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Freeman's mass action

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Freeman's Mass Action (FMA) refers to the collective synaptic actions that neurons in the cortex exert on each other in vast numbers by synchronizing their firing of action potentials. In the aggregate, FMA is a powerful force that creates bursts of cortical neural activity that resemble the vortices of tornadoes and hurricanes. The bursts rapidly and repeatedly retrieve memories and bind them with sensory information into percepts. In this way, FMA expresses and transmits the meaning of sensory information in spatial patterns of cortical activity that resemble frames in a movie.

Introduction: The percept in FMA: five phenomenological features

Everyone has experienced the hunger triggered by the odor of a favorite food, the cascade of associations on glimpsing a familiar face, the surge of dread or delight on recognizing a familiar voice, and so on. That is perception: 'the meaningful impression of any object obtained by use of the senses.' We ask the question: How do brains perceive the meanings of stimuli in flashes of recognition?

To get the data needed to answer this question, we surgically place electrodes directly on cortical surfaces of experimental animals and record their brain waves [Freeman, 2001]. These electrical waves are signs of the activity of neural populations. The signs don't do any work. They are like the sounds from an engine – a comforting reassurance when it works well, a diagnostic tool when it doesn't. The signs include electroencephalograms (EEG) recorded from the scalp and electrocorticograms (ECoG) recorded directly from the cortical surfaces. EEG/ECoG waves are supported by and correlated with myriad action potentials (spikes, units), together comprising FMA, but they differ crucially in that the spikes are points and the waves are fields (see Box). Furthermore, the critical understanding that should emerge from reading this article is that the field of FMA is a vector field that creates and destroys information, whereas the electric field of the EEG/ECoG merely reflects and carries information.

In order to have our subjects perform, we train them to perceive conditioned stimuli (CS). We search their ECoG for patterns that we call percepts, which are correlated with perception. We know that during perception many neurons fire synchronously, though we cannot say precisely how many neurons or with how much synchrony. We know that the mean firing rates are correlated with the wave amplitudes. We know that the action potentials relayed from sensory receptors to sensory cortex excite the excitatory neurons; that they excite each other; and that they also excite the inhibitory neurons. And we know that the negative feedback between excitatory and inhibitory neurons causes ECoG oscillations at frequencies of 12 to 80 Hz called beta and gamma waves. From all these premises we infer that the impact of a CS on a sensory cortex causes FMA to construct a percept, which we recognize by the sign of a pattern in the ECoG.

We found such patterns in the olfactory system [Freeman, 1991] and now find them in all sensory cortices. We have identified five characteristic features in them that are needed to describe the percepts and deduce how the cortices make them. We focus our essay on these features, because in order to understand brain theory we have to know the patterns of brain waves that the theory predicts, and on which further theory is to be based. We describe our theory elsewhere (see Recommended Reading). Here we begin with illustrations from the olfactory ECoG (Figs. 2, 3), because olfaction is the simplest sensory system. Then we proceed to the visual, auditory and somatic ECoG (Figs. 4, 5). Although their microscopic functions are far more complex than those in olfaction, the basic mesoscopic operations are quite similar, not surprisingly, seeing that they evolved from the olfactory pioneer.

The beta-gamma wave packet, resembling a tone burst

We did our first study of perception by asking a hungry cat to perceive an odor of food (a CS), while we observed its olfactory brain in action. We made the cat wait for a couple of hours with nothing to do. It sat patiently. Then a mere whiff of fish that signaled a favored food galvanized the cat into meowing and searching. The CS caused the olfactory cortex to issue dramatic gamma bursts that we call *wave packets* [Freeman, 1975]. But an hour later after feeding to satiety the cat ignored the stimulus, and no bursts were seen.

The olfactory ECoG (Fig. 2) illustrates three important properties of cortical dynamics. First, the normal cortex at *rest* always has *spontaneous activity* that is almost completely devoid of patterns. This noise is sustained by excitatory cortical neurons that excite each other. The noise is self-regulated (we say *stabilized*) by the *refractory periods* [Freeman and Erwin, Scholarpedia; Freeman and Zhai, 2009]; after each firing every neuron has to rest. This basic property of neurons stabilizes every local cortical population at all times without need for global regulatory mechanisms. (For deeper investigation of this steady state we describe it with the theories of *self-organized criticality* [Kozma, 2007], *metastability* [Bressler and Kelso, 2007], and *chaotic itinerancy* [Tsuda, 2001]).

Second, the signal that receptors send to the cortex when a CS stimulates them is far weaker than the cortical response. The cortex doesn't simply amplify the CS. It increases its background activity in proportion to the degree of arousal (Fig. 2), and it *reorganizes* the background activity into the patterns that we see as gamma wave packets.

Third, when the cat sniffs repeatedly, a wave packet appears with each sniff, but the time difference between the start of the sniff and the start of the wave packet varies with each sniff. That variation in the *latencies* implies that the onset of a percept depends not just on the start of the CS. Onset also requires a spontaneous break, a *discontinuity* in the background activity that unpredictably varies the precise time of gamma onset [Tallon-Baudry et al., 1998]. In Section 4 we claim that the random event that initiates percept formation is a *null spike*.

The spatial AM pattern, resembling a cinematographic frame

Just as in a movie frame, a wave packet has a spatial pattern. To see the pattern we use an 8x8 electrode array fixed on the cortical surface to sample the ECoG at 64 points. The waveform of the gamma oscillation is similar at all 64 points but the 64 amplitudes differ across the surface (Fig. 3). We call these differences spatial amplitude modulation (AM) of a carrier wave. We display the AM pattern with the 64 amplitudes of the carrier wave as a contour plot. The patterns seem to vary as unpredictably as ocean waves, but that is not so. We find that the AM pattern for each subject is like a signature; easily recognized though never twice identical. When a

Box 1.1 Mesoscopic vs. Microscopic Neurodynamics: A paradigm shift

The concepts prevailing in neurodynamics until now are based on neural networks. Neural networks are Newtonian models, because they treat microscopic neural pulses as point processes at trigger zones and synapses. Sherrington [1951] speculatively described the action potentials as "myriads of trains of moving lights" in an "enchanted loom" (pp. 177-178). In a tour de force of computational neuroscience Izhikevich and Edelman [2008] modeled his vision in a magnificent display of points of light.

FMA theory is Maxwellian, because it treats mesoscopic neural activity as a continuous distribution. Just as the Maxwellian paradigm subsumes the Newtonian laws of Coulomb and Oersted, the neurodynamics of FMA [Freeman, 2000] includes the microscopic neural operations that bring sensory information to sensory cortices, and that carry the early percepts from sensory cortex to other parts of the brain. Newtonian dynamics can model cortical input and output functions but not the formation of percepts.

FMA requires a paradigm shift, because the theory is based on new techniques, new exemplary experiments, and new rules of evidence. A comparable shift occurred in the 19th century, when electricity and magnetism were widely conceived in Newtonian terms as forces exerted by point charges acting at a distance instantly on other point charges. Michael Faraday reconceived the forces as fields, and James Clark Maxwell devised new vectorial mathematics that led to discovery of the electromagnetic spectrum [Arianrhod, 2005].

Figure 1: Box: A Paradigm Shift

subject has learned to perceive and respond selectively to a CS, a spatial AM pattern unique to that CS appears whenever the subject responds to the CS. We conclude that the wave packet carries the percept, and that the spatial pattern of

amplitude modulation (AM) of the carrier wave expresses the content (that which is perceived) [Freeman, 2005].

We infer that the early change in AM pattern (e.g., from "Air" to "Amyl" in Trial Set 1, Fig. 3) is due to the strengthening of

synapses between only those pairs of pyramidal cells that are simultaneously excited by the CS in reinforcement learning, meaning that the stimulus is accompanied by a reward or penalty that makes the CS important to the subject. This inference is based on Hebb's Rule: "Neurons that fire together wire together." Such a *neural assembly* of mutually excitatory neurons ignites entirely when a CS excites any part. Evidence for such assemblies is provided by the relative ease with which cortical neurons are found that fire vigorously in conjunction with a CS that is perceived by an alert subject [e.g., Singer and Gray, 1991; Gross, 2002; Quiroga and Panzeri, 2009].
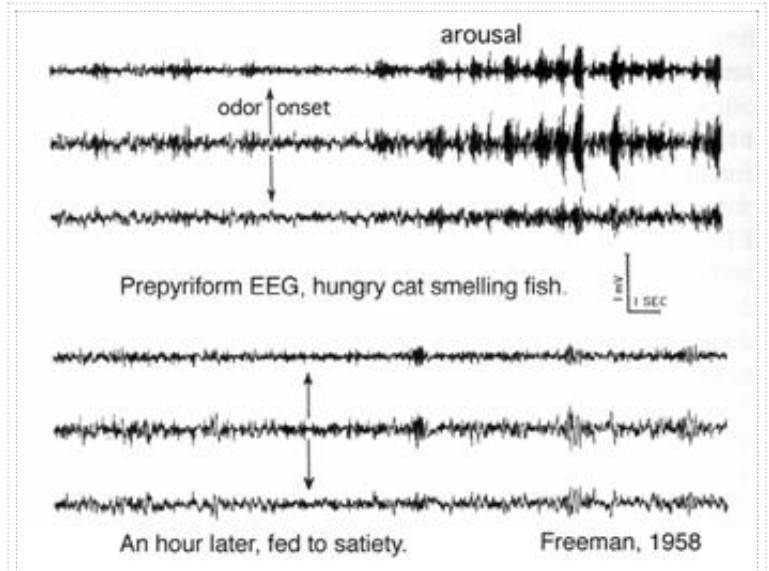

Figure 2: The ECoG from the olfactory cortex illustrates (i) the ever-present background *spontaneous* activity of cortex; (ii) the increase in power with arousal following a sniff of fish (arrows); and (iii) the intermittency of wave packets. We propose that the wave packets provide what we conceive as cinematographic *frames*. Each frame has a shared waveform, its *carrier wave*. Reprinted from Fig. 7.1, p. 404 in Freeman [1975].

The assembly sensitizes the cortex to the CS and amplifies the impact. Most importantly, it averages over variations in CS from trial to trial, so it enables the cortex to generalize the CS inductively to a category, no matter which among equivalent receptors receive the stimulus. We infer that a new assembly forms when a subject learns a new CS,

which explains the initial formation of a new AM pattern. The olfactory system can form a new assembly in 3 to 5 trials with multiple sniffs of a new CS on each trial, and it has an assembly for every class of stimulus that it can discriminate. We speak of a landscape of chaotic attractors, each of which is accessed by a neural assembly [p. 80 in Freeman, 2001; Kozma and Freeman, 2001; Ohl et al., 2001; Principe et al., 2001].

The AM pattern is not a transcription or representation of a stimulus, because it changes overnight and for days afterward during *consolidation*. That is the permanent change in the brain when the cortex forms a new *associative memory*. The same stimulus results in a different AM pattern when it is given a different context. For example, when the reward is switched from one stimulus to another, the subject stops responding to the first and starts responding to the second. Both AM patterns change, and so also does the control pattern, because the AM pattern signals the contextual meaning and significance of a CS.

The memory is stored in very widespread synaptic changes. We know this because all pre-existing AM patterns change, whenever the cortex creates a new one. That is how associations form; each memory that supports an AM pattern is connected to every other memory with its AM pattern. Every memory is a configuration of long-lasting synaptic changes, which are structural. Every act of remembering is dynamic; the AM pattern is never twice identical. It combines a retrieved memory with the information in the current CS and the current context. These properties (widespread connections, modifiability with learning, long-term storage, rapid access, and flexibility in the incorporation of changing contexts) are all prerequisites for a percept.

The null spike, resembling a tornado

Perception advances in a sequence of frames, so the question arises, how can the cortex switch from each frame to the next without freezing? Remember that FMA creates *order,* because all the neurons constrain each other into patterns. The

amplitude of the ECoG reveals the degree to which they bind each other into low-grade synchrony. We say that the ECoG serves as a measure of the degree of order and call it an *order parameter*. When the amplitude is high, an AM pattern may appear. When it goes to zero, the order disappears, and the neurons lose themselves in disorder. When we look very closely at the ECoG, we see that several times each second at rates in the theta range (3 to 7 Hz, technically an instance of *theta-gamma linkage* [Buzsáki, 2006]), the amplitude does indeed abruptly go to zero. At those instants the frequency suddenly jumps to a new value, and a new AM pattern emerges. We call this change a *phase transition* of cortex from a receiving phase to a transmitting phase [Freeman, 2008; cf. Freyer et al., 2009], because the old order evaporates into noise, and the new order condenses from the noise.

The changes in carrier frequency and AM pattern from frame to frame are obvious, but the actual phase transition is difficult to see. We start by searching the power spectrum for a
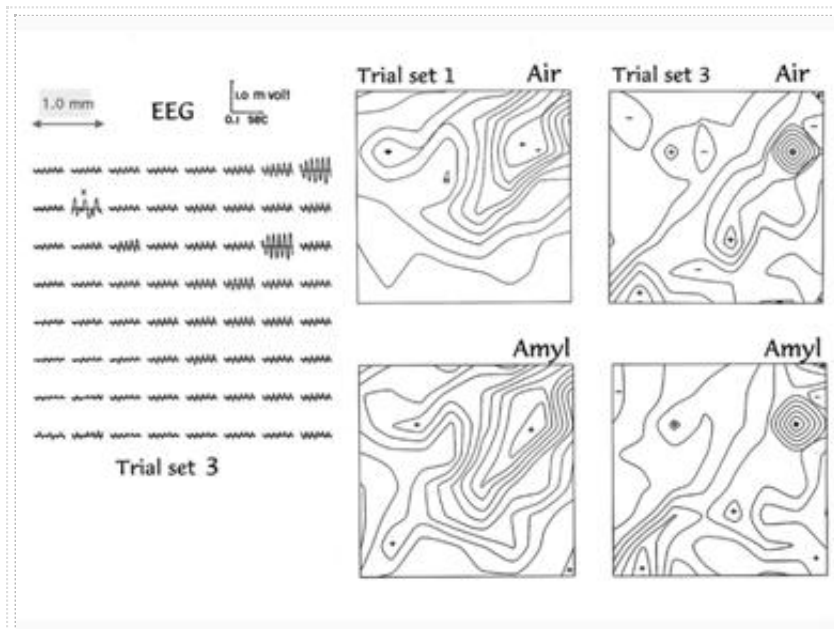

Figure 3: Left: The 8x8 signals are from a 3.5x3.5 mm square grid of electrodes (spacing 0.5 mm) on the olfactory bulb. Right: The amplitudes of the mean AM patterns are displayed in contour plots. The pattern difference in Trial Set 1 (above to below) reflects the formation of a *neural assembly* during training. The pattern differences from Set 1 to Set 3 with the same control and CS inputs reflect permanent changes in memory with consolidation. The lack of AM pattern invariance with invariant stimuli shows that AM patterns are retrieved from memory and modified by input. They are not representations of sensory stimuli; they are memories that are created by the sensory cortex. Reprinted from Fig. 12, p. 73 in Freeman [2001].

peak that shows the frequency of the carrier wave. However, each frame has a different carrier frequency, and frames last only about 0.1 s. The spectrum of a long time segment (1 to 6 s or more) has high frequency resolution, but it resembles that of noise, because the frequency jumps randomly from frame to frame. The spectrum of a short segment (0.1 s, Fig. 4, A) has poor resolution of frequencies, but still we can identify the narrow pass band (optimally 5 Hz centered in the theta range, 3-7 Hz [Freeman, 2009]) that includes a carrier frequency, so the trade of losing frequency resolution to gain temporal resolution is worth while. Typically there are multiple coexisting frequencies, each of which in turn we may select for close examination.

When we filter the ECoG in the selected pass band, we see the amplitude wax and wane in *beats* (Fig. 4, B). That is because the mixture of distributed frequencies of oscillation generated by the neural interactions in each pass band alternatively adds and cancels. To quantify the beats we calculate the instantaneous power (the square of the instantaneous amplitude [Freeman, 2004a]) and the instantaneous frequency (the rate of change in power) by using the Hilbert transform [Freeman, 2004b, 2009]. We use the log10 of the instantaneous power of each signal (Fig. 4, C), because the decrease in amplitude during a beat can be very deep (Fig. 5) and very brief. The instantaneous carrier frequency holds steady only during the high amplitudes of wave packets (Fig. 4, D). During the beats it is undefined and shows only noise [Freeman, 2009] from which AM patterns emerge.

The spatial pattern of wave modulation, resembling a hurricane

Recall that in sensation the CS brings to the cortex information that selects and activates a Hebbian assembly, which guides FMA to an attractor that forces the neurons into an AM pattern. By amplifying the input as it generalizes, the assembly also provides the tinder needed to ignite the entire cortex into the AM pattern. We propose that the null spike

provides the necessary spark. This seemingly trivial event carries the cortex across a threshold that otherwise prevents random phase transitions. The spike not only looks like a tornado; it acts like one in the sense that it destroys lingering AM patterns. It clears the way for FMA to construct a new AM pattern.

The pattern spreads over the entire sensory cortex, but it takes time to do so. That is typical of a phase transition in a distributed medium. For example, the condensation of a raindrop begins at a site of nucleation, such as a grain of dust, and it grows radially as the drop gets bigger. We find evidence for similar time lags in cortex [Freeman, 2004a,b]. The evidence for the spread is given by a spatial pattern of the latency of the wave that carries the AM pattern (Fig. 5, D). We express the latency at each point as a phase of the wave and locate the highest or lowest point. The phase decreases or increases with distance from that point in all directions, as if we were descending from the top of a hill or climbing out of a crater. We measure the location and steepness of the phase pattern by fitting to it a conic surface. We call the spatial pattern a *phase cone* [Freeman, 2004a,b].
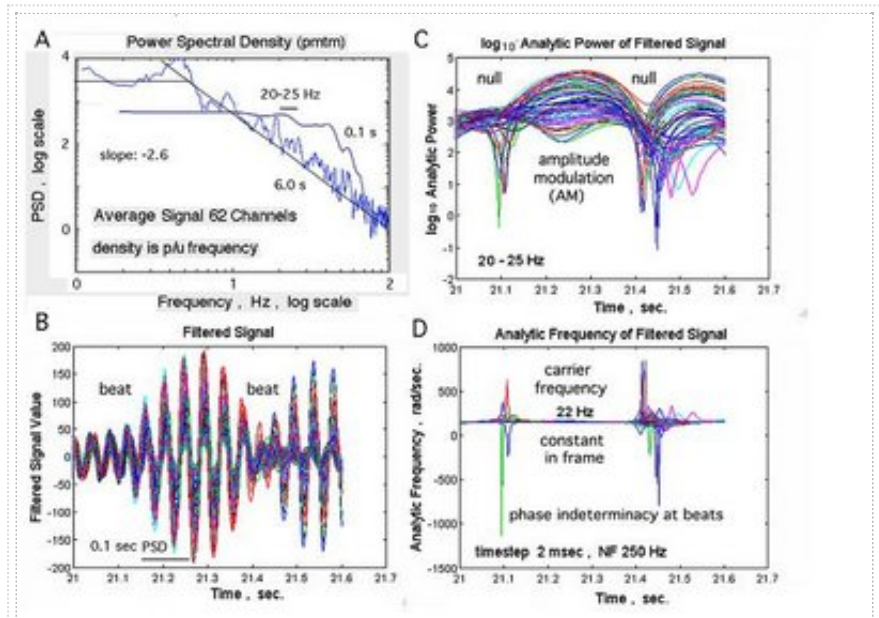

Figure 4: Extraction of the dynamic patterns of FMA from ECoG requires high resolution in spectrum, time, and space. **A.** The search begins with calculating the spectrum in a short time window (0.1 s) stepped along the 64 ECoG signals. The peaks in the power spectrum reveal possible carrier waves. One peak is selected for filtering in a narrow band (optimally 5 Hz, which is the modal frequency of the null spikes, estimated from the mean width of the wave packet pass bands [Freeman, 2009]). **B.** The 64 filtered signs of ECoG (superimposed colors) reveal bursts of oscillation with 64 amplitudes and 64 frequencies that are distributed around the peak frequency (22 Hz). The 64 signs preserve their amplitudes relative to each other in a pattern as they wax and wane together in beats. **C.** Null spikes in log10 power in one or more ECoG signals delimit the start and end of a wave packet. The stable distribution of instantaneous power on the surface suggests an AM pattern. **D.** The 64 carrier frequencies show small spatial and temporal variations in the burst when power is high and wide variations between bursts. From [Freeman, 2009].

The steepness of the phase gradient is a measure of the velocity of the traveling wave. We find that the mean conduction velocity of axons running parallel to the cortical surface determines the phase gradient. Our analysis of the literature on anatomical connections in cortex [Freeman et al., 2009] shows that the power-law distribution of connection distances between neurons is exactly that which is optimal to support rapid phase transitions of neural populations, irrespective of how large they are [Kozma, 2007]. We say that the connectivity and the dynamics are *scale-free* [Freeman and Breakspear, 2007; Freeman et al., 2009], which states that the dynamics of cortex is independent of size, so the brains of mice, men, elephants and whales work the same way. Once the cortex has been tipped over its threshold, a large area of cortex is engulfed inexorably in new AM and phase patterns, even though the size is truly immense in comparison to the sizes of the neurons.

The size limit is the distance at which the cumulative phase difference between neurons approaches +/- 45 degrees. That is the phase difference at which the shared power decreases below 50%. The phase difference imposes what is called a *soft boundary condition* on the wave packet. There is no mean diameter; the distribution is power-law, with occasional wave packets that appear to encompass the entire hemisphere.

Cinematographic displays [1] (http://soma.berkeley.edu/videos/?video=2) of the spatial patterns of the recorded amplitude of the band-pass filtered ECoG (not the instantaneous amplitude) show repeated outward or inward thrusts

with each half cycle. Some displays also show rotation, either clockwise or counter-clockwise [Freeman and Kozma, 2008; Freeman and Vitiello, 2009]. The patterns resemble the appearance of a hurricane viewed from a satellite, hence the analogy to a hurricane.

Conclusions and future directions

FMA theory has been a rich source of new features in the ECoG. Those summarized here — the gamma wave packet; the AM pattern; the null spike; the phase cone; and the ECoG vortex — are the best documented. The wave packet is a perceptual carrier. We access the percept that it carries by calculating its AM feature vector. The loss of FMA during the null spike releases the neurons from self-imposed order. They are susceptible to capture by the next memory that is elicited by the CS. The phase cone shows that the AM pattern is self-organized, that it spreads over the cortex with the velocities of action potentials, and that it broadcasts the percept throughout the forebrain as required for multisensory integration. The vortex may stabilize the AM pattern in the turbulence of the cortical dynamics. It shows that every point in an FMA field has an amplitude and directions of change in space and time, so it is a Maxwellian *vector field* [Freeman and Vitiello, 2009], not a Newtonian scalar field such as the EEG and ECoG (See Box, Fig.1). The distinction can be seen on comparing a sensory cortex with a holograph; both systems process information in two-dimensional arrays; both have many highly interconnected nodes. A holograph stores all the information in a stimulus and retrieves it by an inverse operation; it is non-categorizing and non-decisional. Cortex irreversibly deletes extraneous information from a CS and replaces it with a categorical meaning.

We propose the null spike as the ultimate marker for the onset of each new percept. It shows the beat of the perceptual clock that enables each sensory cortex to follow rapid changes in the world and the brain. In theory the locations of the null spike, the conic apex, and the center of the vortex should coincide. In practice they seldom do. We think that there are at least three reasons.

First, the spatiotemporal resolution of our measurements is marginal. For future recording the digitizing step should be decreased from 2 ms to 0.2 ms in order to sample the high frequency gamma oscillations. The interelectrode distance should be decreased below 0.8 mm with increased number of electrodes in order to improve the movies in scope and resolution.

Second, the signal processing methods must be improved. The decomposition of ECoG by Fourier, Hilbert and wavelet transforms fails to take advantage of our new knowledge about the intrinsic features of percepts by using them as basis functions. Every segment in the ECoG shows multiple overlapping and possibly
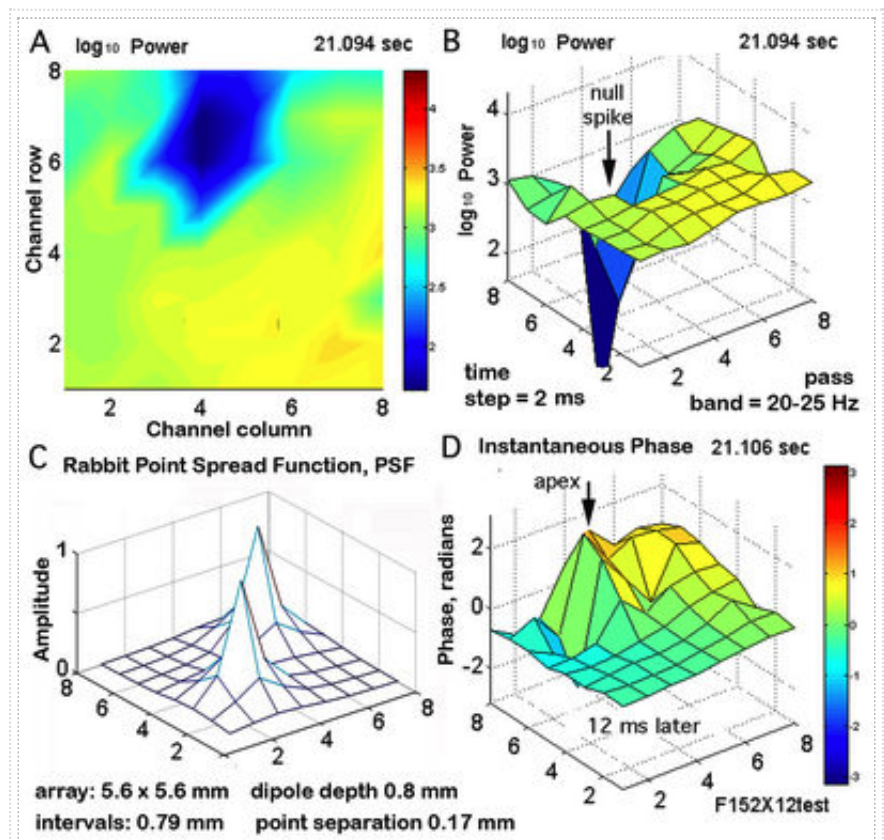

Figure 5: The fine structure of the instantaneous amplitude and phase can only be seen with closely spaced electrodes (here 0.79 mm in an 8x8 electrode grid on rabbit visual cortex). **A.** The color-coded contour plot shows the instantaneous power (the amplitude squared). **B.** A perspective view of a null spike shows its funnel-like appearance. **C.** Simulation of the surface potential amplitude from two point dipoles 17 mm apart and located at the depth of the ECoG generating layer shows the spatial resolution that can be achieved with array recording. [Adapted from Fig. 2, A, p. 575, Freeman, 2006]. **D.** A perspective view of a phase pattern (12 ms after the null spike) shows its maximum near the site of the null spike and its downward slope with distance from the peak (negative

interacting carrier waves, each with its own AM and patterns. Until we can separate them, we cannot tell whether they coexist like solitons or interact in making higher-order patterns.

Third, present FMA theory is largely borrowed from physics [Freeman and Vitiello, 2006] and mathematics [Kozma, Scholarpedia] and does not yet stand on its own. Brain science is still in adolescence. The next decade will surely bring explosive growth with stronger union of brain theory and experimental bioscience through neurocomputation, but with the proviso that brains don't compute; humans use computers to emulate with binary digits what brains do using vector fields of axonal and dendritic activities.

phase gradient). This shape can be fitted with a conic surface, which evaluates a *phase cone* [Freeman, 2004b]. The spatial display of the null spikes shows that they are extremely localized (Fig. 5, A), which suggests that they reveal a *singularity* in cortical dynamics [Fig. 6.30, p.388 in Freeman, 1975, 2009; Freeman and Vitiello, 2009]. The spike location differs from each AM pattern to the next without relation to the CS. The shape of the funnel of log10 power (Fig. 5, B) has the narrow width that is consistent with a point in an extremely small area of the cortex, in which the power in the ECoG has momentarily vanished. We show this by calculating the surface field of a current *dipole* at the depth of the ECoG generator (Fig. 5, C). From [Freeman, 2006].

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External Links

- http://sulcus.berkeley.edu/
- http://en.wikipedia.org/wiki/Rice_distribution
- http://soma.berkeley.edu/videos/?video=2

Dr. Robert Kozma, Computational NeuroDynamics Lab, University of Memphis, TN, was invited on 27 January 2009.

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