TRIUNE–BRAIN INSPIRED UNIFYING VIEW OF INTELLIGENT COMPUTATION

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Abstract

Paul MacLean, following the evolutionary scheme, proposed the idea of "triune–brain," in which the cortex is organised into three layers. He proposed that the three layers are responsible for instinctual behaviour, the motivational and emotional influences, and the rational influences on decision making, respectively. We borrow this metaphor of triune–brain to propose a unifying viewpoint for bringing together disparate themes of intelligent computation. In this framework, quantitative methods of statistics are the equivalent of behaviours at the instinctual layer, rule–based approaches of the symbol processing–kind, being rational and logical, sit at the top and methods of soft computing (neural networks, fuzzy logic, genetic algorithms, etc.) operate at the intermediate level. It is argued that just as all the levels are important for a functioning organism, this three-level interaction is crucial for theories of intelligent computation.

1. Introduction

Intelligence and computability are discussed in this section. In the next section various methods of intelligent computation are introduced. In the third section, a unified view of all these techniques is offered. The last section offers conclusions and pointers to future work.

1.1 Definitions of Intelligence

Defining intelligence is arguably one of the most difficult tasks. There has been little agreement as to what aspects need to be included in such a definition. In what follows, we summarise some of the definitions used by psychologists and then quote the definition of an artificial intelligence system theorist.

Wechsler, the designer of Wechsler Adult Intelligence Scale (WAIS) which is used extensively to assess human intelligence, gave his working definition of intelligence (in [1]): "Intelligence, as a hypothetical construct, is the aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his environment" (p. 79). Matarazzo [1] emphasised that functional intelligence is not identical with the mere sum of these abilities, however inclusive. The reasons, according to him, are, "(1) the ultimate products of intelligent behaviour are a function not only of the number of abilities or their quality but also of the way in which they are combined, that is, their configuration, (2) factors other than intellectual ability, for example, those of drive and incentive, are involved in intelligent behaviour, and (3) finally, whereas different orders of intelligent behaviour may require varying degrees of intellectual ability, an excess of any given ability may add relatively little to the effectiveness of the behaviour as a whole" (p. 79).

Howard Gardner [2], a Harvard Psychologist, defined intelligence "as the ability to solve problems, or to create products, that are valued within one or more cultural settings" (p. xiv), and he warned that his definition does not say anything about either the sources of these abilities or the proper means of testing them. Further he argued that "a human intellectual competence must entail a set of skills of problem solving — enabling the individual *to resolve genuine problems or difficulties* that he or she encounters and, when appropriate, to create an effective product — and must also entail the potential for *finding or creating problems* — thereby laying the groundwork for the acquisition of new knowledge" (p. 60). This definition emphasises the importance of the cultural context in which intelligent capabilities are acquired and assessed.

Earl Hunt [3] gave a lucid account of the recent controversies in the notions of intelligence and heritability. The details of this discussion are not relevant to the present exposition. However, it is worth looking at the differences he identifies between the notions of intelligence in psychometry and cognitive psychology.

According to psychometric views, human intellectual competence appears to divide along three dimensions, fluid intelligence, crystallised intelligence, and visual-spatial reasoning. *Fluid intelligence* is the ability to develop techniques for solving problems that are new and unusual, from the perspective of the problem solver. *Crystallised intelligence* is the ability to bring previously acquired, often culturally defined, problem-solving methods to bear on the current problem. *Visual-spatial reasoning* is the specialised ability to use visual images and visual relationships in problem solving. Cognitive psychology views intelligence in an information processing sense: Intelligence is the process of creating a mental representation of the current problem, retrieving relevant information from storage, and manipulating the representation in order to obtain an answer. Thus cognitive psychology views cognition as a process, whereas the psychometric view makes it a collection of abilities.

Allen Newell, an artificial intelligence system theorist and designer, takes a pragmatic view in defining intelligence. Newell [4] defined that "a system is intelligent to the degree that it approximates a knowledge-level system" (p. 90). A knowledge-level system is one that possesses a medium of knowledge and has a body of knowledge. This body of knowledge contains details of the external environment in which the system is embedded, its goals about how the environment should be, the sequence of actions it took over time, and the relations between them. Thus, as per this definition, if a system uses all of the knowledge that it has, it must be perfectly intelligent and if a system does not have some knowledge, failure to use it cannot be a failure of intelligence. If a system has some knowledge and fails to use it, then there is certainly a failure of some internal ability. This failure can be identified with a lack of intelligence.

Clearly, the common theme in all these definitions is that the system, artificial or natural, possesses general underlying abilities that are useful in perceiving the external world and acting on it to fulfill external or internal goals. Also most of these definitions distinguish between the abilities that are situation specific and those that are general and thus are applicable across situations. The other important distinction that Newell made is between possessing knowledge versus ability to bring all of it to bear on a given problem. These distinctions will be useful for any theory of intelligent computation. In the next section it will be shown how the metaphor of computability limits the space of possibilities in ways of thinking about natural intelligence (human cognition, mind) and artificial intelligence. This then would pave the way for the discussion of alternative perspectives.

1.2 Computability and Intelligence

Metaphors, the linguistic devices that provide insights into the nature of an unknown in terms of a known, have a significant heuristic value as guides to further investigation. In the realm of intelligent systems (artificial and natural), the computational metaphor has been a persistent one. It has been used to propose information processing view of the mind, i.e., mind as a computer and also the other way round, the computations in a computer as the analogue of the thinking aspect of mind. The computational metaphor also led to the formal systems view point of thinking and intelligence. For example, thinking has been equated to symbol manipulation and first order predicate logic has been used extensively as a representational framework for many AI systems (Newell, [4]). These formalisms have also been used to explain the workings of the mind (Fodor, [5]).

West & Travis [6] reflected on the computational metaphor and its use in artificial intelligence. They concluded that "the main consequence of the computational metaphor and formalist perspective is the need to recreate, inside the mind and inside the computer, a symbolic simulacrum of an extensive portion of the external world in such a manner that it is amenable to processing in pragmatically finite time. This need is not a consequence of the objective to emulate the mind but the perspective from which this problem was approached" (p.76). Thus they claimed that need for computability forced intelligence to be formalised. This formalist tradition has further restricted what mechanisms could count as intelligent processes. Although this computational metaphor is not in itself useful, it stands now as the declaration of the dualistic tradition in the design of intelligent systems: "(1) mind and nature are absolutely separate; (2) the mind manipulates abstract representations of the environment, never the environment directly, and it is this manipulation that constitutes thinking; and (3) the manipulations that make up mental functions can be expressed in a formal language; and (4) this formal language is basically mechanical and deterministic, at least sufficiently so that it can be embodied in a machine (computer) where it can function as a replicant of the functioning of the human mind" ([6], p.74). In a subsequent section, mechanisms that are non-deterministic and self-organising will be discussed as an alternative to these formalist systems.

The other shortcoming of the symbol manipulating approaches is the "grounding" problem. A discussion of how the "grounding" problem can be overcome using connectionist methods can be found in Honavar & Uhr [7] and Bapi et al. [8]. Harnad [9] argued that the woes of symbol manipulating machines (proposed in AI) relate to the "ungrounded" nature of the atomic symbols. He pointed out that the initial set of symbols, being arbitrary, is flexible enough to support compositionality (atomic symbols can be combined and molecular representations can be decomposed according to a formal syntax) and systematicity (the atomic and molecular symbols and the rules of syntax can be systematically assigned a meaning). He asserted however, that the very fact that these symbols are arbitrary, means they become "ungrounded", i.e., their meaning and interpretation reside in the subject's 'head' and are otherwise 'rootless.' His solution calls for grounding the categorisation in motor and sensory perception. By enabling the organism to interact with the environment, the resulting perceptions will have an action-based anchoring and the meaning does not depend on arbitrary interpretation by an external agent. The formalisms of self-organising dynamical systems and autopoiesis, to be discussed in a subsequent section, offer alternative ways of achieving the symbiosis of the organism (artificial or natural) with the environment.

2. Dynamical Systems Theory Viewpoints

In this section, two viewpoints based on dynamical systems approach will be discussed. Discussion of other viewpoints such as, the various soft computing methods (neural networks, fuzzy logic, genetic algorithms), artificial life, and genetic programming, is not attempted here as they are by now well known (for a discussion on AI perspectives see [10]). The primary aim of this article is to offer alternative and unifying views.

2.1 Self-Organisation

Erich Jantsch, a Viennese astrophysicist turned organisational theorist and futurist, proposed the notion of co-evolution (Jantsch, [11]). He tried to combine the dissipative system approach of Ilya Prigogine, who received a Nobel prize in chemistry in 1977, with the system's theory ideas of Ludwig von Bertalanffy. He synthesised the above ideas with the notion of *autopoiesis*, a process by which living organisms renew themselves by regulating processes that are responsible for the integrity of their structure. The idea of autopoiesis was first introduced by the Chilean biologists, Humberto Maturana and Francisco Varela (see Maturana & Varela, [12] for a detailed exposition of this idea). West & Travis [13] supported Maturana and Varela's autopoiesis idea as a viable formalism for intelligent system design.

Jantsch's goal was to propose a General Dynamic System Theory. Jantsch's attempt was to offer alternative paradigms for evolution. He thought that the Darwinian view of evolution as a process of adaptation through competition, was limited. His proposal was for evolution through mutual co-operation, and termed it *co-evolution*. The basic principle of co-evolution is that evolution at the micro and macro structural levels proceeds hand-in-hand as a whole. Co-evolution calls for a mutual influence of changes at the micro-level and the changes in the macro structural level on each other, without one being causal for the other. The causal connection is simultaneous and instantaneous. As a result of this complex feedback connection, the micro does not build the macro in gradual steps and also great shifts in macro-level are not necessarily reciprocated at the micro-level. He elaborated these co-evolution ideas using dissipative system framework. These co-evolution ideas are now being seriously pursued in the area of evolutionary computing [14].

A dissipative structure is one which is continuously dissipating entropy. Entropy represents the amount of unavailable (unavailable to the host system for any useful work) energy in the process of energy transformation from one form to another. Dissipative systems are self-organising and nondeterministic and operate far from equilibrium conditions. A vortex in a pool of water is an example of such a system. Vortex comes about due to the dynamic equilibrium between the inrush and outflow of water. Jantsch realised that increased autonomy means more instability and openness to change. Although this seems paradoxical, this is precisely what gives the system dynamic stability, that is openness to change than a state of static equilibrium. He arrived at this view finding that a dissipative structure is in a constant need of new input to maintain its form and hence is in intimate contact with the flow of the surrounding environment. In this view, John Doe, a generic human is pictured as a self-organising (autopoietic dissipative) process rather than merely as a distinct part of a whole. He is a collection of and is part of a collection of self-organising structures. He is simultaneously a macro structure feeding energy input into his internal processes to sustain himself as well as being the part of the other structures such as the corporation he works for, the city he lives in, the culture he belongs to, and the other external structures such as the ecosystem, solar system etc. There is a dynamic interaction among these various structures. One of the views this picture emphasises is the importance of the dynamic process between the so-called individual parts and the whole. Briggs & Peat [15] elegantly summarised this point:

> Co-evolution overthrows neo-Darwinism and asserts that life forms are not created piece by piece in small changes: they are dissipative structures arising spontaneously and holistically out of the flux and flow of macro and micro processes. Co-evolution explains the gentleness of the whale, the delicacy of the tropical fish, the gay markings of the butterfly, the curiosity of the human mind not as simply responses to the demands for survival but as the creative play and co-operative necessity of an entire evolving universe. (p. 214)

The language of nonlinear mathematics of the dynamical systems theory gives ways of capturing these insights in the design of systems and in understanding complex systems such as the Stock market, Global Economics, etc. He had a unifying vision of the relations between levels of planning, world views, guiding images, and system theoretic approaches. He demonstrated how planning may be organised as an evolutionary process. Jantsch's key idea in this hierarchical arrangement and also in his co-evolution theory, is that the top levels are open for entry and absorption of novelty and change. With the 'opening upward,' the manager of the higher conceptual levels (which are not necessarily the higher power levels) become the managers of change, whereas the lower conceptual levels need administrators, they serve as the dependable operators of established and only slowly changing processes. The three-level hierarchy will be discussed again when the triune brain theory is introduced in the next section. Jantsch also introduced the idea of mind and intelligence as the *quality* of the self-organising dynamics. These ideas of self-organisation and views of complex systems such as societies, markets are very useful in thinking about alternative ways of designing intelligent systems and the underlying algorithms for intelligent computation.

2.2 Dynamical Cognition

Jordan Pollack, an AI and Neural network researcher, in his book review of Allen Newell's *Unified theories of cognition*, offered a vivid picture of how the viewpoint of dynamical systems theory is very relevant to bringing in biological realism in artificial systems and in modelling complex systems [16]. He asserted that complex control systems such as — the insect and animal colonies, the immune system in the human body, the genetic control of fetal development, the evolutionary control of populations of species, co-operative control in social systems, autopoietic control system for maintaining the planet — all of these have some means of self-control while allowing for extreme creativity. He lamented that the current formalisms do not consider them as viable theories of computational intelligence. His research in neural networks had led him to believe that fractals and chaos have a role to play. Based on this research, he proposed a *dynamical cognition hypothesis*:

> The recursive representational and generative capacities required for cognition arise directly out of the complex behaviour of non-linear dynamical systems. (p. 367)

Although such dynamical systems formalisms offer qualitative advantages over the more logical formalisms, we are long way from using these in practical applications. However, the point we would like to make is that the field of computational intelligence, being still in its infancy, needs to explore various viewpoints and not get stuck in 'local minima.' In the next section, various viewpoints discussed in this article as well as the other softcomputing methods will be unified using the framework of triune–brain theory.

3. Triune–Brain Theory Based Unifying View

MacLean [17] hypothesised, based on extensive behavioural studies, that the human brain is divided into three 'layers' that arrived at different stages of evolution — the deepest layer is the "reptilian brain," responsible for automatic instinctive behaviour reflected in some basic maintenance patterns, and some habitual patterns. Above the reptilian brain is the "paleomammalian (old mammalian) brain," responsible for emotions such as fear, love, and anger, which focus on the needs for individual and species survival. Finally, at the top is the "neomammalian (new mammalian) brain," responsible for rational strategies and verbal capacities. This framework has been used by Bapi & Denham [18] to propose a unification approach for methods of computational intelligence. The underlying conceptual framework is due to Leven [19] who distinguished between three different problem solving styles, which he named after three well known mathematicians: DANTZIG problem solvers typically use direct-solving techniques — tackle one problem at a time; BAYESIAN solvers attempt to find the best possible solution; GODEL problem solvers seek meaning, look for causes, and adopt novel approaches. Also, Raghupathi, Levine, Bapi, & Schkade [20] used this framework to introduce three-level hierarchies in the process of legal reasoning.

This idea of triune–brain, that is that the brain can be viewed at three levels; instinctual, emotional and rational; can be used to unify various computational styles. One way to look at the computational theories is that the quantitative schemes such as the statistical and mathematical methods fit in with the instinctual level, as these schemes usually are rigid and depend on the nature of input exclusively. Usually there are no built in mechanisms in these techniques to adapt themselves to varying situations. The learning schemes of traditional AI, such as frames, scripts, case based reasoning systems, etc., on the other hand, fit in at the rational level where the behaviour is more logical and rational. Most of the soft-computing schemes, such as neural networks, fuzzy logic, genetic algorithms, classifier systems, etc., fit in at the emotional level or at the instinctual-emotional or emotional-rational borders. It is these schemes at the intermediate level that offer ways of studying how emotion colours perception, of deciding when to employ rational techniques and of promoting a shift between the levels of instinct, emotion and reason. The beginnings of how this can be achieved in neural networks has been indicated in Levine & Leven [21] and Bapi [22].

Table 1. Three-fold models in various domains

	Evolutionary Brain	
Reptilian	Paleomammalian	Neomammalian
	Forms of Rationality	
Calculative	Arational	Deliberative
	Decision Making	
Dantzig	Godelian	Bayesian
	Guiding Image for Manager (Intelligent Agent): Jantsch’s Viewpoint	
Administrator	Co-ordinator	Catalyst
	Theories of Intelligent Computation	
Quantitative Methods	Soft Computing	Symbolic AI
(Statistics, Mathematical methods)	(NN, Fuzzy Logic, GA, etc.)	(Frames, Scripts, CBR)

Note. From *Motivation, emotion, and goal direction in neural networks* (Chap. 8, p. 293) by D. S. Levine and S. J. Leven (Eds.), 1992, Hillsdale, NJ: Lawrence Erlbaum Associates. Copyright 1992 by Lawrence Erlbaum Associates, Inc. Adapted by permission.

Leven [23] culled three-fold models from various domains and discussed them in the light of the triune brain theory of MacLean [17]. Table 1 lists various three-fold models. Dreyfuss and Dreyfuss (see the discussion in [23]) argued, from their study of experts and nonexperts, that nonexperts employed *calculative rationality*, which involves looking for context-free cues and using precise rules. Competent thinkers developed hierarchical rule bases, organised information in semantic nets and use *deliberative rationality* to weigh options and make decisions. Whereas the experts, not so surprisingly, employ *arationality*. When things are proceeding normally, Dreyfusses claimed that experts do what normally works for them, they do not have to employ deliberative reasoning. This three-way organisation can also be discerned in Jantsch’s view of the managerial decision process. Additionally, managers here are treated as metaphor for intelligent agents that are potentially performing intelligent computations. In Table 1, Jantsch's guiding image for managers is organised at three levels. A manager assuming responsibilities at the higher level needs to be open for change and needs to act as a *catalyst* for change. The middle-level manager acts as a *co-ordinator*, acting to convey the visions of the higher conceptual levels to the lower-level managers. The lower-level manager, can also be viewed as an *administrator*, the level at which the actual execution of plans and collection of information takes place. It needs to be emphasised here that, by virtue of their roles in an organisation, managers are placed at different levels of the hierarchy, their interactions, however, place them in a holistic heterarchy. This key point is applicable in all the other three-way organisations shown for various domains in the table.

4. Implications of Triune Models in Engineering Design and Manufacture Problems

Solution to engineering design and manufacture problems can also be attempted in a three-tier approach. Standard mathematical and engineering techniques sit at the lowest–tier, symbolic and rule–based methods lie at the highest–tier, and soft computing approaches such as neural networks, fuzzy logic, genetic algorithmic methods are situated at the middle–tier.

Given a design/manufacture problem, sub–problems that can be solved using traditional mathematical, statistical, and engineering methods need to be isolated from those sub–areas that need intelligent (heuristic) methods for their solution. This isolation stage is very crucial as heuristic techniques should not be applied when standard, well-understood techniques meet the desired objective. Development costs and times are reduced by using standard methods. There may be some rare exceptions when standard methods can solve the problem but are computationally inefficient. In this case the problem needs to be addressed by heuristic methods.

When it is determined that standard methods can not be utilised, then a solution using symbolic methods such as rule–based approaches, expert systems, case based reasoning, needs to be investigated first. Due to an explicit knowledge structure and a well–defined causal chain in the reasoning process, symbolic methods can trace an explanation of the results. Since such a facility is not always available with various soft computing approaches (NN, GA, etc.), it is recommended that symbolic methods are attempted first before resorting to soft computing methods. Symbolic approaches however assume that domain experts are available and appropriate symbolic representation of the problem is feasible. Additionally, it is assumed that the domain experts are willing and able to help develop a symbolic system.

When all else fails, problems can be attempted with soft computing approaches. Also a combination of approaches (hybrid methods) using standard mathematical, symbolic, and soft computing methods, can be utilised. Currently, one of the problems with methods at the middle–tier is that the solution process is not readily explainable and transparent to the user. For example, the input–output mapping learnt by a neural network from exemplars is not directly accessible. Although progress is being made in extracting rules from neural nets [24], the problem is still open.

There are two underlying themes in the three–tier problem solving process that is being proposed here —(i) to resolve the sub–problems at the middle–tier into either lower–tier or upper–tier problems so that the reasoning process becomes transparent and the solutions explicit and (ii) to organise the solution in an integrated way so that all the available methods are tried in a systematic way but taking care to isolate the problem sub–areas so that sub–problems are solved at an appropriate level. A similar three–layer architecture can be used for real–time control problems where the lower–layer has fast response times, the upper has slow response times and the middle–layer has medium response times. The control techniques that underlie each layer are organised in a similar way as proposed earlier —standard linear/nonlinear control techniques at the lower, neurofuzzy techniques at the middle, and symbolic methods at the upper–layer.

5. Conclusions

The framework of three-way organisation for the different theories of intelligent computation is offered as a guidance. It needs to be remembered that, just as an expert needs deliberative rationality when a decision scenario is out of the ordinary, just as in a functioning human being instinct, emotion and reason operate as a unified whole, various theories of intelligent computation would operate in a seamless and synergistic fashion in the designs of intelligent systems. It is unto us, the researchers in these areas, to build bridges and discern the unity in this trinity. The recent advances in the soft computing field herald some profound developments on the horizon of cutting edge theories of intelligent algorithms. It is hoped that the insights gained in this pursuit push the limits of our understanding of human intelligence and serve as guiding beacons to develop more intelligent machines.

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References

1. Matarazzo, J. D., 1972, *Wechsler’s measurement and appraisal of adult intelligence* (Fifth edition), Oxford University Press, New York, NY.
2. Gardner, H., 1993, *Frames of mind: The theory of multiple intelligences* (Second edition), Fontana Press, Harper Collins Publishers, London.
3. Hunt, E., 1995, The role of intelligence in modern society, *American Scientist*, **83**, 356-368.
4. Newell, A., 1990, *Unified theories of cognition*, Harvard University Press, Cambridge, MA.
5. Fodor, J. A., 1976, *The language of thought*, Harvester Press (Harvard University Press paperback), Sussex, UK.
6. West, D. M., and Travis, L. E., 1991, The computational metaphor and artificial intelligence: A reflective examination of a theoretical falsework, *AI Magazine*, **12 (1)**, 64-79.
7. Honavar, V., and Uhr, L., 1994, *Artificial intelligence and neural networks: Steps toward principled integration*, Academic Press, Boston, MA.
8. Bapi, R. S., McCabe, S. L., and Roy, R., 1996, Book Review of *Artificial intelligence and neural networks: Steps toward principled integration*, V. Honavar and L. Uhr (Eds.), 1994, Academic Press, Boston, MA , *Neural Networks*, **9(3)**, 545–548.
9. Harnad, S., 1990, The symbol grounding problem, *Physica D*, **42**, 335-346.
10. Roy, R., and Bapi, R. S., 1996, AI at the cross-roads: Past achievements and future challenges, Book review of *Artificial Intelligence in Perspective* , D. Bobrow (Ed.), 1993, *SIGART Bulletin*, **7(1)**, 10–13.
11. Jantsch, E., 1980, *The self-organizing universe: Scientific and human implications of the emerging paradigm of evolution*, Pergamon Press, Oxford.
12. Maturana, H. R., and Varela, F. J., 1992, *The tree of knowledge : The biological roots of human understanding* (Rev. ed.), Shambala.
13. West, D. M., and Travis, L. E., 1991, From society to landscape: Alternative metaphors for artificial intelligence, *AI Magazine*, **12 (2)**, 69-83.
14. Langton, C. G. et al., 1991, *Artificial Life II*, Addison-Wesley Publishing Co.
15. Briggs, J. P., and Peat, F. D., 1984, *Looking glass universe: The emerging science of wholeness*, Fontana Paperbacks, Harper Collins Publishers, London.
16. Pollock, J. B., 1993, On wings of knowledge: A review of Allen Newell’s *Unified theories of cognition*, *Artificial Intelligence*, **59**, 355-369.
17. MacLean, P. D., 1990, *The triune brain in evolution*, Plenum Press, New York, NY.
18. Bapi, R. S. and Denham, R. S., 1996, Computational Intelligence: A Synergistic Viewpoint, *International Journal of Computational Intelligence and Organizations*, **1**, 2–9.
19. Leven, S. J., 1987, *Choice and Neural Process*, Unpublished doctoral dissertation, University of Texas at Arlington, Arlington, TX.
20. Raghupathi, W., Levine, D. S., Bapi, R. S., and Schkade, L. L., 1994, Toward connectionist representation of legal knowledge, In D. S. Levine and M. Aparicio IV (Eds.), *Neural networks for knowledge representation and inference*, Lawrence Erlbaum Associates, Hillsdale, NJ, pp. 269–282.
21. Levine, D. S., and Leven, S. J., 1992, *Motivation, emotion, and goal direction in neural networks*, Lawrence Erlbaum Associates, Hillsdale, NJ.
22. Bapi, R. S., 1996, Exploring the role of emotion in the design of autonomous systems, In M. van der Heyden, J. Mrsic-Flögel, and K. Weigl (Eds.), *Proceedings of the Helsinki Neural Network Group Workshop HELNET’95, Vacanciel, France, Oct 4-7, 1995*, VU University Press, Amsterdam, pp. 115–125.
23. Leven, S. J., 1992, Learned helplessness, memory, and the dynamics of hope, In D. S. Levine and S. J. Leven (Eds.), *Motivation, emotion, and goal direction in neural networks*, Lawrence Erlbaum Associates, Hillsdale, NJ, pp. 259–299.
24. Omlin, C. W., and Giles, C. L., 1996, Extraction of rules from discrete-time recurrent neural networks, *Neural Networks*, **9(1)**, 41–52.