A Cognitively Motivated Algorithm for Rapid Response in Emergency Situations

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***Abstract*—Robust response to crisis situations involving complex, large-scale networks with rapidly changing operational conditions is a fundamental task to be addressed in various task domains, including power systems, computer networks, public health, and many other areas. There are many manifestations of rapid, flexible responses to sudden changes in biological systems, from which we can derive basic principles to design robust technical systems for emergency response. In this work we outline the lessons learnt from brains as they respond to sudden changes basic principles of how the brain responds to environmental stimuli. We describe a hierarchical, multi-level model motivated by the structure and function of the brain and indicate possible applications in engineering designs.**

I. Introduction

Current technical approaches lack the capability to rigorously model complex interactions in large-scale networks or to provide efficient tools for enabling the network structures that support adaptive behavior in rapidly changing conditions encountered in real life scenarios. In practical terms, decisions must be made rapidly based on the combination of often hundreds of thousands, or millions of sensory channels, presenting formidable challenges to efficient decision support due to combinatorial explosion of possible interactions between diverse components (Buford et al., 2010). Hence, we experience the paradoxical situation of being able to sense various events without having the capability of processing them efficiently to support robust decisions (Kozma, Tanigawa, et al., 2012). These limits pose particular challenges in complex, dynamically changing scenarios, as in natural or man-made crises (Tango-Lowy, Lewis, 2005; Jakobson, Lewis, 2008). Even increasingly powerful computers built upon fundamental analytical mathematical paradigms may not be able to extract critical information from such a massive amount of data at a reasonable cost in terms of time and resources.

In recent years, cognitively motivated algorithms have gained popularity to address the challenges (Shaefer, Cassati, 2015). In this work we address the question of developing novel, biologically motivated algorithms for systems that respond rapidly and robustly to environmental changes. Specifically, we describe a data processing algorithm based on brain dynamics as described in Freeman K sets (Freeman, 1975, Freeman, 1991; Kozma, Freeman, 2001). Walter Freeman has been an early pioneer of neurodynamics and neural network research, who recently passed away (Kozma, 2016). Freeman K models are multi-scale neural networks with deep layers describing the dynamics of perceptual processing in the 6-layer structure of the cerebral cortex. The developed system facilitates early detection of deviations from normal operations, which help to make the required actions rapidly and to mitigate the consequences of impending disasters.

II. Proposed Cognitively Motivated Algorithm

We analyze and model massive amount of data, in order to identify possible signs of incipient changes due to natural degradation or malicious activity. These incipient changes may lead to situations when the operating conditions deteriorate rapidly and unexpectedly, when the changes in the state of large-scale systems require prompt and robust actions to prevent serious disasters.

A. Freeman K Sets as Pattern Recognition Tools

We propose the development of data processing algorithm based on Freeman K models (Kozma, Freeman, 2001). Freeman K models are multi-scale neural networks with deep layers describing the dynamics of perceptual processing in the 6-layer structure of the cerebral cortex. K sets include K0, KI, KII, and KIII sets, which correspond to the hierarchy of neural networks in the brain with increasing complexity of structure and function. The structure and dynamics of the hierarchy of K sets is illustrated in Fig. 1.

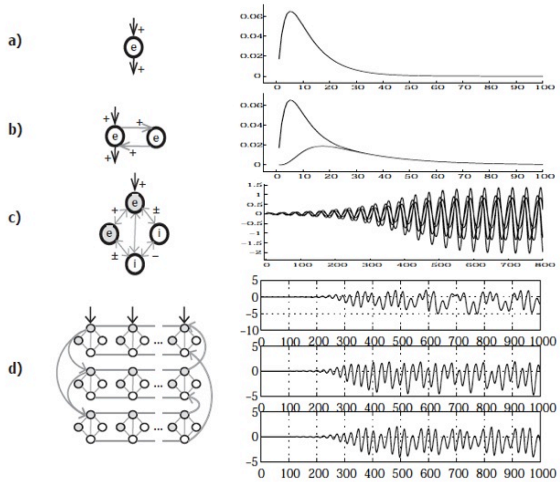

Figure 1. Illustration of the architecture and dynamics of Freeman K sets; (a) K0 set of non-interactive population with stable zero attractor; (b) KI set with mutually excitatory neurons producing non-zero activation level; (c) KII with interacting excitatory and inhibitory KI sets producing narrow-band oscillations; (d) KIII set with interacting KII sets resulting in broad-band oscillations; based on (Kozma, Freeman, 2009).

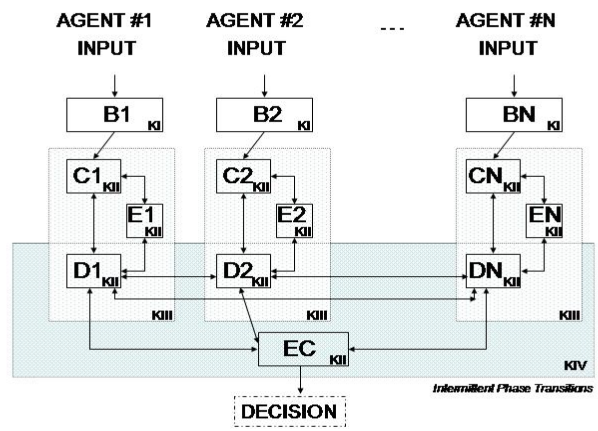

Figure 2. Schematic illustration of the KIV-based decision making system; the case of N interacting agents. Each agent is a KIII set with multi-layer structure including 4 interacting units (B, C, D, and E). The decision is made by the KIV system of interacting KIII units and the EC unit, standing for the entorhinal cortex, which coordinates integration process in the action-perception cycle; adopted from (Kozma et al., 2005).

The Freeman K sets have the following components (Kozma, Freeman, 2009): (a) K0 unit having sigmoid transfer function; (b) KI population of excitatory or inhibitory units: showing fixed point convergence; (c) KII with interacting excitatory-inhibitory populations producing limit cycle oscillations; and(d) KIII with interacting layers of KII sets exhibiting spatio-temporal chaos.

The spatio- temporal oscillations produced by KIII sets form the basis of the proposed pattern-based computing in the style of brains. KIII sets can be used as dynamical memory devices, which encode massive amount of data into non-convergent spatio-temporal oscillations. KIII neural networks can perform efficient classification and anomaly detection tasks. Dynamic KIII memories have several advantages as compared to convergent memory networks:

- KIII sets produce robust memories based on relatively few learning examples even in noisy environment;
- The encoding capacity of a network with a given number of nodes is exponentially larger than their convergent counterparts;
- They can recall the stored data very quickly, just as humans and animals can recognize a learnt pattern within a fraction of a second;
- KIII sets can detect rapidly abnormal patterns and anomalies, even though those have not been experienced previously.

KIII sets have been used successfully as dynamic memory devices for pattern recognition, classification, data clustering, web data mining, and sensory integration (Kozma, Freeman, 2001, 2009; Kozma et al., 2013).

B. Cognitive Decision Support using KIV Sets

Decision-making in crisis situations needs to be instantaneous and robust. There are only very few such robust methods in practically relevant problem domains, due to the overwhelming amount of data to be processed quickly. Brains routinely process large amount of sensory data and make robust decisions fast and reliably. However, in the case of crisis situations, even humans may fail and can make erroneous decisions. Here we build on the insights on the decision making in brains and extend to man-made systems.

In the proposed approach, we combine several KIII sets, each of which may correspond to a sensory modality of decision-making factor. The combined system is called the KIV set, as illustrated in Fig. 2 following (Kozma et al., 2005; Pazienza, Kozma, 2011). In general we have N agents, each of which has its dedicated inputs and corresponding low-level task. The components of the decision support system are specified in Table I.

The preprocessor, classifier, comparator, and controller modules perform tasks belonging to the individual agents. The extractor module (EC) is privileged with connections to all N agents through connection to the comparator units. EC has a crucial high-level function (KIV), i.e., it extracts the coherent components from the individual agents. The coherent component can be very small, typically < 1%. However, this small covariant fraction of the signals indicates the high-level interaction in the network. EC makes the decision based on the covariant component, as it is manifested through the intermit tent phase transitions (Kozma, Freeman, 2009; 2015).

Table I
Components of the KIV Decision System

TYPE	NOTATION	FUNCTION
Preprocessor	B1, B2, …, BN	Input compression, Normalization
Classifier	C1, C2, …, CN	Identification, Recognition of data
Comparator	D1, D2,…, DN	Low-level decision making
Controller	E1, E2,…, EN	Achieve dynamical balance
Extractor of common modes	EC	Detect covariant oscillations in separate KIII sets

The defining feature of the multi-level decision support is the high-level operation of constructing an image of a future state of itself in relation to its environment and its goal. The system generates nested frames of actions to be taken step-by-step, as well as serial predictions of the frames of multi-sensory inputs. Its advance in each serial step is conditional on conformance of predicted and actual frames within the limits of abstraction and generalization. Past experiences are stored in the connectivity arrays of the component layers. These arrays (matrices) store the perceptual consequences of the intentional actions taken earlier, which constitute all what the agent can 'know' about the environment. The resulting multi-agent approach serves as a prototype of future cognitively motivated decision support systems.

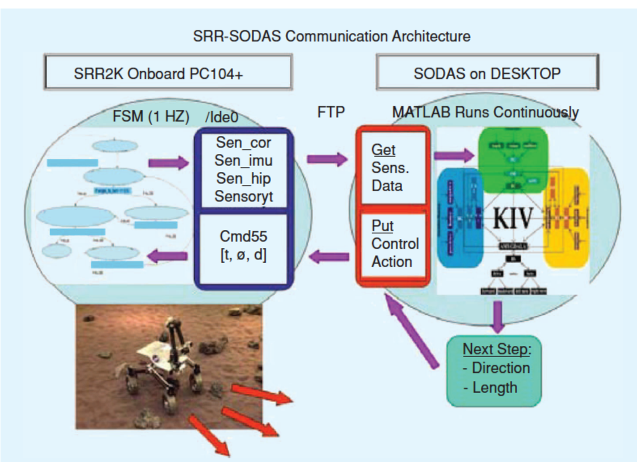

Figure 3. Example of the implementation of KIV-based control system using NASA Mars Rover prototype SRR-2K. The sensory modalities include stereo camera, accelerometers (IMU), and global positioning system (GPS); from (Kozma, 2007).

The utility of KIV sets has been demonstrated in decision support for autonomous robots and distributed sensor systems (Kozma, Freeman, 2009). Examples of using KIV for solving the task of action selection includes an autonomous robot control platform developed for the NASA Mars Rover prototype SRR-2K (Kozma, 2007; Kozma et al., 2008); see Fig. 3. The self-organized control algorithm provides rapid action selection from a set of behavioral prototypes in response to environmental clues. Possible scenarios include obstacle avoidance, goal orientation, and escape modes. SRR-2K has demonstrated her learning capabilities using a landmark system in open environment and in the presence of obstacles, as well. We have quantitatively characterized learning effects in the model using reinforcement, combined with short and long-term memories.

The successful implementation of embodied intelligent control has been characterized as a unique way to solve the notorious "symbol grounding" problem faced by many traditional AI designs (Dreyfus, 2009). In the next section, we introduce practical considerations for implementing KIV sets in emergency response scenarios.

III. Practical Aspects of Implementing KIV Model in Emergency response Scenarios

A. Phase Transitions in Emergency Situations

An important challenge we face in emergency scenarios is the limitation of current approaches to rigorously model complex interactions in large-scale networks and to provide efficient tools for enabling the network structures that support adaptive behavior. Random graphs and network theory provide a new way of looking at those problems and will be used to develop novel methods to model the evolution of graphs with desired optimal dynamic properties. We leverage recent developments in the theory of random graphs and percolation to formulate new theoretical problems for structural evolution and efficient communication in large-scale networks (Bollobas et al., 2009).

Information processing in brains employs phase transitions manifested in rapid switches in the system dynamics. Here we employ graph theoretical implementation of K sets in large-scale networks, called neuropercolation (Kozma, Puljic, 2015), to describe phase transitions as a fundamental mathematical approach to address the demand of rapid response. Phase transitions in the network implementation of KIV-based decision support are used to achieve the required rapid response.

B. Key Tasks Towards Robust Cognitive Decision Support

The ultimate goal is designing and implementing fully integrated data processing systems operating adaptively in real-time, starting with data acquisition and feature extraction, moving to pattern identification, high-level classification, and decision support. The corresponding computing platforms must be organized in a non-homogenous, hierarchical configuration in order to achieve better performance.

The multi-level KIV model provides exactly this feature. The advantages include the opportunity to deploy the powerful mathematical theory of phase transitions in heterogeneous populations of nonlinear components, including hierarchical structures. The mathematical characterization includes rigorous description of emergent pattern formation and phase transitions in populations of interacting units.

The theory provides the foundations for identifying critical parameters to control the dynamic behavior of the system, in which the co-evolution of structure and function leads to meaningful behaviors. The proposed approach provides a model as a dynamic system with quasi-stable states (basins) embodying various real life scenarios. This dynamical system is able to switch rapidly between various states (basins), which manifest robust decisions in the framework of an integrated distributed decision support.

III. CONCLUSIONS

We propose a decision support system in emergency scenarios, based on lessons learnt for cognitive neuroscience. This effort addresses practical challenges in complex, dynamically changing scenarios requiring robust and rapid decision-support. By studying robust decision making in brains, we address the issue of flexible reconfiguration in large-scale, spatially distributed networks.

We give the example of the biologically motivated KIV model, which has been used successfully in action selection and control of autonomous systems. The KIV platform provides a practical tool for developing systems for rapid response. The results are applicable in emergency scenarios and critical infrastructure in the case of normal operation, as well in abnormal situations, in order to prevent potentially catastrophic consequences.

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