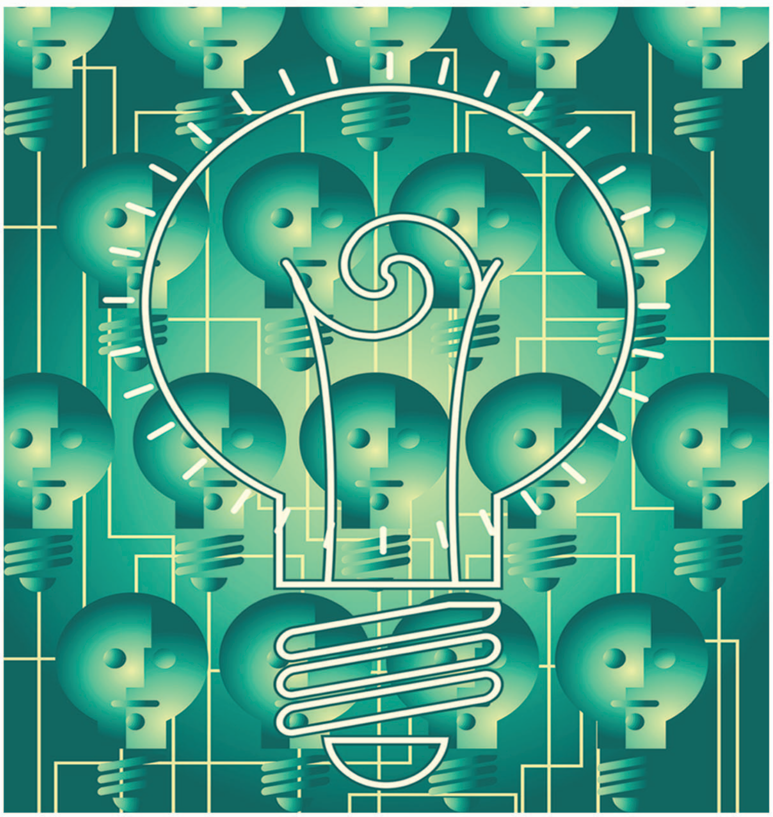
Robert Kozma
University of Memphis and US Air Force Research Laboratory, USA
Hrand Aghazarian, Terry Huntsberger, and Eddie Tunstel
NASA Jet Propulsion Laboratory, USA
Walter J. Freeman, *University of California at Berkeley, USA*

Computational Aspects of Cognition and Consciousness in Intelligent Devices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Abstract: We review computational intelligence methods of sensory perception and cognitive functions in animals, humans, and artificial devices. Top-down symbolic methods and bottom-up sub-symbolic approaches are described. In recent years, computational intelligence, cognitive science and neuroscience have achieved a level of maturity that allows integration of top-down and bottom-up approaches in modeling the brain. Continuous adaptation and learning is a key component of computationally intelligent devices, which is achieved using dynamic models of cognition and consciousness. Human cognition performs a granulation of the seemingly homogeneous temporal sequences of perceptual experiences into meaningful and comprehensible chunks of concepts and complex behavioral schemas. They are accessed during action selection and conscious decision making as part of the intentional cognitive cycle. Implementations in computational and robotic environments are demonstrated.

In memoriam of Homayoun Seraji (1947–2007)

Prologue on multisensory percepts as attributes of higher cognition and consciousness:

> *"And suddenly the memory revealed itself. The taste was that of the little piece of madeleine which on Sunday mornings [...] my aunt Leonie used to give me, dipping it first in her own cup of tea or tisane. The sight of the little madeleine had recalled nothing to my mind before I tasted it; perhaps because I had so often seen such things in the meantime, without tasting them, [...]; perhaps because, of those memories so long abandoned and put out of mind, nothing now survived, everything was scattered; the shapes of things, including that of the little scallop-shell of pastry [...] were either obliterated or had been so long dormant as to have lost the power of expansion which would have allowed them to resume their place in my consciousness. But when from a long-distant past nothing subsists, after the people are dead, after the things are broken and scattered, taste and smell alone, more fragile but more enduring, more immaterial, more persistent, more faithful, remain poised a long time, ..."*
>
> *From "In search of lost time" by Marcel Proust (1913)*

1. Introduction to Models of Cognition and Consciousness

Intelligent behavior is characterized by the flexible and creative pursuit of endogenously defined goals. Humans are not passive receivers of perceptual information. They actively search for sensory input. To do

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Intelligent behavior is characterized by the flexible and creative pursuit of endogenously defined goals. Humans are not passive receivers of perceptual information. They actively search for sensory input.

so they must form hypotheses about expected future states, and express these as goals. They must formulate a plan of exploration and action, and they must inform their sensory and perceptual apparatus about the expected future input in a process called re-afference. They must manipulate their sense organs, take information in the form of samples from all of their sensory ports, then generalize, abstract, categorize, and combine into multisensory percepts (Gestalts). This cyclic operation of prediction, testing by action, sensing, perceiving, and assimilation is called intentionality (Freeman, 2001). The archetypal form of intentional behavior is an act of observation through time and space, by which information is sought for the guidance of future action. Sequences of such acts constitute key components of increasingly complex cognitive functions. Previous works on a variety of cognitive and behavioral paradigms were restricted to symbolic manipulation of the available data.

Symbolic approaches to knowledge and cognition proved to be powerful concepts dominating the field from the 60s through the 80s. The physical symbol system hypothesis illustrates key components of the symbolic approach (Newell & Simon, 1972; Newell 1980, 1990). According to this hypothesis, a physical symbol system has the necessary and sufficient means for intelligent action. In practical terms this means that the types of syntactic manipulation of symbols found in formal logic and formal linguistic systems typify this view of cognition. In this viewpoint, external events and perceptions are transformed into inner symbols to represent the state of the world. This inner symbolic code stores and represents all of the system's long-term knowledge. Actions take place through the logical manipulation of these symbols. This way, solutions are found for current problems presented by the environment. Problem solving takes the form of a search through a problem space of symbols, and the search is performed by logical manipulation of symbols through predefined operations (copying, conjoining, etc.). These solutions are implemented by forming plans and sending commands to the motor system to execute the plans to solve the problem. According to symbolic viewpoint, intelligence is typified by and resides at the level of deliberative thought. Modern examples of systems that fall within this paradigm include SOAR (Laird et al, 1987) and ACT-R (Anderson et al., 1977).

The symbolic approach models certain aspects of cognition and it is capable of providing many examples of intelligent behavior. However, challenges to this viewpoint of cognition have appeared. On the practical side, symbolic models are notoriously inflexible and difficult to scale up from small and constrained environments to real world problems. Dreyfus' situated intelligence approach is a prominent example of a philosophical alternative to symbolism. Dreyfus ascertains that intelligence is defined in the context of the environment. Therefore, a preset and fixed symbol system can not grasp the essence of intelligence (Dreyfus, 1992). Pragmatic implementations of situated intelligence find their successful applications in the field of embodied intelligence and robotics (Brooks, 1999).

Consciousness has been studied extensively using scientific methods in recent years and various neurophysiologic correlates of consciousness have been identified, based on evoked potentials, EEG, MEG, fMRI and other methods. According to the popular theory by Baars (1988), consciousness arises from the competition of the coalitions of populations of attention agents. This competition takes place over the global workspace of attentions, thus called the global workspace theory. Once a coalition gains dominance, it attracts the 'spotlight' in the 'theater of consciousness' and rises to consciousness. All other coalitions are informed about this event through a process called conscious broadcast through the workspace. Once the conditions of the global competition are changed, the spotlight fades, the winning coalition loses dominance, and the competitive process starts again. Potential evidences of behaviors described by Global Workspace theory in neural processes have been identified in the form of sudden transitions in synchronization patterns that spontaneously emerged in the background brain waves recorded in the EEG (Freeman, 2003).

During the past years, consensus has emerged in the literature about the existence of sudden jumps in measured cortical activities. Lehmann et al. (1998) identifies "micro-sates" in brain activity and jumps between them. Rapid switches in EEG activity have been described by Stam et al. (2004) and Fingelkurtz & Fingelkurtz (2001, 2004). Synchronization of neural electrical activity while completing cognitive tasks is studied in various animals, e.g., in cats, rabbits, gerbils, and macaque monkeys (Barrie et al, 1996; Ohl, et al, 2001, 2003, Freeman et al, 2003; Bressler, 2003). Behavioral correlates of transitions between metastable cortical states have been identified (Kelso, 1995; Bressler, Kelso, 2001; Bressler, 2002; Kelso and Engstrom, 2006). Comprehensive overview of stability, metastability, and transitions in brain activity is given by Le Van Quyen et al. (2003), Werner (2006).

Connectionist view of cognition provides a complementary theory of the mind with respect to the symbolic approach. Connectionist models emphasize parallel-distributed processing, while symbolic systems tend to process information in a serial fashion. Connectionist approaches represent adaptive and distributed structures, while symbols are typically static, localized structures. Connectionist models offer many attractive features when compared with standard symbolic approaches. They have a level of biological plausibility absent in symbolic models that allows for easier visualization of how brains might process information. Parallel-distributed representations are robust and flexible. They allow for pattern completion and generalization performance. They are capable of adaptive learning. In short, connectionism provides a useful model of cognition, which is in many ways complementary to symbolic approaches. Significant efforts have been devoted to combine the advantages of both approaches (Towell and Shavlik, 1994). Clark (2001) categorizes modern connectionism into three generations. We add the fourth generation, reflecting the newest development in the field (see Box 1).

2. Cortical Correlates of Cognition and Consciousness

Sudden changes in cortical neural activity have been identified in EEG experiments performed with animals and humans (Freeman, 2003, 2005). Experiments over the gamma frequency band (20Hz–80Hz) indicated sustained quasi-stable patterns of activities for several 100 ms, extending over spatial scales comparable to the size of the hemisphere (Box 2). Freeman interpreted these findings using dynamic systems theory. Accordingly, the brain's basal state is a high-dimensional/chaotic attractor. Under the influence of external stimuli, the dynamics is constrained to a lower-dimensional attractor wing. The system stays in this wing intermittently and produces an amplitude modulation (AM) activity pattern. Ultimately, the system jumps to another wing as it explores the complex attractor landscape. Chaotic itinerancy (Tsuda, 2001) is a mathematical theory that describes the trajectory of a dynamical system, which intermittently visits the "attractor ruins" as it traverses across the landscape. Chaotic itinerancy has been successfully employed to interpret EEG measurements.

3. Population Models of Cognitive Functions

K sets were introduced first by Freeman in the 70s, named in the honor of Aharon Kachalsky, an early pioneer of neural dynamics (Freeman, 1975). K sets are mesoscopic models that represent an intermediate level between microscopic neurons and macroscopic brain structures. K sets consist of a hierarchy of components with increasing complexity, including K0, KI, KII, KIII, KIV, and KV systems (Box 3). They model the hierarchy of the brain starting from the mm scale to the complete hemisphere. The basic K0 set, for example, describes the dynamics of a cortical microcolumn with about 10^4 neurons. K-sets are topological specifications of the hierarchy of connectivity in neuron populations. The dynamics of K-sets are modeled by a system of nonlinear ordinary differential equations with distributed parameters. K-dynamics predict the oscillatory waveforms that are generated by neural populations. K-sets describe the spatial patterns of phase and amplitude of the oscillations, generated by components at each level. They model observable fields of neural activity comprising EEG, LFP, and MEG.

KIII sets are complex dynamic systems modeling the classification in various cortical areas, having typically hundreds of degrees of freedom. In early applications, KIII sets exhibited extreme sensitivity to model parameters, which prevented their broad use in practice (Chang et al, 1996; Freeman et al., 1997). In the past decade, systematic analysis has identified regions of robust performance (Kozma and Freeman, 2001), and stability

Box 1: Extension of Clark's categorization of connectionism

Clark (2001) introduces three types of connectionism. We add a fourth type to describe newest developments in the field.

1. *First-generation connectionism:* It began with the perceptron and the work of the cyberneticists in the 50s. It involves simple neural structures with limited capabilities. Their limitations draw criticism by representatives of the symbolist AI school in the 60s, which resulted in abandonment of connectionist principles by mainstream research establishments for decades. The resistance to connectivist ideas is understandable; it is in fact a repetition of a millennia-old philosophical shift from nominalism to realism (Perlovsky, 2001). Connectionism has been revived in the mid 80s, thanks to the activities of the PDP research groups work (among others) on parallel distributed processing (Rumelhart and McClelland, 1986).
2. *Second-generation connectionism:* It gained momentum since the 80s. It extends first-generation networks to deal effectively with complex dynamics of spatio-temporal events. It involves advanced recurrent neural network architectures and a range of advanced adaptation and learning algorithms. (For an overview, see Bishop, 1995; Haykin, 1998).
3. *Third-generation connectionism:* It is typified by even more complex dynamic and time involving properties (Thelen, Smith, 1994). These models use biologically inspired modular architectures, along with various recurrent and hard-coded connections. Because of the increasing emphasis on dynamic and time properties, third-generation connectionism has also been called dynamic connectionism. Third generation connectionist models include DARWIN (Sporns et al., 1999; Edelman and Tononi, 2000), and the Distributed Adaptive Control models (Verschure et al, 1992; Pfeifer and Scheier, 1999; Verschure and Althus, 2003).
4. *Fourth generation connectionism:* The newest development of neural modeling, which represents an additional step going beyond Clark's original categorization schema. It involves nonconvergent/chaotic sequences of spatio-temporal oscillations. It is based on advances in EEG analysis, which gave spatio-temporal amplitude modulation patterns of unprecedented clarity. The K (Katchalsky) models are prominent examples of this category, which are rooted in intuitive ideas from the 70s (Freeman, 1975) and gained prominence since the turn of the century (Chang et al., 1998; Freeman et al., 2001; Kozma and Freeman, 2001; Li et al., 2006). Fourth generation connectionism is a dynamic approach to intelligence and it creates the opportunity of integrating bottom-up and top-down methods.

The archetypal form of intentional behavior is an act of observation through time and space, by which information is sought for the guidance of future action.

properties of KII sets have been derived (Xu and Principe, 2004; Ilin and Kozma, 2006). Today, K sets are used in a wide range of applications, including classification (Chang et al, 1998, Freeman et al, 2001), image recognition (Li et al., 2006), detection of chemicals (Gutierrez et al, 2005), time series prediction (Beliaev & Kozma, 2006), and robot navigation (Harter & Kozma, 2005, 2006). Recent developments include KIV sets (Kozma and Freeman, 2003; Kozma et al., 2003) for sensory fusion and modeling intentional behavior. They are applicable to autonomous control (Kozma et al., 2005; Huntsberger et al, 2006). The dynamic behavior observed in KIV is compatible with experimental observations, which are summarized as basic principles of neurodynamics (Box 4). The basic principles of neurodynamics outline a platform for the development and testing of biologically plausible models of cognition and consciousness.

4. Construction of Intentional Dynamic Systems

Key features of intentionality as the manifestation of high level intelligent behavior and cognition in humans and animals can be summarized as follows: intelligence is characterized by the flexible and creative pursuit of endogenously defined goals; humans and animals are not passive receivers of perceptual information, and they actively search for sensory input. In the process they complete the following sequence (Nunez & Freeman, 1999):

1. Form hypotheses about expected states the individual may face in the future;
2. Express the hypotheses as meaningful goals to be aimed at;
3. Formulate a plan of action to achieve the goals;
4. Inform the sensory and perceptual apparatus about the expected future input, which is a process called re-afference;
5. Act into the environment in accordance with the action to achieve the formulated goals;
6. Manipulate the sensors, adjust their properties and orientations to receive the sensory data;

Box 2: Synchronization and Gestalt Formation in EEG Experiments

EEG recordings from an array of 8×8 electrodes implanted on the visual, auditory or somatosensory cortices of trained rabbits have been band-pass filtered over the gamma range (20–80 Hz) (Barrie, Freeman and Lenhart, 1996). Each subject was trained in an aversive classical conditioning paradigm with 20 trials using a reinforced conditioned stimulus (CS+) and 20 trials of an unreinforced conditioned stimulus (CS−) in each session, all with correct conditioned responses. The amplitudes of the gamma oscillations formed spatially distributed amplitude-modulation patterns, which showed correlation with the presence of conditioned or unconditioned stimuli. This indicated that the AM patterns carry important information on the discrimination and categorization task of the rabbits. In other words, the categories are manifested in the form of spatially synchronous AM patterns. The synchrony between pairs of EEG records can be measured by various methods. FFT-based analysis is widely used for this purpose. When calculating FFT, a window function of length typically 50 ms or longer must be applied in order to achieve proper statistical accuracy over the gamma band. Such a broad window, however, may smooth over brief transient effects, leading to difficulties in detecting the transient effects of shorter duration.

Hilbert transform has the potential to avoid these difficulties, and it has been applied successfully to EEG analysis in the past few years (Lachaux et al., 1999; Le Van Quyen et al., 2001; Freeman and Rogers, 2002, 2003; Quiroga et al., 2002). Hilbert analysis introduces the analytic phase $P_j(t)$ and amplitude $A_j(t)$ measures, and phase differences at the given frequency band. Here t is the time and j is the channel index, distributed across space, $j = 1, \ldots, 64$.

Analytic phase differences between successive temporal instances are shown in Figure 1 as the function of time (y axis) and channel number (x axis). In the figure the channels are rearranged into a linear array, for the sake of simplicity, although the experiments have been performed on an 8x8 array. Figure 1 shows that for certain time segments, the phase increase has a low, relatively constant level over the entire array. During the plateaus, a sustained and synchronized AM pattern is maintained, indicating the emergence of category formation by the subject. At some short time intervals, the phase differences are highly variable across the array and cover the range between 0 and 2*pi. The plateaus of constancy in phase difference were separated by jumps and dips with variable phase values. Our interpretation was that the jumps and dips manifested discontinuities in the phase demarcating phase transitions in the cortical dynamics.

Experiments with cats provide direct physiological evidence for multisensory binding of simultaneously recorded neural gamma oscillations (Freeman, Gaál and Jornten, 2003). Arrays of electrodes were placed on the four sensory cortices serving distance perception and on the entorhinal cortex to which they all transmitted. The number of electrodes were 16 for visual cortex (VC), 16 for auditory (AC), 16 for entorhinal (EC), 14 for somatosensory (SM), and 2 for olfactory bulb (OB). The 64 EEG signals were band pass filtered to extract the gamma oscillations (20–80 Hz). AM patterns have been extracted as described previously. Similar AM patterns formed clusters,

7. Generalize and categorize the sensory data and combine them into multisensory percepts called Gestalts;
8. Verify and test the hypotheses, and update and learn the brain model to correspond better to the perceived data.

1*. From new/updated hypotheses and continue the whole process again.

The cyclic operation of prediction, testing by action, sensing, perceiving, and assimilation to the perceived sensory consequences of the action is called intentionality. The significance of the dynamical approach to intelligence is emphasized by our hypothesis that nonlinear dynamics is a necessary condition of intentional behavior and intelligence in biological systems (Harter and Kozma, 2004). Therefore, understanding dynamics of cognition and its relevance to intentionality is a crucial step toward building more intelligent machines (Kozma and Fukuda, 2006). Specifically, nonconvergent dynamics continually creates new information as a source of novel solutions to complex problems. The proposed dynamical hypothesis on intentionality and intelligence 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 and it cannot be implanted into it from outside by any external agency.

The brain's basal state is a high-dimensional/chaotic attractor.

The system's memory is defined through the collection of metastable basins and attractor wings, and a recall is the induction by a state transition of a spatio-temporal gamma oscillation with a sequence of spatial AM patterns. The following learning processes are used in dynamic memories (Kozma, et al, 2001): (i) Hebbian reinforcement learning of stimulus patterns—this is fast and irreversible; (ii) Habituation of background activity—slow, cumulative, and reversible; (iii) Normalization of nodal activities to maintain homeostasis and overall stability—very long-range optimization outside 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

each with a center of gravity. Classification by spatial AM patterns with respect to clusters was by the distance of each point to the closest center. The cats were trained to respond with a conditioned response (CR) to either a visual or auditory discriminative conditioned stimulus with reinforcement (CS+) by pressing a bar for milk and refrain from pressing with an unreinforced CS−. The analytic phase of the gamma signals on every electrode was calculated using the Hilbert transform as described previously.

Evidence was found for intermittent phase locking of gamma oscillations across all electrodes in brief epochs between the onsets of the CS and the CR. Two clusters were found in the multichannel EEGs, one with the CS+ and the other with the CS− (Freeman and Burke, 2003). The goodness of classification was reduced by removing the data from each of the five brain areas. Deletion of the EEG data from each cortical area reduced the classification assay in the test period but had no significant effect in the control period. The strongest effect was by removal of the olfactory signals, while the least was by deletion of the entorhinal signals. The mean t:c-ratios from the control period from 1.6 to 2.4 s and the test period from 3.6 to 5.4 s were derived after the deletions specified as follows. None: .34 vs. 2.71. EC: −.01 vs. 2.36. VC: .01 vs. 2.17. SM: .00 vs. 2.04. AC: .01 vs. 1.60. OB: .07 vs. 0.74. (Freeman, Burke, 2003). The level of statistical significance was established in the control period as $p = .01$ for t:c ratio $= 1.96$.

These findings demonstrated the existence of repeated frames of gamma oscillatory activity that were phase locked over widely separated brain areas including all major sensory cortices and the entorhinal cortex to which they converged their output and from which they received input. The frames were sudden in onset and offset, indicating formation of each frame by state transitions at recurrence rates in the theta range (3–7 Hz). The correlation length approached the diameter of the cerebral hemisphere. The AM patterns revealed the cognitive contents of the phase-locked oscillations that were related to the intentional behaviors of the animals. The data provide direct evidence for multisensory fusion of activity in to patterns that must underlie Gestalt formation, which recur in the epochs of relatively stationary activity shown in Figure 1.

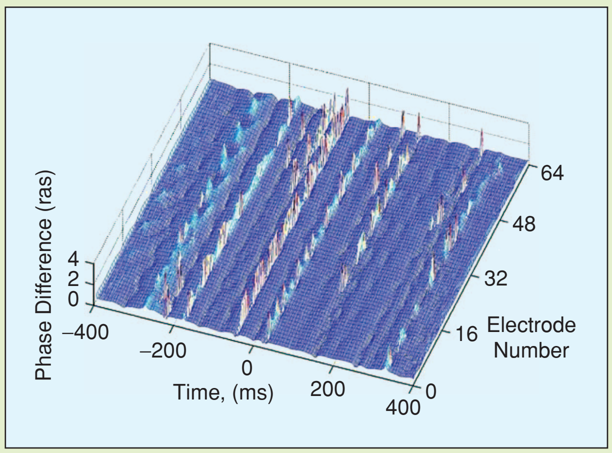

FIGURE 1 The raster plot shows the successive differences of the unwrapped analytic phase, changing with channel serial number (right abscissa) and time (left abscissa) (Freeman, 2004).

that serves to screen out stimuli that are irrelevant, confusing, ambiguous or otherwise unwanted. It constitutes an adaptive filter to reduce the impact of environmental noise that is continuous and uninformative. It is a central process that does not occur at the level of sensory receptors. It is modeled by incremental weight decay that decreases the sensitivity of the KIII system to stimuli that are not designated as desired or significant by accompanying reinforcement. Learning effects contribute to the formation of convoluted attractor basins, which facilitate phase transitions in the dynamical model.

5. Simulating Computational Intelligence for Cognitive Agents

Computer simulations have been conducted to demonstrate the potential of KIV operating using intentional dynamic principles. In the experiments, an autonomous agent moves in a two-dimensional environment. During its movement, the agent continuously receives two types of sensory data: distance to obstacles, and orientation toward some preset goal location. The control system makes decisions about its actions toward the goal without bumping into obstacles. Data concerning the obstacles is processed by a sensory cortex KIII

Box 3: Overview of K sets

The **KO set** represents a noninteracting collection of neurons. They are described by a state-dependent, linear, second order ordinary differential equation. The KO set is governed by a point attractor with zero output and stays at equilibrium except when perturbed. KO models a neuron population of about 10^4 neurons. The second order ordinary differential equation describing it is written as:

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

Here a and b are biologically determined time constants. P(t) denotes the activation of the node as a function of time. F(t) includes a nonlinear mapping function Q(x) acting on the weighted sum of activation from neighboring nodes and any external input. This sigmoid function is modeled from experiments on biological neural activation (Freeman, 1975).

KI sets represent a collection of K0 sets, which can be either excitatory or inhibitory units, i.e., KI_E and KI_I, respectively. The dynamics of a KI is described as a simple fixed point convergence. If KI has sufficient functional connection density, then it is able to maintain a non-zero state of background activity by mutual excitation (or inhibition). KI typically operates far from thermodynamic equilibrium. Its critical contribution is the sustained level of excitatory output. Neural interaction by stable mutual excitation (or mutual inhibition) is fundamental to understanding brain dynamics.

A **KII** set represents a collection of excitatory and inhibitory cells, KI_E and KI_I. KII has four types of interactions: excitatory-excitatory, inhibitory-inhibitory, excitatory-inhibitory, and inhibitory-excitatory. Under sustained excitation from a KI_E set, but without the equivalent of sensory input, the KII set is governed by limit cycle dynamics. With simulated sensory input comprising an order parameter, the KII set undergoes a state transition to oscillation at a narrow band frequency in the gamma range.

The **KIII** model consists of several interconnected KII sets, and it describes a given sensory system in brains, e.g., olfactory, visual, auditory, and somatosensory modality. It has been shown that KIII can be used as an associative memory that encodes input data into nonconvergent spatio-temporal oscillations (Chang et al., 1996; Kozma and Freeman, 2001). The KIII chaotic memories have several advantages as compared to convergent recurrent networks: (1) they produce robust memories based on relatively few learning examples even in noisy environments; (2) the encoding capacity of a network with a given number of nodes is exponentially larger than their convergent counterparts; (3) they can recall the stored data very quickly, just as humans and animals can recognize a learned pattern within a fraction of a second.

A **KIV** set is formed by the interaction of three KIII sets. It is used to model the interactions of the primordial vertebrate forebrain in the genesis of simple forms of intentional behavior (Kozma et al, 2003; Kozma & Freeman, 2003). KIV models provide a biologically feasible platform to study cognitive behavior associated with learning and action-perception cycle, and as such will be the focus of this review. Figure 2 illustrates the hierarchy of K sets.

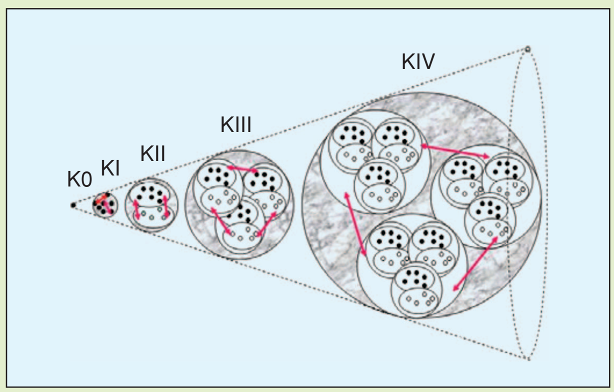

FIGURE 2 The K-set hierarchy showing progression of neural population models from cell level to hemisphere wide simulation, K0 through KIV. The progression of models of increasing complexity follows the organizational levels of brains. K0 is a noninteracting collection of neurons governed by a point attractor with zero output in the absence of perturbation. KI corresponds to a cortical column. It represents a collection of neurons having sufficient functional connection density to maintain a state of non-zero background activity. KII represents a collection of excitatory and inhibitory populations, which can exhibit limit cycle periodic oscillations at a narrow band frequency in the gamma range. KIII is formed by the interaction of several KII sets. It simulates the known dynamics of sensory areas that generate aperiodic, chaotic oscillations with $1/f^2$ spectra. KIV is formed by the interaction of three KIII sets. It models the hemisphere with multiple sensory areas and the genesis of simple forms of intentional behaviors.

model, while global orientation data enter the hippocampal KIII set. The sensory-control mechanism of the system is a simple KIV set consisting of the cortical and hippocampal KIII systems (Voicu et al., 2004; Kozma & Myers, 2005; Kozma et al, 2005).

The basic principles of neurodynamics outline a platform for the development and testing of biologically plausible models of cognition and consciousness.

We have two types of learning: Hebbian correlation learning, and habituation. Hebbian learning is paired with reinforcement, reward or punishment; i.e., learning takes place only if the reinforcement signal is present. Namely, the vicinity of an obstacle presents a negative reinforcement to the cortical system, while a correct movement towards the goal gives positive reinforcement in the hippocampal subsystem. Figure 4 illustrates the learning sequence and the decision making for the hippocampal KIII system.

The spatio-temporal dynamics of this system shows sudden changes in the simulated cortical activity, which is in agreement with properties of metastable AM patterns observed in EEG data. An example of the calculated analytical phase difference is shown in Figure 5, for a simulated period of four seconds and for an entorhinal array consisting of 80 nodes. The intermittent 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 described previously.

6. Robot Control using Cognitive Dynamic Models

6.1 Biologically-Inspired Approaches to Navigation and Control

Biologically-inspired architectures are widely used for control of mobile robots and demonstrating robust navigation capabilities in challenging real life scenarios. These approaches include subsumption methods (Gat et al., 1994); BISMARC—Biologically Inspired System for Map-based Autonomous Rover Control (Huntsberger and Rose, 1998, Huntsberger, 2001); ethology inspired hierarchical organizations of behavior (Tunstel, 2001); and behavior-based control algorithm using fuzzy logic (Seraji and Howard, 2002). Brain-like architectures and modeling cognitive activity is an increasingly popular area of intelligent control, including learning cognitive maps in the hippocampus (O'Keefe and Recce, 1993); the role of place cells in navigation (Touretzky and Redish, 1996); visual mapping and the hippocampus (Bachhelder and Waxman, 1994; Arleo & Gerstner, 2000; Hasselmo et al, 2002); and learning in the KIV model of the cortico-hippocampal system (Voicu et al., 2004). An important difference between K models and other biologically-

Box 4: Basic principles of neurodynamics of cognition and consciousness

The hierarchical K model-based approach is summarized in the 10 "Building Blocks" of neurodynamics (Freeman, 1975; Freeman, 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.
3. State transition from a point attractor to a limit cycle attractor that regulates steady state oscillation of a mixed E-I 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 re-afference in KIV through the convergence of external and internal sensory signals leading to the activation of 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 and elements of consciousness 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 cognition and consciousness.

inspired control architectures is the way in which information is processed. K models encode information in AM patterns of oscillations generated by the Hebbian synapses in layers of the KIII subsystems, the other models use firing rate and Hebbian synapses (Blum and Abbott, 1996, Trullier et al., 1997). Experience shows that the performance of K model matches or exceeds that of the alternative approaches (Harter & Kozma, 2005, Voicu et al., 2004).

6.2 SRR2K Robot Test Bed

We demonstrate the operation of the cognitive control and navigation system for online processing of sensory inputs and onboard dynamic behavior tasking using SRR2K (Sample Return Rover) a planetary rover prototype at the Jet Propulsion Laboratory (JPL). The control system is called SODAS (self-organized ontogenetic development of autonomous systems) based on a KIV model. The experiments

Box 5: KIV Model of Cognition and Intention

Figure 3 illustrates the connections between components of KIV. The connections are shown as bidirectional, but they are not reciprocal. The output of a node in a KII set is directed to nodes in another KII set, but it does not receive output from the same nodes but other nodes in the same KII set. In Figure 3, 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); (iii) orientation signals.

The environmental sensory information enters through broad band exteroceptors (visual, audio, somatosensory, etc.) and is processed in the OB and the PC in the form of a spatially distributed sequence of AM patterns. These AM patterns are superimposed on the spatial maps in CA3 that are derived from the orientation beacons. In the present model, separate receptor arrays are used for simplicity of receptor specialization and internal connectivity. The cortical KIII system initiates the function of pattern recognition by the agency of sensory input-induced destabilization of high-dimensional dynamics. The input is gated by the septal generator (like a sniff or saccade). This actualizes an attractor landscape formed by previous experience in the OB/PC, which in our model is the common sensorium. The hippocampal KIII system, on the other hand, uses the classification embodied in the outputs of the OB and PC as its content-laden input, to which the DG contributes the temporal and spatial location of environmental events. These events contributed to the previously learned relationships between the expectations and the experience of the system in search of its assigned goal.

A component of the integrated KIV system, the Midline Forebrain formation, receives the interoceptor signals through the basal ganglia, and processes them in the hypothalamus and the septum. MF provides the value system of the KIV, using information on the internal goals and conditions in the animal. It provides the "Why?" stream to the amygdala, which combines this with the "What?" and "Where?" information coming from the cortex and the hippocampus to make a decision about the next step/action to be taken. MF is also a KIII unit, which contributes to the formation of the global KIV coherent state. The coherent KIV state evolves through a sequence of metastable AM patterns, which is also described as the cinematographic principle (Freeman, 2004) of brain operation.

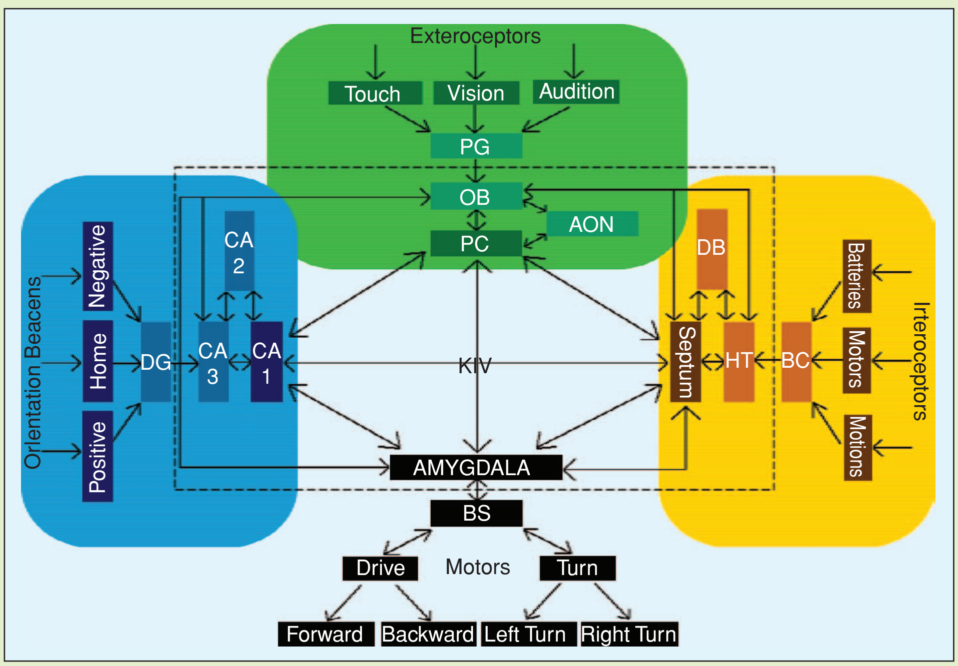

FIGURE 3 KIV model of the brain, which consists of three KIII sets (cortex, hippocampal formation, and midline forebrain), the amygdala striatum and brain stem. The amygdala is a KII set, while the brain stem and drives are conventional. The sparse long connections that comprise the KIV set are shown in blue. They are shown as bidirectional, but they are not reciprocal. The convergence location and output are provided by the amygdala, including its corticomedial and basolateral nuclear parts. In this simplified model with no autonomic nervous system, the amygdala provides the goal-oriented direction for the motor system that is superimposed on local tactile and other protective reflexes.

illustrate robust obstacle avoidance combined with goal-oriented navigation (Huntsberger et al, 2006). Experiments have been conducted at the Planetary Robotics Laboratory, and indoor research facility at JPL. It includes an approximately 5m × 5m irregularly shaped test area covered by sand and rocks imitating natural terrain in exploration environments. The terrain layout is variable from smooth surfaces for easy advance to rough terrain with various hills and slopes posing more challenges to SRR2K traversing through it. The lighting conditions are adjustable as needed. Details of the robot experiments are given in Box 6.

The cyclic operation of prediction, testing by action, sensing, perceiving, and assimilation to the perceived sensory consequences of the action is called intentionality.

We apply KIV-based SODAS system for robot navigation. KIV is the brain of an intentional robot that acts in its environment by exploration and learns from the consequences of its actions. KIV operates on the principle of encoding in spatio-temporal oscillations, in analogy with EEG oscillations in the vertebrate brain. By cumulative learning, KIV creates an internal model of its environment and uses it to guide its actions while avoiding hazards and reaching goals that the human controller defines. We set the simple task of starting from a corner and reaching a goal position *GOAL_XY* specified at the start of the experiment. The straight road may not be the best when there are some rough areas that are difficult to cross, or some hills, which are difficult to scale, etc. In this situation we expect that a properly trained SRR2K robot would decide to take a path that avoids the difficult areas, or at least tries to do so. If proper learning and generalization took place, one could change the terrain into a layout which SRR2K had never seen before; still should achieve good performance. The KIV-guided robot uses its experience to continuously solve problems in perception and navigation that are imposed by its environment as it pursues autonomously the goals selected by its trainer (Kozma, Muthu, 2004).

In the experiments SRR2K used two sensory modalities: orientation and short-range vision. We did not use far-field visual information on landmarks and on goal positions; that is we do not aim at creating an internal cognitive map based on landmarks, see Mataric & Brooks (1999). Rather we studied how KIV builds multisensory associations and how it uses those associations for selection of actions in the intentional system. In a typical scenario, the visual sensing contained information on the terrain that would be traveled by a forward moving robot in the next few steps. Wavelet-based visual processing converted the raw image data into an array of wavelet coefficients that characterized the roughness of the terrain.

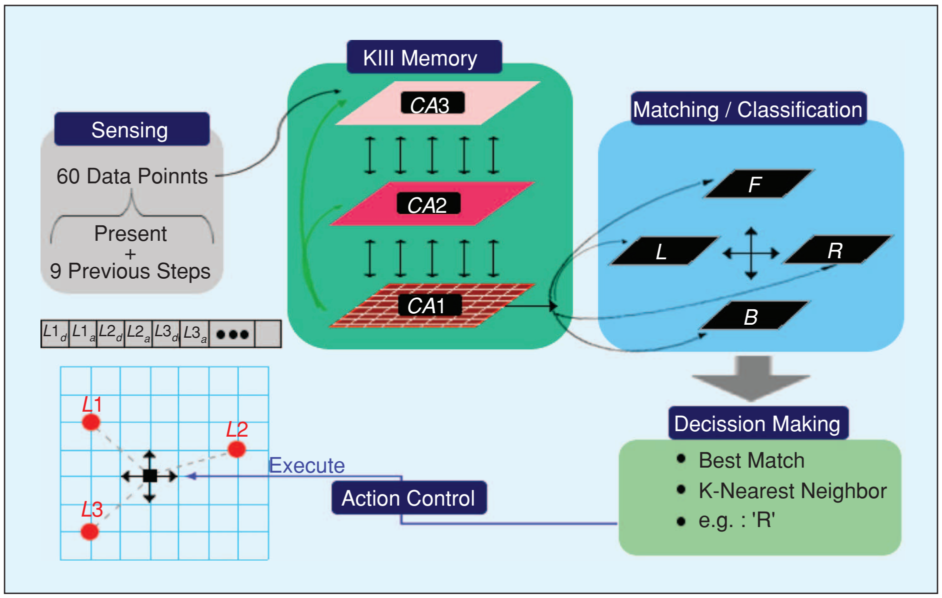

FIGURE 4 Illustration of learning and control in the hippocampal KIII system; case of the navigation task in the simulated 2D environment. Learning and readout is based on the CA1 activations. The agent has the following possible actions: go one step forward, backwards, left, or right. The decisions are made based on the best match between the reference patterns and the activation at the given situation.

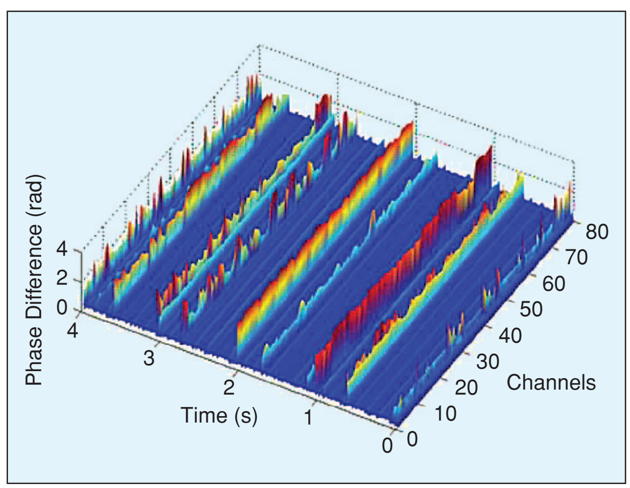

FIGURE 5 Illustration of simulations with a KIV model of the hemisphere; phase differences are shown in the entorhinal cortex across time and space (80 spatial nodes). The intermittent desynchronization periods for a large part of the array are clearly seen (Kozma & Myers, 2005).

Understanding dynamics of cognition and its relevance to intentionality is a crucial step toward building more intelligent machines.

Oscillatory components of the gyroscope were used to provide sensory information on the terrain during traversal.

In order to develop an efficient control paradigm, SRR2K should avoid obstacles, instead of trying to climb over them even if that means a detour towards the goal. Whenever the robot encounters bumps on the terrain, it experiences high oscillations and high RMS values of the gyroscope. This turns on a learning mode in order to avoid similar situations in the future; therefore the RMS recording of the gyroscope is used as a negative reinforcement learning signal. On the other hand, moving toward the goal location is desirable and produces a positive reinforcement learning signal.

The essence of the task is to anticipate the undesirable bumpy oscillation a few steps ahead based on the visual signal. SRR2K needs to develop this association on its own. A typical

Box 6: Cognitive Navigation of SRR2K Robot

SRR2K is a four-wheeled mobile robot with independently steered wheels. Its mass is seven kg, and the maximum power use during its fastest movement (30–50 cm/s) is around 35 W. In the small experimental environment in this study, no large distances are traveled, the battery capacity is not an actual limitation. SRR2K has a 266 MHz Pentium II processor in a PC/104+ stack that operates under the real time OS VxWorks5.4. The primary sensing modalities on SRR2K include: (1) a stereo camera pair of five cm separation, 15 cm of height and 130 degree field of view (Hazcam); (2) a goal camera mounted on a manipulator arm with 20 degree field of view (Viewcam); (3) internal DMU gyroscope registering along orientations of pitch, roll, and yaw; (4) Crossbow accelerometer in x, y, and z coordinates; (5) a Sun sensor for global positioning information (Huntsberger et al., 2003). To simplify measurement conditions and data acquisition, the top-mounted goal camera on the robot arm, and the global positioning sensor are not used in the present experiments. This work is based on measurements by the stereo camera and the DMU unit only. This approach simplifies the technical support and signal monitoring needs, but it also poses a more challenging task for efficient and reliable goal completion.

At regular time intervals the sensory vectors are written on the on-board computer in a file, which are accessed by the KIV system for further processing. The update of the sensory data arrays happens at about every 30–40 s, which is determined by the speed of SRR2K and the computational time of calculating KIV output. We have the following sensory data: (1) visual data vector consisting of 10 wavelet coefficients determined from the recorded 480×640 pixel image of a Hazcam; (2) recordings using the mean and variance of the gyroscope and accelerometer readings along the three spatial coordinates. Statistical moments are determined over the data recording window given by the file refreshment rate as described above; (3) rover heading which is a single angle value determined by comparing the orientation of the rover with respect to the direction of the goal. The possible control actions have been the following; make one step (25 cm) forward, turn left or right, or backup.

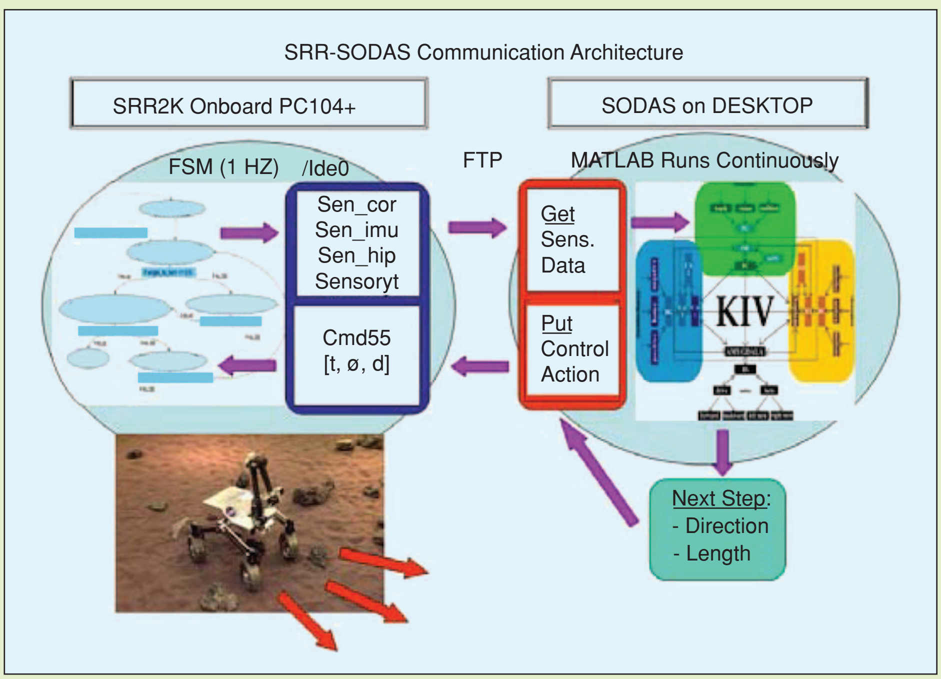

FIGURE 6 Sample Return Rover (SRR2K) situated in the Planetary Robotics indoor facility imitating natural terrain in planetary environments. The following sensors were used: CMOS stereo cameras, accelerometers, and global orientation sensors. Based on the sensory readings, the KIV-based SODAS control system decides the next step, which is communicated to SRR2K and executed. (Huntsberger et al., 2006).

supervised approach would provide some rules based on the visual signal. For example, turn left if you see a bump on the right, etc. This may be a successful strategy on relatively simple tasks, but clearly there is no way to develop a rule base that can give instructions in a general traversal task with unexpected environmental challenges. SRR2K has demonstrated that it can learn the association between different sensory modalities, and it traverses successfully a terrain with obstacles, reaching the target goal (Huntsberger et al, 2006). It is worth mentioning that KIV based control has the option to take not only instantaneous sensory values, but also data observed several steps earlier. This involves a short-term memory with a given memory depth. In the given task, a memory could be 3–4 steps deep, or more. One can in fact optimize the learning and system performance based on the memory depth (Kozma & Muthu, 2004). This has not been used in the SRR2K experiments yet, but is planned to be completed in the future.

Biologically-inspired architectures are widely used for control of mobile robots and demonstrating robust navigation capabilities in challenging real life scenarios.

7. Computational Intelligence and Machine Cognition and Consciousness

Biologically-motivated principles are outlined to achieve intelligence through modeling intentional behavior and consciousness. The introduced models represent a drastic departure from today's digital computer designs, which are based on computation with numbers represented by strings of digits. Brains do not work with digital numbers. Rather, they operate using a sequence of amplitude-modulated patterns of activity, which are observed in EEG, MEG, and fMRI measurements. Using neurodynamical principles, symbol-based computation can be replaced with pattern-based processing. This leads to the emulation of brain-like behavior in the computational device.

Cognitive dynamic systems are introduced in the form of the KIV model. KIV has the potential of producing macroscopic phase transitions, which provide the mechanism for fast and robust information processing in KIV, in the style of brains. KIV is a biologically based cognitive brain model capable of learning and responding to environmental inputs robustly and creatively, based on its experience. The KIV-based intentional dynamic brain model addresses the classic symbol grounding problem by means of linking intentional behavior with known mesoscopic neural dynamics. Large-scale synchronization in the cortex, interrupted intermittently by brief periods of desynchronization through phase transitions, is an emergent property of the cortex as a unified organ. The intermittent synchronization-desynchronization cycle is postulated as a neurophysiological correlate of intentionality and consciousness. The KIV model is capable of emulating such dynamic behavior.

KIV describes the cognitive action-perception cycle at the core of intentionality, consisting of prediction, planning action, execution, sensing results of action, evaluating predictions, and updating predictions. The cognitive cycle in the dynamical model takes place in real time with frame rates corresponding to ranges observed in humans. The timing of the cycle depends on the shutter mechanism that is inherent in the background 'noise' that maintains all oscillations (Freeman, 2007). KIV has been implemented using robot control test beds in computational simulations and in real life environments. Experiments have been conducted to generate intentional behavior leading to learning, category formation and decision making based on knowledge learned in previous scenarios. Perspectives of future development of intentional systems have been outlined.

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