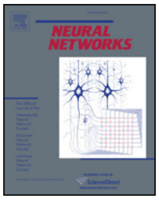
ARTICLE IN PRESS

Neural Networks ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet



2009 Special Issue

The KIV model of intentional dynamics and decision making

Robert Kozma[a,*], Walter J. Freeman[b]

[a] Computational Neurodynamics Laboratory, Department of Computer Science, University of Memphis, Memphis, TN 38152, United States
[b] Division of Neurobiology, University of California at Berkeley, Berkeley, CA 94720, United States

ARTICLE INFO

Article history:
Received 21 January 2009
Received in revised form
16 March 2009
Accepted 19 March 2009

Keywords:
Neurodynamics
KIV
Intention
Phase transition
Intermittent chaos

ABSTRACT

Human cognition performs granulation of the seemingly homogeneous temporal sequences of perceptual experiences into meaningful and comprehensible chunks of fuzzy concepts and behaviors. These knowledge granules are stored and consequently accessed during action selection and decisions. A dynamical approach is presented here to interpret experimental findings using K (Katchalsky) models. In the K model, meaningful knowledge is repetitiously created and processed in the form of sequences of oscillatory patterns of neural activity distributed across space and time. These patterns are not rigid but flexible and intermittent; soon after they arise through phase transitions, they dissipate. Computational implementations demonstrate the operation of the model based on the principles of intentional brain dynamics.

1. Introduction

Various brain regions contribute to the decision making processes, including the basal ganglia, parietal cortex, orbitofrontal cortex and prefrontal cortex (Dayan & Daw, 2008; Frank & Claus, 2006; Levine, in this issue). The role of top–down and bottom–up approaches in anticipatory control has been analyzed, and onset of synchronized oscillations in prefrontal cortex on attention focus has been demonstrated (Liang & Wang, 2003). Comprehensive modeling of the interactions between large-scale brain areas is beyond our reach at present; however, relatively simple modular models have been proposed, which reflect basic properties observed in experiments, including cortical and subcortical areas (Houk & Wise, 1995; O'Reilly & Frank, 2006). Game theory approaches (Von Neumann & Morgenstern, 1944) have been used to analyze decision making in the prefrontal cortex (Barraclough, Conroy, & Lee, 2004). The role of the interaction between prefrontal cortical regions and subcortical areas in decision making has been studied extensively, including the amygdala (Bechara, Damasio, Tranel, & Anderson, 1998; Damasio, Everitt, & Bishop, 1996; Werbos, in this issue). Experiments indicate that the amygdala, together with the orbitofrontal cortex, is involved in decision making (Bechara, Damasio, & Damasio, 2000; Le Doux, 2000; Zhou & Coggins, 2002). The interaction between entorhinal cortex, amygdala, hippocampal and cortical areas is studied in Kozma and Freeman (2003) and Kozma and Muthu (2004). The role of entorhinal cortex in decision making under the influence of sensory, orientation, and motivational clues has been evaluated (Kozma, 2007a).

During the past years, strong evidence has emerged in the literature about the existence of sudden jumps in measured cortical activities. Lehmann, Strik, Henggeler, Koenig, and Koukkou (1998) identify "micro-states" in brain activity and jumps between them. Rapid switches in EEG activity have been described (Fingelkurts & Fingelkurts, 2001, 2004; Freeman, Burke, & Holmes, 2003; Stam, Breakspear, & Cappellen, 2003). Synchronization of neural electrical activity while completing cognitive tasks has been studied in various animals, e.g., in cats, rabbits, gerbils, and macaque monkeys (Barrie, Freeman, & Lenhart, 1996; Bressler, 2003; Ohl, Scheich, & Freeman, 2001; Ohl, Deliano, Scheich et al., 2003). Behavioral correlates of transitions between metastable cortical states have been identified (Bressler & Kelso, 2001; Bressler, 2002; Kelso, 1995; Kelso & Engstrom, 2006). A comprehensive overview of stability, metastability, and transitions in brain activity is given in Le Van Quyen, Boucher et al. (2001) and Werner (2007). Chaotic itinerancy (Tsuda, 2001) is a mathematical theory that describes the trajectory of a dynamical system, which intermittently visits "attractor ruins" as it traverses across the landscape. A popular approach to consciousness is based on the global workspace theory (Baars, 1988). There is striking similarity between the spatio-temporal features of cortical phase transitions and the act of conscious broadcast in global workspace theory. Therefore, it can be hypothesized that a large part of cortical

---

[*] Corresponding address: Department of Mathematical Sciences, The University of Memphis, 373 Dunn Hall, TN 38152, United States. Tel.: +1 901 678 2497; fax: +1 901 678 2480.
E-mail addresses: robert.kozma.ctr@hanscom.af.mil, rkozma@memphis.edu (R. Kozma).

0893-6080/$ – see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.neunet.2009.03.019

phase transitions are in fact manifestations of conscious broadcast events.

The experimental findings have been interpreted using dynamic systems theory (Freeman et al., 2003; Freeman, 2005). According to dynamical system models of neural dynamics, the brain's basal state is a high-dimensional/chaotic attractor, and cognition is described through a trajectory moving across a convoluted attractor landscape like a high-dimensional Lorenz butterfly with multiple wings corresponding to memory patterns (Korn & Faure, 2003; Skarda & Freeman, 1987). In the basal mode, the system is in a high-dimensional dynamic state, and the trajectory of the system has direct and immediate access to all lower-dimensional attractors comprising the landscape. When an input pattern is presented to the model, the oscillations undergo a phase transition and the trajectory is switched to a localized, low-dimensional memory wing. The system stays in this wing briefly as it produces a spatial amplitude modulation (AM) activity pattern of a phase-locked oscillation with its frequency modulated (FM) in the gamma range. As the external and internal conditions change, the phase locking dissipates after 3–5 cycles, and the system leaves this wing and returns to high-dimensional space. It then jumps to another wing as it explores the complex attractor landscape while the system evolves. Intensive studies are conducted towards the interpretation of the content of the metastable AM patterns separated by brief transitory periods of phase transitions. The available physiological data are very complex, so that advanced machine learning and feature extraction tools are needed, such as information-theoretic learning, support vector machines, kernel methods (Bishop, 2006; Haykin, 1998; Shawe-Taylor & Cristianini, 2004; Vapnik, 1998; Zhang, in this issue). These tools open a way for better understanding the underlying neurodynamics processes (Perlovsky & Kozma, 2007).

In this work, the biologically-inspired KIV model is described to study intentional dynamics, which phase-locks various sensory and motor cortical areas with the limbic system. It is shown that at the highest level, KIV manifests key features of neurophysiological correlates of intentional behaviors. Mesoscopic neurodynamics is a crucial component of our approach to neural organization, dynamics, and goal-oriented function. It means intermediate spatial organization between microscopic (cellular) and macroscopic (intracortical) scales. At the same time, it is manifested through intermediate temporal effects in the order of 10–50 ms. Intermediate spatial and temporal models present a very challenging mathematical problem and can lead to resonance effects, see, e.g. Kozma, 1998; Kozma & Freeman, 2001. In this paper, two types of mesoscopic models are described: (i) neuropercolation based on discrete random graph theory; (ii) ordinary differential equations in continuous space–time approach. Mesoscopic neurodynamics exhibits intermittent phase transitions originating at the microscopic level, leading to frequent switches between metastable AM patterns of activations. This very property of self-organized intermittent spatio-temporal oscillatory dynamics observed in mesoscopic models is the unique property that will be used in developing mathematical and computational systems that mimic biological intentionality. These observations are used for designing multi-sensory inference and decision making systems.

2. High-level view on neurodynamics — Intentionality and goal-directedness

2.1. Neural correlates of higher cognition measured by EEG

Observing and identifying cortical AM patterns *in vivo* at controlled conditions confirmed that they convey cognitively significant information (Barrie et al., 1996; Makeig, Debener, Onton, & Delorme, 2004). Phase transitions correspond to the acts of identification and decision making, while the given AM pattern manifests the outcome of the decision. Evidence from AM pattern analysis during tasks requiring sensory discrimination demonstrates the potential existence of multiple modes in neocortex that are mutually exclusive and cannot interact when accessed, because the trajectory can only visit one basin of attraction at a time.

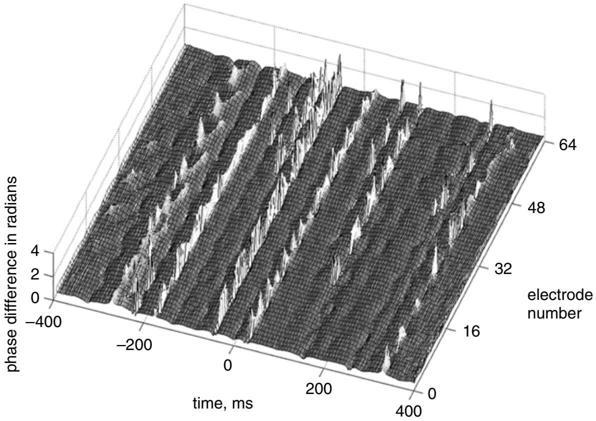


Fig. 1. The raster plot shows the successive differences of the unwrapped analytic phase, changing with time (left abscissa) and channel (right abscissa). When the jumps or dips are aligned with the right abscissa, they occur with nearly zero lags among them (Freeman et al., 2003).

In Fig. 1, results of scalp EEG recordings are shown with human volunteers (Freeman et al., 2003). Analytic phase differences are shown for EEG signals evaluated in the beta band (12–30 Hz) with 3 mm spacing of 64 electrodes in a linear 189 mm array digitized at 1 ms intervals. The perceptual content is found in the collection of wave amplitudes measured during phase plateaus of human scalp EEG (Ruiz, Li, Gonzales, & Freeman, in press). The EEG shows that neocortex processes information in frames like a cinema. The phase jumps show the shutter. The resemblance across a 33-fold difference in width of the zones of coordinated activity reveals the self-similarity of the global dynamics that is required to form multi-sensory percepts by integrating the activity patterns of all sensory and limbic cortices across the beta and gamma spectral ranges in the formation of Gestalts (Freeman, 2007).

2.2. Principles of neurodynamics — Hierarchy of K sets

A hierarchical approach to spatio-temporal neurodynamics, based on K sets, was proposed by Freeman in the 70s, named in the honor of Aharon Katchalsky, an early pioneer of neural dynamics (Freeman, 1975). K sets consist of a hierarchy of components with increasing complexity, including K0, KI, KII, KIII, KIV, and KV systems. They model the hierarchy of the brain starting from the mm scale to the complete hemisphere. Today, K sets are used in a wide range of applications, including classification (Chang, Freeman, & Burke, 1998; Freeman, Kozma, & Werbos, 2001), image recognition (Li, Lou, Wang, Li, & Freeman, 2006), time series prediction (Beliaev & Kozma, 2007), and robot navigation (Harter & Kozma, 2005; Voicu, Kozma, Wong, & Freeman, 2004). Recent developments include KIV sets for sensor fusion (Kozma & Tunstel, 2005; Kozma & Muthu, 2004), and autonomous control (Kozma, 2007a; Kozma et al., 2008).

The hierarchical K model based approach is summarized in the 10 "Building Blocks" of neurodynamics (Freeman, 1975, 2001):

1. Non-zero point attractor generated by a state transition of an excitatory population starting from a point attractor with zero activity. This is the function of the KI set.
2. Emergence of damped oscillation through negative feedback between excitatory and inhibitory neural populations. This is the feature that controls the beta–gamma carrier frequency range and it is achieved by KII having low feedback gain.

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

3. State transition from a point attractor to a limit cycle attractor that regulates steady state oscillation of a mixed excitatory–inhibitory KII cortical population. It is achieved by KII with sufficiently high feedback gain.
4. The genesis of broad-spectral, aperiodic/chaotic oscillations as background activity by combined negative and positive feedback among several KII populations; achieved by coupling KII oscillators with incommensurate frequencies.
5. The distributed wave of chaotic dendritic activity that carries a spatial pattern of amplitude modulation (AM) in KIII.
6. The increase in nonlinear feedback gain that is driven by input to a mixed population, which results in the destabilization of the background activity and leads to emergence of an AM pattern in KIII as the first step in perception.
7. The embodiment of meaning in AM patterns of neural activity shaped by synaptic interactions that have been modified through learning in KIII layers.
8. Attenuation of microscopic sensory-driven noise and enhancement of macroscopic AM patterns carrying meaning by divergent–convergent cortical projections in KIV.
9. Gestalt formation and preafference in KIV through the convergence of external and internal sensory signals activates the attractor landscapes leading to intentional action.
10. Global integration of frames at the theta rates through neocortical phase transitions representing high-level cognitive activity in the KV model.

Principles 1 through 7 have been implemented in KIII models and applied successfully in various identification and pattern recognition functions. They serve as the basic steps to create the conditions for higher cognition. Principles 8 and 9 reflect the generation of basic intentionality using KIV sets, which is the target of the present overview. Principle 10 expresses the route to high-level intentionality and ultimately consciousness, which is not addressed at present.

2.3. *KIV model of intentional behavior*

Higher cognition is modeled here using KIV set. KIV is an *intentional dynamical system*, in which meaningful knowledge is continuously created, utilized, and dissipated in the form of sequences of oscillatory patterns of activity modulated by simulated synaptic connections previously modified by learning sensory data (Kozma & Freeman, 2003; Kozma, Freeman, & Erdi, 2003). The oscillatory patterns are often metaphorically viewed as the representations that are used by generalized symbol systems. However, these dynamical symbols are not rigid but flexible, and they dissipate very soon after they appear, within fractions of a second, at theta rate. They are not passively representational symbols; they are dynamic enactive symbols that execute brain commands. Intentionality means in the context of the present approach the cyclic operation of prediction, testing by action, sensing, perceiving, and assimilation by synaptic modification in associative learning. Specifically, non-convergent dynamics continually creates new information in forming new symbols as a source of novel solutions to complex problems. The intermittent hemisphere-wide synchronization–desynchronization cycle is postulated a neurophysiological correlate of intentionality. The proposed dynamical hypothesis on intentionality goes beyond the basic notion of goal-oriented behavior, or sophisticated manipulations with symbolic representations to achieve given goals. Intentionality is endogenously rooted in the agent by reinforcement learning, and it cannot be implanted into it from outside by any external agency.

Fig. 2 illustrates the structure of a KIV model (Kozma & Freeman, 2003). The connections are shown as bidirectional, but they are not reciprocal. Three types of sensory signals can be distinguished. Each of these sensory signals provides stimulus to a given part of the brain, namely the sensory cortices, midline forebrain, and the hippocampal formation, respectively. The corresponding types of sensory signals are listed below: (i) exteroceptors ; (ii) interoceptors, including proprioception from the musculoskeletal system and interoception from the vital organs including the cardiovascular and respiratory systems; (iii) orientation signals. The convergence location and output are provided by the amygdala. KIV has a number of major components, which correspond to functions answering the following key questions: *"What?"* — using sensory cortices, *"Where?"* — By the hippocampal model,*"When?"*—through dynamic encoding of sensory data, and *"Why?"* — using the internal motivation and valence system linked to the amygdala and entorhinal cortex (not shown in Fig. 2). In the present systems, such components are incorporated by design, to address the required functionality. We model the decision making by integrating all the signals from the cortical and hippocampal units into the amygdala.

2.4. *Learning in KIV models*

In order to use the arrays of K sets as novel computational and memory devices, we need to study the effect of learning on the system dynamics. In particular, we need to describe the role of learning and adaptation on phase transitions. The system memory is defined as the collection of basins and attractor wings, and a recall is the induction by a state transition of a spatio-temporal gamma oscillation with a spatial AM pattern. Three learning processes are defined (Kozma & Freeman, 2001):

- Hebbian reinforcement learning of stimulus patterns; this is fast and irreversible, always pair-wise between neurons.
- Habituation of background activity; slow, cumulative, and reversible, and only at the output synapses of neurons activated without reinforcement.
- Normalization of nodal activities to maintain overall stability; very long-range optimization outside local on-line time and extending deeply into real time.

Various learning processes exist in a subtle balance and their relative importance changes at various stages of the memory process. Habituation is an automatic process in every primary sensory area that serves to screen out stimuli that are irrelevant, confusing, ambiguous or otherwise unwanted. It constitutes an adaptive filter that serves to identify "signals" and then to reduce the impact of environmental noise that is continuous and uninformative. It is continually up-dated in a form of learning, and it can be abruptly canceled ("dis-habituation") by novel stimuli and almost as quickly reinstituted ("re-habituation") if the novel stimuli are not reinforced. It is a cortical process that does not occur at the level of sensory receptors. It is modeled by incremental weight decay that decreases the sensitivity to stimuli that are not designated as desired or significant by accompanying reinforcement. Learning effects form a Hebbian nerve cell assembly for each class of stimulus that a subject can discriminate, and they contribute to the formation of convoluted attractor basins, which establish generalization gradients and facilitate phase transitions in the dynamical model at the edge of chaotic activity.

3. Modeling mesoscopic neural populations

3.1. *Neuropercolation approach to population dynamics*

Cognitive models of brain functions can utilize various approaches, e.g., a continuum description of space–time dynamics based on differential equations, or an alternative discrete approach using random graph theory. Neuropercolation is a graph-theoretical approach for neurodynamics (Kozma, Puljic, Balister et al., 2005). Neuropercolation is a generalization of cellular automata, Hopfield memory arrays and Conway's game of life (Berlekamp, 1982; Hopfield, 1982), by merging the concepts of random graph theory (Bollobas, 2001; Erdos & Renyi, 1960) and non-

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

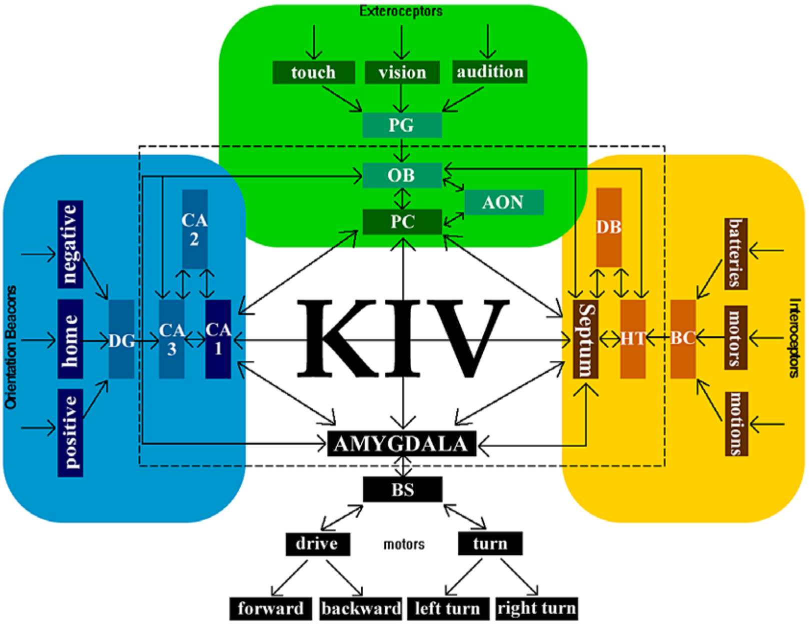


Fig. 2. KIV model of the brain, which consists of three major components: cortex, hippocampal formation, and midline forebrain, shown by green, blue, and yellow in the case of color reproduction. The amygdala striatum and brain stem are at the bottom of the figure and they provide link to the external motor part of the limbic system (Kozma et al., 2007). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

local interactions represented by axonal connections, in the style of neural networks. It bridges the gap between Ising-type models and mean field approaches (Kozma et al., 2005; Kozma, 2007b).

Neuropercolation is a class of probabilistic cellular automata defined as follows (Balister, Bollobas, & Kozma, 2006). We consider the 2-dimensional discrete torus Z_n^2 of size $n \times n$ as a model of the cortical sheet. For $x \in Z_n^2$, let $\|x\| = |x_1| + |x_2|$, where $x = (x_1, x_2)$ and each x_i each is chosen to be at most $n/2$ in modulus. Let $1 \le a < n/2$ and $A = \{x \in Z_n^2 : ||x|| \le a\}$. Each site x can be active or inactive, and there is a rule to update the states of the sites iteratively. The activation of site x will be influenced by the sites in the domain $x + A$, which is also called the a-ball around x. We introduce the *arousal function* r and the *depression* function defined over all subsets of A as follows: $j : P(A) \to [0, 1]$ and r: $P(A) \to [0, 1]$. At time 0, the sites are active with probability p. At each time step t, every site is updated simultaneously according to the following rule. Write S_t for the set of active sites at time t and set

$$B = [S_t \cap (A + x)] - -x = (S_t - x) \cap A.$$

If $x \notin S_t$ (i.e., $0 \notin B$) then x will become active with probability $j(B)$, and if $x \in S_t$ (i.e., $0 \in B$) then x will be deactivated with probability $r(B)$.

The family of random cellular automata is much richer than the family of bootstrap percolations. In particular, if all the probabilities are 0 or 1 we recover the theory of deterministic cellular automata, such as that of Conway's Game of Life. These models are known to be capable of extremely complex behavior. On the other hand, if we choose $j(B), r(B) \neq 0, 1$ for all B then there is no need for an initial probability p, and with a suitable choice of the arousal and depression functions, we may achieve that the system hovers around a certain density of active sites. As a simple example of models with local neighborhoods of 5 nodes ($a = 1$) and

$$j(B) = \{p, \text{ if } |A \cap B| < 3; 1 - p \text{ otherwise}\},$$
$$r(B) = \{p, \text{ if } |A \cap B| > 2; 1 - p \text{ otherwise}\}.$$

In this case the site is active with probability p if at most 2 of the four neighbors and the site itself are active at time $t - 1$. Otherwise the site is inactive with this probability. As we vary p this model shows a phase transition similar to that seen in the Ising model. Results on neuropercolation concern conditions of sustained background activity of neural populations, and conditions leading to band-passed oscillatory spatio-temporal patterns in interacting excitatory–inhibitory populations (Balister et al., 2006; Kozma et al., 2005; Puljic & Kozma, 2008). These models correspond to the hierarchy of K models from K0 up to KIII, while present and future studies aim at neuropercolation implementations of KIV models. Neuropercolation incorporates the following major conditions inferred based neurobiological motivation: interaction with noise, long axon effects, inhibitory effects (Kozma, 2007b).

Interaction with noise: The dynamics of interacting neural populations are inherently non-deterministic due to dendritic noise and other random effects in the nervous tissue and external noise acting on the population. This is expressed by Szentagothai (1978, 1990): "Whenever he is looking at any piece of neural tissue, the investigator becomes immediately confronted with the choice between two conflicting issues: the question of how intricate wiring of the neuropil is strictly predetermined by some genetically prescribed blueprint, and how much freedom is left to chance within some framework of statistical probabilities or some secondary mechanism of trial and error, or selecting connections according to necessities or the individual history of the animal". Neuropercolation includes randomness in the evolution rules, and it is described in random cellular automata and in other models. Randomness plays a crucial role in neuropercolation models. The situation resembles the case of stochastic resonance (Bulsara & Gammaitoni, 1996; Kosko, 2006; Moss & Pei, 1995). An important difference from chaotic resonance is the more intimate relationship between noise and the system dynamics, due to the excitable nature of the neuropil (Kozma & Freeman, 2001; Kozma et al., 2003).

Long axon effects: Neural populations stem ontogenetically in embryos from aggregates of neurons that grow axons and dendrites and form synaptic connections of steadily increasing density. At some threshold the density allows neurons to transmit more pulses than they receive, so that an aggregate undergoes a

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

state transition from a zero point attractor to a non-zero point attractor, thereby becoming a population. In neural populations, most of the connections are short, but there are a relatively few long-range connections mediated by long axons (Das & Gilbert, 1995). The effects of long-range axons are related to small-world phenomena (Watts & Strogatz, 1998) and it is part of the neuropercolation model.

Inhibition: The cortical tissue contains two basic types of interactions: excitatory and inhibitory ones. Inhibition contributes to the emergence of sustained narrow-band oscillatory behavior in the neural tissue (Aradi, Barna, & Erdi, 1995; Arbib, Erdi, & Szentagothai, 1997). Inhibition is key in various brain structures; e.g., hippocampal interneurons are almost exclusively inhibitory (Freund & Buzsaki, 1996). Inhibition is inherent in cortical tissues and it controls stability and metastability observed in brain behaviors (Kelso, 1995; Kelso & Engstrom, 2006). Inhibitory effects are part of neuropercolation models.

In local models, a rigorous proof has been found of the fact that for extremely small noise levels the model spends a long time in either low- or high-density configurations before the very rapid transition to the other state (Balister et al., 2006). Fairly good bounds have been found on the very long time the model spends in the two essentially stable states and on the comparatively very short time it takes to cross from one essentially stable state to another. The behavior of the lattice models differs from that in the mean field model in the manner of these transitions. For the mean field model, transitions typically occur when random density fluctuations result in about one half of the states being active. When this occurs, the model passes through a configuration which is essentially symmetric between the low- and high-density configurations, and is equally likely then to progress to either one. Mean field models have at least one stable fixed point and can have several stable and unstable fixed points, limit cycles, and chaotic oscillations. In the lattice models, certain configurations with very low density can have a large probability of leading to the high-density configuration, and transitions from low to high density typically occur via one of these non-symmetric configurations. As opposed to mean field models, analytical solution is not available for the local and mixed local mean field models, in which case computer simulations are used to study these systems. Finite size scaling theory of statistical physics is applied to characterize the observed critical behavior which indicates the presence of a weak-Ising universality class (Puljic & Kozma, 2005, 2008).

3.2. ODE based approach to neural populations

KIV models have been implemented using the solution of a set of ordinary differential equations with distributed coefficients using the Runge–Kutta method. The model solves the differential equations using a fixed time step of 0.5 ms, which gives sufficient accuracy for the studied neural processes (Freeman et al., 2001). A Matlab Neurodynamics Toolbox package with the hierarchy of K sets from KO up to KIII, is available on-line at the Computational NeuroDynamics Lab site (Beliaev, Ilin, & Kozma, 2005).

The basic K-unit, called K0 set, models a neuron population of about 10^4 neurons. Its dynamics are governed by a second order ordinary differential equation (Freeman, 1975):

$$(a * b)\frac{\mathrm{d}^2 P(t)}{\mathrm{d}^2 t} + (a + b)\frac{\mathrm{d}P(t)}{\mathrm{d}t} + P(t) = F(t). \qquad (1)$$

Here a and b are biologically determined time constants; $a = 0.22$, $b = 0.72$. $P(t)$ denotes the activation of the node as function of time; $F(t)$ is the summed activation from neighbor nodes and any external input. The K0 set has a weighted input and an asymptotic sigmoid function for the output. The sigmoid function $Q(x)$ is given by the equation:

$$Q(x) = q * \left\{1 - \exp\left(-\frac{1}{q(\mathrm{e}^x - 1)}\right)\right\} \qquad (2)$$

where $q = 5$, is the parameter specifying the slope and maximal asymptote of the curve. Coupling two or more K0 sets with excitatory connections, we get a KI. The next step in the hierarchy is the KII model. KII is a double layer of excitatory and inhibitory units. In the simplest architecture there are 4 nodes: two excitatory, denoted e, and two inhibitory, denoted i, nodes. The excitatory and inhibitory nodes in a KII set are arranged in corresponding layers, so KII has a double-layer structure. Given proper initial conditions, this model may produce sustained periodic oscillations the frequency and magnitude of which are determined by the interconnection weights between units. KIII consists of three double layers of KII sets that are connected with no-delay feed-forward connections and delayed feed-back connections. Properly tuned KIII models typically exhibit non-convergent chaotic behavior due to the competition of KII oscillators. KIII is the model of sensory cortices. Finally, several KIII and/or KII sets form the multi-sensory KIV set, as shown in Fig. 2. KIV is capable of exhibiting intermittent spatio-temporal synchronization, as the result of interacting chaotic KIII and KII oscillatory units.

The operation of the KIV model has three major phases: learning, labeling and control (Kozma et al., 2003). At the learning phase, the input data are presented to the system using a predefined strategy. In the presence of positive reinforcement signal, learning occurs in the KIII unit. We apply positive reinforcement when KIV produces a correct decision, i.e., it moves towards the specified goal state. On the other hand, KIII learning can use negative reinforcement when the sensory data indicate undesirable conditions. Reinforcement learning is implemented using the Hebbian correlation rule in KIII units. During the labeling phase no learning takes place. Instead, KIV collects reference activation patterns from the decision module. Typically a handful of possible activation patterns are considered, corresponding to potential actions. At the control phase, these reference patterns are used to make decision on the direction of the next step.

4. Macroscopic generation of large-scale phase transitions

4.1. Phase transitions in neuropercolation

Phase transitions play a central role in our cognition model, embodying the idea of an emergent computation that progresses by a staccato trajectory through the high-dimensional attractor space that constitutes the memory/knowledge store of the brain. During phase transitions, mesoscopic dynamic structures of cooperative activity dissolve, and the component neurons enter a state of uniform randomness that is symmetric. This disorder is due to the precipitous reduction in cooperative activity, the order parameter, which is manifested by a sudden decrease in brain wave amplitude. This indicates spontaneous symmetry breaking near the critical state.

Several key factors have been identified that determine phase transitions in the neuropercolation models, including: endogenously generated noise, structure and extent of non-locality of neural populations (long axons), sparseness of inhibitory links. The resulting tools have been used to study the intricate complexity of various dynamic behaviors of neural populations (Kozma, Puljic, & Perlovsky, 2009; Puljic & Kozma, 2005). Neuropercolation gives a mathematical framework for systematic studies of phase transitions in neural populations.

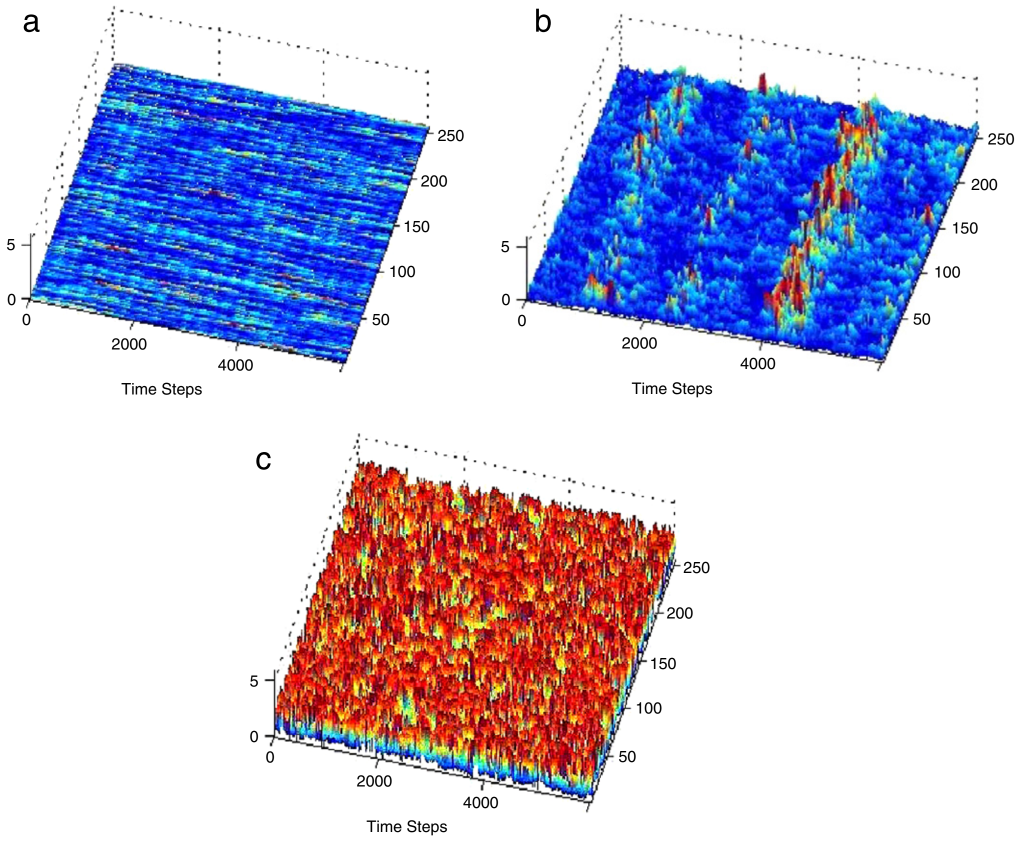


Fig. 3. Intermittent synchronization in the neuropercolation model as the function of the system noise level; the noise changes from 13%, 15%, and 16% on figures (a), (b), and (c), respectively. Intermittent synchronization–desynchronization is seen at critical noise level 15% in figure (b) (Kozma et al., 2009).

The behavior of the neuropercolation model with excitatory and inhibitory nodes is illustrated on Fig. 3. Due to the negative feedback, these models can generate sustained limit cycle and non-periodic oscillations, similar to the behavior observed in models based on coupled ODEs. At certain critical parameter values, the behavior of the system changes suddenly, which is described as a phase transition (Kozma et al., 2005). Subcritical and supercritical behaviors are separated by critical parameter combinations. The spatial distribution of synchronization shows that the subcritical regime is characterized by rather uniform synchronization patterns. On the other hand, the supercritical regime shows high-amplitude, unstructured oscillations.

Near critical parameters, intermittent oscillations emerge, i.e., relatively quiet periods of weak oscillations followed by periods of intensive oscillations in the synchronization. This type of behavior is observed qualitatively in EEG and ECoG arrays as illustrated in Fig. 1, and it is postulated as a neurodynamic correlate of intentionality. The degree of sparseness of connectivity to and from inhibitory populations acts as a control parameter, in addition to the system noise level and the rewiring ratio. The system shown in Fig. 3(a)–(c) has a few % of connectivity between excitatory and inhibitory units.

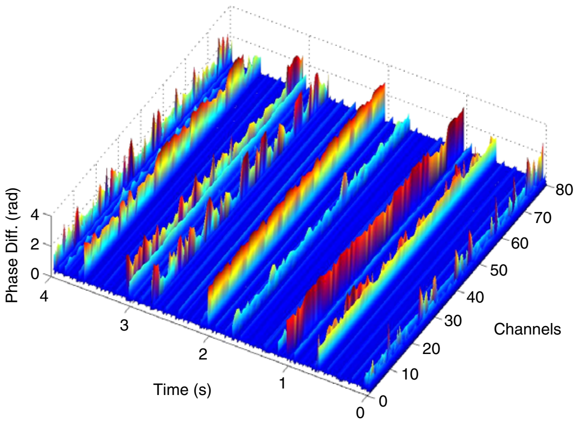


Fig. 4. Illustration of simulations with a KIV model of the hemisphere; phase differences are shown in the entorhinal cortex across time and space (80 spatial nodes). The intermittent desynchronization periods for a large part of the array are clearly seen (Kozma & Myers, 2005).

4.2. *Simulation of phase transitions in ODE models*

In a set of experiments, we used a simulated autonomous agent moving in a 2-dimensional environment. During its movement, the agent continuously receives two types of sensory data: (1) distance to obstacles; (2) and orientation toward some preset goal location. KIV makes decisions about its actions toward the goal. The sensory-control mechanism of the system is a simple KIV set using two sensory channels (KIII sets) and the amygdala as the convergence region for decisions (KII set) (Kozma & Myers, 2005; Voicu et al., 2004). We analyze the activation of the amygdala and find sudden changes in its spatio-temporal dynamics, identified as phase transitions.

Results show the existence of brief periods with sudden changes in the simulated EEG activity, which are in qualitative agreement with properties of metastable AM patterns observed in cortical EEG data. Cognitive processing utilizes global phase jumps to cortico-cortical communication across the hemisphere at high speed. An example of the calculated analytical phase differences is shown on Fig. 4, for a simulated period of 4 s and amygdala array consisting of 80 nodes. The intermittent

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

desynchronization is clearly seen at a rate of several times per second. These results indicate that the KIV model is indeed a suitable level of abstraction to grasp essential properties of cortical phase transitions as evidenced in intracranial and scalp EEG and MEG data.

5. Discussion

With the advent of the digital computer more than half a century ago, researchers working in a wide range of scientific disciplines have obtained an extremely powerful tool to pursue a deep understanding of natural processes in physical, chemical, and biological systems. Computers pose a great challenge to mathematical sciences, as the range of phenomena available for rigorous mathematical analysis has been enormously expanded, demanding the development of a new generation of mathematical tools. Mathematics have progressed intensively in the past centuries, and it generated outstanding theories originating from practical needs, and produced powerful tools for the technical challenges faced by the society. Functional analysis and calculus lead the way in practical implementations, using tools of differential equations. Differential equations have a huge variety of types, such as ordinary and partial, linear and nonlinear, deterministic and stochastic. They manifest high-level abstraction and provide excellent examples of the finest mathematical theories. There is, however, a critical mismatch between the powerful computational tools and the mathematical models dominated by the formalism of differential equations. Mathematical theories provide existence conditions for solutions in various conditions, but most of the practical problems have complexity that demand differential equations which do not have analytic solutions, therefore various approximations are required. These issues lead to the problem of computational complexity, which often prevent obtaining practically meaningful solutions within given constraints. To provide solutions to these complex problems, there is a need for a breakthrough and paradigm shift in scientific thinking, in particular in mathematics, comparable to the one Newton and other outstanding mathematicians of his age brought about over three hundred years ago. The theory of large-scale networks and random graphs arguably can provide help in creating the conditions for the breakthrough.

In contrast to the digital computer memories presently used, where information is encoded in the form of a string of binary digits, we propose a novel approach, in which the encoding is embodied in oscillations of the activity of the memory nodes. Biological evidence suggests that sensory information encoded by receptors activates the retrieval of memories in the form of oscillatory patterns is advantageous compared to convergent, fixed-point-type memories. These oscillatory patterns of neural activity serve as enactive symbols in cortical dynamics. We implement this approach using neurodynamics principles embodied in Freeman's K set theory, with the highest level at present having the KIII and KIV models. The approach is strongly biologically motivated and based on the observation that humans and animals can solve difficult identification tasks fast and with high accuracy based on limited and noisy information.

We have introduced two types of models to implement the developed the theory of chaotic dynamics of the cerebral cortex, namely, based on ordinary differential equations and on random graph theory, respectively. In our approach, these two implementations played different roles. The differential equation based approach has produced the high-level KIV model, which is an example of an operational chaotic memory neural network demonstrating multi-sensory integration and decision support. Theoretical and numerical studies of the integrated system yielded a landscape of aperiodic attractors in the basal state. Each attractor corresponds to a class of stimuli that the agent was capable of discriminating. Its basin of attraction corresponds to its range of generalization. Capture of the trajectory in a higher dimension confined the agent to a lower dimension. Convergence to the attractor constituted abstraction from the properties of the stimulus to the properties of the class. These features solve the classic psychological problems of generalization and abstraction over equivalent stimuli.

Neuropercolation theory at present is constrained to the equivalent of KII and KIII sets. It has been used to build a solid mathematical theory of dynamical memories using phase transitions in lattices. When an input pattern is presented to the model, the aperiodic oscillations undergo a phase transition and the trajectory is switched to a localized memory wing. In this framework, the memory and classification process can be described as percolation phenomenon of percolation through the neuropil medium. These conclusions are underpinned by numerous simulations and by precise mathematical results.

The work described here has important implication on interpreting neurobiology observations and in computer modeling of brains and neural networks. However, the breakthrough is so far mainly in biology and computation. What is now needed, and only just starting, is the application of mathematical tools to describe rigorously and understand the behavior of the model. This can lead to large-scale models of higher brain functions, which is applicable in computational neuroscience and also in the implementation of these biological principles in practical artificially intelligent designs.

6. Conclusions

In the past decades, intensive research has been conducted on emergent behavior in complex systems, including biological systems, and it is concerned with the very nature of life and intelligence. The forefront of research touches the boundaries of human cognitive functions and consciousness, both in individuals and in populations of individuals. Methods of discrete mathematics, probabilistic combinatorics, random graph theory and statistical physics are proving to be especially useful in analyzing such complex phenomena. The goal of this work is to pose these exciting problems and to describe several methods available for the description and analysis of large-scale, complex structures, including ordinary differential equations and random graph theory. Our approach is strongly motivated by biology, and strongly related in particular to higher brain functions, as cognition and decision.

Complex decision support systems must provide quick response to sudden changes in the environment. Data must be processed from high-dimensional, heterogeneous sensor resources. Due to the complexity of the problem, this requires integration of often contradictory information. The present work is based on recent progress on phase transitions in brains using advanced, high-resolution spatio-temporal EEG measurements (Freeman et al., 2003; Freeman, 2007). Large-scale synchronization in the cortex, interrupted intermittently by short periods of desynchronization through phase transitions, is an emergent property of the cortex as a unified organ. The intermittent synchronization–desynchronization cycle is the manifestation of intentionality as observed in brains.

We designed computational KIV models which manifest dynamical behaviors attributed to intentionality in brains. Simulated EEG signals generated by the KIV model are analyzed and show striking similarity to biological EEG signals, in particular concerning sudden transitions in spatio-temporal oscillation patterns. The KIV system integrates the sensor information and provides the basis for decision making. Decisions are made between various potential scenarios and actions are executed accordingly. The integrated system cumulatively creates and learns its internal model,

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

and adapts it based on the error between model prediction and actual data.

The obtained results can be used for designing a multi-purpose decision support system, in which information is not passively received and reactively utilized but proactively predicted and immediately integrated into associative memory. Assigned goals and guidelines serve as constraints in the knowledge base available *a priori*for the system. The KIV model demonstrates this intentional dynamics and it is a candidate for implementing intentionality and robust decision making in artificial systems.

Acknowledgements

This work is supported in part by the Air Force Office of Scientific Research through a grant to one of the authors (RK). Part of this work has been completed while RK was with the Air Force Research Laboratory, Sensors Directorate, Hanscom AFB, MA, with the support of a National research Council NRC Senior Fellowship. Useful discussions with Dr. Leonid Perlovsky are greatly appreciated.

References

Aradi, I., Barna, G., & Erdi, P. (1995). Chaos and learning in the olfactory bulb. *International Journal of Intelligent Systems*, *10*(1), 89–117.

Arbib, M. A., Erdi, P., & Szentagothai, J. (1997). *Neural organization: Structure, function, dynamics*. Cambridge, MA: MIT Press.

Baars, B. J. (1988). *A cognitive theory of consciousness*. MA: MIT Press.

Balister, P., Bollobas, B., & Kozma, R. (2006). Large deviations for mean field models of probabilistic cellular automata. *Random Structures & Algorithms*, *29*, 399–415.

Barraclough, D., Conroy, M., & Lee, D. (2004). Prefrontal cortex and decision making in a mixed-strategy game. *Nature Neuroscience*, *7*(2), 404–410.

Barrie, J. M., Freeman, W. J, & Lenhart, M. (1996). Spatiotemporal analysis of prepyriform, visual, auditory, and somesthetic surface EEGS in trained rabbits. *Journal of Neurophysiology*, *76*, 520–539.

Bechara, A., Damasio, H., Tranel, D., & Anderson, S. W. (1998). Dissociation of working memory from decision making within the human prefrontal cortex. *Journal of Neuroscience*, *18*, 428–437.

Bechara, A., Damasio, H., & Damasio, A. R. (2000). Emotion decision making and the orbitofrontal cortex. *Cerebral Cortex*, *10*(1), 295–307.

Beliaev, I., Ilin, R., & Kozma, R. (2005). Nonlinear neurodynamics tool for system analysis and application for time series prediction. In *Proceedings IEEE 2005 Systems, Man, & Cybernetics Conference. Vol. 2 (pp. 1011–1016)*.

Beliaev, I., & Kozma, R. (2007). Time series prediction using chaotic neural networks on the CATS benchmark. *Neurocomputing*, *70*(13–15), 2426–2439.

Berlekamp, E. R. (1982). *Winning ways for your mathematical plays, 1: Games in general*. NY: Acad. Press.

Bishop, C. (2006). *Pattern recognition and machine learning*. Springer.

Bollobas, B. (2001). *Random graphs* (2nd Ed.). UK: Cambridge University Press.

Bressler, S. L. (2003). Cortical coordination dynamics and the disorganization syndrome in schizophrenia. *Neuropsychopharmacology*, *28*, S35–S39.

Bressler, S. L., & Kelso, J. A. S. (2001). Cortical coordination dynamics and cognition. *Trends in Cognitive Sciences*, *5*, 26–36.

Bressler, S. L. (2002). Understanding cognition through large-scale cortical networks. *Current Directions in Psychological Sciences*, *11*, 58–61.

Bulsara, A., & Gammaitoni, L. (1996). Tuning in to noise. *Physics Today March*, 39–45.

Chang, H. J., Freeman, W. J., & Burke, B. C. (1998). Optimization of olfactory model in software to give $1/f$ power spectra reveals numerical instabilities in solutions governed by aperiodic (chaotic) attractors. *Neural Networks*, *11*, 449–466.

Damasio, A. R., Everitt, B. J., & Bishop, D. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex. *Philosophical Transactions of the Royal Society B*, *351*(1346), 1413–1420.

Das, A., & Gilbert, C. D. (1995). Long-range horizontal connections and their role in cortical reorganization revealed by optical recording of cat primary visual cortex. *Nature*, *375*, 780–784.

Dayan, P., & Daw, N. D. (2008). Decision theory, reinforcement learning, and the brain. *Cognitive, Affective, & Behavioral Neuroscience*, *8*(2), 429–453.

Erdos, P., & Renyi, A. (1960). On the evolution of random graphs. *Publications Mathematical Institute of the Hungarian Academy of Sciences*, *5*, 17–61.

Fingelkurts, A. A., & Fingelkurts, A. A. (2001). Operational architectonics of the human brain biopotential field: Towards solving the mind-brain problem. *Brain & Mind*, *2*, 261–296.

Fingelkurts, A. A., & Fingelkurts, A. A. (2004). Making complexity simpler: Multivariability and metastability in the brain. *International Journal of Neuroscience*, *114*, 843–862.

Frank, M. J., & Claus, E. D. (2006). Anatomy of a decision: Striato-orbitofrontal interactions in reinforcement learning decision making, and reversal. *Psychological Review*, *113*(2), 300–326.

Freeman, W. J. (1975). *Mass action in the nervous system*. NY: Acad. Press.

Freeman, W. J. (2001). *How brains make up their minds*. New York: Columbia University Press.

Freeman, W. J., Kozma, R., & Werbos, P. J. (2001). Biocomplexity: Adaptive behavior in complex stochastic dynamical systems. *BioSystems*, *59*(2), 109–123.

Freeman, W. J., Burke, B., & Holmes, M. (2003). Aperiodic phase re-setting in scalp EEG of beta–gamma oscillations by state transitions at alpha–theta rates. *Human Brain Mapping*, *19*, 248–272.

Freeman, W. J. (2005). Origin structure, and role of background EEG activity. Part 3. Neural frame classification. *Clinical Neurophysiology*, *116*, 1118–1129.

Freeman, W. J. (2007). Proposed cortical 'shutter' mechanism in cinematographic perception. In L. Perlovsky, & R. Kozma (Eds.), *Neurodynamics of cognition and consciousness* (pp. 11–38). Springer.

Freund, T. F., & Buzsaki, G. (1996). Interneurons of the hippocampus. *Hippocampus*, *6*, 347–470.

Harter, D., & Kozma, R. (2005). Chaotic neurodynamics for autonomous agents. *IEEE Transactions on Neural Networks*, *16*(2), 565–579.

Haykin, S. (1998). *Neural networks – A comprehensive foundation*. Prentice Hall.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences USA*, *79*, 2554–2558.

Houk, J. C., & Wise, S. P. (1995). Distributed modular architectures linking basal ganglia cerebellum, and cerebral cortex: Their role in planning and controlling action. *Cerebral Cortex*, *5*, 95–110.

Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. MIT Press.

Kelso, J. A. S., & Engstrom, D. A. (2006). *The complementary nature*. MIT Press.

Korn, H., & Faure, P. (2003). Is there chaos in the brain II. Experimental evidence and related models. *Comptes Rendus Biol*, *326*(9), 787–840.

Kosko, B. (2006). *Noise*. Viking Press.

Kozma, R. (1998). Intermediate-range coupling generates low-dimensional attractors deeply in the chaotic region of one-dimensional lattices. *Physics Letters A*, *244*(1–3), 85–91.

Kozma, R., & Freeman, W. J. (2001). Chaotic resonance – Methods and applications for robust classification and of noisy and variable patterns. *International Journal of Bifurcation & Chaos*, *11*, 1607–1629.

Kozma, R., & Freeman, W. J. (2003). Basic principles of the KIV model and its application to the navigation problem. *Journal of Integrative Neuroscience*, *2*(1), 125–146.

Kozma, R., Freeman, W. J., & Erdi, P. (2003). The KIV model – Nonlinear spatio-temporal dynamics of the primordial vertebrate forebrain. *Neurocomputing*, *52–54*, 819–826.

Kozma, R., Puljic, M., Balister, P., et al. (2005). Phase transitions in the neuropercolation model of neural populations with mixed local and non-local interactions. *Biological Cybernetics*, *92*(6), 367–379.

Kozma, R., & Tunstel, E. (2005). A novel approach to distributed sensory networks using biologically-inspired sensory fusion. In *Proceedings IEEE 2005 Systems, Man, & Cybernetics Conference. Vol. 2 (pp. 1005–1010)*.

Kozma, R., & Muthu, S. (2004). Implementing reinforcement learning in the chaotic KIV model using mobile robot AIBO. In *Proceedings IEEE/RSJ Intelligent Robots and Systems. Vol.3 (pp. 2337–2342)*.

Kozma, R., & Myers, M. (2005). Analysis of phase transitions in KIV with amygdala during simulated navigation control. *Proceedings IEEE/INNS Joint Conference on Neural Networks*, 125–130. Montreal, Canada.

Kozma, R. (2007a). Intentional systems: Review of neurodynamics modeling, and robotics implementations. *Physics of Life Reviews*, *5*(1), 1–21.

Kozma, R. (2007b). Neuropercolation. *Scholarpedia*, *2*(8), 1360.

Kozma, R., Huntsberger, T., Aghazarian, H., Tunstel, E., Ilin, R., & Freeman, W. J. (2008). Intentional control for planetary rover SRR. *Advanced Robotics*, *22*(12), 1309–1327.

Kozma, R., Puljic, M., & Perlovsky, L. (2009). Modeling goal-oriented decision making through cognitive phase transitions. *New Mathematics & Natural Computation*, *5*(1), 143–158.

Le Doux, J. E. (2000). Orbitofrontal cortex and basolateral amygdala encode expected outcomes during learning. *Annual Reviews Neuroscience*, *23*, 155–184.

Levine, D. (2009). Brain pathways for cognitive-emotional decision making in the human animal. *Neural Networks*, in this issue (doi:10.1016/j.neunet.2009.03.003) (Contribution to this Special Issue).

Lehmann, D., Strik, W. K., Henggeler, B., Koenig, T., & Koukkou, M. (1998). Brain electric microstates and momentary conscious mind states as building blocks of spontaneous thinking: I Visual imagery and abstract thoughts. *International Journal of Psychophysiology*, *29*, 1–11.

Le Van Quyen, M., Boucher, J., et al. (2001). Comparison of Hilbert transform and wavelet methods for the analysis of neuronal synchrony. *Journal of Neuroscience Methods*, *111*, 83–98.

Li., G., Lou, Z., Wang, L., Li, X., & Freeman, W. J. (Eds.) (2006). *LNCS*: *Vol. 3610*. *Face recognition using a neural network simulating olfactory systems* (pp. 378–381). Springer.

Liang, H., & Wang, H. (2003). Top-down anticipatory control in prefrontal cortex. *Theory in Biosciences*, *122*(1), 70–86.

Makeig, S., Debener, S., Onton, J., & Delorme, A. (2004). Mining event-related brain dynamics. *Trends in Cognitive Sciences*, *8*(5), 204–210.

Moss, F., & Pei, X. (1995). Stochastic resonance — neurons in parallel. *Nature*, *376*, 211–212.

Ohl, F. W., Scheich, H., & Freeman, W. J. (2001). Change in pattern of ongoing cortical activity with auditory category learning. *Nature*, *412*, 733–736.

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019

Ohl, F. W., Deliano, M., Scheich, H., et al. (2003). Early and late patterns of stimulus-related activity in auditory cortex of trained animals. *Biological Cybernetics*, *88*, 374–379.

O'Reilly, R. C., & Frank, M. J. (2006). Making working memory work: A computational model of learning in the frontal cortex and basal ganglia. *Neural Computation*, *18*, 283–328.

Perlovsky, L., & Kozma, R. (Eds.) (2007). *Neurodynamics of higher-level cognition and consciousness*. Heidelberg, Germany: Springer Verlag.

Puljic, M., & Kozma, R. (2005). Activation clustering in neural and social networks. *Complexity*, *10*(4), 42–50.

Puljic, M., & Kozma, R. (2008). Narrow-band oscillations in probabilistic cellular automata. *Physical Reviews E*, *78*, 026214.

Ruiz, Y., Li, G., Gonzales, E., & Freeman, W. J. (2009). Detecting stable phase structures of EEG signals to study brain activity amplitude patterns. *Journal of Zhejiang University* (in press).

Shawe-Taylor, J., & Cristianini, N. (2004). *Kernel methods for pattern analysis*. Cambridge, UK: Cambridge University Press.

Skarda, C., & Freeman, W. J. (1987). How brains make chaos in order to make sense of the world. *Behavioral & Brain Sciences*, *10*, 161–195.

Stam, C. J., Breakspear, M., Cappellen,, et al. (2003). Nonlinear synchronization in EEG and whole-head MEG recordings of healthy subjects. *Human Brain Mapping*, *19*, 63–78.

Szentagothai, J. (1978). Specificity versus (quasi-) randomness in cortical connectivity. In M. A. B. Brazier, & H. Petsche (Eds.), *Architectonics of the cerebral cortex connectivity* (pp. 77–97). New York: Raven Press.

Szentagothai, J. (1990). Specificity versus (quasi-) randomness revisited. *Acta Morphologica Hungarica*, *38*, 159–167.

Tsuda, I. (2001). Toward an interpretation of dynamic neural activity in terms of chaotic dynamical systems. *Behavioral & Brain Sciences*, *24*(5), 793–810.

Vapnik, V. N. (1998). *Statistical learning theory*. New York: Wiley.

Voicu, H., Kozma, R., Wong, D., & Freeman, W. J. (2004). Spatial navigation model based on chaotic attractor networks. *Connection Science*, *16*(1), 1–19.

Von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. NJ: Princeton University Press.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature*, *393*, 440–442.

Werbos, P. J. (2009). Intelligence in the brain: A theory of how it works and how to build it. *Neural Networks*, in this issue (doi:10.1016/j/neunet.2009.03.012) (Contribution to this Special Issue).

Werner, G. (2007). Metastability, criticality and phase transitions in brain and its models. *BioSystems*, *90*(2), 496–508.

Zhang, J. (2009). Adaptive learning via selectionism and bayesianism part I: connection between the two. *Neural Networks*, in this issue (doi:10.1016/j.neunet.2009.03.018) (Contribution to this Special Issue).

Zhou, W., & Coggins, R. (2002). Computational models of the amygdala and the orbitofrontal cortex. In R. I. McKay, & J. Slaney (Eds.), *Lecture Notes AI: LNAI*: *Vol. 2557*. *A hierarchical reinforcement learning system for robotic control.* (pp. 419–430).

Please cite this article in press as: Kozma, R., & Freeman, W. J. The KIV model of intentional dynamics and decision making. Neural Networks (2009), doi:10.1016/j.neunet.2009.03.019