Journal of Neuroscience Methods 270 (2016) 102–110

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Investigation of rat exploratory behavior via evolving artificial neural networks

Ariadne de Andrade Costa [a,*], Renato Tinós [b]

[a] Department of Physics, FFCLRP, University of São Paulo, 14040-901 Ribeirão Preto, SP, Brazil
[b] Department of Computing and Mathematics, FFCLRP, University of São Paulo, 14040-901 Ribeirão Preto, SP, Brazil

HIGHLIGHTS

- We propose a neuroevolutionary model for studying anxiety in the elevated plus-maze.
- It is based on the evolution of artificial neural network weights and architecture by a genetic algorithm.
- Most results for different drug conditions are statistically significant.
- We analyze the relevance of sensory units and hidden neurons for the virtual rats.
- Results reinforce that automatic design is very useful for studying complex problems.

ARTICLE INFO

Article history:
Received 28 March 2016
Received in revised form 8 June 2016
Accepted 15 June 2016
Available online 17 June 2016

Keywords:
Elevated plus-maze
Rat
Exploratory behavior
Neuroevolution
Genetic algorithm
Artificial neural network

ABSTRACT

Background: Neuroevolution comprises the use of evolutionary computation to define the architecture and/or to train artificial neural networks (ANNs). This strategy has been employed to investigate the behavior of rats in the elevated plus-maze, which is a widely used tool for studying anxiety in mice and rats.
New method: Here we propose a neuroevolutionary model, in which both the weights and the architecture of artificial neural networks (our virtual rats) are evolved by a genetic algorithm.
Comparison with existing method(s): This model is an improvement of a previous model that involves the evolution of just the weights of the ANN by the genetic algorithm. In order to compare both models, we analyzed traditional measures of anxiety behavior, like the time spent and the number of entries in both open and closed arms of the maze.
Results: When compared to real rat data, our findings suggest that the results from the model introduced here are statistically better than those from other models in the literature.
Conclusions: In this way, the neuroevolution of architecture is clearly important for the development of the virtual rats. Moreover, this technique allowed the comprehension of the importance of different sensory units and different number of hidden neurons (performing as memory) in the ANNs (virtual rats).

1. Introduction

Artificial agents are an important tool for the investigation of animal behavior. They have been used in the development and test of cognitive and behavioral models (Webb, 2001). Among the artificial agents, those based on *artificial neural networks* (ANNs) are particularly attractive (Donnarumma et al., 2015). Connectionist models, like ANNs and some deep learning architectures, are based on the interconnection of simple non-linear units disposed in layers. They are capable of learning intricate patterns in large datasets (LeCun et al., 2015), and, when used in artificial agents, can reproduce animal behavior (Beer and Gallagher, 1992). We are interested in developing artificial agents based on ANNs for the investigation of exploratory behavior of rats in the *elevated plus-maze* (EPM).

The EPM is one of most used tools for studying anxiety and exploratory behavior in rodents (Hogg, 1996). Several neurobiological studies have been performed with mice and rats in the EPM, which received its name because of its shape; also because it is elevated about 50 cm above the floor. Two opposed plus-maze arms are surrounded by walls (closed arms), while the remaining arms

* Corresponding author.
E-mail addresses: ad.andrade.costa@gmail.com (A.A. Costa), rtinos@ffclrp.usp.br (R. Tinós).

http://dx.doi.org/10.1016/j.jneumeth.2016.06.010
0165-0270/

do not have walls (open arms). In general, rats spend more time in the closed arms in the experiments with the EPM.[1]

The fear of exploring the maze is directly related to the animal's anxiety (Pellow et al., 1985; Hogg, 1996). As the fear influences the activity of the animal in the maze, the EPM is a practical tool for estimating the anxiety of the rodent. Data obtained over the trajectory of the animal, as the percentage of time spent in closed and open arms, are important indicatives of the individual anxiety level. In this way, the EPM can be used to test the effects of anxiogenic and anxiolytic drugs. Rodents that receive a dosage of an anxiogenic drug, in general, reduce the exploration and the time they spend in the open arms. The opposite occurs for rats under effects of anxiolytic drugs. In many cases, drug dosages are correlated with the levels of EMP exploration by the animal.

In recent years, there is a growing interest in developing artificial agents for the investigation of the behavior of rats in the EPM (Salum et al., 2000; Giddings, 2002; Miranda et al., 2009; Shimo et al., 2010; Tejada et al., 2010; Costa et al., 2012, 2013, 2014; Costa and Tinós, 2014). One of the advantages of computational models is their ability to predict real phenomena. In this way, it can reduce the number of experiments with real rats, which implies less suffering and death for those animals. To the best of the authors knowledge, just two of the models proposed in the literature do not use ANNs; instead, they use Markov models to compute different probabilities for transitions of the artificial agent in different maze positions[2] (Giddings, 2002; Tejada et al., 2010).

The neuroevolution, i.e., the use of evolutionary computation to define the architecture and/or to train ANNs, was firstly proposed to investigate the behavior of rats in an EPM in 2010 (Shimo et al., 2010). Shimo et al. (2010) used a *genetic algorithm*[3] (GA) to train the weights of an ANN. The appeal for using evolutionary computation for developing artificial agents is that, like in reinforcement learning (Littman, 2015), it is not necessary to know the best action for each instant of time in advance. In other words, desired outputs for training are not necessary because we are interested in optimizing an evaluation function over the entire trajectory and not for each time step. The evolutionary ANN proposed by Shimo et al. (2010), as well the other computational models proposed so far for investigating the behavior of rats in the EPM, was built using data obtained from trajectories of real rats. The fitness function of the GA used to train the ANN is based on the difference between measures obtained from the trajectories of real rats and artificial agents, called here *virtual rats*.

Since 2012, we have been exploring neuroevolutionary models from a different perspective, where it is not necessary to employ data obtained from the trajectory of real rats to build the virtual rat (Costa et al., 2012, 2013, 2014; Costa and Tinós, 2014). The artificial agent is built by optimizing an evaluation function based on the premise that rodent exposure to a new environment causes simultaneous feelings of fear and curiosity in the animal (Montgomery, 1955). Data from trajectories of real rats are used only to validate the optimized virtual rat, i.e., data from real rats are used after the optimization of the artificial agent. The recent models with neuroevolution have provided the most promising results until now, including good simulations of rats under effects of anxiolytic and anxiogenic drugs (Arantes et al., 2013; Costa et al., 2014). Furthermore, the neuroevolutionary models correspond to a general framework that can be easily adapted to other behavioral tests developed with real rats in Psychobiology.

In all the neuroevolutionary models proposed so far, the weights of the ANN are trained using a GA. The architecture of the ANN, e.g., the number of inputs and neurons in the hidden layer, is fixed. Investigating the best architectures for an ANN employed in the virtual rat can provide important insights about strategies used by the rats while navigating in the EPM. In the neuroevolutionary models (Costa et al., 2012, 2013, 2014; Costa and Tinós, 2014), the choice of the ANN's architecture is defined by the designer using heuristic rules and/or a trial and error approach. However, the number of possible architectures is huge, and, as a consequence, such approaches can result in unsatisfactory models.

Yao (1999) cites three main strategies for using evolutionary computation in ANNs: (i) adjusting the weights of ANNs; (ii) finding the best architectures of ANNs; (iii) both tasks (i) and (ii). Here, we propose to co-evolve the architecture and the weights of the ANN in a model for investigating the behavior of rats in the EPM. In other words, while the past works used neuroevolution strategy (i), here we propose to use strategy (iii). In order to evaluate the quality of the new model, we compare it with the previous model, that is, a neuroevolutionary model with fixed architecture. We also analyze the best evolved architectures. The best architectures can also provide important insights about the type of sensory information (input units) and usage of memory (hidden layer units) necessary for a simple agent to reproduce the behavior of rats in the EPM. As a consequence, they can also provide information about the strategy used by the rat while navigating in the maze. This paper is organized as it follows. In Section 2, we present the two models in detail, whereas in Section 3 we show the methods used to compare them. The results are exhibited in Section 4 and discussed in Section 5.

2. Methodology

Two models are presented in this section. Model 1, similar to the one used in Costa et al. (2014),[4] is composed by an ANN with fixed architecture (Section 2.1). The GA is used to train the weights of the ANN. In Model 2, proposed in this work, the weights and the architecture of the ANN are co-evolved (Section 2.2). In both models, each arm of the virtual EPM is divided into five equal rectangles (named *positions*), in which the virtual rat navigates. The rectangles totalize 21 positions: five in each arm type, and one in the center, as shown in Fig. 1.

2.1. Model 1: evolving ANNs with fixed architecture

The virtual rat is controlled by a *multilayer perceptron* (MLP) with fixed architecture. The MLP has: six units in the input layer, four neurons in the single hidden layer, and four neurons in the output layer. Each hidden neuron has recurrent connections to all other hidden neurons, i.e., the MLP is an Elman network (Elman, 1990).

[1] The experiments have, as standard, a 5-min duration. Some studies have shown that, after this period, rat's interest in the maze is naturally decreased (Montgomery, 1955).

[2] In order to facilitate the study of rodent trajectories in the maze, the EPM arms are divided into equal positions (rectangles).

[3] Genetic algorithms are a metaheuristic population inspired in Darwin's theory of evolution by natural selection. Metaheuristics are higher-level procedures used to find good heuristics for problem solving and machine learning. The key idea in genetic algorithms, and also in other population metaheuristics, is to evolve in parallel a population of candidate solutions, instead of a single solution, to a given problem. The candidate solutions are selected and transformed using operators inspired by natural genetic variation and natural selection (Mitchell, 1998).

[4] There is a difference between the model presented by Costa et al. (2014) and the Model 1 presented here. In (Costa et al., 2014), the sensory data used as inputs of the ANN during the training was obtained by positioning a robot in each position of an EPM replica, and recording the reading of infrared sensors. Here, the virtual rat is considered a point in the EPM, and the sensory data is directly computed. This was done in order to make the model more general. Similar results were obtained for both approaches; however, the parameters found for each model are different.