Guest Editorial

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Special Issue on Evolutionary Neural Systems

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Over the past decade, a growing number of researchers have become interested in applying evolutionary algorithms to the creation of neural network structures and dynamics. Many people have felt that the complex parameter search spaces of neural networks would be an appropriate domain in which to apply the Darwinian search techniques of evolutionary algorithms. Probably more than 100 researchers are involved full time, world wide, in this task. It was therefore felt by the editor in chief of this Neurocomputing journal Dr. David Sanchez, to be an appropriate time to devote a special issue to this theme. I was invited by him to be its guest editor. I accepted this honor, interpreting it as recognition to some extent of the type of work that I do, namely attempting to build an artificial brain with nearly 100 million neurons, by evolving tens of thousands of cellular automata based neural network circuit modules in special evolvable hardware at electronic speeds.

Putting together a special issue is a lot of work, so of course I needed an editorial team to help me do the reviewing. My immediate thought was to invite Dr. David Fogel, whom I have known for years, to join me. David has a reputation for being a human dynamo when it comes to evolutionary computation. He was the second youngest person in history to be made a fellow of the IEEE. He is editor in chief of the IEEE Transactions on Evolutionary Computation. He has written a string of books and has published over 200 technical papers, and he is a member of the editorial board of several other journals. All this, and he's still in his 30s! In other words, he is a man who gets things done, just the sort of person I needed to help me on the road to getting out a special issue, which would be a first time experience for me. David accepted, and never disappointed me. He was terrific - fast, efficient, knowledgable, experienced, dependable. If ever readers find themselves in a similar position to mine, then David Fogel is your man. He was my nitro to the gas tank. He immediately suggested names for the editorial committee, which included Prof. Xin Yao of the University of Birmingham, UK, and Prof. Michael Conrad of Wayne State University, USA, plus names of a few other people who were too busy with their own special issues, etc. to accept. So with the four of us, we set about writing a call for papers, which was duly broadcast. Several months later, 15 groups of authors submitted papers, of which 10 passed the two review rounds. These 10 papers you can read in this special issue.

Unfortunately, during the review process, Prof. Michael Conrad, pioneer in molecular computing and evolutionary computation, died of cancer, so we dedicate this special issue to him. His role as reviewer and committee member was taken over by 3 of his colleagues, Prof. Kevin Kirby of Northern Kentucky University, USA, Prof. Jong-Chen Chen of the National Yunlin University of Science and Technology, Taiwan, and Prof. Mateen Rizki of Wright State University, USA.
By evolutionary neural systems, we do not restrict ourselves to the application of evolutionary algorithms to artificial neural networks. With the word "neural", we include its biological sense. Hence we were not surprised, when all the candidate articles were received, to find that they could be classified broadly into two categories, namely, work on the evolution of artificial neural networks, and work on the evolution of biological neural networks. The 10 papers in this journal provide a sampling of the type of research work being undertaken within this growing and broadening field. The papers are presented in an order which reflects this broad polarization, beginning with the "Artificial". They include -

A1) hardware design of a multilevel neural computing system
A2) work on building an artificial brain
A3) evolving a neural net based checkers player
A4) comparing evolution strategies and backprop for neural net training
A5) robot evolution without internal states
A6) automatic design of artificial brains
A7) evolutionary synthesis of neural network recognition systems

The second and smaller group of papers, dealing with the "Biological", includes work on -

B1) self-regulation of neuronal plasticity as a principle underlying neo-cortical function
B2) modeling interactions between filial imprinting and a predisposition
B3) enhancement of evolvability and adaptation in evolutionary dynamics.

The following paragraphs provide a short description of the work of the 10 papers, one paragraph per paper, in alphabetical order.

Artificial Pole

Chen and Chen's "Toward an Evolvable Neuromolecular Hardware : A Hardware Design for a Multilevel Artificial Brain with Digital Circuits" proposes a hardware design of a multilevel neuronal architecture integrating memory and internal dynamics with conventional digital circuits. The important features of the integrated model include nonlinear neuronal dynamics, multilevel evolutionary learning, and evolution-friendly structure-function relations. The implementation of this model on digital circuits would allow it to perform in real-time and to provide an architectural paradigm for emerging molecular or neuromolecular electronic technologies.

def Garis and Korkin's "The CAM-Brain Machine (CBM) : An FPGA-Based Hardware Tool that Evolves a 1000 Neuron-Net Circuit Module in Seconds and Updates a 75 Million Neuron Artificial Brain for Real-Time Robot Control" deals with their FPGA based brain-building machine "CAM-Brain Machine (CBM)" which uses evolvable hardware technology. They evolve 3D cellular automata (CA) based neural networks of some 1000 neurons per circuit. 64000 of these circuit modules are evolved in a few seconds each in Xilinx XC6264 FPGAs and downloaded one at a time into a gigabyte of RAM memory. Human "BAs" (brain architects) then interconnect these modules according to their humanly designed artificial brain architectures. The CBM then updates the neural signaling of the artificial brain at 130 billion CA cell updates a second, which is fast enough for real time control of robots.

Fogel and Chellapilla's "Verifying Anaconda's Expert Rating by Competing Against Chinook : Experiments in Co-Evolving a Neural Checkers Player" treats the challenge of having a computer teach itself how to solve a problem without relying on human expertise. Experiments are described in
which a population of artificial neural networks serve as board evaluation functions in the game of checkers. An evolutionary algorithm is used to compete these neural networks, starting with randomly weighted connections, with selection favoring those that perform better than others. The result of over 800 generations of variation and selection on these neural networks was a neural network that can play competitively with an expert-level version of the world-champion checkers program called Chinook. It is important to recognize that the neural networks relied only on the information contained in the number, type, and location of pieces on the board, and no sophisticated features were prescribed. Also, selection was based on performance over a series of games, where the neural networks were unable to discern which individual games were won, lost, or played to a draw. Thus, the evolving neural networks were able to extract their own features while avoiding the well-known credit assignment problem.

Mandischer's "A Comparison of Evolution Strategies and Backpropagation for Neural Network Training" investigates evolution strategies (ESs are a subclass of evolutionary algorithms) as an alternative to gradient-based neural network training. Based on an empirical comparison of population and gradient based search, hints for parameterization are derived and conclusions drawn concerning the usefulness of evolution strategies for this purpose. ESs only compete with gradient-based search in the case of small problems and that ESs are good for training neural networks with a non differentiable activation function. Insights into how evolution strategies behave in search spaces generated by neural networks are given. For this class of objective function, the dimensionality of the problem is critical. With increasing numbers of decision variables, the learning becomes more difficult for ESs, and an "efficient" parameterization becomes crucial.

Nolfi's "Power and the Limits of Reactive Agents" shows how evolving robots can solve complex tasks without requiring any internal state, due to their ability to coordinate perception and action. By acting, i.e., by modifying their position with respect to the external environment and/or the external environment itself, robots partially determine the sensory patterns they receive from the environment. Nolfi shows how evolving individuals can take advantage of this ability in qualitatively different ways. Moreover he shows how more complex individuals able to integrate information over time might rely on mixed strategies in which basic sensory-motor mechanisms are complemented and enhanced by additional internal mechanisms.

Sanchez's "Searching for a Solution to the Automatic RBF Network Design Problem" describes different approaches forming the foundations for further research in the area of the automatic design of artificial brains. In this context, connections between conventional pattern recognition techniques, evolutionary approaches, and newer results from computational and statistical learning theory are examined and their synergy is used in the framework of the systematic and automatic design of RBF regression networks. Some of the methods investigated include clustering, constructive design procedures, support vector machines, and evolutionary approaches. The perspective of searching for a solution to the design problem at different levels, from the originating posture of the optimization problem associated to the learning problem from a computational learning theoretical perspective to the solution of subproblems makes the evolutionary approach a natural choice and in many cases a competitive choice. On the other hand, after posing the optimization problem, the incorporation of requirements specific to the underlying learning problem and goal, i.e., the maximization of the network generalization, can guide the search process very effectively. Network design examples and theoretical analyses which include the computational complexity of the procedure used were reported to visualize the key ingredients of the systematic and automatic design process.

Wicker, Rizki and Tamburino's "E-Net : Evolutionary Network Synthesis" employs evolutionary processes that construct neural features and classifiers to form pattern recognition systems. It successfully evolves network topologies and trains their weights to form accurate recognition
systems using a new computationally efficient process. This process gradually extends primitive network
topologies to form increasingly discriminating structures while simultaneously employing techniques to
seek smaller solutions. Because E-Net performs both synthesis and optimization, many novel concepts
and techniques are used to expedite the gradual synthesis of structure. To demonstrate the flexibility of
the approach, recognition systems are generated across several different problems. These systems
compared well to those generated by Cascade Correlation for the same problems.

Biological Pole

Adams and Cox's "Synaptic Darwinism and Neocortical Function" reinterprets the basic design of
the neocortex, claiming that most of its circuitry is concerned not with processing information, but with
regulating the learning rate of the connections made or received by its information-processing neurons. It
argues that the inevitable anatomical errors made in strengthening connections provide a useful means to
form new connections, a necessity in any sparsely connected network. However, these synaptic
"mutations" also degrade network performance. An optimal balance between these can be established if
certain layer-6-like neurons measure firing correlations between both currently connected and
incipiently-connected neurons, using this ratio to control the plasticity on a cell-by-cell basis.

Hadden's "Modeling Interactions between Filial Imprinting and a Predisposition using Genetic
Algorithms and Neural Networks" presents a neural network model of the complex interactions
between filial imprinting and a naive preference for heads and necks in domestic chicks. The fixed
weights in the network were evolved in a genetic algorithm simulation which emphasized the survival
value of both innate and learned information, having the networks recognize their "mothers". The
architecture and genetic algorithm regimen were able to produce five different behaviors exhibited by
chicks in laboratory experiment emulations dissimilar to the training regimen used in the genetic
algorithm simulations. These networks learn about their own biases given random inputs, as well as
learning about their environments through simulated visual inputs, and these kinds of learning interact to
produce the behaviors seen in chicks. This architecture, in the context of selection for an ability to
distinguish something that might be a mother from other objects in the environment, is a candidate
architecture for the neural system underlying the full range of imprinting-related behavior in chicks.

Ugur and Conrad's "Techniques for Enhancing Neuronal Evolvability" deals with an enzymatic
neuron model called the cytomatic neuron and the training of such neurons for pattern recognition and
generalization tasks. The cytomatic neuron is a softened cellular automaton model that allows for
structure-function plasticity. The model is motivated roughly by interactions that could occur in a
molecular or cellular complex. The system is trained through a multiparameter variation-selection
algorithm that acts on the various parameters. Experiments show that the dynamics can be molded to
produce different structures of generalization. Dimensionality can be increased by augmenting the
number of dynamical parameters open to evolution. Experiments also demonstrate that opening more
parameters to evolution increases the flexibility in structures of generalization exhibited by the processor.

The Future of Evolutionary Neural Systems

A special issue such as this aims to bring to its readers an overview of current research work in the field
that the special issue is devoted to. Perhaps also the guest editor should say a little something about the
probable future of the field, trying to spell out the most likely trends one can expect over the next decade
or so. In the case of evolutionary neural systems, that will not be difficult, as we now live in a very
exciting era in the development of electronics. By 2020 or thereabouts, humanity will have the ability to
build "Avogadro Machines", meaning devices with a trillion trillion components, or molecular scale  
engineering, or simply, as it is known nowadays, "nanotech", i.e. nanometer scale engineering. If Moore's  
law, the doubling of electronic capacities of chips every year or so, continues for the next 20 years, then  
by 2020, humanity will probably be able to store a single bit of information on a single atom. Since there  
are a trillion trillion atoms in an object of human scale, such as an apple in one's hand, we are talking  
about vast computational resources. Atoms could switch their state in femtoseconds, and be the vehicles  
for quantum computing with its potential of exponentially superior computational abilities compared to  
classical computing. Since 20 years is well within the lifetimes of the majority of the readers of this guest  
editorial, most of us can expect to live through this incredibly exciting period which will give us tools to  
perform such miracles that they must seem like science fiction dreams to us now at the turn of the  
millennium.

With one bit per atom storage, femtosecond switching times, quantum computing, molecular scale  
engineering etc probably all coming within 20 years, what kinds of things will be possible within the  
field of evolutionary neural systems? The sheer scale of computational capacity will be huge. However,  
there will be new problems. With molecular scale circuitry, it will no longer be possible to compute in  
the traditional thermodynamically irreversible way we still do today, because at molecular electronic  
component densities, the heat generation problem will become literally explosive. Landauer and Bennet  
showed in the 1960s and 1970s that the secret to performing heatless computing was not to destroy bits  
of information. One should compute reversibly, and never throw away information. Molecular scale  
computing will inevitably have to be performed reversibly. Another requirement will be the need for self  
assembly. It will probably not be practical to have zillions of molecular scale robots assembling atoms  
one at a time to build human scale objects. These objects will probably have to self assemble in an  
embryogenic manner. However, since the potential mapping between nano scale structure and human  
structure function of such systems will be so complex as not to be humanly understandable or designable, it  
is highly likely that an evolutionary engineering approach will be needed that applies a Darwinian  
mutate-test-select cycle to the creation of such systems. Hence it looks as though the techniques  
mentioned in this special issue will become fundamental to the field of nanotechnology in the next  
human generation. Since virtually everything is made of molecules, we are talking about a methodology  
that will become truly basic.

What could one build with such technologies? The mind boggles. For example, with nanotech tools, one  
could probably inject zillions of nano scale robots into the blood stream to take up positions at every  
synapse in the human brain. These tiny robots could then broadcast their positions and other information,  
so that a complete mapping of the human brain could be provided to hypercomputers which themselves  
could be built from the same new technologies. Since a biological neuron is an incredibly inefficient  
computing device containing trillions of atoms to process only a few bits per second, a hypercomputer  
could do the same with a few quantum computing atoms, and hence provide a mass of supplementary  
circuitry to analyse the functioning of the direct biological mapping circuitry. In such a way, explosive  
growth of our knowledge as to how our human brains function can be expected. This new knowledge can  
then be incorporated quickly into our engineered evolutionary neural systems, or as they will probably be  
called, artificial brains.

Young researchers entering the field of evolutionary neural systems will need to think in terms of the  
above, because such ideas will very probably dominate their research careers. Already established  
researchers in the field will need to adjust their thinking to the revolution that is coming. We already live  
in the era of "Massive Moore Doublings", but what we have seen in the past decade is negligible in  
comparison to what is coming. As researchers in this fascinating and extremely promising field, we need  
to take a deep breath and face the tidal wave of possibilities that is thundering towards us. We also need  
to face up to the moral implications of our longer term research. Could it be that we are about to create
creatures with capacities vastly superior to those of human beings? Do we really want to do that? Should such a development be stopped? Can it be stopped?

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