A Stochastic Evolutionary Neuron Migration Process with Emerged Hebbian Dynamics

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Abstract

In this paper, we propose a phenomenological developmental model based on a stochastic evolutionary neuron migration process (SENMP). Employing a spatial encoding scheme with lateral interaction of neurons for artificial neural networks representing candidate solutions within a neural network ensemble[1], neurons of the ensemble form problem-specific geometrical structures as they migrate under selective pressure. The SENMP is applied to evolve purposeful behaviors for autonomous robots and to gain new insights into the development, adaptation and plasticity in artificial neural networks. We demonstrate the feasibility and advantages of the approach by evolving a robust navigation behavior for a mobile robot. We also present some preliminary results regarding the behavior of the adapting neural network ensemble and, particularly, a phenomenon exhibiting Hebbian dynamics.

Introduction

Brain nerve cells are initially produced in the center of the developing brain. To function normally, neurons must migrate to the brain cortex and other structures. Migration is a process that relies on chemical communication between many different cells. The geometrical structure of the brain is a result of this complex process, following an inside-out sequence of development (Pinel 1997).

Recent discoveries in neuroscience confirm the relation between the shape of neural tissue and its function (Csernansky, Joshi, & Wang 1998). Using a technique called morphometrics, which is a mathematical way of studying shape, investigators have found that, in some brain disorders of developmental origin, a functional abnormality in the brain may be accompanied by a structural malformation. While differences in size seem less important, the deformities appear consistent.

Inspired by the recent findings regarding the development and function of the brain, we implemented a phenomenological developmental model based on the stochastic evolutionary neuron migration process, (SENMP)[2] to gain new insights into the development, adaptation, and plasticity in artificial neural networks.

Employing a spatial encoding scheme with lateral interaction of neurons for artificial neural networks representing candidate solutions within a neural network ensemble and applying an evolutionary algorithm to implement the stochastic motion of neurons through generations of ensembles, problem-specific neural structures emerge that are able to solve real problems in perception and robot control.

This study is part of a long-range goal to understand the universal mechanisms acting in a successfully adapting neural circuit of an artificial life form interacting with its environment. We underline the role of geometrical structures in the computational properties of artificial neural circuits, believing that they also have an essential role in living organisms, providing compact genetic representations and neural plasticity.

We demonstrate the feasibility of our approach by developing a robust navigation behavior for a mobile robot. We also show some preliminary results about the behavior of the adapting neural network ensemble, particularly a phenomenon exhibiting Hebbian dynamics.

The Model

The Encoding Scheme

From a neurobiological viewpoint, there is evidence of lateral interaction between neurons in the sense that a firing neuron tends to excite more the neurons in its immediate vicinity than the more distant neurons (Pinel 1997). Furthermore, the recent findings in neuroscience provide new evidence for the relation between the shape and function of neural tissue (Csernansky, Joshi, & Wang 1998), (Castellano Smith 1999). The abovementioned evidence motivated us to employ a spatial

[1]In this paper, the term 'neural network ensemble' is used to refer to the neural network population in order to emphasize the fact that the continuous behavior of the robot is a result of the evaluation sequence of the individual neural networks.

[2]In this paper, the term 'stochastic evolutionary neuron migration' is used to refer to the stochastic motion of the neurons of the neural network ensemble through generations of ensembles under selective pressure, not the real-time motion of neurons.

encoding scheme for an artificial neural network that exhibits simple lateral interaction of neurons and promotes the role of morphology in the function of the neural circuit.

The idea of using 2-D geometry to evolve neural networks has been studied earlier by at least Nolfi (Nolfi & Parisi 1995), Cangelosi (Cangelosi, Nolfi, & Parisi 1994), Husbands (Husbands 1998), and Kodjabachian (Kodjabachian & Meyer 1998). With the exception of Husbands, the spatial encoding scheme has been mainly a tool for defining the topology of the artificial neural network, i.e. the number of neurons and their connectivity. In Husbands' GasNets, however, network geometry has a crucial role in describing the modulating effect of "diffusing gas" on neuron outputs. Although our approach is based on more connectionistic networks than Husbands', it shares the important role of spatial distribution of neurons to the function of the neural network.

The genotype G of the neural network is a set

$$G = \{g_k : k = 0, 1, \ldots, n-1\}$$

where n is the number of neurons and

$$g_k = (x_k, y_k, \theta_k, \phi_k)$$

where x_k, y_k, θ_k, and ϕ_k are the coordinates in 2-D space, the phase, and the feedback factor (explained in the next section) of neuron k, respectively. The index k specifies whether g_k represents an input neuron, a hidden neuron, or an output neuron. $k = [0, l-1]$ for input, $k = [l, l+m-1]$ for hidden, and $k = [l+m, n-1]$ for output neurons, respectively. l is the number of input neurons, and m is the number of hidden neurons. The number of output neurons is $n - (m+l) > 0$.

The connection weights are implicitly determined by the corresponding spatial distribution of neurons, i.e. the Euclidean distances of neurons and their phases as shown in Equation 1, which indicate the strength of the connection between neuron j and neuron i.

$$w_{ji} = \sin(\theta_j - \theta_i) e^{-d_{ji}^2/2\sigma^2} \tag{1}$$

where d_{ji} is the Euclidean distance between the neurons j and i in 2-D space normalized by the maximum distance between any two neurons in the network. More precisely, if $p_k = [x_k \; y_k]^T$ then

$$d_{ji} = \frac{\|p_j - p_i\|}{\max_{l \neq m}(\|p_l - p_m\|)} \tag{2}$$

The Gaussian neighborhood function in Equation 1 defines the physical constraints for the local interactions between neurons and, thus, for the information pathways present in the network. The neuron phase ϕ provides a mean for the evolutionary algorithm to modulate the neighborhood function and to define the signs of the connection weights between neurons.

The Neural Network Model

The neuron model used in our experiments is shown in Equation 3,

$$\frac{\partial a_i}{\partial t} = -\tau a_i + \sum_{j \neq i}^{n} \Theta(\phi_i) w_{ji} \Phi(a_j) + I_i \tag{3}$$

where a_i, Φ, ϕ_i, I_i are the activation potential, the activation function, the feedback factor, and the current sensory input of neuron i, respectively. w_{ji} is the connection weight between the neurons j and i. The definition of Θ, shown in Equation 4, depends on whether the connection from neuron j to neuron i is a feed-forward (i.e. a connection from the lower layer) or a feedback connection (i.e. a connection from the upper or the same layer).

$$\Theta(\phi) = \begin{cases} 1 & \text{, for feedforward conns.} \\ \tanh(\phi) & \text{, for feedback conns.} \end{cases} \tag{4}$$

The feedback factor ϕ is used to tune the effect of the local environment (i.e. the surrounding neurons) outside the initial topology to the state of the neuron. The activation function $\Phi(x) = \tanh(x)$.

The SENMP

We implemented the stochastic motion of neurons, establishing the geometrical structure of the neural network ensemble, using an evolutionary algorithm (EA). The fundamental reason to use the stochastic motion of neurons over developmental models (i.e. rules) ((Fleischer & Barr 1994), (Nolfi & Parisi 1995), (Astor & Adami 2000), (Cangelosi, Nolfi, & Parisi 1994), (Kodjabachian & Meyer 1998)) was to avoid heuristic constraints in pattern formation. Furthermore, we used the stochastic process to learn how the neurons within the neural network ensemble behave while the ensemble adapts to an environment.

The SENMP is started by creating a set P of random genotypes (i.e. neural networks)

$$P = \{G_n : n = 0, 1, \ldots, N-1\}$$

where N is the population size (i.e. the size of the neural network ensemble). For each neuron k, the phase θ_k gets a random value between $[-\pi, \pi]$ and the coordinates x_k and y_k get random values between $[-\lambda, \lambda]$, where λ is the amplitude of the random noise ν introduced by the mutation operator to the parameters g_k of the neuron k. The feedback factor ϕ is initialized to zero for all neurons, meaning no feedback prior the adaptation process (i.e. no connections outside the initial (feedforward) topology).

When the initial neural network ensemble is created, a fitness function $f(G)$ is used to assign a fitness value for each genotype G (i.e. a neural network within the ensemble). For each neural network k, there is a time window Δt_c for controlling the robot, after which fitness $f(G_k)$ is assigned for the neural network. The next neural network taking control over the robot inherits the neuronal (i.e. the action potentials, ϕ) and environmental state of the previous one. The behavior of the robot is a result of the evaluation sequence of the individual neural networks. State inheritance (both internal and external) is used to establish a state continuum providing information about the actions of the previous neural networks.

When all neural networks have been evaluated, a new neural network ensemble is created of the best m individuals (according to the assigned fitness value) of the previous ensemble. In our experiments, m is 40% of the original population size. The new generation is created out of these m individuals by using roulette wheel selection. Two different parents are selected for the new individual, which is built up by taking each of its g_k (i.e. neuron) from one of its two parents with equal probability and from the same genotype index k. After the recombination, a mutation operator is applied for each neuron of the new individual in such a way that

$$g_k = (x_k + \nu_x, y_k + \nu_y, \theta_k + \nu_\theta, \phi_k + \nu_\phi)$$

for all k. ν_x,ν_y, ν_θ, and ν_ϕ get random values from the interval $[-\lambda, \lambda]$. After the new generation has been created, the evaluation proceeds as explained above.

Figure 1 illustrates how neurons migrate through generations of neural network ensembles. At the beginning of the SENMP, all neurons locate within a circle whose radius is λ. As the SENMP proceeds, the neurons migrate through the 2-D space to their 'final' locations due to the selective pressure.

While the amplitude λ of the noise ν introduced by the mutation operator is constant, the effect of noise on the behavior of the robot (i.e. the connection weights of the neural networks) is most significant at the beginning of the adaptation due to the Equations 1 and 2 and the fact that the diameter of the neuron distribution is of the same order than λ. At this phase, the robot is in its most adaptive state, making most of the mistakes necessary for learning. As the SENMP proceeds and the neurons get farther away from each other, the effect of noise ν decreases and the behavior of the robot stabilizes.

The evolution of the diameter of the neuron distribution is analogous to the cooling schedule of the well known optimization method called simulated annealing (Kirkpatric, C.D. Gelatt, & Vecchi 1983) based on principles found from the statistical mechanics.

Experiment

The purpose of the experiment was to develop a neural network ensemble exhibiting a *working* navigation behavior for a real office environment and to collect data from the SENMP for subsequent analysis.

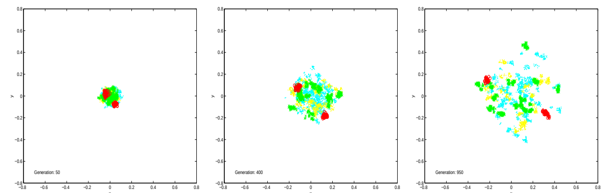

Figure 1: The distribution of neurons of the neural ensemble at generations 50, 400 and 950, respectively. Intermediate gray, light gray and dark gray are used to indicate input, hidden, and output neurons, respectively.

The learning phase was carried out in a simulator implemented for the Nomad Super Scout mobile robot[3].The robot has a differential driving system and 16 ultrasonic sensors. In our navigation experiments, we used only 9 of the sensors covering a sector of 180 degrees in front of the robot. The measuring range of the sensors was limited to 3.5 meters (11 ft).

The navigation experiment was successfully repeated several times. The SENMP parameters used were: $\lambda = 0.01$, $N = 48$ (i.e. population size), $\sigma^2 = 0.025$, and $\tau = 0.1$. The neural network were fully connected with two hidden layers. The numbers of neurons were 11-41-21-2 for the input layer, for the two hidden layers, and for the output layer, respectively. The input layer consists of 9 sonar sensor neurons and two collision detector (i.e. bumper) neurons. The sonar readings were normalized to the range $[0, 1]$ before feeding to the input neurons. If the robot collides with an obstacle, the two bumper readings get the value of 1, while otherwise they get the value 0. The output layer consists of two velocity control neurons, one for each wheel, having a value between $[-1, 1]$. The sign indicates the direction of rotation. The maximum speed of the real robot was limited to 0.3m/s (1 ft/s).

The fitness function used to assign a score for each individual neural network within the neural ensemble was

$$f(d) = d/(1 + pc_r) \qquad (5)$$

where d, p, and c_r are the radial distance traveled by the robot, the collision penalty rate, and the number of collisions, respectively. In our experiments $p = 0.1$.

Figure 2 illustrates how the robot adapts to the three different environments used in the navigation experiment. The results gained in the simulator were successfully verified with a real Nomad Super Scout mobile robot.

Discussion

We have shown here that the SENMP can be applied to evolve and adapt neural control structures for mo-

[3]By Nomadic Technologies, Inc.

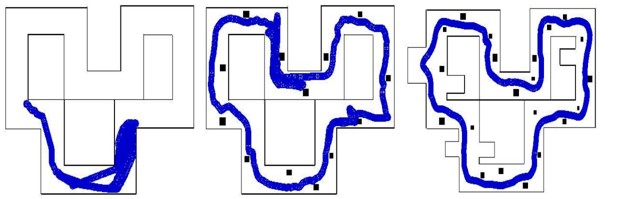

Figure 2: Learning to navigate. Three different environments were introduced to the robot, incrementally increasing the complexity of the world where the robot had to operate. The traces show how the robot gradually adapted to its environment and became able to smoothly navigate through the simulated corridor.

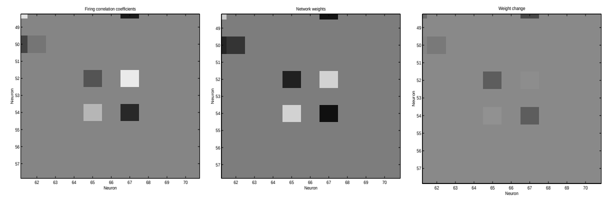

Figure 3: Hebbian dynamics. Closeups from the firing correlation, the connection weight, and the weight change matrices, respectively. The images illustrate the relation between the firing correlation and the evolution of the connection weights. The weight change matrix has been computed for 25 generations of adaptation. The connection weight matrix has been computed from the neural network ensemble at the generation 80. The bright and dark pixels represent positive and negative values, respectively.

bile robots. The SENMP provides a tool for open-ended modification of geometrical neural structures under selective pressure. The spatial encoding scheme couples the geometry and the function of the neural structure enabling modification of the robot's behavior through migration of neurons, which implements the necessary neural plasticity to the neural network ensemble.

Clusters of neurons emerge over time, and the population of neural networks converges. The clusters provide an opportunity to statistically analyze the behavior of neurons in the adapting neural network ensemble. Although the behavior of neurons is not under local control, it seems that the selective pressure may create such an illusion to an external observer.

After an environmental shift, we collected 15000 activation samples (i.e. outputs of the activation function Φ) for each neuron for 25 generations of adaptation. From the samples we computed the mean correlation coefficients for each pair of neurons[4]. By analyzing the firing correlations, the corresponding connection weights, and the connection weight changes between the neurons, we found out that a significant change[5] in a connection weight was consistently[6] accompanied by a firing correlation with equal sign (See Figure 3). This suggests that Hebbian dynamics, in some form, is an emerged property of the SENMP.

Acknowledgments

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[4]Each neuron represents a cluster in the neural network ensemble

[5]The weight change was greater than 75 percent of the maximum weight change

[6]In about 80 and 70 percent of cases with a positive, and a negative weight change, respectively