e(t)$ , because  $D_e(t)$  fell and  $\underline{A}^2(t)$  rose with wave packet evolution:

$$H_e(t) = \underline{A}^2(t)/D_e(t).$$

We named this index *pragmatic information* after Atmanspacher and Scheingraber [80], and used it to construct tuning curves by which to locate AM patterns and find the best settings for the band pass filters needed for application of the Hilbert transform [16,38,39].

### 3. Evidence for multiple overlapping wave packets in brain states

Application of the Hilbert transform to 64 intracranial EEG signals in a designated pass band gave an  $8 \times 8$  matrix of analytic phase values at each digitizing step with respect to the analytic phase of the spatial ensemble average of the waveform at that step. Measurements were made at each step of the spatial gradient of the phase in rad/mm by fitting to the phase surface a 2-D spatial basis function in the form of a cone [38]. The diameter at the base of the cone was defined as the distance from the apex at which the phase difference,  $\Delta\phi$ , from the phase at the apex was  $\pi/4$  rad, giving a soft boundary condition at half power where  $\cos^2 \Delta\phi = 0.5$ . The diameter served as a measure of the prevailing extent of long-range correlation. The ratio of the spatial gradient of phase in rad/mm to the temporal gradient (mean frequency,  $\omega$  rad/ms) gave the phase velocity in m/s, which had values that fell in the range of conduction velocities of axons running parallel to the pial surface [52]. The preservation of the phase gradient and its conformance with conduction velocities implied that the finite velocity of communication in the cortex imposed the phase delay by axosynaptic transmission. Once initiated, the oscillation in each local neighborhood was a standing wave and not a traveling wave, which was crucial for maintenance of stable spatial AM patterns. The phase gradient manifested the delay in the initiation of a phase transition, not a cell-to-cell propagation within the cortex. We inferred that the sparseness of intracortical connectivity [68] could not support strong entrainment of the oscillations in the brief duration of a frame, thereby preserving the phase gradient for the 3–5 cycles at the center frequency of the ensuing oscillation in ordered AM patterns. The location of the conic apex on the pial surface was interpreted as the site of nucleation for the phase transition by which an accompanying AM pattern formed. The sign of phase at the apex was equally likely to be either maximal lead or maximal lag. Within frames the sign was fixed and the changes in estimated location were less than the interelectrode interval that determined spatial resolution. Between frames the location and sign changed randomly over distances that often exceeded the dimensions of the 2-D array. Thus the analytic phase gave estimates of the diameters, durations, locations in time and space, and the time required for re-initialization in wave packets, but the phase gave no information about behaviorally related content. That came solely

from calculations of the analytic amplitude from the Hilbert transform [37] or comparably the 64 root mean square amplitudes in frames after band pass filtering [35].

Every AM pattern was accompanied by a conic phase pattern that retained the history of its site of nucleation and spread, but phase cones were also found between ordered frames and overlapping with them at near and far frequencies. Our effort to determine the mean and range of values for the parameters of phase cones led to the discovery that the values had power-law distributions. Moreover, the means and SDs of the distributions varied with the size of the time window for calculating the rates of change of phase in time and with the interelectrode distance in space [38,72]. Overlaps of 4 to 6 identified phase cones were common [52], so that the phase cones in multiple EEG signals gave the image of neocortex resembling a pan of water with its temperature kept at the boiling point by the release of energy in bubbles, or fog with vapor continually condensing in droplets that quickly evaporated, or a sand pile kept at its critical angle by repeated avalanches having power-law distributions of their sizes and durations [81,82].

As shown by Prigogine [83] and Haken [79] the approach of a system far from equilibrium to a critical phase transition is manifested by slowing of the rate of change in the order parameter, decreasing frequency, and increasing amplitude of oscillations in the output. These changes were revealed by  $R_e(t)$ ,  $D_e(t)$ , and  $\underline{A}(t)$ . We inferred that the emergence of order in each cone was a spontaneous phase transition induced by cortical input, implying that the neocortex held itself in a pseudo-equilibrium state at self-organized criticality [13,81,82], so that the order parameter,  $A^2(t)$ , might vary with time at a pseudo-equilibrium, which it cannot do in a system at a true equilibrium. We inferred that the critical variable being locally stabilized everywhere in neocortex was the local mean firing rates in neighborhoods of cortical neuropil engaged in mutual excitation, which were homeostatically regulated everywhere by the refractory periods of the neurons without need for inhibition or any global monitor and feedback [1,2,38]. Stable mutual excitation achieved a ground state of minimal energy that provided the unpatterned background activity neurons require in order to survive, the excitatory bias required for oscillatory activity in the EEG by feedback inhibition, and a state of readiness to jump to a different ground state under the impact of weak inputs in accordance with constraints posed by processes of intention and attention.

We came to view the background fluctuations in the EEG as manifestations of its trajectories of continual relaxation toward an optimal energy-efficient rest state of the cortex under bombardment within itself and from subcortical modules including the thalamus [19] and basal ganglia [22]. In accord with Prigogine's conception the great majority of fluctuations were quenched, but some crossed a threshold and carried large areas of cortex into new domains of brain state space (projected into  $n$ -space) that organized new AM patterns. The importance of sensory input for destabilization of neuropil was obvious for the olfactory EEG, because AM patterns were detected and measured only with inhalations. Comparable roles of fluctuating sensory inputs for visual, auditory, and somesthetic cortices (e.g., microsaccades, finger tremor) were inferred from the onsets of repetitive ordered AM patterns within a few ms after onsets of CS and before the onsets of conditioned responses. Moreover, during deep slow-wave sleep the AM patterns disappeared, and occasionally the phase cones likewise disappeared, indicating that EEG disclosed a basal state in sleep when sensory and other inputs to cortex were blocked or withdrawn [72] though not totally as in surgical deafferentation [84–86] that gave a flat EEG.

We observed the transition from awake rest to deep sleep in an epileptic subject as graded with little change in form until the onset of intermittent episodes of a flat field and its equally abrupt termination about 1 s later. Whatever might be its significance for the physiology of sleep, which is unknown, or for epileptogenesis equally unknown, from the standpoint of the application of field-theoretic models to nonlinear brain dynamics this event offered an anchor for the theory in three respects. First, the onset and offset for each flat epoch provided clear instances of phase transitions. Second, the absence of spatial patterns of both phase and amplitude constituted a high degree of symmetry in the transient state during deep sleep. This state approached but did not reach that seen when EEG was flattened by deep anesthesia or by surgical isolation of cortical slices. We described this state of minimal spatiotemporal structure as a *vacuum state* with minimal order parameters, to which we assigned the value of zero. It provided a reference level for other states, most immediately for the embedding state of sleep in which there were phase cones but no verifiable or classifiable AM patterns. Third, we interpreted the emergence of wave packets and the return of waking behaviors as SBS to a more ordered regime characterized by a range of parameters allowing repeated phase transitions to any of a range of domains in brain state space, each domain supporting attentive engagement of the subject with the environment and providing for the high likelihood of incipient intentional action.

In this state our animals were open to and searching for sensory stimulation, operationally defined as CS. The receipt of expected input precipitated phase transitions in which further symmetry breaking took the form of emer-



gence of AM patterns [16,39]. The AM patterns lacked invariance with respect to the CS under changes in context and reinforcement contingency, so they could not be representations of the CS. Owing to dependence on context, we inferred that AM patterns were shaped by the connectivity of cortical neurons that had been formed by synaptic modifications during prior learning, which formed an attractor landscape with basins of attraction corresponding to the generalization gradients for categories of CS that a subject had learned to discriminate [74,75].

We propose that a CS *selects* a basin of attraction in the primary sensory cortex to which the cortical dynamics is directed, often with very little information as in weak scents, faint clicks, and dim flashes. The astonishingly low requirements for information in high-level perception have been amply demonstrated by recent accomplishments in sensory substitution [87–90]. There is an indefinite number of such basins in each sensory cortical area forming a pliable and adaptive attractor landscape. Each attractor can be selected by a stimulus that is an instance of the category that the attractor implements by its AM pattern. In this view the waking state consists of a trajectory through a collection of potential states in a high-dimensional space, any one of which but only one at a time can be realized through a phase transition that drops the cortical system to a lower dimension. We can readily understand in classical terms the formation of local firing patterns in sensory and motor modules. However, the variety of these highly textured, latent AM patterns, their exceedingly large diameters in comparison to the small sizes of the component neurons and modules, the long ranges of correlation despite the conduction delays among them, and the extraordinarily rapid temporal sequence in the neocortical phase transitions by which the AM patterns are selected in sequences, all these properties provide the principal justification for exploring the interpretation of nonlinear brain dynamics in terms of many-body theory and multiple ground states to complement basin-attractor theory.

#### 4. The spontaneous breakdown of symmetry in many-body physics

In this and in the following section we switch to the qualitative presentation of basic concepts in the many-body field theory with spontaneous breakdown of symmetry. Our presentation is necessarily focused solely on the few aspects that are most relevant to our task. The interested reader may find full mathematical details in Bratteli and Robinson [91], and Umezawa [56]. For an extended qualitative presentation, see Vitiello [4]. Our main goal here is to illustrate how many-body theory bridges between microscopic quantum dynamics and macroscopic behavior. The key point is the existence implied by SBS of long-range correlation modes that are responsible for ordering the system and therefore for the collective behavior of the system components, which manifests in the order parameter of classical fields characterizing the macroscopic system behavior.

##### 4.1. From microscopic quantum dynamics to the macroscopic behavior of the system

Statistical mechanics is devised to deal with systems formed by a large collection of indistinguishable components, such as a fluid or a solid. The mathematical formalism allows statistical averages and probability distributions [92,93]. An early example of an application to cortical dynamics was by Wilson and Cowan [94], who used KII topology [95] but incorrectly opted for solutions as traveling waves not conforming to the standing waves observed in wave packets. There are, however, structures observed at the macroscopic level such as AM patterns that cannot be treated as regularities *only in the average*, as the statistical treatment requires. The complexity of patterning and the constrained reproducibility with which such regularities recur suggest that the AM patterns are generated by highly structured dynamical processes, rather than by the random kinematics that rule the collisions of the many elementary components on which the formalism of statistical mechanics is based. Structures resembling mesoscopic AM patterns in wave packets typically occur in quantum many-body systems. Examples of such ordered patterns in physical systems are the spatial ordering of atoms in a crystal or in a protein, the coherence in the time ordering of phase oscillations of the photons in the laser beam, the coherence in space ordering and in phase oscillation of the atomic or electronic magnetic moments in magnetic memories, and the strict temporal sequences of interlocked chemical reactions such as the chains of time ordered chemical steps in some metabolic activities (e.g., [96]). Dealing with realistic many-body systems means to deal with an exceedingly high number of diverse elementary components; it is then necessary to describe the quantities of interest in terms of fields.

The questions then arise: how to derive from the microscopic quantum dynamics the regularities and the ordered patterns observed at macroscopic level, and how to describe the process of formation of these ordered patterns, namely the transitions from the disordered phase, where no distinguishable patterns exist, to the ordered phase? This involves

a problem of *change of scale*: from the microscopic scale (typically fixed by the Planck unit of action  $\hbar$ ), where the dynamical description involves quantum particles, to the macroscopic scale, where the system macroscopic properties manifestly do not depend anymore on the individual behavior of the particles, but on their collective motion and are described in terms of classical fields, namely collective waves or modes. At the macroscopic level, the relevant scale for the resulting field theory is conditioned by the large (as compared to the component typical size) volume scale. The answers to such questions, widely tested in experiments, are provided by many-body theory. There one can show that by SBS the quantum field dynamics ruling the interactions of elementary components predicts their collective motion (ordering) in the form of macroscopic waves that characterize the system's classical behavior (see, e.g., [56] and references therein).

#### 4.2. *Spontaneous breakdown of symmetry and phase transitions*

Let us recall that in the field theory of many-body systems the fields may undergo symmetry transformations that leave the field equations unchanged in their form. However, we are interested in those states of the system that are *not symmetric* under the symmetry transformations of the field equations. Indeed, there are physical properties characterizing the physical behavior of the system, which change during its evolution under certain boundary conditions. When this happens we say that the system undergoes a phase transition. As already mentioned, examples of phase transitions are the ones leading to the formation (or, vice versa, to the destruction) of ordered patterns, e.g. the formation of a crystal out of a solution of ions, the formation of a magnet out of a collection of atoms carrying magnetic moment; the condensation of water; or the reverse of such processes. As we will see, the possibility of formation of ordered patterns is achieved when the constraints imposing the invariance of the state of the system under symmetry transformations are removed, so that the symmetry is broken. Order thus appears as the loss of symmetry, and conversely symmetry is restored in the transition from order to disorder. This conception may seem paradoxical to neurobiologists, for whom bodies with mirror symmetry are more ordered than those that are disfigured; however, broken symmetry gives more information and hence more order.

One possible way to break the symmetry is to modify the dynamical equations by adding one or more terms that are explicitly not consistent with the symmetry transformations (are not symmetric terms). This is called *explicit breakdown of symmetry*. The system is forced by the external action into a specific non-symmetric state that is determined by the designated imposed breaking term. This is what we observe in the response of cortex to perturbation by an impulse, such as an electric shock, sensory click, flash, or touch: the evoked or *event-related potential* (ERP). The explicit breakdown in cortical dynamics is observed by resort to stimulus-locked averaging across multiple presentations in order to remove or attenuate the background activity, so as to demonstrate that the location, intensity and detailed configuration of the ERP is predominantly determined by the stimulus, whereby the ERP can be used as evidence for information processing by the cortex. A simple example of the difference between explicit breakdown of symmetry and spontaneous is found by comparing the phase gradient of an oscillatory ERP evoked in the olfactory bulb by an electric shock to the primary olfactory nerve, which gradient is a plane wave sweeping over the bulb at the rate and direction of the action potentials in the nerve, vs. an oscillatory EEG burst in response to a sniff, which gradient is a phase cone [97] for which the rate of spread is determined by the propagation speed of action potentials on diverse intracortical axons, and the location of the apex is determined by the sum of imposed and endogenous activity levels.

The alternative possibility, that of spontaneous breaking of symmetry (SBS), is to break the symmetry by submitting the system to a weak, sustained stimulus: in cortex either by prolonging a CS several tens of ms comparably to a sniff or by relying on the subcortical after-discharge from sensory impulse driving to provide the prolongation. In such circumstances, in order to break the symmetry, some pre-stimulus parameters, such as the coupling constants (synaptic strengths) among the components or other physically relevant parameters entering the dynamical equations, must have values in well defined ranges, in which ranges we can show by perturbation that the system is stable. These parameters may depend on temperature and therefore their range of stability in poikilotherms may be probed by varying the brain temperature. The temperature of the mammalian brain is homeostatically regulated, so instead we manipulate chemical potentials such as the concentration gradients of extracellular ions, neurotransmitters and neuromodulators, or we impose sustained electric or magnetic gradients through the cortical tissues, or we modulate the synapses by reinforcement learning. One peculiar property of quantum field dynamics, which makes it so successful in the description of many-body systems presenting different phases, and which motivates us to apply it to brain dynamics, is that there are many of these stability parameter ranges, each one characterizing a specific phase of the system with

specific physical properties that differ from phase to phase, or from each AM pattern to the next. Each of the system phases is indexed by a value of the macroscopic classic field, which we call the order parameter,  $A^2(t)$ , and its label,  $\underline{A}^2(t)$ . If the dynamical regime is characterized by that range of parameter values which does not allow the breakdown of the symmetry, the system does not perceptibly or meaningfully react (as in sleep to weak stimuli). When one or more control parameters, such as the strength of action at one class of synapse in the cortical pool under the influence of the weak external stimulus, or even by indeterminate drift, exceed the range of stability where the system originally sits, the transition is induced to another stability parameter range, different from the previous one in that it now allows symmetry breakdown and appearance of order (as in arousal from deep sleep). Contrariwise, the loss of order as in shutting down under anesthesia or in deep sleep corresponds to symmetry recovery or restoration, the formlessness of background activity or in the extreme the loss of activity approaching brain death.

The *spontaneous breakdown of symmetry* is thus, itself, a property of the system internal dynamics, dependent on the internal boundary conditions for what concerns the appropriate control or tuning of the parameters, but it is independent of the specificities of the triggering stimulus, which may fall on differing equivalent sensory receptors on successive trials. The stimulus characterizes the cortical response in the *explicit* breakdown as in ERPs, often irrespective of the state of the system. In SBS the response of the system to the breaking stimulus depends on the situation as it impacts the state of the system, bringing in such biological and psychological factors as prior learning, context, attention, motivation, fatigue, etc. The non-symmetric state into which the system transits (at the end of the phase transition process) can be any one among those *compatible* with the actual dynamical regime. The dynamics, provided the system is in a parameter regime neighboring to the previous range, constitutes a choice among the compatible non-symmetric states available to the system, which in Section 3 we characterized as an attractor landscape. The breakdown of the symmetry is then said to be *spontaneous*, in much the same sense as the term is commonly used to describe the background EEG as ‘spontaneous’. Most obviously in experimentation the time of onset of the SBS varies with respect to stimulus onset, in contrast to the fixed latencies of explicit symmetry breaking, and the emergent pattern is determined by the parameters of the system, only remotely by the stimulus that has selected the pattern. We say that the attractor governing the AM pattern is *selected* and modified by the stimulus (up-dated in continuous on-line learning). The output AM pattern is an internal construction and not a literal representation of the stimulus.

## 5. Order, symmetry and long-range correlations

We have seen that the SBS is a microscopic dynamical phenomenon that manifests in the generation of ordered patterns at the macroscopic level; it involves a change of scale: from microscopic to mesoscopic. It correlates elementary components in an ordered pattern. This is normally expressed also by saying that order is a collective phenomenon and that SBS amounts to creation of a communication, or correlation, or coherence among the elementary components that extends over the system or over the domain of the ordered pattern, a correlation of long range indeed. It might be spatial coherence, as for spatial ordering, or temporal coherence, as for in-phase oscillation, or both, as in cortex. The non-zero value of the order parameter is a measure of the nature and degree of coherence among the elementary system components. Our choice of a vector as our order parameter is dictated by its effectiveness in specifying the complexity of ordered brain states in terms of AM patterns and their rates of change in  $D_c(t)$ . Many-body communication, in order to be effective, even at the lowest value of the order parameter, must be robust and immune to distortion or failure. Therefore it cannot originate only by short-range interactions. In such a case, indeed, local defects or fluctuations would preclude the ordering on a macroscopic scale, contrary to what is observed in many-body physics: for example, a dislocation in a crystal does not destroy the whole crystalline ordering but deforms it only locally, and comparably a microlesion in cortex does not abolish large-scale EEG or behavioral patterns. And at each transmission over a divergent–convergent pathway the spatially coherent oscillation is enhanced as signal, while the initiating spatially incoherent activity is smoothed as noise.

Theoretical derivations and experimental observations in physical systems show that SBS is always accompanied by the dynamical formation of collective waves, the Nambu–Goldstone (NG) modes or bosons or waves that span the whole system and sustain the ordering communication. Physicists also say that these ordering waves (or bosons) condense in the system ground state, and that ordering is the result of a boson condensation. The phonons or elastic waves detected in crystals and the magnons or spin waves observed in magnets are examples familiar to physicists of these carrier NG waves responsible for the respective macroscopically observed ordered patterns. The modulus square

of the amplitude of these ordering waves for each given value of the associated wave number (spatial wavelength) is proportional to their density (how densely NG waves are present) in a given state of the system. Such a density is thus a measure of the NG mode condensation: the higher is the condensation, the higher is the degree of ordering. Increasing (condensation) or decreasing (evaporation) the NG wave density thus drives the system through its different physical phases. In this way the boson condensation (or the evaporation process), and therefore ordering (or disordering) process, becomes possible due to the SBS mechanism [98]. We propose that our ratio of variances,  $R_e(t)$ , can serve as a normalized experimental index of the density of condensation, and that our Euclidean distance,  $D_e(t)$ , can serve as an index of the stability over time of the condensate in cortical wave packets.

## 6. Multiple ground states, external stimuli and dissipation

### 6.1. Dissipation and a multiplicity of ground states

We have seen that in the process of phase transition the system evolves from one state to another, each with given physical properties, for example, from a state with zero ordering to another state with a non-zero value of the ordering, as from the flat field of deep sleep to the background state of sleep and beyond to a multiplicity of ground states. The existence of the multiplicity characterized or, say, labeled by all possible values of the vectorial order parameter is ensured by the mathematical structure of the many-body field theory [91]. The possibility for the system to be in a state that is a collection (or superposition) of co-existing and overlapping ground states labeled by different values of the order parameter, yet without, or with reduced, reciprocal interferences, results from the mathematical structure of the field theory for dissipative, open systems [4,67,99]. These are systems that exchange energy with the environment in which they are embedded. The brain is an example of an intrinsically open system, in permanent although discretionary interaction with the environment.

The possibility of the existence of a multiplicity of ground states in dissipative systems can be understood in the following way (see Appendix B, Part 2). Let us consider the situation in which the system coupled with the environment evolves in time through a sequence of states where the balance of the energy fluxes at the system-environment interface including heat exchanges, is reached, say  $E = E_{\text{Syst}} - E_{\text{Env}} = 0$ , with  $E_{\text{Syst}}$  denoting the system energy and  $E_{\text{Env}}$  the environment energy. Although the brain holds itself far from equilibrium, this energy balance is manifested, for example, in the homeothermic regulation of mammalian brain temperature and body weight. We call this equilibrium state the ground state; by definition it is the  $E = 0$  state. Clearly, balancing  $E_{\text{Syst}} - E_{\text{Env}}$  to be zero, does not fix the value of either  $E_{\text{Syst}}$  or  $E_{\text{Env}}$ . It only fixes their difference. To each couple of values ( $E_{\text{Syst}}$ ,  $E_{\text{Env}}$ ) such that  $E_{\text{Syst}} - E_{\text{Env}} = 0$ , there is one associated ground state. The important result [67,99] is that each couplet of specific values ( $E_{\text{Syst}}$ ,  $E_{\text{Env}}$ ) uniquely characterizes an associated ground state; in different words, ground states corresponding to couplets of different values ( $E_{\text{Syst}}$ ,  $E_{\text{Env}}$ ) may overlap without (or almost without) destructive interference. We may then use the value of  $E_{\text{Syst}}$  as a label to specify the ground states in the brain at any given instant of time. Moreover, we can show that what makes the difference among ground states of different label values is their different degree of ordering due to some collective mode. These states denote the physical phases of the system. The relations thus found among the energy  $E_{\text{Syst}}$  include heat,  $Q$ , free energy and its rate of dissipation estimated by  $\underline{A}^2(t)$ , and our vectorial order parameter that measures the ordering,  $A^2(t)$ , labeled by the scalar  $\underline{A}^2(t)$  (Section 2). Then  $E_{\text{Syst}}$  and its variations are directly related to the collective mode density (Appendix B, Part 2 and 4), which is indexed by the boson condensation density,  $R_e(t)$ . As we have already observed, ordering means spatial structure seen in the emergence of phase cones and of spatial patterns measured by  $A^2(t)$  and  $D_e(t)$ , as well as temporal synchrony measured by the variance of the instantaneous phase differences across the array,  $\text{SD}_X(t)$ , and by the ratio of variances,  $R_e(t)$  (Section 2). No one of these parameters suffices to capture the relations in a single scale.

The brain in its relation with the environment, owing to its property of being a dissipative, open system, may occupy any one of this multiplicity of ground states, depending on how the  $E = 0$  balance or equilibrium is approached. Or else, it may sit in any state that is a collection or superposition of these brain-environment equilibrium ground states. The system may shift, under the influence of one or more stimuli acting as a control parameter, from ground state to ground state in this collection (from phase to phase) (Appendix B, Parts 2, 4 and 5), namely it may undergo an extremely rich sequence of phase transitions, leading to the actualization of a sequence of dissipative structures [83] formed by wave packets. The system trajectory through these phases may also be chaotic [100,101] (Appendix B, Part 5) and *itinerant* through a chain of ‘attractor ruins’ [102] embedded in a set of attractor landscapes [103] accessed

serially or merely approached in the coordinated dynamics of a metastable state [65,104,105]. We stress that the possibility of deriving from the microscopic dynamics the classicality of such trajectories is one of the merits of the many-body field model to be exploited. For example, we know that multiple wave packets having different carrier frequencies co-exist in each sensory cortex, and that one or more of these is local while one or more is global, yet we do not yet know whether or how these wave packets might influence each other in the determination of sensory cortical output. Many-body physics may provide the tools needed to measure, analyze and explain these complex events.

## 6.2. Selection of AM patterns by conditioned stimuli

In Section 3 we saw that the cortical standing wave resulting from a phase transition forming a wave packet, which is essential for AM pattern formation, was given the illusion of a traveling wave by the delay in initialization embodied in the phase cone. On successive trials with the same CS the location of the apex varied randomly within the primary receiving area for the CS modality, and its sign (maximal lead as in an explosion or maximal lag as in an implosion) likewise varied randomly from each transition to the next. These random variations gave further evidence for SBS. The sudden change in system with order parameter evolution could be classically described in terms of a subcritical Hopf bifurcation or departure from an unstable point repeller at a saddle node. Indeed, this would agree with the theoretical feature that variations in an order parameter can serve to describe classical trajectories in the order parameter space, which appear to be chaotic (Appendix B, Part 5) [100,101,106].

At first view the AM patterns appeared to be cortical representations of CS. However, the patterns that were elicited by an invariant CS held only within each training session and then only if there were no changes in the schedule of reinforcement or addition of a new CS in serial conditioning. Measurements of AM patterns within sessions showed pattern variation within each category despite CS invariance. Between sessions with no new CS added the averages of the patterns tended to drift. When the subjects were trained to respond to a new CS, or when the reinforcement was reversed between CS<sup>+</sup> and CS<sup>-</sup>, all of the patterns changed including the pattern for the background, and the amount of change with new learning was 2 to 4 times the average change with drift across multiple sessions [107]. A collection of AM patterns that we established by training persisted with drift through multiple sessions until we introduced the next contextual change. Pattern variation without change in CS but with change in context and import such as by reversal of reinforcement contingency showed that the AM patterns were determined mainly by the cortical dynamics, as the many-body model predicted, and only slightly by each incoming stimulus. This inference was consistent with the fact that most neocortical synapses on the pyramidal cells generating the EEG came from neurons in the cortex; only a small fraction came from thalamic neurons.

Here we describe the behavioral state of engagement with the environment as based in a collection of ground states that differ from the awake rest state in being potentially distinguishable from each other, if and when they are accessed by a relevant input. The set of these ground states constitutes a family of *compatible states*, which constitute the array of expected possible outcomes preceding an act of observation, of which only one at a time can be actualized. The possibility of immediate access to any one of such a collection of states is evidence of the dissipative character of the many-body dynamics, as noted in Section 6a. Evidence for dissipation is that the ground states during engagement, when actualized in the post-stimulus period, differ in having levels of power above or below that of the undifferentiated pre-stimulus control state but always above the rest state. The dissipative many-body model predicts that these power differences relate to energy differences caused by the boson condensation process, owing to variations in the density and structure of the condensate, as discussed in Section 9 (see also Section 5 and Appendix B, Part 4).

## 6.3. Levels of activity achieved by SBS or its reverse

Summarizing, we have identified five levels of cortical activity that we describe by the dissipative many-body field theory model:

- (a) The transient “vacuum” state of the cortex is characterized by unbroken symmetry: a flat field of fluctuations with no discernible patterns. The system dynamical regime is characterized by parameters whose values do not allow for the symmetry breakdown. Even in the presence of an external stimulus (provided it is below a threshold)

the system “cannot” react to it (breakdown is not possible). The system “sleeps”. External inputs at most create uninteresting perturbations.

- (b) These transient epochs of deep sleep interrupt a longer-lasting state of slow-wave sleep characterized by multiple short-lasting and overlapping phase cones. We suggest that these fluctuations result from continuous bombardment of all areas of neocortex by other parts of the brain, including inputs from the sensory receptors that are relayed mainly through the thalamus and that are mainly irrelevant, because it is the work of cortex by habituation to establish filters to mitigate the impact of such unavoidable bombardment on cortices by irrelevant energies from the environment. The continual perturbation gives rise to myriad local phase transitions characterized by the conic phase gradients, which are quenched as rapidly as they are formed, thereby maintaining the entire cortex in a robust state of conditional stability (called *metastable* by Kelso [65], Bressler and Kelso [104] and Fingelkurts and Fingelkurts [108]) that we propose conforms with self-organized criticality [13,81,82]. The critical parameter is the mean firing rate of neurons that is homeostatically maintained by mutual excitation everywhere by thresholds and refractory periods [38]. The phase cones are brief with no distinguishable AM patterns, so we infer that they are related to SBS with vanishingly short-lived order parameters.
- (c) In the awake rest state the ranges of parameter allowing higher-order SBS (cf. Section 4) become potentially accessible under the influence of external weak but behaviorally significant stimuli. The temporal phase differences appear as coordinated analytic phase differences (CAPD, [77]) in which each epoch of minimal  $SD_X(t)$  is accompanied by a peak in mean amplitude, but without discernible or reproducible spatial AM patterns, owing to the lack of engagement of the subject with the environment.
- (d) The rest state evolves into an aroused state with increased amplitude of oscillations in the background dendritic current that accompanies incipient engagement of the brain with the external world through the body. There is an implicit differentiation among the set of compatible states, which is only realized by the overt emergence of an amplitude pattern as reported above that is classifiable, and that arises from SBS triggered by a relevant stimulus that breaks the symmetry of the expectant state. The sequence of states is reversed on the return from engagement to expectancy through rest to sleep and then to transients with maximal disorder.
- (e) A departure from this sequence was observed [72] prior to the onset of a complex partial seizure consisting of spikes at  $3/s$  accompanied by loss of consciousness (“absence”) and stereotypic motor automatisms. During the pre-ictal phase a substantial reduction was calculated in the diameters of phase cones, owing to doubling of the phase gradients and implying a significant impairment of long-range correlation, preceding the loss of spatially coherent carrier waves. This observation attests to the importance of long-range correlation for the maintenance of normal metastability of the cerebral cortex. The seizure was simulated [103,109] with solutions of differential equations constituting a model of the dynamics of the olfactory system. We use the model to infer that the loss of long-range correlation prior to seizure onset is due to abnormally high levels of activity of inhibitory neurons from unspecified causes, and that the loss releases local domains from cooperative activity and enhances spatial contrast by lateral inhibition, hence an instability by mutual inhibition constituting a form of positive feedback.

## 7. Amplitude and phase patterns suggest a carrier for long-range communication

A detailed examination of the wave packets in the visual, auditory and somesthetic cortices in rabbits and cats under classical aversive or instrumental appetitive conditioning paradigms has shown that between the arrival of a CS and the execution of a conditioned response (CR) there were typically 3 to 4 ordered AM patterns with their attendant phase cones [16,39]. The properties of the first and second (on some trials) wave packets had the following properties: carrier waves in the gamma range (30–80 Hz), durations seldom exceeding 100 ms; diameters seldom exceeding 25 mm; low power in the  $1/f^\alpha$  relation; repetition at rates in the high theta range (5–7 Hz); and relatively steep phase gradients corresponding to lower phase velocities. The later wave packets had carrier frequencies in the beta range (12–30 Hz); durations often exceeding 100 ms; estimated diameters large enough to include multiple primary sensory areas and the limbic system; greater power by  $1/f^\alpha$  (as predicted by the model, see above); repetition rates in the low theta range (3–5 Hz); and shallower phase gradient with, in some cases, extreme phase velocity at present beyond measurement. Whereas the gamma events were found infrequently in the pre-stimulus control period, the beta events appeared with equal frequency in the pre-stimulus control and post-stimulus test periods at frame repetition rates consistent with psychophysical measurements of the minimum duration of a perception [110].

Both types of wave packet had onsets by phase transition based in SBS but with differing forms or degrees of symmetry. The beta and gamma carrier waves were clearly macroscopic properties of the populations of cortical neurons that were responsible for the oscillations, and the waves were clearly manifested not in the individual pulse trains of the neurons by time-locked firing but by oscillations in the probability or relative frequency of firing of the neurons in the domain, especially when, as was typical, the neurons only fired pulses at time intervals on average much longer than the mean wavelengths of the oscillation in ms [1]. The formation and maintenance of the shared oscillations with inconstant instantaneous frequencies,  $\omega(t)$ , depended on rapid communication among the neurons effectively out to the spatial soft boundary condition (Section 3) in the two surface dimensions of the cortical domain of coherence. That communication required a channel to convey influence from each part of the domain to every other part. Reasons have already been given in Section 1 for the inadequacy of classical explanations based on nonsynaptic diffusion, the action potential, Coulomb forces, or electric, magnetic and radio fields. The difference between the slow rate of serial synaptic transmission of energy laterally in cortical networks and the high phase velocity of phase cone formation was described as anomalous dispersion without further explanation. That concept may be inadequate to encompass beta and gamma phase transitions. The field theoretic model offers an alternative view of the phase transition as a condensation comparable to the formation of fog and raindrops from water vapor that might serve to model both the gamma and beta phase transitions.

That leaves the resolution of the problem of long-range correlation and the genesis of macroscopic order parameter fields to the mechanism of SBS in the dissipative many-body model. The boson condensate that emerges within the domain of the phase cone has one AM pattern from a compatible set of distinguishable ground states that is latent in the synaptic connectivity of the domain comprising the collection of sub-areas making up each primary receiving area with synaptic connections that have been shaped by prior learning. The rapid re-initialization is then enabled through the relatively sparse long axons linking all cortical areas that constitute an essential link in the chain between atomic and molar phenomena. Long axons require large cell bodies, complex mechanisms for guidance during brain development, and expensive blood supplies for maintenance and operations to provide the fast communication that enables small-world effects and scale-free dynamics. Their action potentials shape the properties of the spatial and temporal patterns described above at the mesoscopic and macroscopic levels that cannot be derived only from properties at the atomic and molecular levels. In the absence of these SBS waves the action potentials of long axons cannot easily explain, as already said above, the spatial coherence often with negligible phase dispersion at every transmission frequency.

These considerations raise the question of the physical nature of the SBS carrier wave describing the diffuse synaptic influence. We propose in answer that the carrier wave is a dipole wave in which the 3-D rotational (electric) dipole symmetry is spontaneously broken [63,64,67,111–113]. The physical justification for this inference is rooted in the fact that most biochemical molecules sustaining the neural activity and the water matrix in which the neural activity is embedded are physically characterized by possessing non-zero electrical dipole moments (not to be confused with cortical *dipole fields* engendered by sources and sinks of dendritic current). The crucial point to be stressed again is that the SBS mechanism involves the change of scale, from the microscopic dynamics to the macroscopic order parameter field dynamics. The system is thus a macroscopic quantum system, which means that the observed classical behavior of the system cannot be explained without resorting to the quantum dynamics of the SBS. It is not the Planck constant scale that dominates the observed phenomenology, but, rather, the long range of the observed correlations in accord with the *large volume limit* that dominates field theory.

We propose that the NG cortical boson condensate or *symmetron* in the Ricciardi and Umezawa original terminology [60] or our wave packet might be used to explain the rapid course of perception: how for example neocortex can respond selectively to the impact of photons from a face in a crowd on a handful of retinal neurons that transmit impulses mixed among uncountable impulses elicited by light from the crowd. The further impact of the action potentials on the visual cortex elicits countless more action potentials relating to all the edges, points, colors, motions, and contours in both background and foreground of the scene. Then suddenly there emerges by phase transition order from disorder: the neural “vapor”, as it were, condenses into neural droplets, the first step in face recognition within the time lapse from stimulus arrival at the cortex of at most a few tens of ms, which is insufficient to allow operations of gradient descent in classical models.

## 8. Superposition and the emergence of meaning

The gamma condensate is only the first of two or more phase transitions between the CS and perception leading to the CR, and it appears to be restricted to the primary receiving area for each modality. It can suffice to solve the “binding problem” [5], but it does not support the multimodal recognition that accompanies the sight of a face, the sounds of voices, the press of bodies, and the odors of sweat and perfume, in a word, the multisensory information inflow through all of the sensory ports. The responses of the several receiving areas are already shaped by attractor landscapes assisted through prefference [114,115] to the expected sights, sounds, pressures and smells in the situation, so that each area constructs and maintains a collection of ground states *in potentia* as the basis for expectancy and selective attention. The dissipative many-body model allows indeed the possibility of classical chaotic trajectories in the high-dimensional order parameter space, the space whose local hypervolumes signify the ground states ([100, 101]; see Section 6). The arrival of an expected stimulus triggers SBS, selects a ground state (cf. Appendix B), and places the dynamics of the relevant cortex into the basin of an attractor, which abstracts by deletion of nonessential information as the trajectory spirals to the attractor, and generalizes to the category of the stimulus that is reported by the cortex in the output of an AM pattern. The several cortices transmit their signals by broadcasting action potentials organized in gamma wave packets to each other and to the limbic system. The information carried by the wave packets is spatially distributed in the manner of a hologram, so that every subset of axons from a cortical area transmits the same information with the resolution proportional to the size of the subset. The entorhinal cortex integrates all of the transmitted signals; orientation in space and time are introduced in the hippocampus; and a combined signal is broadcast to all of the primary areas [3,115], priming the several cortices for the formation by SBS of a series of AM patterns that form carried by beta wave packets. We infer that beta wave packets are multi-sensory events manifesting priming of the primary sensory cortices by prefference in anticipation of the arrival of a CS, and that they update all of the cortices within the time required for the limbic passage [53,54]. We conclude that this cycle provides the dynamic structure of multi-modal attention.

The concept of the boson carrier and the boson condensate does more; it enables an orderly and inclusive description of the phase transition that includes all levels of the macroscopic, mesoscopic, and microscopic organization of the cerebral patterns that mediate the integration of the animal with its environment, down to and including the electric dipoles of all the myriad proteins, amino acid transmitters, ions, and water molecules that comprise the quantum system. This hierarchical system extending from atoms to whole brain and outwardly into engagement of the subject with the environment in the action-perception cycle is the essential basis for the ontogenetic emergence and maintenance of meaning through successful interaction and its knowledge base within the brain. By repeated trial-and-error each brain constructs within itself an understanding of its surround, which constitutes its knowledge of its own world that we describe as its *double* [4]. It is an *active* mirror, because the environment impacts onto the self independently as well as reactively. The relations that the self and its surround construct by their interactions constitute the meanings of the flows of information that are exchanged during the interactions. We stress once more that neuronal cells and their organelles are not considered quantum objects in our analysis. No ambiguity should be born on this point. The SBS provides in the ways above explained the bridge, or change of scale, from the microscopic quantum dynamics to the macroscopic behavior of classical cells and their constructs.

## 9. Free energy, dissipation, ordering, and fMRI

In this section we present further details of our analysis by interrelating free energy, ordering and stability of the amplitude patterns. Neural activity exists in pulse densities of axons, wave densities of dendrites and in various forms of thermal, electric, magnetic and especially chemical energy. At the mesoscopic and macroscopic levels of neural populations the forms of neural activity constitute a group invariant over the transformations among these vehicles, subject only to the minimization of the loss of free energy required to stabilize brain patterns in the overall transit of energy carried to the brain by the arterial supply as glucose and removed by the venous return as waste heat. The most readily accessible measure of the rate of free energy dissipation over the diverse conversion operations is the square of mean analytic amplitude,  $\underline{A}^2(t)$  (Section 3), in the beta or gamma pass band.

The desirability of using  $\underline{A}^2(t)$  as an index of power and therefore indirectly of the rate of heat dissipation is made possible by the sequence of four stages with each phase transition. At the time of the fourth stage the phase transition concludes with a dramatic increase in  $\underline{A}^2(t)$  to a peak value, at which the EEGs remain synchronized and the AM



pattern and carrier frequency remain stabilized. At the peak the normalized AM patterns are maximally distinguishable between those on trials with a reinforced  $CS^+$  and those without reinforcement  $CS^-$  [39]. During each frame a wide area of neocortex transmits 3–5 cycles of synchronized wave carrying a stable AM pattern at high intensity synaptic current controlling volleys of action potentials. These volleys carrying the same signal on multiple divergent pathways cannot fail to have significant impact on neural networks and populations in the brainstem, cerebellum and spinal cord, so the boson condensate in the frame provides a plausible descriptor of the neural mechanism for neocortical read-out by divergent-convergent axonal pathways that perform spatial integral transformations on the output [72].

The cost in dissipated free energy of the electrochemical work done to create the AM pattern is high; the brain has only 2% of body mass, yet it consumes 20% of basal metabolic energy, which is measured in heat,  $Q$ , and entropy,  $S$ , that must be discarded to avoid increases in temperature and pressure in the fixed volume and mass of the brain. These and other waste products are removed by continuous adaptation of blood flow to rates of energy dissipation. The poorly understood homeostatic link between metabolic demand and arterial perfusion is the thermodynamic basis for hemodynamic techniques of brain imaging that have been derived from theoretical physics: fMRI, PET, SPECT and BOLD. What they lack in temporal resolution is more than compensated by their broad spatial views at high resolution, so that the electroencephalographic and hemodynamic approaches are strongly complementary. As noted earlier, the analytic amplitude squared is the sum of squares of the real part proportional to the energy expended in the current of excitatory neurons and the imaginary part in quadrature proportional to the energy expended by inhibitory neurons in negative feedback [16], so that  $\underline{A}^2(t)$  offers an optimal parameter of neural activity for correlation with indirect measures of blood flow, especially in the beta and gamma ranges of EEG oscillations. In most physical systems the energy expenditure is proportional to the frequency of oscillation; the fact that the observed power in gamma waves is only 1% of that in theta waves in the  $1/f^2$  clinical  $PSD_T$  may be misleading. The actual metabolic costs may be comparable in the two frequency ranges, so when properly normalized the gamma power might be found to be the variable that is most strongly correlated with levels of metabolic demand.

## 10. Conclusions and outlook

We believe we have made a strong case to identify the EEG phase discontinuities and the neocortical phase transitions with SBS, and the multiplicity of coexisting phase cones and AM patterns with the ground states predicted by the dissipative many-body model. We have described our case in qualitative terms without equations in order to make it intelligible to physicists, neurobiologists, psychologists, engineers, and cognitive theorists having diverse backgrounds and languages. We have emphasized that our proposed synthesis depends heavily on new experimental data derived from novel techniques for measuring brain field potentials with unprecedented spatial and temporal resolution, and for exploring dissipative dynamics in the context of quantum field theory. We have cited the extensive mathematical structures on which we base our descriptions of EEG data in Sections 2 and 3 and of basic concepts in many-body theory in Sections 4–6, and we have included Appendices that summarize our mathematics. Thirty years ago we stepped beyond linear analysis into nonlinear neurodynamics; now the new data are carrying us to new and baffling levels of complexity.

Therefore in Section 7 we have introduced for further exploration the identification of the wave packet with the Nambu–Goldstone boson as a carrier for long-range correlation with two main classes or types having the beta and gamma carrier waves. We foresee substantial experimental and theoretical difficulties in determining whether these bosons superimpose or interact, each by modifying the other, and in extending the analysis into the molecular realm in terms of theories such as those of volume transmission of Fuxe and Agnati [42] and Bach-y-Rita [90] and the catalytic model of Davia [96]. In Section 8 we have posed the unsolved problems of extending many-body theory to modeling the higher cognitive functions of the brain (e.g., [31]) and the construction of the knowledge base by which brains sustain meaningful interactions with their environments. In Section 9 we offer for exploration a link to current techniques in brain imaging.

We propose that a promising area of research will be the found in tapping the vast reservoir of information in scalp EEGs of human subjects, who can report their experiences as their spatiotemporal structures evolve, both normal and pathological. A prime difficulty will be to adapt the theory flexibly to treat the unique properties of neuropil and avoid forcing onto the models the conditions that hold for other forms of condensed matter. It is essential that neurobiologists and theoretical physicists listen carefully to each other in order to determine what can and should be done next.

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## Appendix A

We describe the mesoscopic neural activity of neocortex as comprising wave packets having properties of location, size duration, and rates of change. They are generated by a hierarchy of neural groups that we have designated as  $K$ -sets [1]. The electric and magnetic potentials by which we indirectly observe the wave packets are the classical fields of Faraday and Maxwell; the activities we designate as activity density functions or  $K$ -fields, because each  $K$ -set generates its characteristic type of  $K$ -field and accompanying observable fields. The most fundamental physical description is of the topology of neocortex: a bounded assembly of  $10^{10}$  neurons (estimated in humans) and  $10^{14}$  synapses forming functional connections that constitute a unified structure of neuropil in each hemisphere. The neuropil extends without anatomical interruptions or obstructions to the lateral transmission of neural activity to the boundaries of the neocortex at the midline and rhinal fissures. In humans the two neocortices have a surface area approaching half a square meter with a thickness of 1 to 3 millimeters. Multi-electrode EEG signal observations and measurements are made in the two surface dimensions, so the dynamics is comparably developed in 2-D, in the sense that photographs are 2-D. Embedded within this neuropil are well-known specialized domains of synaptic connectivity that are induced, elaborated, and maintained by axonal projections from and to sensory, motor, and basal ganglia systems. The otherwise near-random local connectivity is sparse, with each neuron connecting to only about 1% of neurons within the radius of its dendritic arbor [68]. A small proportion of axons form connections that extend far from nearest neighbor, up to the length of each hemisphere. These long axons enable the distant transmission of activity that can create seeds that spread locally, enabling the emergence of ‘small-world’ effects [44,45], so each neuron is at most only 4 or 5 synapses distant from any other in neocortex.

The neocortical neurons also form connections with neurons in subcortical structures in the striatum, thalamus, midbrain, pons and (through relays) cerebellum that loop back in multisynaptic chains. These connections [22] requiring 3-D representation impose multisynaptic delays. These loops together with the corticocortical long connections support spatiotemporal patterns of neural activity that provide in each cerebral hemisphere the organization of motor output [22] and the predictions of the sensory input that result from acts of observation. Histograms of the lengths of these connections form approximate power-law distributions, suggesting that the connectivity is fractal [69] with a small number of sites having very high numbers, which are sites of catastrophic loss of function from very small lesions, such as those to the midbrain reticular formation and the perforant path of the hippocampal formation.

We elaborate on this basic topology of the neocortex with a hierarchy of  $K$ -sets. It rests on the KO set used to model a 2-D array of neurons, either excitatory (KOe) or inhibitory (KOi), with no connections among them but with input and output connections for every neuron. The dendritic dynamics is modeled by a linear second order ordinary differential equation [1,95] in the state variable,  $v$ , representing the magnitude of neural activity in the wave density mode:

$$d^2v/dt^2 + a dv/dt + bv = I,$$

where  $a$  is the rise time of a postsynaptic potential,  $b$  is the decay time, and  $I$  is impulse input. The magnitude of neural activity in the pulse density mode on axons,  $p$ , is modeled [2] with the solution to a second order static nonlinear equation in normalized coordinates:

$$p = p_0 \{1 + \exp[-(e^v - 1)/Q_m]\},$$

where  $p_0$  is mean background pulse density and  $Q_m$  is the maximum normalized pulse density. The KO set models the dynamics of an average neuron that has only a zero point attractor, to which it returns after perturbation. All interesting activity patterns come from interactions among KO sets. The Kie (or Kli) set models a collection of excitatory neurons that excite each other by coupling two KOe (or KOi) sets in positive feedback. If the density of connections exceeds a certain threshold, the KOe set can sustain a non-zero point attractor. During development all neurons at KO begin to

sprout axons and dendrites extending widely into their surrounds. They must repeatedly fire action potentials in order to survive and at first do so by membrane leakage; when the threshold of connection density is reached at which each neuron could receive more pulses back than it transmits, the activity of the now K1e collection is sustained without need for membrane leakage.

In a 2-D K1e set a uniform field of random pulses and  $1/f$  dendritic waves emerges [16] that is limited by thresholds and refractory periods without need for inhibitory neurons, which emerge later in development. When they do so at around birth, a K2 set forms by the union of KOe and KOi sets. When sufficiently dense negative feedback connections form, a limit cycle attractor emerges with a characteristic frequency in the gamma range. The K2 sets model local collections of neurons in cortex with conduction delays among them that are small enough to be absorbed into the synaptic and dendritic delays of the rise time of a postsynaptic potential (PSP) prior to passive membrane decay. The dynamics of the component KO sets are modeled by a 2nd order ordinary differential equation performing integration on synaptic input prior to the operation of bilateral saturation at the output modeled with a static sigmoid function.

The assembly of three K2 sets with long feedback connections among them is modeled by a K3 set [1,76] that supports nonconvergent “chaotic” attractor landscapes. The K3 set contains 8 K1 sets, each with its K1-field that suffices to model the EEG and pulse density outputs of the component. The distributed K3 set models the operations of sensory cortices in categorizing conditioned stimuli (CS) after learning [116–119].

The K4 set serves to model the primitive forebrain by the assembly of three K3 sets representing the sensory and motor cortices and the hippocampal system that provides for short-term memory and a cognitive map that provide the spatial and temporal orientation required for animal and robotic navigation [115].

The K5 set models the scale-free dynamics of the neocortex in each cerebral hemisphere. The undivided neocortical neuropil embeds the ipsilateral primary sensory and motor areas with the limbic system, and by its connectivity patterns provides the dynamics that is required for the rapid global integration and evolution of behavior. The observable mesoscopic electric fields are all generated by K1 sets, while their spatiotemporal AM patterns are governed by their embedding in higher order  $K$ -sets together with their controlling parameters.

## Appendix B

Some aspects of the mathematical formalism of the dissipative brain model are here very shortly summarized for the reader familiar with the terminology and the mathematics of QFT. For a more detailed account of the formalism we refer to the original papers [67,100,101,106,120,121].

### Part 1

As already mentioned in the text, patterns of correlated elements (ordered patterns) which are macroscopically observable in physical systems are described in QFT by the mechanism of spontaneous breakdown of symmetry (SBS). Symmetry is said to be spontaneously broken when the Lagrangian is invariant under a certain group of continuous symmetry, say  $G$ , and the vacuum or ground state of the system is not invariant under  $G$ , but under one of its subgroups, say  $G'$ . The ground state then exhibits observable ordered patterns corresponding to the breakdown of  $G$  into  $G'$ . These patterns are generated by the coherent condensation in the ground state of massless quanta called Nambu–Goldstone (NG) particles, or waves, or modes. These modes, which are the carriers of the ordering information in the ground state, are dynamically generated by the process of the breaking of the symmetry. They manifest themselves as collective modes since their propagation covers extended domains, or, in the infinite volume limit, the whole system. The observable specifying the degree of ordering of the vacuum (called the order parameter) acts as a macroscopic variable for the system and is specific of the kind of symmetry into play. Its value is related with the density of condensed NG bosons in the vacuum. Such a value may thus be considered to be the *code* specifying the vacuum of the system (i.e. its macroscopically observable ordered state, namely its physical phase) among many possible degenerate vacua.

In the quantum model of the brain [60–62] the code of the ground state specifies its memory content: the memory recording process is depicted by the NG boson condensation in the brain ground state. The external informational input acts as the trigger of the symmetry breakdown out of which the NG bosons and their condensation are generated. The symmetry which gets broken is the rotational symmetry of the electrical dipoles of the water molecules [64] and the

NG modes are the vibrational dipole wave quanta (DWQ) [111–113]. The recall of the recorded information occurs under the input of a stimulus “similar” to the one responsible for the memory recording.

### Part 2

In the dissipative brain model a central role is played by the fact that the brain is an *open system* continuously *linked* (coupled) with the environment, namely that its dynamics is intrinsically dissipative [67]. The procedure of the canonical quantization of a dissipative system requires the “doubling” of the degrees of freedom of the system [99]. Such a requirement ensures that the flow of the energy exchanged between the system and the environment is balanced.

Let  $A_k$  and  $\tilde{A}_k$  denote the annihilation operators for the DWQ mode and its “doubled mode”, respectively.  $k$  denotes the momentum and other specifications of the  $A$  operators (similarly, we denote by  $A_k^\dagger$  and  $\tilde{A}_k^\dagger$  the creation operators).

The initial value problem is defined by setting the *code*  $\mathcal{N}$  imprinted in the vacuum at the initial time  $t_0 = 0$  by the external input and representing the *memory record* of the input. The code  $\mathcal{N}$  is the set of the numbers  $\mathcal{N}_{A_k}$  of modes  $A_k$ , for any  $k$ , condensate in the vacuum state which thus can be taken to be the memory state at  $t_0 = 0$  and which we denote by  $|0\rangle_{\mathcal{N}}$  [67,120].  $\mathcal{N}_{A_k}(t)$  turns out to be given, at each  $t$ , by:

$$\mathcal{N}_{A_k}(t) \equiv_{\mathcal{N}} \langle 0(t) | A_k^\dagger A_k | 0(t) \rangle_{\mathcal{N}} = \sinh^2(\Gamma_k t - \theta_k), \quad (\text{B.1})$$

and similarly for the modes  $\tilde{A}_k$ . The state  $|0(t)\rangle_{\mathcal{N}} \equiv |0(\theta, t)\rangle$  is the time-evolved of the state  $|0\rangle_{\mathcal{N}}$ .  $\Gamma$  is the damping constant (related to the memory life-time) and  $\theta_k$  fixes the code value at  $t_0 = 0$ .  $|0\rangle_{\mathcal{N}}$  and  $|0(t)\rangle_{\mathcal{N}}$  are normalized to 1 and in the infinite volume limit we have

$$\mathcal{N} \langle 0(t) | 0 \rangle'_{\mathcal{N}} \xrightarrow{V \rightarrow \infty} 0 \quad \forall t \neq t_0, \forall \mathcal{N}, \mathcal{N}', \quad (\text{B.2})$$

$$\mathcal{N} \langle 0(t) | 0(t') \rangle'_{\mathcal{N}} \xrightarrow{V \rightarrow \infty} 0, \quad \forall t, t' \text{ with } t \neq t', \forall \mathcal{N}, \mathcal{N}', \quad (\text{B.3})$$

with  $|0(t)\rangle_{\mathcal{N}} \equiv |0(\theta', t)\rangle$ . Eqs. (B.2) and (B.3) also hold for  $\mathcal{N} \neq \mathcal{N}'$  but  $t = t_0$  and  $t = t'$ , respectively. Eqs. (B.2) and (B.3) show that in the infinite volume limit the vacua of the same code  $\mathcal{N}$  at different times  $t$  and  $t'$ , for any  $t$  and  $t'$ , and, similarly, at equal times but different  $\mathcal{N}$ 's, are orthogonal states and thus the corresponding Hilbert spaces are unitarily inequivalent spaces.

The number  $(\mathcal{N}_{A_k} - \mathcal{N}_{\tilde{A}_k})$  is a constant of motion for any  $k$  and  $\theta$ . The physical meaning of the  $\tilde{A}$  system is the one of providing the representation of the sink where the energy dissipated by the  $A$  system flows. Thermal properties of the vacuum  $|0(t)\rangle_{\mathcal{N}}$  can be then analyzed and the  $\tilde{A}$  modes appear to represent the thermal bath (the environment) modes.

In order to ensure the balance of energy flow between the system and the environment, the difference between the number of tilde and non-tilde modes must be zero:  $\mathcal{N}_{A_k} - \mathcal{N}_{\tilde{A}_k} = 0$ , for any  $k$ . Note that the requirement  $\mathcal{N}_{A_k} - \mathcal{N}_{\tilde{A}_k} = 0$ , for any  $k$ , does not uniquely fix the code  $\mathcal{N} \equiv \{\mathcal{N}_{A_k}, \text{ for any } k\}$ . Also  $|0\rangle_{\mathcal{N}'}$  with  $\mathcal{N}' \equiv \{\mathcal{N}'_{A_k}; \mathcal{N}'_{A_k} - \mathcal{N}'_{\tilde{A}_k} = 0, \text{ for any } k\}$  ensures the energy flow balance and therefore also  $|0\rangle_{\mathcal{N}'}$  is an available memory state: it will correspond however to a different code number (i.e.  $\mathcal{N}'$ ) and therefore to a different information than the one of code  $\mathcal{N}$ . In the infinite volume limit  $\{|0\rangle_{\mathcal{N}}\}$  and  $\{|0\rangle_{\mathcal{N}'}\}$  are representations of the canonical commutation relations each other unitarily inequivalent for different codes  $\mathcal{N} \neq \mathcal{N}'$ . We have thus at  $t_0 = 0$  the splitting, or *foliation*, of the space of states into infinitely many unitarily inequivalent representations. Thus, infinitely many memory (vacuum) states, each one of them corresponding to a different code  $\mathcal{N}$ , may exist: A huge number of sequentially recorded inputs may *coexist* without destructive interference since infinitely many vacua  $|0\rangle_{\mathcal{N}}$ , for all  $\mathcal{N}$ , are *independently* accessible in the sequential recording process.

In conclusion, the “brain (ground) state” is represented as the collection (or the superposition) of the full set of states  $|0\rangle_{\mathcal{N}}$ , for all  $\mathcal{N}$ . The brain is thus described as a complex system with a huge number of macroscopic states (the memory states).

### Part 3

By considering the propagation speed, say  $c$ , of the NG modes in the system, we can show that the time derivative with respect to  $t$  of the frequency  $\Omega_k$  common to the  $A$  and  $\tilde{A}$  modes, i.e. the power, is a decreasing function of  $k$ .

Similarly, we find that the inverse of  $\Omega_k$  (the “duration”) and the domain size  $d_\Omega(t) = c(\Omega_k)^{-1}$  are also decreasing functions of  $k$ .

It is possible to show that the degree of the coupling of the system  $A$  with the system  $\tilde{A}$  can be parameterized by an index, say  $n$ , in such a way that in the limit of  $n \rightarrow \infty$  the possibilities of the system  $A$  to couple to  $\tilde{A}$  (the environment) are “saturated”: the system  $A$  then gets *fully* coupled to  $\tilde{A}$ .  $n$  can be thus taken to represent the number of *links* between  $A$  and  $\tilde{A}$ . When  $n$  is not very large (infinity), the system  $A$  (the brain) has not fulfilled its capability to establish links with the external world [120]. It can be shown that more the system is “open” to the external world (more are the links), better its neuronal correlation can be realized. However, in the setting up of these correlations also enter quantities which are intrinsic to the system, they are *internal* parameters and may represent (parameterize) subjective attitudes. Our model, however, is not able to provide a dynamics for the variations of  $n$ , thus we cannot say if and how and under which specific boundary conditions  $n$  increases or decreases in time. In any case, a higher or lower *degree of openness* (measured by  $n$ ) to the external world may produce a better or worse ability in setting up neuronal correlates, respectively (different under different circumstances, and so on, e.g. during the sleep or the awake states, the childhood or the older ages).

In conclusion, functional or effective connectivity (as opposed to the structural or anatomical one which we do not consider here) is highly dynamic in the dissipative model. Once these functional connections are formed, they are not necessarily fixed. On the contrary, they may quickly change and new configurations of connections may be formed extending over a domain including a larger or a smaller number of neurons. The finiteness of the correlated domain size implies a non-zero effective mass of the DWQ. These therefore propagate through the domain with a greater “inertia”are (quasi-)massless. The domain correlations are consequently established with a certain time-delay. This concurs in the delay observed in the recruitment of neurons in a correlated assembly under the action of an external stimulus.

#### Part 4

The free energy functional for the system  $A$  is

$$\mathcal{F}_A \equiv_{\mathcal{N}} \langle 0(t) | \left( H_A - \frac{1}{\beta} S_A \right) | 0(t) \rangle_{\mathcal{N}}, \tag{B.4}$$

with the time-dependent inverse temperature  $\beta(t) = \frac{1}{k_B T(t)}$ ;  $S_A$  is the entropy operator and  $H_A$  denotes the Hamiltonian at  $t = t_0$  relative to the  $A$ -modes only,  $H_A = \sum_k \hbar \Omega_k(t_0) A_k^\dagger A_k$ . Let  $\Theta_k \equiv \Gamma_k t - \theta_k$  and  $E_k \equiv \hbar \Omega_k(t_0)$ . The stationarity condition to be satisfied at each time  $t$  by the state  $|0(t)\rangle_{\mathcal{N}}$  is

$$\frac{\partial \mathcal{F}_A}{\partial \Theta_k} = 0, \quad \forall k \tag{B.5}$$

and gives  $\beta(t) E_k = -\ln \tanh^2(\Theta_k)$ , i.e.,

$$\mathcal{N}_{A_k}(\theta, t) = \sinh^2(\Gamma_k t - \theta_k) = \frac{1}{e^{\beta(t) E_k} - 1}, \tag{B.6}$$

which is the Bose distribution for  $A_k$  at time  $t$ .

One can see that the entropy  $\mathcal{S}(t) = \langle 0(t) | S | 0(t) \rangle_{\mathcal{N}}$  is a decreasing function of time in the interval ( $t_0 = 0, \tau \equiv \frac{\theta_k}{\Gamma_k}$ ) meaning that the state  $|0(t)\rangle_{\mathcal{N}}$ , although evolving in time, is however “protected” from “going back” to the “uncorrelated” vacuum state. Of course, here the exchange of energy with the environment is crucial and we are also assuming finite volume effects. One can also see that the entropy, for both  $A$  and  $\tilde{A}$  system, grows monotonically from 0 to infinity as the time goes from  $t = \tau$  to  $t = \infty$ . However, for the complete system  $A - \tilde{A}$ , the difference  $(S_A - S_{\tilde{A}})$  is constant in time:  $[S_A - S_{\tilde{A}}, \mathcal{H}'] = 0$ .

Also, it can be shown that, as time elapses, the change in the energy  $E_A \equiv \sum_k E_k \mathcal{N}_{A_k}$  and in the entropy is given by

$$dE_A = \sum_k E_k \dot{\mathcal{N}}_{A_k} dt = \frac{1}{\beta} dS_A, \tag{B.7}$$

i.e.,

$$dE_A - \frac{1}{\beta} dS_A = 0, \quad (\text{B.8})$$

provided changes in inverse temperature are slow, i.e.,

$$\frac{\partial \beta}{\partial t} = -\frac{1}{k_{\tilde{A}} T^2} \frac{\partial T}{\partial t} \approx 0.$$

In this case, Eq. (B.8) expresses the minimization of the free energy:  $d\mathcal{F}_A = dE_A - \frac{1}{\beta} dS_A = 0$ . One may define as usual heat as  $dQ = \frac{1}{\beta} dS$ . Thus the change in time of condensate (Eq. (B.7)) turns out to be heat dissipation  $dQ$ .

### Part 5

As already observed, the state  $|0(t)\rangle_{\mathcal{N}}$  is a normalized state at any  $t$ . Moreover, in the infinite volume limit Eqs. (B.2) and (B.3) also hold true for  $\mathcal{N} = \mathcal{N}'$ . Time evolution of the state  $|0\rangle_{\mathcal{N}}$  is thus represented as the (continual) transition through the representations  $\{|0(t)\rangle_{\mathcal{N}}, \forall \mathcal{N}, \forall t\}$ , namely by the “trajectory” through the “points”  $\{|0(t)\rangle_{\mathcal{N}}, \forall \mathcal{N}, \forall t\}$  in the space of the representations (each one minimizing the free energy functional (B.4)). The trajectory initial condition at  $t_0 = 0$  is specified by the  $\mathcal{N}$ -set. It has been shown [59,100,101] that: (a) these trajectories are classical trajectories and (b) they are chaotic trajectories. This means that they satisfy the requirements characterizing the chaotic behavior [122]:

- (i) the trajectories are bounded and each trajectory does not intersect itself (trajectories are not periodic).
- (ii) there are no intersections between trajectories specified by different initial conditions.
- (iii) trajectories of different initial conditions are diverging trajectories.

The meaning of (i) is that the “points”  $|0(t)\rangle_{\mathcal{N}}$  and  $|0(t')\rangle_{\mathcal{N}}$  through which the trajectory goes, for any  $t$  and  $t'$ , with  $t \neq t'$ , after the initial time  $t_0 = 0$ , never coincide.

Eq. (B.3) also holds for  $\mathcal{N} \neq \mathcal{N}'$  in the infinite volume limit for any  $t$  and any  $t'$ . Thus it shows that trajectories specified by different initial conditions ( $\mathcal{N} \neq \mathcal{N}'$ ) never cross each other, which is the meaning of (ii).

The property (ii) thus implies that no *confusion* (interference) arises among the codes of different neuronal correlates, even as time evolves. In realistic situations of finite volume, states with different codes may have non-zero overlap (the inner products Eqs. (B.2) and (B.3) are not zero). In such a case, at a “crossing” point between two, or more than two, trajectories, there can be “ambiguities” in the sense that one can switch from one of these trajectories to another one which there crosses. This may be felt indeed as an association of memories or as switching from one information to another one and it reminds us of the “mental switch” occurring, for instance, during the perception of ambiguous figures and, in general, while performing some perceptual and motor tasks as well as while resorting to free associations in memory tasks [123].

In order to see that the requirement (iii) is also satisfied we study how the “distance” between trajectories evolves as time evolves. Consider two trajectories of different initial conditions,  $\mathcal{N} \neq \mathcal{N}'$  ( $\theta \neq \theta'$ ). At time  $t$ , each component  $\mathcal{N}_{A_k}(t)$  of the code  $\mathcal{N} \equiv \{\mathcal{N}_{A_k} = \mathcal{N}_{\tilde{A}_k}, \forall k, \text{ at } t_0 = 0\}$  is given by Eq. (B.1). We then have:

$$\begin{aligned} \Delta \mathcal{N}_{A_k}(t) &\equiv \mathcal{N}'_{A_k}(\theta', t) - \mathcal{N}_{A_k}(t) \\ &= \sinh^2(\Gamma_k t - \theta_k + \delta\theta) - \sinh^2(\Gamma_k t - \theta_k) \approx \sinh(2(\Gamma_k t - \theta_k)) \delta\theta_k, \end{aligned} \quad (\text{B.9})$$

where  $\delta\theta_k \equiv \theta_k - \theta'_k$  (which, in full generality, may be assumed to be greater than zero). The last equality holds for small  $\delta\theta_k$ , i.e. for a very small difference in the initial conditions of the two initial states. The time-derivative then gives

$$\frac{\partial}{\partial t} \Delta \mathcal{N}_{A_k}(t) = 2\Gamma_k \cosh(2(\Gamma_k t - \theta_k)) \delta\theta_k \quad (\text{B.10})$$

thus showing that the difference between originally even slightly different  $\mathcal{N}_{A_k}$ 's grows as time evolves. For large enough  $t$ , the modulus of the difference  $\Delta \mathcal{N}_{A_k}(t)$  and its time derivative diverge as  $\exp(2\Gamma_k t)$ , for all  $k$ 's. The quantity

$2\Gamma_k$ , for each  $k$ , appears thus to play a role similar to that of the Lyapunov exponent in chaos theory [122]. In conclusion, we see that trajectories differing by a small variation  $\delta\theta$  in the initial conditions, diverge exponentially as time evolves. This may account for the high perceptive resolution in the recognition of the perceptual inputs.

The difference between  $k$ -components of the codes  $\mathcal{N}$  and  $\mathcal{N}'$  may become zero at a given time  $t_k = \frac{\theta_k}{T_k}$  (cf. Eq. (B.9)). However, the difference between the codes  $\mathcal{N}$  and  $\mathcal{N}'$  does not necessarily become zero. The codes are different even if a finite number of their components are equal since they are made up by a large number of  $\mathcal{N}_{A_k}(\theta, t)$  components (infinite in the continuum limit). On the other hand, suppose that, for  $\delta\theta_k \equiv \theta_k - \theta'_k$  very small, the time interval  $\Delta t = \tau_{\max} - \tau_{\min}$ , with  $\tau_{\min}$  and  $\tau_{\max}$  the minimum and the maximum, respectively, of  $t_k = \frac{\theta_k}{T_k}$ , for all  $k$ 's, be very small. Then the codes are recognized to be *almost* equal in such a  $\Delta t$ . Eq. (B.9) then expresses the recognition (or recall) process and it shows how it is possible that “slightly different”  $\mathcal{N}_{A_k}$ -patterns (or codes) are identified (recognized to be the *same code* even if corresponding to slightly different inputs). Roughly,  $\Delta t$  may be taken as a measure of the recognition time.

In conclusion, trajectories in the representation space are classical chaotic trajectories in the large (infinite) volume limit. We observe that the rules (i), (ii) and (iii) are for deterministic chaos, which is low dimensional, noise-free, autonomous and stationary. Such a chaotic motion is indeed in the abstract space of the parameters labelling the system ground state in the dissipative model. This motion in such a mathematical space must be projected in a more realistic frame considering that brains are infinite dimensional, noisy, engaged and time-varying. Work in such a direction is in progress.

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