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## MODELING GOAL-ORIENTED DECISION MAKING THROUGH COGNITIVE PHASE TRANSITIONS

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**ABSTRACT** - Cognitive experiments indicate the presence of discontinuities in brain dynamics during high-level cognitive processing. Nonlinear dynamic theory of brains pioneered by Freeman explains the experimental findings through the theory of metastability and edge-of-criticality in cognitive systems, which are key properties associated with robust operation and fast and reliable decision making. Recently, neuropercolation has been proposed to model such critical behavior. Neuropercolation is a family of probabilistic models based on the mathematical theory of bootstrap percolations on lattices and random graphs and motivated by structural and dynamical properties of neural populations in the cortex. Neuropercolation exhibits phase transitions and it provides a novel mathematical tool for

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studying spatio-temporal dynamics of multi-stable systems. The present work reviews the theory of cognitive phase transitions based on neuropercolation models and outlines the implications to decision making in brains and in artificial designs.

**Keywords:** Neurodynamics, Phase Transition, Neuropercolation, Metastability, Decision Theory.

### 1. Introduction

EEG analysis gave spatiotemporal amplitude modulation patterns of unprecedented clarity<sup>20,21</sup> and supported the theory of self-organized criticality in neural dynamics<sup>2,29</sup>. These results indicate that brains maintain themselves at the edge of global instability by inducing a multitude of small and large adjustments in the form of phase transitions<sup>31,17</sup>. Phase transitions mean that each adjustment is a sudden and irreversible change in the state of a neural population. Because sensory cortices maintain themselves in highly sensitive meta-stable states, they can transit instantly to any designated part of their state space when destabilized by expected stimuli.

Synchronization of neural electrical activity while completing cognitive tasks is studied in animals and humans<sup>8,43,21,12,33,23</sup>. It has been demonstrated that classification of input stimuli emerges as a sudden change in the brain's cognitive activity. EEG and ECG recordings show that transitions are accompanied by a change in the dynamics of cortical stimulus representation, which represent a mechanism underlying the recognition of the abstract quality (or qualities) that defines the categories. Synchrony of firing of widely distributed neurons in large numbers is necessary for

emergence of spatial structure in cortical activity by reorganization of un-patterned background activity.

Oscillations measured by EEG, MEG, and other brain monitoring techniques arise from extensive feedback interactions among neurons densely connected in local neighborhoods, in combination with the effects of long axons. Axonal effects have high conduction velocities and support synchronization over large areas of cortex<sup>12,13,21</sup>, creating small-world effects<sup>49,48</sup> in analogy to the rapid dissemination of information through social contacts. The importance of long-distance correlations has been emphasized by numerous brain theorists<sup>28,27,25,24,42,30,35,47</sup>. In certain networks, like the www, biological systems, the degree distribution follows a power law, i.e., it is scale-free<sup>1,6,7,11</sup>. Some real-world networks have scaling behavior that is not scale free.

Neuropercolation has some common aspects with the small-world and scale-free network studies. Neuropercolation is a generalization of cellular automata, Hopfield memory arrays and Conway's game of life<sup>26,9</sup>, by merging the concepts of random graph theory<sup>14,10</sup> and non-local interactions represented by axonal connections. It bridges the gap between Ising-type models and mean-field approaches<sup>37,3</sup>. Our studies identified several key factors that determine phase transitions in neuropercolation models, including endogenously generated noise and the structure and extent of the non-locality of neural populations, as well as inhibitory gains. The resulting novel tools have been used to study the intricate complexity of various dynamic behaviors of neural populations<sup>46</sup>.

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Neuropercolation theory uses a sequence of approximations to describe connectivity patterns in random graphs motivated by brains. Starting with the mathematical theory of probabilistic cellular automata (PCA), methods of random graphs and percolation theory are applied to describe the evolution of random objects. Mathematically rigorous methods exist to describe two extreme cases of the evolution of PCAs, ie., global mean-field effects and local interactions. The concepts of phase transitions and criticality have been rigorously defined and mathematically analyzed in these extreme cases. Real life problems in neurodynamics do not lend themselves to the dichotomy of local-global separation due to anatomical and physiological conditions of the neuropil. The description of collective dynamics of the cortical tissue requires the combination of multi-level approaches, leading to intermediate range or mesoscopic theories. Unfortunately, no rigorous proofs exist in the general case of intermediate effects, and certain approximations are required for such systems.

By introducing neuropercolation approach, we build on graph theoretical and percolation tools established for local and global models, and extend the studies to more general mathematical constructs. Our aim is to study the system, while relaxing the established conditions leading to known behaviors. Most of the time, this study is based on computational studies. If the observed system behavior changes smoothly when relaxing certain constraints, we extend the original concepts to those generalized conditions, by virtue of analogy. The criterion of applicability of the analogy is that the basic observable characteristics of the system exhibit the same qualitative behavior as the original system without relaxation. Possible

exceptions from this requirement are the exact numerical values of certain quantitative measures. Such general criteria include the existence of finite-size scaling near a critical point with scale-free behavior and the existence of critical exponents of the observed variables. For example, using the terminology of Ising models, we require that critical exponents for key inferred quantities, such as the correlation length, magnetization, and susceptibility are well-defined and that they satisfy an Ising-type identity relationship. The analysis introduced in <sup>37,46</sup> shows that in biologically realistic neuropercolation models the generalization approach is applicable, and the concepts of *generalized phase transitions* and criticality in neural systems are well-defined. Thus the use of the corresponding terminologies of phase transition and criticality in the neural tissues is justified in the above sense.

The present paper introduces neurobiological evidences of phase transitions in cognitive processing, and a brief overview of the neuropercolation method for modeling these effects. This is followed by the description of implications of the neuropercolation theory for developmental processes and for cognition. Emphasis is given to goal-oriented decision making and intentional neurodynamics, in the context of the hierarchical Freeman K-models <sup>16,18,34</sup>. These results are applicable not only for the interpretation of cognitive experiments, but also can serve as design principles of integrated distributed decision support systems in various application areas.

## 2. Principles of Neurodynamics

The last half a century produced crucial advances in brain research, in part due to advances in experimental techniques. It has been a major challenge to reconcile the apparent contradiction between the absence of clearly defined symbolic representations in brains, as evidenced by physiological experiments, and the symbolic nature of higher-level cognition and consciousness. In the philosophy of artificial intelligence this is addressed as the notoriously difficult symbol grounding problem. Namely, if there are abstract symbols in intelligent systems like brains, how these symbols acquire meaning in the context of the very specific and unique life experience of the individual? The neurodynamic approach to cognition and intelligence provides a solution to this problem using the concept of metastability of brain dynamics<sup>31,17,15,22,32</sup>.

Neurodynamics considers brains as dynamic systems moving along a complex non-convergent trajectory influenced by the subject's past and present experiences and anticipated future events. The trajectory may rest intermittently, for a fraction of a second, at a given spatio-temporal pattern. This pattern has meaning to the subject based on its previous experiences and intentions. In this sense one may call this pattern a representation of the meaning of the given sensory influence, in the context of the present internal state and the intended future states. However, the spatio-temporal patterns are not stable. Swift transitions destroy them again and again, as the system moves along its trajectory. The transient, intermittent spatio-

temporal patterns can be considered as metastable symbols, and the transitions among patterns as decision sequences in the brain, during its never ending cognitive processing cycles<sup>38</sup>. Such behaviors have been described by Model Field Theory (MFT)<sup>44,45</sup>. MFT is used for the mathematical characterization of the evolution of the cognitive system from vague and uncertain states to conditions with well-defined structure and relationship between its components.

A hierarchical approach to neurodynamics is formulated by Freeman<sup>16,18</sup>. It is summarized as the 10 Building Blocks of the dynamics of neural populations:

- (1) State transition of an excitatory population from a point attractor with zero activity to a non-zero point attractor with steady-state activity by positive feedback.
- (2) Emergence of oscillations through negative feedback between excitatory and inhibitory neural populations.
- (3) State transitions from a point attractor to a limit cycle attractor that regulates steady-state oscillation of a mixed excitatory-inhibitory cortical population.
- (4) Genesis of chaos as background activity by combined negative and positive feedback among three or more mixed excitatory-inhibitory populations.
- (5) Distributed wave of chaotic activity that carries a spatial pattern of amplitude modulation made by the local heights of the wave.
- (6) The increase of non-linear feedback gain that is driven by input to mixed population, which results in construction of an amplitude-modulation pattern as

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the first step in perception.

- (7) The embodiment of meaning in amplitude-modulation patterns of neural activity, which are shaped by synaptic interactions that have been modified through learning.
- (8) Attenuation of microscopic sensory-driven noise and enhancement of macroscopic amplitude modulation patterns by divergent-convergent cortical projections.
- (9) Gestalt formation and prefference through the convergence of external and internal sensory signals leading to the activation of the attractor landscapes, and leading to intentional action.
- (10) The formation of a sequence of global amplitude-modulation patterns of chaotic activity that integrates and directs the intentional state of an entire hemisphere.

These principles have been implemented in various models. The Katchalsky models (K models) use a set of ordinary differential equations with distributed parameters to describe dynamics of neural populations starting from micro-columns to the hemispheres<sup>19,34</sup>. Neuropercolation approach, on the other hand, uses tools of percolation theory and random graphs to model these principles. To date, neurodynamic principles 1 – 4 have been implemented in neuropercolation, and further steps are in progress as described in this review.

### 3. Neuropercolation Overview

#### 3.1. Definitions

Here basic principles of neuropercolation are summarized<sup>3,40</sup>. Neuropercolation is a family of probabilistic models based on the mathematical theory of bootstrap percolations on lattices and random graphs and motivated by structural and dynamical properties of neural populations in the cortex. A family of random bootstrap percolations is defined over  $d$ -dimensional discrete tori  $\mathbb{Z}_N^d$ . Let  $A$  be the set of possible states. In the simplest case there are just 2 states: active (+) or inactive (-). The neighborhood of node  $x$  is denoted by  $\Gamma_x \subset \mathbb{Z}_N^d$ . At a given time instant  $t$ ,  $x$  becomes active with probability  $p$  which is the function of the state of the sites in  $\Gamma_x$  and the state of  $x$  itself. Accordingly,  $p$  is a function  $p: A^\Gamma \times A \rightarrow [0, 1]$  that assigns for each configuration  $\phi: \Gamma \rightarrow A$  and each  $a \in A$  a probability  $p_{\phi,a}$  with  $\sum_{a \in A} p_{\phi,a} = 1$  for all  $\phi$ . We define a sequence of configurations  $\Phi_t: \mathbb{Z}^d \rightarrow A$  by setting  $\Phi_{t+1}(x) = a$  independently for each  $x \in \mathbb{Z}^d$  with probability  $p_{\phi,a}$ . We start the process with some specified initial distribution over the torus  $\Phi_0$ . The process  $\Phi_t$  is called *probabilistic cellular automaton* or *PCA*.

Probabilistic cellular automata generalize deterministic cellular automata and they can display very complex behaviors, including fixed points, stable limit cycles, and chaos. Some rigorous mathematical results have been achieved in specific configurations. It is often assumed that  $p_{\phi,a}$  depends only on the cardinality of the set of the neighbors which are in active state, and on the state of the given site.

These models are called *isotropic*. Isotropic models are substantially more restrictive than the general case, but they still have complex behavior, sometimes including spontaneous symmetry breaking<sup>3</sup>. In the special case of fully isotropic models, the site is treated the same ways as its neighbors. If the probability of activation and de-activation are equal in a fully isotropic model, then the model is described by a single probability parameter  $p$ . Parameter  $p$  is used to demonstrate phase transitions and critical behavior in the neuropercolation models of the present review.

### **3.2. Phase Transitions in Local, Mean-Field, and Mixed Models**

In the mean field model, instead of considering the number of active nodes in the specified neighborhood  $\Gamma$ , the activations of  $|\Gamma|$  randomly selected grid nodes are calculated in the update rule (with replacement). Since there is no ordering of the neighbors, the transition probabilities depend only on the number of active states in the selected  $|\Gamma|$ -tuples. It is clear that the mean field model does not depend on the topology of the grid. The density of active points  $\rho_t \in [0, 1]$  is defined as  $\rho_t = \frac{\# \text{ of Active sites at time } t}{N}$ , where  $N$  is the size of the torus. Density  $\rho_t$  acts as an order parameter and it can produce a wide range of dynamic behaviors.

In local lattice models, a rigorous proof has been found of the fact that the model spends a long time in either low- or high-density configurations before crossing very rapidly to the other state<sup>4</sup>. Fairly good bounds have been found on the (very long) time the model spends in the two meta-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. In the lattice models, certain configurations with very low density can have a large probability of leading to the high-density configuration.

In mixed models with long-range and short-range connections, the dynamic behavior becomes even more complex and no rigorous mathematical analysis of the dynamic processes exists at this time. However, large-scale Monte-Carlo simulations indicate critical behavior which is consistent with the notion of phase transitions<sup>37,46</sup>. It is shown, that in addition to the transition probability  $p$ , the ratio of rewired non-local connections acts as an additional critical parameter. The observed behavior is consistent with that of the Ising, or weak-Ising universality class<sup>40</sup>.

### ***3.3. Intermittent Synchronization in Inhibitory Populations***

The behavior of the neuropercolation model with excitatory and inhibitory connections is illustrated in Fig. 1. We have calculated the synchronization and desynchronization across the layers shown in Fig. 1 along the vertical axis  $z$ . The system has 256 nodes shown along axis  $x$ , and the evolution is depicted for 6000 iterations ( $y$  axis). Low value of desynchronization ( $\approx 0$ ) means good synchrony, while high desynchronization ( $\approx 3$ ) indicates lack of synchrony across the array. The

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spatial distribution of synchronization shows that the subcritical regime is characterized by highly synchronized patterns. On the other hand, supercritical regime shows high-amplitude, unstructured oscillations. Near critical parameters, intermittent oscillations emerge, i.e., relatively quiet periods of synchronized oscillations are followed by periods of intensive oscillations with highly variable synchronization index. The intensity of inhibitory cross-connections also acts as a control parameter, in addition to the system noise level and the non-local rewiring ratio. The system shown in Fig. 1 demonstrates spontaneous emergence of synchronized and unsynchronized regions and it serves as a building block of neurodynamics with inhibitory populations.

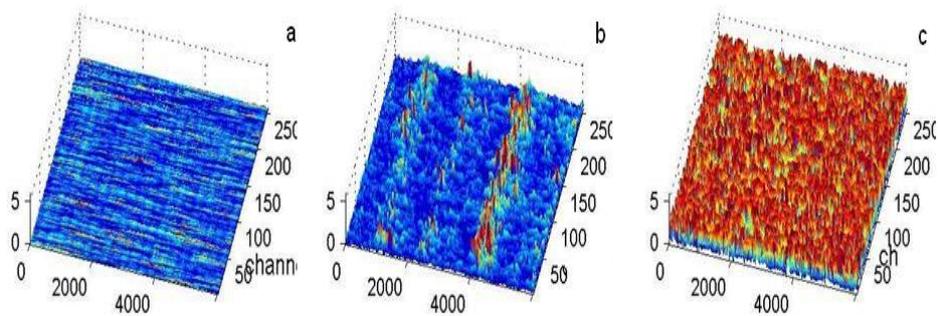


Fig. 1. Demonstration of intermittent synchronization in a system with 256 excitatory and 256 inhibitory populations and with mixed local and mean field connections. The noise level changes from left to right:  $p = 0.13$  (a),  $0.15$  (b), and  $0.16$  (c). Strong synchrony is seen below critical noise, and absence of synchrony above critical noise. There is spontaneous, intermittent desynchronization across the array at critical noise level of  $0.15$ ; see Ref.<sup>38</sup>.

### **3.4. Neuropercolation Hypothesis of the Evolution of Critical Behavior**

The following hypothesis has been proposed on the emergence of critical behavior with the potential of frequent phase transitions in the neuropil<sup>37</sup>. The neural connectivity is sparse in the neuropil at the embryonic stage. Following birth, the connectivity increases and ultimately reaches a critical level, at which the neural activity becomes self-sustaining. The brain as a collective system is at the edge of criticality, and it now can undergo repeated phase transitions in a self-organized way, under the influence of external and internal factors. We suggest to implement this approach in a computational model as follows. Start with an initial population of nonlinear units, which model neural populations with given local properties. Incrementally increase the long-range connectivity using any desired strategy, producing, e.g., a scale-free network with preferential attachment, or other objects. Stop changing the connectivity when the critical state is approached. From this stage on, the structure is essentially fixed. Modifications still happen, e.g., due to learning effects. Use the effects of inputs and endogenous noise to balance the system at the edge of phase transitions. Operate the system through repeated phase transitions as it processes, retrieves, and transforms data.

The above strategy is schematically illustrated in Fig. 2. By way of structural evolution, the neuropil evolves toward regions of criticality or edge-of-criticality.

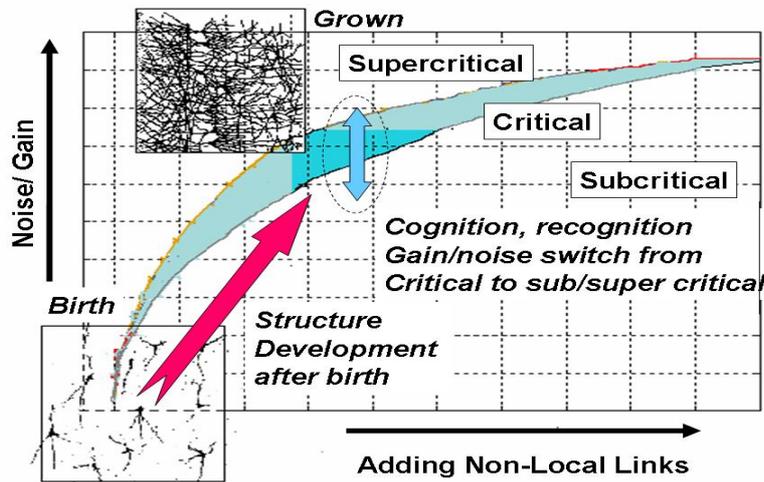
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Fig. 2. Illustration of self-organization of critical behavior in the percolation model. The system is initiated at a low connectivity and low noise state, and it evolves towards high connectivity with increased noise gains. During the evolution, the system reaches states near criticality (gray shaded area), where small changes in system parameters can cause transitions between subcritical and supercritical states <sup>37</sup>.

Once critical states are established, the structure remains essentially unchanged. By adjusting the noise and/or gain levels, the system can be steered towards or away from critical regions. This is a control mechanism that provides the conditions to phase transitions in the neuropil. Obviously, the outlined mechanism is incomplete and in realistic neural systems a host of additional factors play crucial role. However, the given mechanism is very robust and it can provide the required dynamical behavior in a wide range of real life conditions.

## 4. Phase Transitions-based Theory of Decision Support

### 4.1. *Cognitive Phase Transitions and Memory Patterns*

Recent advances in research on neurobiological correlates of intentionality and decision making provides new tools to advance knowledge-based adaptive data processing and decision support systems. Experimental evidence indicates that cognition exhibits an intermittent character. Namely, the cognitive state is relatively stable for a fraction of a second, then suddenly switches to a new state. The new state is maintained until conditions for a new switch are formed, and the whole cycle starts again. This process is characterized as meta-stability or edge-of-stability in intentional dynamic systems<sup>17,35,38,32</sup>. Higher cognition has a mechanism of maintaining meta-stable states, which allow for efficient and robust decision in dynamically changing scenarios.

The intermittent nature of higher cognition switching between attractors appear to be the mechanism that the brain uses to implement dynamic logic<sup>44,45</sup>. Dynamic logic is an abstract description level of the cognitive cycle in which neurodynamics evolves from less conscious to more conscious states, from vague and uncertain to more explicit knowledge. Initial states are vague, uncertain, and less conscious. They are described by highly chaotic states over the complex attractor landscape. They evolve into more concrete, certain, conscious states, described by less chaotic states. According to dynamic logic, brain states reflect the surrounding world and they are characterized by models and by measures of similarity between the mod-

els and input signals. Vague cognitive states are described by low similarity values between data and the internal models. Conscious states are described by models with high similarity values and they correspond to processes of perception, cognition, and decision making. Conscious models are better adapted-matched to input signals. Adaptation of models is driven by maximization of similarity. This drive is a mathematical representation of a fundamental instinct for more knowledge and more consciousness. The description of cognitive cycles in terms of dynamic logic was recently confirmed in neuroimaging experiments<sup>5</sup>. It has been demonstrated that during visual perception a vague representation in the memory converges to a crisp perception.

Cognitive phase transitions and dynamic logic are closely related aspects of the dynamics of brain states. Dynamic logic is a cognitively-motivated model-based approach to describe the emergence of models of increasing clarity as the cognitive action-perception cycle progresses. Dynamic Logic provides the tools to analyze the ways brains form sequences of spatio-temporal oscillations through cognitive phase transitions. The cognitive attractor landscape represents memory-models, and maximization of similarity is represented by the evolving neural dynamics leading to phase transitions. The vague representations as well as the convergence process are unconscious. Only the final crisp state which has converged on the attractor landscape to a localized memory wing is available to consciousness. This converged state can be called as intermittent representation of the conscious state through metastable neural dynamics. Dynamic Logic describes the emergence of symbolic

representations from subsymbolic background and it has been used to elicit knowledge from spatio-temporal oscillations observed in brains<sup>35,41</sup>.

#### **4.2. Conceptual Framework of Integrated Distributed Decision**

##### ***Support***

An integrated decision support system (IDDS) based on intermittent phase transitions is outlined here. The lessons learned from cognitive processing can be applied to the design of intelligent data processing and decision support systems, to improve their reliability and speed of operation. Instead of using a preset rule base as in traditional knowledge-based systems, an adaptive learning process is applied to generate an attractor landscape with desired structure. The advantage of this approach is the fast switch that produces the decision. The system is robust to variations in the environment and it can be continuously updated when new information becomes available.

In order to use neuropercolation as a novel computational and memory device, learning and adaptation has to be implemented. The memory of the system is defined as the collection of basins and attractor wings across the dynamic landscape. Learning contributes to the formation of convoluted attractor basins in the heterogeneous neuropercolation model. Recall of previously learned memory patterns is manifested through the collapse of the spatio-temporal oscillations to localized memory wings through phase transition. Experiments demonstrate the potential of dynamical memories operating on the principle of encoding in frames of spatio-

temporal activity patterns <sup>39</sup>.

Components of the dynamical decision support system have been implemented in robotic and distributed sensors platforms <sup>35,39</sup>. Data are obtained from high-dimensional, heterogeneous sensor resources. The task is integrating the data systematically and providing the basis for fast and reliable decision making, flexible reconfiguration and control. In IDDS information is not passively received but actively predicted and sought. Assigned goals and known system properties serve as model constraints, which are used in the dynamic logic formalism to build and refine the model field theory. The integrated sensor system cumulatively creates, learns, and adapts its internal models, and uses them to guide its actions. The system continuously solves problems imposed by the environment as it autonomously pursues its goals.

Figure 3 shows a generalized approach for cooperation in the case of networks of distributed sensor agents. The agents have their dedicated inputs and corresponding low-level processing tasks. The system has the following components:

- Preprocessor: Input compression, normalization, units B1, B2, , BN.
- Classifier: Identification/recognition of data, C1, C2, , CN;
- Comparator: Low-level decision making, D1, D2, , DN;
- Controller: Achieve dynamical (chaotic) balance, E1, E2, , EN;
- Extractor of common modes and decision center DC: Detect covariant oscilla-

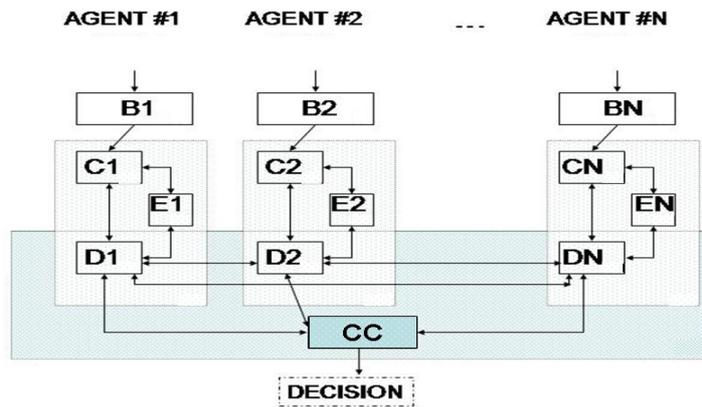


Fig. 3. Schematic view of the IDDS system in the network of  $N$  agents. The notations for the  $i$ -th agent are:  $B_i$  - preprocessor,  $C_i$  - classifier,  $D_i$  - comparator,  $E_i$  - controller. DC is the node representing the overall decision convergence center. The DC in cooperation with the  $D_1, D_2, \dots, D_N$  sets represents the high-level decision system which exhibits intermittent phase transitions.<sup>39</sup>

tions in individual agents.

The preprocessor, classifier, comparator, and controller modules perform tasks belonging to the individual agents. The extractor module (DC) is privileged with connections to all agents through connection to the comparator units. DC has a crucial high-level function, i.e., it extracts the coherent components of the individual units<sup>20,39</sup>. This coherent component is very small, typically  $< 1\%$  of the total signal power. However, this small covariant fraction of the signals indicates the high-level interaction in the network<sup>35</sup>. DC makes the decision based on the covariant component, as it is manifested through intermittent phase transitions.

The defining feature of IDDS is the high-level operation of constructing internal models of its own future states and goals. The system generates nested frames of intended actions and serial prediction models of increased accuracy using Dynamic Logic formalism. Its advance at each serial step is conditional on conformance of predicted and actual frames. As the mismatch between predictions and perceived data decreases, the models become more and more crisp. This iterative process ultimately leads to a transition threshold and the system dynamics collapses to a low-dimensional space. High-level decisions are made in this low-dimensional space. The decision is executed in the form of an action, which leads to a new situation, whereas the dynamics drastically expands to a highly chaotic regime, and the whole cycle starts again.

## **5. Conclusions**

By describing topological and dynamical properties of the neuropil, phase transitions are modelled in brains during higher cognitive functions. Destabilization by sensory stimuli and sudden changes in the spatio-temporal neurodynamics in cortices resemble phase transitions in physical systems. However, phase transitions are much more complex in brains than in physics. In brains, transitions to a more organized phase are intermittent. Multiple states commonly exist in both time and space in each cerebral hemisphere. The neuropercolation approach to phase transitions in brains has the prospect of creating powerful, robust computational models that match the performance of neural systems. The proposed method of controlling

phase transitions has been tested in neuropercolation models.

The proposed Integrated Distributed Decision Support system offers crucial advantages as an information storage and retrieval device: noise-resistance, robustness to system degradation, fast and efficient evaluation for decision making using limited resources and incomplete information. When the distributed sensing system tackles a given task, like identification or tracking, the above functional components intimately interact through resonance coupling and produce the required answer. The convergence to the desired identification happens through a sequence of sudden transitions in the spatio-temporal dynamics, which is manifested as the emergence of increasingly refined concept models. At this stage, the feasibility of dynamic logic iterative procedure approximating an expectation maximization algorithm is used. As the result of the oscillatory coupling among the components, the system settles to a dynamic state, through which it generates an optimal strategy for actions to be taken for reconfiguration and behavior adaptation in anticipation of the changing conditions. Earlier implementations have been used for robot navigation applications<sup>39,38</sup>. Here a distributed sensor system is outlined with its own autonomy for decision making in the context of the systems stated goal. This can include using multiple sensor platforms for target detection, identification, and tracking, which is the objective of ongoing studies.

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