# TOPOS 2: Spiking Neural Networks for Bipedal Walking in Humanoid Robots

Pablo González-Nalda and Blanca Cases

Computer Languages and Systems, University of the Basque Country (UPV/EHU)
pablo@si.ehu.es
blancarosa.cases@ehu.es
http://lsi.vc.ehu.es/pablogn/

**Abstract.** This work analyses the state of the art in the field of Evolutionary Robotics and marks the path we select in the design of evolutionary strategies. The aim of this text is to describe the lines that we are going to follow in the foreseeable future. Our goal is to create through evolution the neural network that couples with a complex humanoid robot body. For us the problems of a non-structured environment and of Evolutionary Robotics need a sub-symbolic conexionist approach based in *Nouvelle AI* that can cope with the coupling among sensorimotor, neural and environment parts. We also describe the tools we choose to accomplish this task.

**Keywords:** Evolutionary Robotics, Spiking Neural Networks, Artificial Life, sub-symbolic, small-world topologies, CUDA

## 1 Introduction

Current computer power brings us the opportunity to search for new paths in Robotics but most of the research is based on the classical Artificial Intelligence paradigm, which relies on a top-down human design. Sometimes the problems are too complex to solve them by hand. The alternative is to build systems with a strong bio-inspired bottom-up structure, to let the evolutionary algorithms to select the appropriate links and relations among the basic parts, taking into account new theories in the field of graphs and networks. In this work we propose a system to exploit the computer power and get not-so-simple behaviours from very low-level primitives with the aim to obtain a truly scalable system.

Evolutionary Robotics [1] has its roots in Artificial Intelligence [2, 3], Artificial Life [4], evolutionary strategies [5, 6], and in neural networks [7].

## 2 State of the art

Our recent work [8–10] describes the state of the art in Evolutionary Robotics. ER is a type of Behaviour-based Robotics and hence there are two forms of understanding: the classical approach to robotics and the line defined by Rodney

Brooks to avoid the problems caused by the use of representations. Ronald Arkin depicts these ideas as a continuum in a spectrum. The Spectrum of Robot Control [11] represents the range of of robot control strategies from a deliberative symbolic, classic AI, high level cognitive approach for a structured environment and a reactive, sub-symbolic, *Nouvelle AI* conexionist based system that can cope and couple with a non-structured environment. The latter is more suitable for a embodied and situated robot controller since it applies the Symbol Grounding Hypothesis, and the former excludes the connection between the world and the system [12] because the designer has to set symbol primitives to *represent* the atomic stimuli.

Embodiment and situatedness are two ideas that we have to take into account if we want to get a robot for a non-structured environment, because the information that the robot needs is closely related to the filtering that the body and sensors physically do. There is a coevolution between the neural system and the shape and function of the sensors. The body as a whole determines and modifies the given response to a stimulus.

Evolutionary Robotics is a young discipline that has followed this approach achieving complex behaviours that emerge from simple interactions among the parts of the system. Nevertheless, there are two problems that have to be addressed in order to obtain more powerful robots: morphogenesis and scalability. First attempts of morphogenesis were a simple and direct expression of the robot parameters and neural weights from the genetic information to the actual controller and the physical robot. This is not a scalable system. Genetic Algorithms cannot find the correct relations among the values that shape the individual. Instead of this, the evolutionary algorithm has to set as an individual the set of parameters of a dynamical system whose final result is the robot. In our opinion, this is the way to develop a body and sensorimotor structure coupled with the topology of the neural network, that can be parametrized and evolved.

In other words, if the environment is complex and it only can be described in a non-linear form, the robot and its evolution has to be equally complex, as a new born child that has to learn to coordinate vision, proprioception and environment. The whole mechanism has to be scalable to allow the growing of the robot capabilities to quantitatively more complex ones.

Some authors have created new models of neural networks, more bio-inspired and with a rich dynamics, time delays and interesting effects on computational capabilities [7, 13–15]. There has been also a lot of exciting new work on network topologies [16–18] that has been applied to Neural Networks but in a theoretical level to study their properties [19, 20]. As a clue on how the neuroscience could change with these theories, in [20] we can read:

> *"Our results suggest that mammalian cortical networks, by virtue of being both small-world and topographically organized, seem particularly well-suited to information processing through polychronization."*

It is clear that an experiment in Evolutionary Robotics could help to the progress in these areas.

If this knowledge could be applied to Evolutionary Robotics, within the described framework the so called small-world networks and their algorithms could give us the tools to tackle both problems, morphogenesis and scalability. With these ideas, through simple algorithms the net would grow and connect to form the sensorimotor loop, parametrized with the help of the evolutionary strategies.

The lines that Di Paolo [21] marks as the future of Evolutionary Robotics are on one hand, more and more high-level cognitive behaviours, and on the other hand, experiments as a synthetic biology:

> *"The purpose of work in ER is less centred on trying to obtain more 'cognitively' complex performance —a goal that has not been abandoned— and more on understanding other dimensions of adaptation and the role of different kinds of underlying mechanisms. The design and study of novel integrated systems of this sort may well be one way for evolutionary robotics to contribute useful information back to biology, especially neuroscience, in the proximate future."*

Both objectives could merge and obtain complex cognitive mechanisms based on the last discoveries in neuroscience, with the help of graph theory and new methods of describing, building and connecting the body and the control of the robot.

## 3 Objectives

After the critical analysis of the situation in Evolutionary Robotics we can describe the main goal that we want to achieve. We want to build mechanisms to get an advance in complex sensorimotor behaviours (as bipedal walking of a humanoid robot) in a completely sub-symbolic conexionist system, that is, the designer deals with neuron definitions, without setting architectures, hierarchies, or at least not directly, but through bio-inspired developmental algorithms.

For this task we need a big spiking neural network to connect to simulated muscles as a proprioceptive and motor system in a humanoid robot with tens of degrees of freedom. The neural network has to have thousands of neurons because it is easier to extract and set the correct information for each joint, and this topology also has to reflect the somatotopic arrangement (spatial organisation that maintains the body topology within the brain [22]) and to show a small-world connectivity [23].

So this development would give a step further in the fields of morphogenesis, scalability, robotic neuroscience and globally in Evolutionary Robotics. The interaction between the body and the growing network could be the way of emerging a meaningful structure of the neural network in the previously described framework and consequently at least a partial solution to the problems that usually arise when building new robots using evolution.

## 4 Tools

The first thing we need is a simulation of a humanoid robot. The need of a simulation is because it is much easier and cheaper to apply evolutionary strategies in simulation due to the available computational power and the lack of damages in the robot. After a search we choose SimSpark simulator [24, 25], the one used in RoboCup 3D Soccer Simulation League. The reasons are that is free software (*libre*), it uses the Open Dynamics Engine (ODE) for simulating physics as velocity, inertia and friction, rigid body dynamics and collisions. It has a model of a Nao-like robot with a lot of sensors and 22 degrees of freedom (see fig. 1).

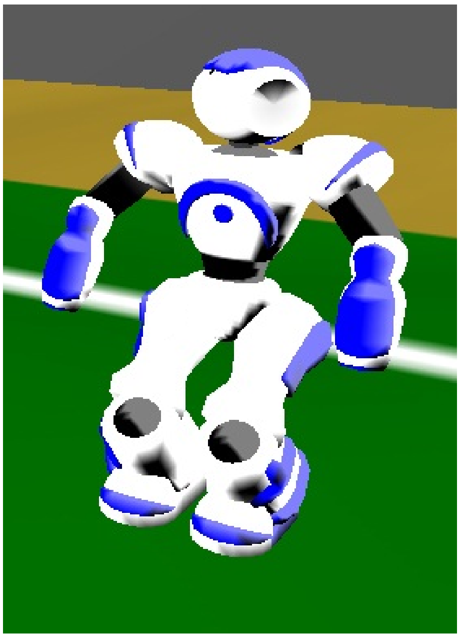

**Fig. 1.** A Nao-like humanoid robot in the SimSpark simulation.

A software that helps to use SimSpark is the `libbats` library [26], which also it is *libre* (GPL). This library deals with some common operations that we do not need to change from the usual way and let us to read and set joint angles easily.

We also need a fast simulation of a spiking neural network. We select the Izhikevich model [14]. The reasons to pick out this one are explained in [27]. In short, this model is one of the fastest and also it has most of the necessary characteristics. The formulas that rule the neuron dynamics are the following (eq. 1).

$$
\begin{aligned}
\dot{v}_i &= 0.04v_i^2 + 5v_i + 140 - u_i + I \\
\dot{u}_i &= a(bv_i - u_i) \\
if \quad v_i &\geq 30mV \\
v_i &\leftarrow c \\
u_i &\leftarrow u_i + d
\end{aligned}
\tag{1}
$$

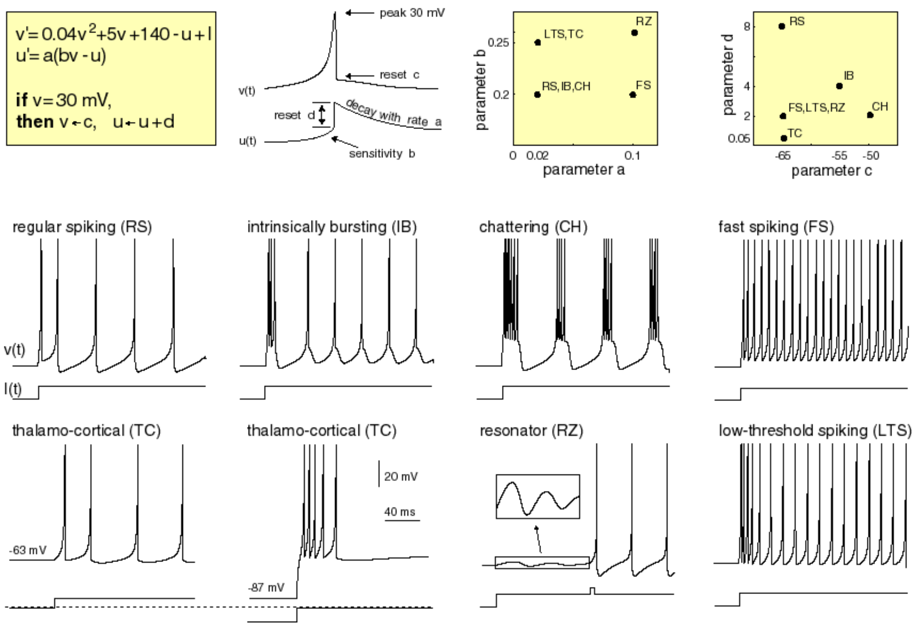


**Fig. 2.** Some of the neuron dynamics in the Izhikevich model, from [14].

The robot controllers for the SimSpark are written in `C++`, so we can run them at high speed, but the neural networks are fully "parallelisable", that is, they are matrix calculus that can be done in parallel. Nowadays, we have powerful rendering graphical processor units (GPU) that are designed to calculate at each processing core the colour, brightness and shadows for each pixel in a 3D scene. There are programs that allow to send non-graphical computing to GPU to perform general-purpose computing. In this case the hardware and software pack that we have chosen is CUDA [28]. It is a mature technology and it is demonstrated that can be 26 times faster than a common CPU software when simulating a neural network based on the Izhikevich model [29].

The design of the *fitness functions* is always a problem in Evolutionary Robotics. We have to design an experiment in which a function has to tell how good is a robot (one of the possible solutions of a problem subject to evolution) in order to select or discard the parameters that define the robot. In this case it is easy to design the experiment thanks to the problem that we want to work, the bipedal locomotion. The fitness value can be calculated as the covered distance in a fixed time. It could be also added a value related to the time that the robot has maintained the standing position while walking.

## 5 Conclusions

In this work we have set the basis for a search of new techniques in Robotics. We continue our previous in Evolutionary Robotics, remarking the bio-inspired bottom-up structure, and adding new works on graphs to permit evolutionary strategies to build the neural controller of the robots that fits with a complex humanoid robot body.

## References

1. I. Harvey, The artificial evolution of adaptive behaviour. Ph.D. thesis, University of Sussex. (1995).
2. S. J. Russell, P. Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 1994.
3. R. Brooks, Intelligence without representation, Artificial Intelligence 47 (1991) 139–159.
4. C. G. Langton (Ed.), Artificial Life: the proceedings of an interdisciplinary workshop on the synthesis and simulation of living systems, Addison-Wesley, Redwood City, CA, 1989, workshop held September, 1987 in Los Alamos, New Mexico.
5. J. Holland, Adaptation in Natural and Artificial Systems, U. Michigan Press, 1975.
6. D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Weley, Reading, 1989.
7. W. Maass, C. M. Bishop (eds.), Pulsed Neural Networks, MIT Press, 1999.
8. González-Nalda, P. y Cases, B., 2008. Topos: Spiking neural networks for temporal pattern recognition in complex real sounds. *Neurocomputing*, **71**(4-6), 721–732. ISSN 0925-2312. URL `http://dx.doi.org/10.1016/j.neucom.2007.07.032`.
9. P. González-Nalda, B. Cases, Topos: generalized Braitenberg vehicles that recognize complex real sounds as landmarks, in: L. Rocha, L. Yaeger, M. Bedau, D. Floreano, R. Goldstone, A. Vespignani (Eds.), Alife X: 10th International Conference on the Simulation and Synthesis of Living Systems, Cambridge, MIT Press, 2006, pp. 213–219.
10. González-Nalda, P. *Navegación mediante Evolución de Redes Neuronales Recurrentes y Dinámicas.* PhD thesis, University of the Basque Country, october 2008. URL `http://lsi.vc.ehu.es/pablogn/investig/ficheros/PGN-Tesis.pdf`.
11. R. Arkin. *Behavior-Based Robotics.* MIT Press, Cambridge, MA., 1998.
12. R. Brooks, Elephants don't play chess, Robotics and Autonomous Systems 6 (1990) 3–15.
13. W. Maass, Networks of spiking neurons: the third generation of neural network models, Neural Networks 10 (1997) 1659–1671.

14. Izhikevich, E. M., 2003. Simple model of spiking neurons. *IEEE Trans Neural Netw*, **14**(6), 1569–1572.
15. E. Izhikevich. Polychronization: Computation with spikes. *Neural Comput.*, 18(2): 245–282, 2006.
16. D. J. Watts, S. H. Strogatz, Nature 393, 440 (1998).
17. A. L. Barabási, R. Albert, Science 286, 509 (1999).
18. L. A. N. Amaral, J. M. Ottino, Eur. Phys. J. B. 147-162 (2004).
19. Hoi Fei Kwok, Peter Jurica, Antonino Raffone, Cees van Leeuwen, 2007. Robust emergence of small-world structure in networks of spiking neurons. *Cogn Neurodyn*, **1**:39–51.
20. P. E. Vertes, T, Duke, 2010. Effect of network topology on neuronal encoding based on spatiotemporal patterns of spikes. *HFSP J.*, **4**(3-4):153–163.
21. Di Paolo, E. A., 2002. *Evolutionary robotics (S. Nolfi and, D. Floreano)*, Volumen 14 de *Connection Science*, cap. Review. MIT Press.
22. E. Manni, L. Petrosini, 2004. A century of cerebellar somatotopy: a debated representation *Nature Reviews Neuroscience*, **5**, 241–249.
23. D. Smith-Bassett, E. Bullmore, 2006. Small-world brain networks *Neuroscientist*, **12**(6), 512–523.
24. SimSpark project, `http://sourceforge.net/projects/simspark/`
25. O. Obst, M. Rollmann, 2005. Spark - A generic simulator for physical multiagent simulations. *Computer Systems Science and Engineering*, **20**(5).
26. Libbats Library, `https://launchpad.net/littlegreenbats`
27. Izhikevich, E. M., 2004. Which model to use for cortical spiking neurons? *IEEE Trans Neural Netw*, **15**(5), 1063–1070. ISSN 1045-9227.
28. What is CUDA?, `http://www.nvidia.com/object/what_is_cuda_new.html`
29. J. Moorkanikara Nageswaran, N. Dutt, J. L. Krichmar1, A. Nicolau, A. Veidenbaum, Efficient Simulation of Large-Scale Spiking Neural Networks using CUDA Graphics Processors , In: Intl. Joint Conf. on Neural Networks (IJCNN), 2009