Guest Editors' Introduction—Self-Organizing Knowledge and Data Representation in Distributed Environment

I. Introduction

IN recent years there has been a tremendous spurt in research and activity in self-organizing data and knowledge representation in the context of neural networks in distributed environments. Notwithstanding major strides in symbolic computing and knowledge-based systems (KBS), several researchers have expressed a concern regarding the brittleness and rigidity of current intelligent systems. The technical inclinations to date have focused toward regular and static knowledge representation, e.g., scripts, production systems, frames, etc. Self-organization and adaptation is an alternative paradigm that offers new insights into designing intelligent information processing systems. It enables a system to adapt dynamically to cope with unspecified domains, thereby displaying reasoning and common sense characteristics.

A. Computational Characterization

The quest for efficient computational approaches to self-organized data representation in distributed environment has undergone a significant evolution in the last few years. Specifically, the application of neural computing concepts to some of the many tasks performed by machines must be complemented by some deep insight into how to embed self-structured reasoning with massively parallel processing abilities. Therefore, we as computer scientists seek to understand the computational potential of this emerging paradigm and further explain the fundamental limitation and capabilities of such approaches to handling unstructured problems. For a broader treatment on this see [1].

Recent transformation from discrete symbolic reasoning to massively parallel connectionist neuroprocessing has compelling scientific interest, and is also of paramount practical importance. In general, the scientific community is confronted with two problems. Problems that are clearly defined and deterministic. They are targeted for situations that are completely deterministic, are precisely controllable, and can be handled by high performance computers employing rigorous and precise logic, algorithms, or production rules. This class deals with structured problems such as sorting, data processing, and automated assembly in a controlled workspace. On the other hand, there are scenarios such as the maintenance of nuclear plants, undersea mining, battle management, manufacturing environment, and assembly/repair of space satellites that lead to computational problems that are inherently ill posed and ill conditioned [2]–[4]. Such unstructured problems entail providing for situations that may have received no prior treatment or thought. Decisions that need to be made may be based on incomplete, often ambiguous information that may be plagued with imperfect or inexact knowledge, and may involve the handling of large sets of competing constraints that can tolerate close enough solutions. The outcome depends upon very many inputs and their statistical variations, and there is no clear logical method for arriving at an answer. In summary, this category encapsulates problems that cannot be satisfactorily addressed using traditional computational paradigms such as random-access machines [5], [6], Markov algorithms [7], Universal Turing machines [8], cellular automata [9], recursive function theory [10], production systems [11]–[13], and so on. The focus of artificial intelligence and machine learning has traditionally been to understand and engineer systems that can address such unstructured computational problems; for details on these see [1].

Intelligent Systems, using expert systems with some embedded reasoning, behave poorly in their ability to process visual or speech information, to adapt to unstructured environments, or to learn from past experience, as compared to biological systems. Intelligent systems lack some inherent capabilities of biological systems, such as common sense knowledge and reasoning, structuring knowledge to recognize complex paterns, adaptation and reorganization to domain specific queries, etc. Also, intelligent systems fall way behind in taking sensory information and acting on it, especially when sensors are bombarded by a range of different and competing stimuli. On the other hand, the machinery of biological systems is capable of providing satisfactory solutions to such ill-structured problems with remarkable ease and flexibility [14]–[18]. A key emphasis underlying any paradigmatic development for unstructured computation today is to understand how the aforementioned unstructured computations are carried out in biological systems. The latter exhibit a spontaneous emergent ability that enables them to self-organize and adapt their structure and function.

The central part in emulating biological systems by neuronal learning lies in narrowing the difference between the organization and structuring of knowledge, and the dynamics of biological neuronal circuitry and the symbolic processing paradigm [19]–[21]. For example, it has been widely hypothesized [22]–[25] that the hallmark of intelligence is the ability of remembrance, analogy, and resemblances, so that logical manipulation of symbolic descriptions is not an adequate tool to emulate biological systems. Also, there is substantial evidence [3], [24], [26] of the difference between the learning methods of a beginner and that of an expert. A beginner learns through rules, whereas the expert uses his expertise acquired through experience in the selection of learning rules. Briefly, the elements that characterize neuronal learning formalisms are the nature of states of individual neurons and the temporal nature of synaptic updating. The states of individual neurons may be either discrete or continuous. Further, the nature of time variable in neural computation may be either discrete or continuous. It has been shown that continuous-time networks can resolve human reasoning and perception and could be emulated by following rules or manipulating symbols, without regard to the varying interpretations of symbols.

Expert systems are a product of such a line of investigation. However, over the years AI researchers have unsuccessfully struggled against fundamental systems-engineering issues, such as the coding problem [28], the category problem [29], the procedure problem, the Homunculus problem, the developmental problem, and the nonmonotonic-reasoning problem. Since formal AI has not been able to surmount the preceding problems using logical reasoning alone, researchers have suggested recourse to alternate scientific paradigms of neural networks. The neural network community argues that logical reasoning is not the foundation on which cognition is based, but, instead, on emergent behavior that results from observing a sufficient number of regularities in the world. They hold the view that cognitive machinery is built from many simple nonlinear interacting elements—neural networks that store knowledge in their internal states and self-organize in response to their environments. Intelligent behavior, then, manifests from the collective interactions of these units.

In order to make progress in self-organizational knowledge and data representations, it is important to examine innovations in both the processing and storage of these structures. The speed of retrieval and computation plays a dominant role in manipulating self-organizing structures. Efficient knowledge and data representation need to be studied, which can easily be tailored to the computational paradigms of massively parallel processing and distributed processing.

In this Special Section we focus on identifying, applying, and analyzing various self-organizing paradigms. An attempt is made to quantify the limitations observed in knowledge-based systems as a result of static representations, and as a byproduct to motivate fresh ideas on the dynamics of representation itself. The main focus will be on rigorously derived data and knowledge structures, evolutionary dynamics of such structures, and novel mechanisms for exploiting self-organizing representations.

II. Overview of the Papers

This Special Section contains four regular papers and six concise papers. The topics covered range from new insights into self-organizing systems to their use in various applications, such as image processing, target recognition, and production systems.

Two papers in this Special Section present new results in neural network theory. In "The Science of Making *Erors*: What Error Tolerance Implies for Capacity in Neural Networks," Venkatesh addresses the important question of how constraints on the reliability of neural network affect its learning ability. The author presents formalism for rigorously analyzing the relationship between error tolerance and storage capacity in binary neural networks. The main result is that relaxing the reliability constraint increases the capacity by only a constant factor without improving its rate of growth as the network dimension is increased. In "Generalization by Neural Networks," Shekhar and Amin discuss the requirements of neural network learning for generalization. They present a new stochastic learning algorithm based on simulated annealing in weight space. The authors also describe an implementation of the algorithm and its validation.

Five papers in this Special Section are related to image recognition. In "Gray-Scale ALIAS," Bock, Klinnert, Kober, Rovner, and Schmidt focus on the detection, discrimination, and localization of anomalous features in otherwise normal images. They present a novel and important approach to image processing based on an interesting combination of scale and feature encoding to achieve a significant level of anomaly detection capability. The system is fully parallel and adaptive. It acquires its knowledge through learning using trial and error interaction with its environment and can be trained with fewer than 100 training images. In "A Recurrent Cooperative Competitive Field for Segmentation of Magnetic Resonance Brain Imagery," Worth, Lehar, and Kennedy develop a Grey-White Decision Network for labeling each pixel of a brain image as either grey matter, white matter, or other matter. The network operates without using explicit rules; instead, the decision emerges from local information and interactions of units in an on-center, off-surround recurrent cooperative competitive neural network. The analog nature of such a mechanism makes the system less brittle and allows it to be gracefully influenced by other external factors. In "Automatic Target Recognition Using a Neocognitron," Himes and Iñigo describe the use of a neocognitron in an automatic target recognition system. The first layer of the neocognitron is trained using supervised learning, but all subsequent layers are trained using unsupervised learning. The authors also present methods to determine the convergence of the neocognitron during training and to determine the maximum allowed inhibition to guarantee shift invariant recognition. In "A Multilayered Self-Organizing Artificial Neural Network for Invariant Pattern Recognition," Minnix, McVey, and Iñigo present a self-organizing neural network. The authors highlight the need for invariance in pattern recognition and present a modified Walsh–Hadamard transform based invariant image representation scheme and a self-organizing neural network based recognition. In "Generalization Capabilities of Subtle Image Pattern Classifiers," Egbert, Goodman, Kaburlasos, and Witchey evaluate the generalization capabilities of several neural networks as well as algorithmic classification techniques for image patterns. The results indicate that the backpropagation neural network produces the best classification results and provides significantly better generalization from a set of training patterns.

The remaining three papers in this section deal with learning and self-organization in distributed computer environments. In "Organizing Self-Design of Distributed Production Systems," Ishida, Gasser, and Yokoo present a computational scheme for self-organization in a distributed environment. The authors

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highlight two new reorganization primitives, namely, composition and decomposition, which improve the ability to build distributed production systems that can adapt to dynamic real-time constraints. The approach exploits an adaptive tradeoff of resources and reorganization form to satisfy time and performance constraints. In "Development of a Class of Distributed Termination Detection Algorithms," Kumar deals with the problem of detecting when a distributed learning system has completed its learning activity. The author systematically derives a class of efficient termination detection algorithms that can be used in solving several distributed network learning problems. The assumptions regarding the underlying systems are easy to satisfy in practice. In particular, the topological requirements are simple and flexible and the communication channels need not be FIFO. In "A Self-Organizing Knowledge Representation Scheme for Extensible Heterogeneous Information Environment," Sull and Kashyap investigate the problem of automating the schema integration process in heterogeneous information bases. They develop methods that derive an object-oriented data schema from relational schema and rule-bases. They also present an algorithm for schema integration between different object-oriented schemas.

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