Applying Genetic Algorithms to Control Gait of Simulated Robots

Milton Roberto Heinen
UFRGS – Informatics Institute
CEP 91501-970, Porto Alegre, Brazil
mrheinen@inf.ufrgs.br

Fernando Santos Osório
UNISINOS – Applied Computing
CEP 93022-000, São Leopoldo, Brazil
fosorio@unisinos.br

Abstract

This paper describes the LegGen simulator, used to automatically create and control stable gaits for legged robots into a physically based simulation environment. In our approach, the gait is defined using two different methods: a finite state machine based on robot's leg joint angles sequences; and a recurrent neural network. The parameters for both methods are optimized using genetic algorithms. The model validation was performed by several experiments realized with a robot simulated using the ODE physical simulation engine. The results showed that it is possible to generate stable gaits using genetic algorithms in an efficient manner, using these two different methods.

1 Introduction

The autonomous mobile robots have been attracting the attention of a great number of researchers, due to the challenge that this new research domain proposes: make these systems capable of intelligent reasoning and able to interact with the environment they are inserted in, through sensor's perception (infrared, sonar, bumpers, gyro, etc) and motor's action planning and execution [6]. At the present time, the most part of mobile robots use wheels for locomotion, what does this task easy to control and efficient in terms of energy consumption, but they have some important disadvantages since they have problems to move across irregular surfaces and to cross borders and edges, like stairs. So, in order to make mobile robots better adapted to human environments and to irregular surfaces, they must be able to walk and/or to have a similar locomotion mechanism used by the humans and animals, that is, they should have legs [6, 1].

However, the development of legged robots capable to move in irregular surfaces is a quite difficult task, that needs the configuration of many gait parameters. The manual configuration of these parameters demands a lot of effort and spent time of a human specialist, and the obtained results are usually suboptimal and specific for one robot architecture [4]. Thus, it is interesting to generate the robot gait configuration in an automatic manner, using Machine Learning techniques to perform this task.

One of these Machine Learning techniques that are most adapted for this specific task are the genetic algorithms (GA) [8, 20]. This is a reasonable choice because according to the Evolution's Theory [5], the locomotion mechanisms of several life forms resulted from the natural evolution, what makes the use of genetic algorithms a natural solution since they are biologically inspired and can generate biologically plausible solutions. From the computational point of view, the GAs are also very well adapted for the automatic gait configuration of legged robots, because: (a) they use a multi-criterion optimization method to search solutions in the configuration space, that means in our specific case, they are capable to optimize not only the gait velocity, but also the stability and even other gait parameters; (b) they don't need local information for the error minimization, nor the gradient calculation, what is very important for the gait parameters generation and optimization, since it is very difficult to have available some a priori training data for supervised learning; (c) if correctly used, the GA is capable to avoid local minima [20].

In our previous works, we made a comparative study between robots with four (tetrapod) and six (hexapod) legs [14], and also about the use and the influence of different fitness functions [12, 13] used in GA robot control optimization. This paper shows a comparative study between the following legged robot control strategies: (i) Control based on FSA (finite state automata); (ii) Control based on ANN (artificial neural networks). In both strategies the parameters tuning and optimization was done using GAs.

This paper is structured as follows: The Section 2 describes several concepts relative to mobile robots simulation; The Section 3 describes related works in control of legged robots; The Sections 4 and 5 describes GA and ANN; The Section 6 describes the proposed model, called LegGen; The Section 7 describes the accomplished experiments and the obtained results; and the Section 8 provides some final conclusions and future perspectives of this work.

2 Mobile robot simulation

In order to obtain a more realistic mobile robots simulation, several elements of the real world should be present in the simulated model, doing the simulated bodies to behave in a similar way related to the reality and also to interact with the environment they are inserted in. Especially, it is necessary that the robot suffers from instability and fall down if badly positioned and controlled, and also it should interact and collide against the environment objects in a realistic manner [21]. To accomplish that, it is necessary to model the physics laws in the simulation environment (e.g. gravity, inertia, friction, collision). Nowadays, several physics simulation tools exist used for the implementation of physics laws in simulations. After analyzing different possibilities, we chosed a widely adopted physics simulation library, called Open Dynamics Engine - ODE[1].

ODE is a software library for the simulation of articulated rigid bodies dynamics. With this software library, it's possible to make autonomous mobile and legged robots simulations with great physical realism. In ODE, several different rigid bodies can be created and connected through different types of joints. To move bodies using ODE, it's possible to apply forces or torques directly to the body, or it is possible to activate and control angular motors. An angular motor is a simulation element that can be connected to two articulated bodies, which have several control parameters like axis, angular velocity and maximum force. With these elements, it's possible to reproduce articulations present in real robots with a high precision level [21].

3 Related works

Control of locomotion in legged robots is a challenging multidimensional control problem [6, 1]. It requires the specification and coordination of motions in all robots' legs while considering factors such as stability and surface friction [17]. This is a research area which has obvious ties with the control of animal locomotion, and it is a suitable task to use to explore this issue [24]. It has been a research area for a considerable period of time, from the first truly independent legged robots like the Phony Pony built by Frank and McGhee [19], where each joint was controlled by a simple finite state machine, to the very successful algorithmic control of bipeds and quadrupeds by Raibert [23].

Lewis [18] evolved controllers for a hexapod robot, where the controller was evaluated on a robot which learn to walk inspired on insect-like gaits. After a staged evolution, its behavior was shaped toward the final goal of walking. Bongard [2] evolved the parameters of a dynamic neural network to control various types of simulated robots. Busch [3] used genetic programming to evolve the control parameters of several robot types. Jacob [16], on the other hand, used reinforcement learning to control a simulated tetrapod robot. Reeve [24] evolved the parameters of various neural network models using genetic algorithms. The neural networks were used for the gait control of tetrapod robots.

In the most part of these approaches described above, the fitness function used was the distance traveled by the robot in a predefined amount of time. Although this fitness function is largely used, it may hinder the evolution of more stable gaits [9]. In our approach, we use in the fitness function, beyond distance traveled, sensorial information (gyroscope and bumpers) to guarantee stable and fast gaits [12, 13, 11].

4 Artificial neural networks

Through the use of an abstract and simplified model of human neurons, it is possible to develop a neural simulator capable to classify, to generalize and to learn how to classify and approximate functions. In this work we are particularly interested in the artificial neural networks (ANN) function aproximation properties. One of the most used neural learning models is the so called Multi-Layer Perceptron (MLP) with Back-propagation learning algorithm [25, 10]. In this work, instead of using the standard back-propagation algorithm and its improvements, we used GAs to evolve the synaptic weights, because we do not have any local information for the the gradient calculation [22].

The network topology used in this work was an Elman network, which are multi-layer perceptron networks with feedback connections from the output of the hidden layer to its input. This feedback path in the hidden layer allows Elman networks to learn, to recognize and to generate temporal patterns, as well as spatial patterns [7].

5 Genetic algorithms

Genetic algorithms are optimization methods of stochastic space state search based on the Darwin's Natural Evolution Theory [5], that were proposed in the 60s by John Holland [15]. They work with a population of initial solutions, called chromosomes, which are evolved through several operations during a certain number of generations, usually reaching a well optimized solution, and preserving the best individuals according to a specific evaluation criterion. In order to accomplish this, in each generation the chromosomes are individually evaluated using a function that measures its performance, called fitness function [20]. Usually the chromosomes with the best fitness values are selected to generate the next generation applying the crossover and mutation operations. Thus, each new generation tends to adapt and improve the quality of solutions, until we obtain a solution that satisfies a specific objective.

[1] Open Dynamics Engine (ODE) – http://www.ode.org

The genetic algorithms implementation used in our system was based on the GAlib software library[2], developed by Matthew Wall of Massachusetts Institute of Technology (MIT). GAlib was selected as it is one of the most complete, efficient and well known libraries for GA simulation, and also because it is a free and open source C++ library.

In the proposed model, a genetic algorithm as described by Goldberg in his book [8] was used, and a floating point type genome was adopted. In order to reduce the search space, alleles were used to limit generated values only to possible values for each parameter.

6 Proposed model

The LegGen simulator[3] [12, 13, 14, 11] was developed to accomplish the gait control of simulated legged robots in an automatic way. It was implemented using the C++ programming language and the free software libraries ODE and GAlib. The LegGen simulator reads two configuration files, one describing the robot format and dimensions and the other file describing the simulation parameters.

The LegGen simulator works as follows: initially the file describing the robot is loaded, and the robot is created in the ODE environment according to file specifications. After this, the simulator parameters are loaded, and the genetic algorithm is initialized and executed until the number of generations is reached. The evaluation of each chromosome is realized in the following way:

- The robot is placed in the starting position and orientation in the simulation environment;
- The genome is read and the control parameters are set;
- The physical simulation is executed during a predefined amount of time (30 seconds in our experiments);
- Gait information and sensor data are captured during each individual physical simulation;
- Fitness is calculated from captured data and returned to the GAlib;

During the simulation, if all paws of the robot leave the ground at same time for more than one second, the simulation of this individual is immediately stopped, because this robot probably fell down, and therefore it is not necessary to continue the physical simulation of this individual.

In the LegGen simulator, the gait control is accomplished through two strategies: (i) a finite state machine (FSM); (ii) a artificial neural network. The following sections describe these control strategies.

6.1 Finite state machine control

In the LegGen simulator, the gait control is generated using a finite state machine (FSM), in which is defined for each state and for each robot joint their final expected angles configuration [2]. In this way, the controller needs to continually read the joints angle state, in order to check if the joint motor accomplished the task. Real robots do this using sensors (encoders) to control the actual angle attained by the joints [6, 1]. So, in this approach the gait control is accomplished in the following way: initially the controller verify if the joints have already reached the expected angles. The joints that do not have reached them are moved (activate motors), and when all the joints have reached their respective angles, the FSM passes to the following state.

To synchronize the movements, it is important that all joints could reach their respective angles at almost the same time. This is possible with the application of a specific joint angular velocity for each joint, calculated by the equation:

$$V_{ij} = Vr_i(\alpha_{ij} - \alpha_{ij-1}) \quad (1)$$

where V_{ij} is the velocity applied to the motor joint i in the j state, α_{ij} is the joint angle i in the j state, α_{ij-1} is the joint angle i in $j-1$ state, and Vr_i is the reference velocity of the i state, used to control the set velocity. The reference velocity Vr is one parameter of the gait control that is also optimized by the genetic algorithm. The other parameters are the joints angles for each state. To reduce the search space, the genetic algorithm only generates values between the maximum and minimum accepted values for each specific parameter.

6.2 Neural control

Besides the use of FSMs to control legged robots, we also can use artificial neural networks (*artificial neural networks* – ANN) [10]. This approach has some important and specific limitations: it is quite difficult to have an a priori information about the generation of the control parameters. Since we do not have available the exact and correct sequence of values that should be sent to control the motors (actuators), then it is usually not possible to apply traditional supervised learning algorithms, like *back-propagation* and other similar ones. This is the main reason we decided to adopt genetic algorithms to evolve synaptic weights.

GAs can adjust synaptic weights with the advantage they do not need any local information or local error measure in order to adapt the weights, and so we do not need a training dataset (supervised learning). The weights can be coded into the chromosomes and evolved, using a fitness function to evaluate the robot performance controlled by this evolved ANN. On the other hand, the use of ANNs has some main advantages when used to control robot gait: ANNs are more robust to noise, continue to perform well even when faced to unseen situations, and they usually can obtain a good generalized behavior.

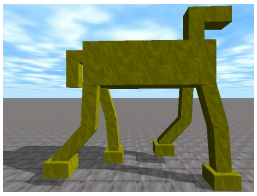
[2]GAlib – http://www.lancet.mit.edu/ga/

[3]LegGen – http://www.inf.unisinos.br/~osorio/leggen

The ANN inputs are the present robot joint angles values (angles at time t, normalized in the range from -1 (α_{mim}) to +1 (α_{max}). In the ANN outputs are obtained the joint angles in the next time step $t + 1$, also normalized in the range [-1:+1]. After some preliminary tests, we choose the Elman model of recurrent ANNs, which was very satisfactory when applied in this problem where we need to predict a temporal behavior (sequencing joint angles). The Elman networks are MLP nets with feedback connections from and back to the hidden layer. These connections allow the Elman nets to learn temporal sequences of patterns and then, from the joint angles patterns in time t, they can generate the next joint angles pattern in their outputs. We adopted the hyperbolic tangent function as neuron's activation function, and also the synaptic weights were limited ranging from -1 to +1, which simplify the GA weights optimization. This ANN model and parameters setup was empirically tested and showed to be well suited to the problem in question.

6.3 Modeled robot

According to the documentation, computational complexity when using the ODE library is $O(n^2)$, where n is the amount of bodies present in the simulated physical world. Thus, in order to maintain the simulation speed in an acceptable rate, we should use few and simple objects. For this reason, all the simulated robots were modeled with simple objects, as rectangles and cylinders, and they have only the necessary articulations to perform the gait. Thus, body parts as the head and the tail are usually not present in the modeled robots. In order to keep our robot project simple, the joints used in the robots legs just move around the z axis of the robot (the same axis of our knees), and the simulations just used robots walking in a straight line. In the near future, we plan to extend our simulator to accept more complex robot models and joints. Several robot types were developed and tested, before we defined the final main model, presented in the Figure 1.



	Dimensions		
Part	**x**	**y**	**z**
Body	45.0cm	15.0cm	25.0cm
Thigh	5.0cm	15.0cm	5.0cm
Shin	5.0cm	15.0cm	5.0cm
Paw	8.0cm	5.0cm	9.0cm

Figure 1. Modeled robot

The simulated robots dimensions are approximately the dimensions of a medium sized dog. The joint restrictions used in the simulated robot are similar as they biological equivalents, with the following values: Hip=[-60°;15°]; Knee=[0°;120°]; Ankle=[-90°;30°]. All the robot legs have these same joint restrictions.

6.4 Fitness function

The fitness evaluation uses the following sensorial information that must be calculated: (a) the distance D covered by the robot; (b) instability measure G; The covered distance D is given by the equation:

$$D = Px_1 - Px_0 \tag{2}$$

where D is the distance traveled by the robot in the x axis (forward walk following a straight line), Px_0 is the x start position and Px_1 is the end x position.

The instability measure is calculated using the robot position variations in the x, y and z axis. These variations are collected during the physical simulation, simulating a gyroscope/accelerometer sensor, which is a sensor present in some modern robots [6]. The instability measure G (Gyro) is then calculated by the following equation [9]:

$$G = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x}_x)^2 + \sum_{i=1}^{N}(y_i - \overline{x}_y)^2 + \sum_{i=1}^{N}(z_i - \overline{x}_z)^2}{N}} \tag{3}$$

where N is the number of sample readings, x_i, y_i and z_i are the data collected by the simulated gyroscope in the time i, and $\overline{x}_x$, $\overline{x}_y$ and $\overline{x}_z$ are the gyroscope reading means, calculated by the equation:

$$\overline{x}_x = \frac{\sum_{i=1}^{N} x_i}{N}, \quad \overline{x}_y = \frac{\sum_{i=1}^{N} y_i}{N}, \quad \overline{x}_z = \frac{\sum_{i=1}^{N} z_i}{N} \tag{4}$$

After finished the sensorial information processing, the fitness function F is then calculated through the equation:

$$F = D/(1 + G) \tag{5}$$

where L is the number of robot legs. Analyzing the fitness function, we see that the individual better qualified will be the one that has the best relationship between velocity and stability, so the best solutions are those that moves fast, but without losing the stability.

7 Results

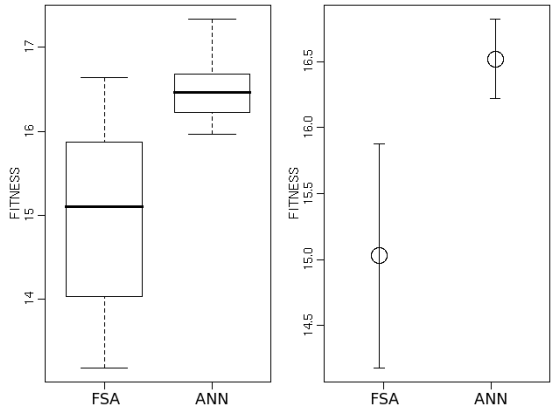
This section describes our experiments and the achieved results. These experiments were done in order to evaluate the GA parameters optimization and robot behavior in both control strategies (FSM and ANN), as described in the previous sections. For each control strategy, we executed 10 different tests, which are presented here. Table 1 shows the obtained results, where we can see each control strategy (FSM and ANN) and the values of the fitness, distance and gyro instability measure respectively (F, D, G) indicated for each experiment (**E**) in both strategies. The two

Table 1. Evaluation of the control strategies

	FSM			ANN		
E	F	D	G	F	D	G
1	14.04	32.17	0.128	16.27	29.19	0.079
2	14.28	32.38	0.126	16.63	28.31	0.070
3	13.18	30.33	0.129	16.99	27.85	0.063
4	15.87	26.81	0.069	16.68	27.91	0.067
5	16.64	36.60	0.120	16.16	28.20	0.074
6	16.48	27.69	0.068	15.97	31.13	0.093
7	14.88	31.69	0.112	17.33	29.63	0.070
8	13.77	29.02	0.110	16.65	29.04	0.074
9	15.33	34.41	0.124	16.29	30.15	0.085
10	15.80	37.01	0.134	16.23	29.81	0.083
μ	**15.03**	**31.81**	**0.112**	**16.52**	**29.12**	**0.076**
σ	**1.19**	**3.48**	**0.024**	**0.42**	**1.08**	**0.009**

lines below in the table are the average (μ) and standard deviation (σ) indicated over the 10 experiments.

In the experiments using the FSM, we fixed the number of states in the automata to four. In the experiments using the neural network we adopted a network with three neurons in the hidden layer. These parameters were defined after a careful preliminary study based on experiments. We spent a total of 149.22 hours processing the final experiments of Table 1. The Figure 2 shows the box plot graph and the confidence interval (CI) of 95%, related to the fitness values obtained in the experiments presented in Table 1.



(a) Boxplot (b) Confidence interval

Figure 2. Boxplot and confidence interval

According to Figure 2 we can affirm that the results obtained by the ANN are clearly superior to those obtained using the FSM, since the confidence intervals are not superposed. Besides that, the results obtained using the FSM are more instable with a large variability. The Figure 3 compares the fitness improvement of the population during the evolution (best and average fitness) obtained for each control strategy. The experiments showed in this figure are those that achieved the best results in our simulations.

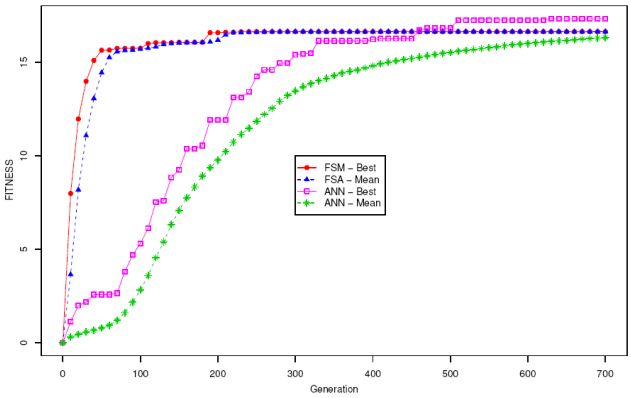


Figure 3. GA optimization

It is clear that the evolution of the neural control parameters needs more generations (epochs) in order to achieve good results. This is due to the fact that we have a bigger parameters state space when optimizing the ANN (we optimize 13 parameters in the FSM and 44 weights in the ANN). The Figure 4 shows one example of the robot gait controlled by an optimized FSM and the Figure 5 shows one example of a robot gait obtained using a trained ANN[4].

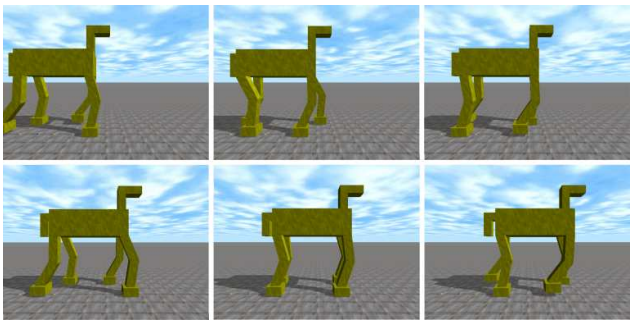


Figure 4. FSM robot control

8 Conclusions and perspectives

The main goal of this paper was to describe the LegGen simulator, which was developed in order to study the automatic configuration of parameters used to control the gait of legged robots. In our simulator, the gait control was achieved using genetic algorithms. The GA evolves parameters used to control the robot actuators and this evolution was tested into a virtual environment using the ODE rigid

[4]Some demostration videos are available in the LegGen website

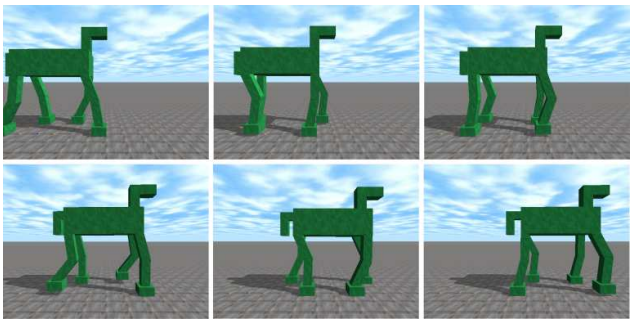


Figure 5. ANN robot control

body dynamics simulation tool. The robot joints are controlled using two different strategies: (i) GA evolved FSM - finite state machine and (ii) GA evolved ANN - artificial neural network. Several experiments were achieved, comparing both approaches and demonstrating (with a valid statistical analysis) that the neural controller is superior to the FSM controller (superior fitness), obtaining a better performance (more stable, better displacement).

The future works include improving the robot gait in order to walk on irregular surfaces and go upstairs or downstairs, as well as, to implement in hardware the simulated robot, once we had now acquired sufficient experience in order to design, implement and fine tune the control of the legged robots. We are sure that the virtual robot control system can be easily adapted to control real robots.

References

[1] G. A. Bekey. *Autonomous Robots: From Biological Inspiration to Implementation and Control*. MIT Press, Cambridge, MA, 2005.

[2] J. C. Bongard and R. Pfeifer. A method for isolating morphological effects on evolved behaviour. In *Proc. 7th Int. Conf. Simulation of Adaptive Behaviour (SAB)*, pages 305–311, Edinburgh, UK, Aug. 2002. MIT Press.

[3] J. Busch, J. Ziegler, C. Aue, A. Ross, D. Sawitzki, and W. Banzhaf. Automatic generation of control programs for walking robots using genetic programming. In *Proc. 5th European Conf. Genetic Programming (EuroGP)*, volume 2278 of *LNCS*, pages 258–267, Kinsale, Ireland, Apr. 2002. Springer-Verlag.

[4] S. Chernova and M. Veloso. An evolutionary approach to gait learning for four-legged robots. In *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, Sendai, Japan, Sept. 2004.

[5] C. Darwin. *Origin of Species*. John Murray, London, UK, 1859.

[6] G. Dudek and M. Jenkin. *Computational Principles of Mobile Robotics*. Cambridge Univ. Press, Cambridge, UK, 2000.

[7] J. L. Elman. Finding structure in time. *Cognitive Science*, 14:179–211, 1990.

[8] D. E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley, Reading, MA, 1989.

[9] D. Golubovic and H. Hu. Ga-based gait generation of sony quadruped robots. In *Proc. 3th IASTED Int. Conf. Artificial Intelligence and Applications (AIA)*, Benalmadena, Spain, Sept. 2003.

[10] S. Haykin. *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Upper Saddle River, NJ, 2 edition, 1999.

[11] M. R. Heinen. Controle inteligente do caminhar de robôs móveis simulados. Master's thesis - applied computing, Universidade do Vale do Rio dos Sinos (UNISINOS), São Leopoldo, RS, Brazil, 2007.

[12] M. R. Heinen and F. S. Osório. Applying genetic algorithms to control gait of physically based simulated robots. In *Proc. IEEE Congr. Evolutionary Computation (CEC)*, Vancouver, Canada, July 2006.

[13] M. R. Heinen and F. S. Osório. Gait control generation for physically based simulated robots using genetic algorithms. In *Proc. Int. Joint Conf. 2006, 10th Ibero-American Conference on AI (IBERAMIA), 18th Brazilian Symposium on AI (SBIA)*, LNCS, Ribeirão Preto - SP, Brazil, Oct. 2006. Springer-Verlag.

[14] M. R. Heinen and F. S. Osório. Evolving gait control of physically based simulated robots. *Revista de Informática Teórica e Aplicada (RITA) – to appear*, 2007.

[15] J. H. Holland. *Adaptation in Natural and Artificial Systems*. Univ. Michigan Press, Ann Arbor, MI, 1975.

[16] D. Jacob, D. Polani, and C. L. Nehaniv. Legs than can walk: Embodiment-based modular reinforcement learning applied. In *Proc. IEEE Int. Symposium on Computational Intelligence in Robotics and Automation (CIRA)*, pages 365–372, Espoo, Finland, June 2005.

[17] N. Kohl and P. Stone. Policy gradient reinforcement learning for fast quadrupedal locomotion. In *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, pages 2619–2624, New Orleans, LA, Apr. 2004.

[18] M. A. Lewis, A. H. Fagg, and A. Solidum. Genetic programming approach to the construction of a neural network for control of a walking robot. In *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, pages 2618–2623, Nice, France, 1992.

[19] R. B. McGhee. Robot locomotion. *Neural Control of Locomotion*, pages 237–264, 1976.

[20] M. Mitchell. *An Introduction to Genetic Algorithms*. MIT Press, Cambridge, MA, 1996.

[21] F. S. Osório, S. R. Musse, R. Vieira, M. R. Heinen, and D. C. Paiva. *Increasing Reality in Virtual Reality Applications through Physical and Behavioural Simulation*, volume 2, pages 1–45. Springer-Verlag, Berlin, Germany, 2006.

[22] R. Pfeifer and C. Scheier. *Understanding Intelligence*. MIT Press, Cambridge, MA, 1999.

[23] M. H. Raibert. *Legged Robots That Balance*. MIT Press, Cambridge, MA, 1986.

[24] R. Reeve and J. Hallam. An analysis of neural models for walking control. *IEEE Trans. Neural Networks*, 16(3):733–742, May 2005.

[25] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning Internal Representations by Error Propagation*. MIT Press, Cambridge, MA, 1986.