Crossing the Reality Gap: a Short Introduction to the Transferability Approach

Jean-Baptiste Mouret[1,2], Sylvain Koos[1,2] and Stéphane Doncieux[1,2]

[1]ISIR, Université Pierre et Marie Curie-Paris 6, France
[2]CNRS UMR 7222, France
mouret@isir.upmc.fr

Abstract

In robotics, gradient-free optimization algorithms (e.g. evolutionary algorithms) are often used only in simulation because they require the evaluation of many candidate solutions. Nevertheless, solutions obtained in simulation often do not work well on the real device. The transferability approach aims at crossing this gap between simulation and reality by *making the optimization algorithm aware of the limits of the simulation*.

In the present paper, we first describe the transferability function, that maps solution descriptors to a score representing how well a simulator matches the reality. We then show that this function can be learned using a regression algorithm and a few experiments with the real devices. Our results are supported by an extensive study of the reality gap for a simple quadruped robot whose control parameters are optimized. In particular, we mapped the whole search space in reality and in simulation to understand the differences between the fitness landscapes.

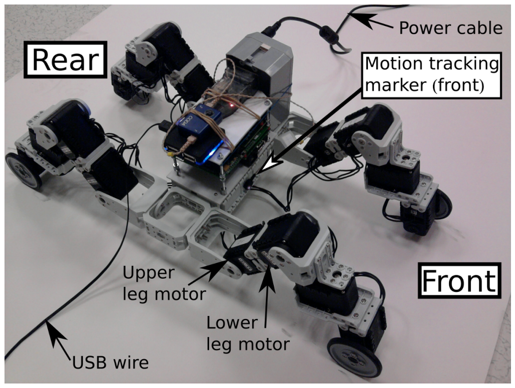
Introduction

Gradient-free optimization algorithms underlie many machine learning methods, from policy search techniques (Whiteson and Stone, 2006; Heidrich-Meisner and Igel, 2008) to automatic design approaches (Lohn and Hornby, 2006; Lipson and Pollack, 2000). They are also one of the tool of choice for researches in embodied intelligence because they make possible to obtain artifacts (e.g. neural networks to control a robot) without having to describe their inner workings (Pfeifer and Bongard, 2006).

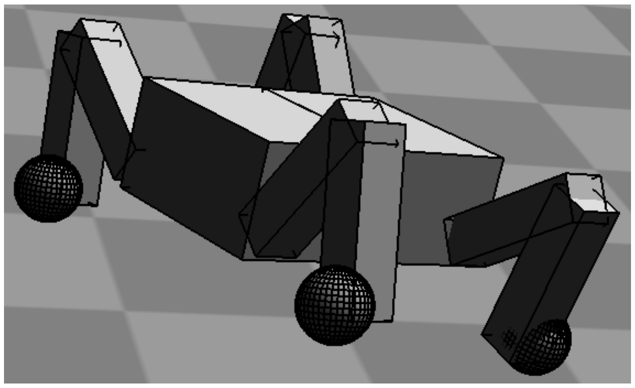
In many of their applications, these algorithms spend most of their running time in evaluating the quality of thousands of potential solutions. This observation encourages many researchers to work with simulations instead of real devices, because simulations are usually cheaper and faster than real experiments. For instance, most published work in evolutionary robotics (ER) — in which researchers typically aim at finding original controllers for robots — is carried with simulated robots (Doncieux et al., 2011; Nelson et al., 2009). At first sight, robots are articulated rigid bodies for which many simulations tools exist; it is therefore tempting to suppose that an efficient result obtained by optimizing in simulation will work similarly on the real robot. Unfortunately, no simulator is perfect and optimization algorithms have no reason to avoid exploiting every badly modeled phenomena that increase performance. It is thus often observed that solutions optimized in simulation are inefficient on the real robot. On the contrary, most engineers intuitively know the limit of their simulation tools and avoid relying on what is incorrectly modeled.

This difference in performance with a simulation and with the real device has been termed the *reality gap*. It is of course not restricted to ER since the same issues are encountered with all the other optimization algorithms and with many other experimental setups. However, we will restrict our current discussion to ER because the reality gap is central in this community. The reality gap is indeed arguably one of the main issue that prevent a widespread use of evolutionary algorithms to optimize parameters of robot controllers: evaluating every potential solutions in reality is very costly because it requires complex experimental setups and a lot of time; evaluating potential solutions in simulation is cheaper and faster but it often leads to solutions that cannot be used on the real device. How could we proceed?

If we do not reject the use of simulators, the first idea to reduce this gap is to design better simulators. Such an approach can work up to a certain extent but complex simulators are slow (e.g. simulating fluids can be slower than reality) and even the best simulators cannot be infinitely exact. An attractive idea is to automatically design a simulator, for instance by learning a surrogate model of the fitness function (Jin, 2005), or, following a related idea, to automatically improve an existing simulator (Bongard et al., 2006; Zagal and Ruiz-Del-Solar, 2007). Nevertheless, creating an algorithm that automatically designs the perfect simulator appears at least as difficult as designing evolutionary algorithms to learn the optimal behaviors of a robot. Moreover, these methods will never accurately model every possible force that can act on a device. For instance, it is hard to expect that an algorithm will automatically discover a good model of fluid dynamics in a classic rigid-body simulator, whatever the improvements of the simulator are.



(a)



(b)

Figure 1: (a) The quadruped robot is based on a Bioloid robotic kit (Robotis). It has 8 degrees of freedom (wheels are not used in this experiment). We track its movement using a 3D motion capture system. (b) The simulation is based on the Bullet dynamic simulator (Boeing and Bräunl, 2007).

As an alternative approach, Jakobi (1997) proposed to prevent the optimization algorithm to exploit badly modeled phenomena by hiding them in an "envelope of noise". Despite some success with the evolution of a controller for an hexapod robot, Jakobi did not describe any generic method to choose what has to be noised and how this noise should be applied. Applying the "envelope of noise" technique therefore often requires a lot of experiments and fine-tuning of the simulator, which is exactly what researchers try to avoid when designing optimization algorithms. For instance, it is hard to know how to add noise when evolving locomotion controllers for legged robots.

In the present paper, we describe a recently introduced approach to cross the reality gap: the transferability approach (Koos et al., 2012). Our aim is to give a didactic presentation of the intuitions that guide this method as well as the main results obtained so far. The interested reader can refer to (Koos et al., 2012) for detailed results and discussions.

Experimental Apparatus

Robot and controller We studied the reality gap with an 8-DOFs quadruped robot made from a Bioloid Kit (Fig. 1). Another experiment inspired by Jakobi's T-maze is reported in (Koos et al., 2012).

The angular position of each motor follows a sinusoid. All these sinusoidal controllers depend on the same two real parameters $(p_1,\ p_2) \in [0,1]^2$ as follows:

$$\alpha(i,t) = \frac{5\pi}{12} \cdot dir(i) \cdot p_1 - \frac{5\pi}{12} \cdot p_2 \cdot \sin(2\pi t - \phi(i))$$

where α denotes the desired angular position of the motor i at time-step t. $dir(i)$ is equals to 1 for both motors of the front-right leg and for both motors of the rear-left leg; $dir(i) = -1$ otherwise (see Fig. 1 for orientation). The phase angle $\phi(i)$ is 0 for the upper leg motors of each leg and $\pi/2$ for the lower leg motors of each leg. Both motors of one leg consequently have the same control signal with different phases. Angular positions of the actuators are constrained in $[-\frac{5\pi}{12}, \frac{5\pi}{12}]$.

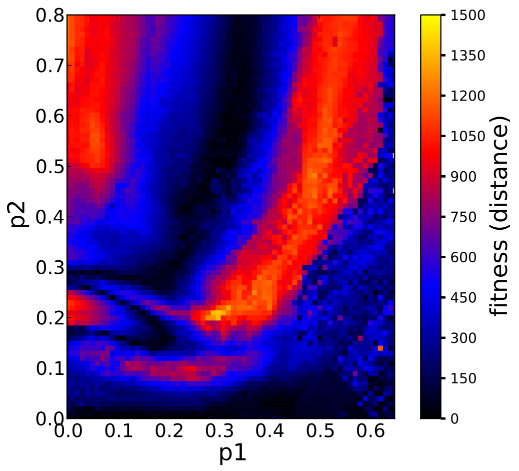
The fitness is the distance covered by the robot in 10 seconds.

Reality gap We first followed a typical ER approach: we evolved controllers in simulation and then transferred the best solution on the robot. On average (10 runs), the best solution in simulation covered 1294 mm (sd = 55mm) whereas the same controller leads to only 411 mm in reality (sd = 425mm); thus we observe a clear reality gap in this task.

This reality gap mostly stems from classic issues with dynamic simulations of legged robots. In particular, contact models are not accurate enough to finely simulate slippage, therefore any behavior that relies on non-trivial contacts will be different in reality and in simulation. Dynamical gaits (i.e. behaviors for which the robot is often in unstable states) are also harder to accurately simulate than more static gaits because the more unstable a system is, the more sensitive it is to small inaccuracies.

The small number of parameters of this controller allows the mapping of the whole search space. We realized 5500 experiments on the real robot and interpolated the rest of the search space (Fig.2(a)). We also mapped the fitness landscape in simulation (5500 experiments, Fig.2(b)). To our knowledge, this is the first time that we are able to visualize a fitness landscape for a real robot and its simulation.

The differences between the two landscapes correspond to the reality gap. The landscape in simulation contains four main fitness peaks and one global optimum. The landscape obtained in reality is noisier but simpler and it seems to contain only one important fitness peak. In both landscapes, we observe a large low-fitness zone but the main high-fitness zones match only a small zone and for only one fitness peak.



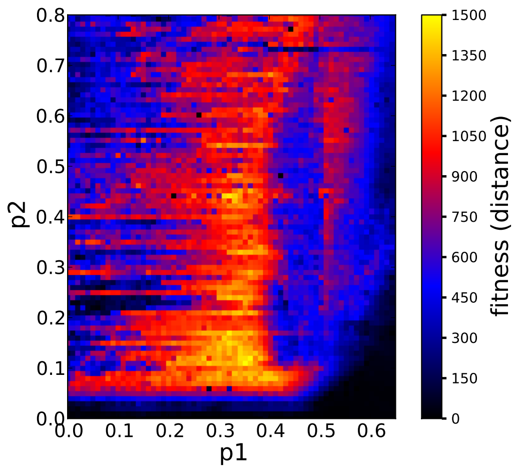


Figure 2: (left) Fitness landscape in the dynamic simulator (5500 experiments). (right) Fitness landscape with the real robot (5500 experiments). In both maps, p_1 and p_2 are the evolved parameters of the controller.

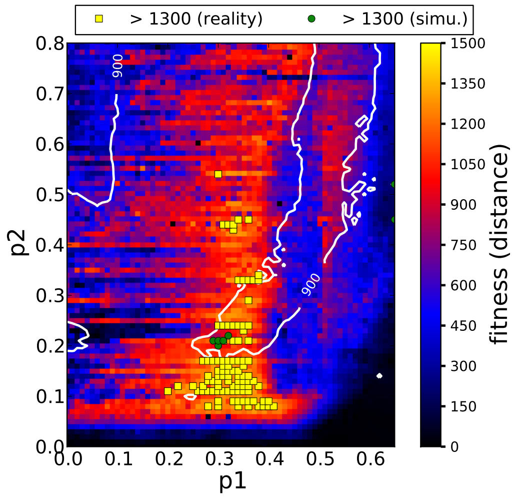


Figure 3: Superposition of the fitness landscape in reality with the one obtained in simulation. The contour line denotes the zones for which the simulation leads to high fitness values (greater than 900mm).

A typical example of reality gap will occur if the optimization in simulation leads to solutions in the top left corner of the fitness landscape, for which solutions have a high fitness in simulation but a very bad one in reality.

While the fitness landscapes in simulation and in reality are very different, there exist a lot of controllers with a good fitness (greater than 900 mm; these controllers achieve gaits comparable to those obtained with hand-tuned controllers) in both simulation and reality (Fig.3). If we visually compare gaits that correspond to this zone in simulation and in reality, we observe a good match.

Our interpretation is that the simulation is accurate in at least this sub-part of the search space

The Transferability Function

This interpretation leads to the fundamental hypothesis of the transferability approach: *for many physical systems, it is possible to design simulators that work accurately for a subset of the possible solutions*. In the case of dynamic simulators, physicists work on the dynamic of rigid body since the XVII-th century and the accumulated knowledge allows engineers to make good predictions for many physical systems.

Since simulations will never be perfect, our approach is to *make the system aware of its own limits* and hence allows it to avoid solutions that it cannot correctly simulate. These limits can be captured by a transferability function:

Definition 1 (Transferability function) *A* transferability function *is a function that maps, for the whole search space, descriptors of solutions (e.g. genotypes, phenotypes or behavior descriptors) to a* transferability score *that represents how well the simulation matches the reality.*

There are many ways to define a similarity, therefore there are many possible transferability functions. Describing the similarity of behaviors in robotics has recently been investigated in the context of diversity preservation (Mouret and Doncieux, 2012) and novelty search (Lehman and Stanley, 2011). Many measures have been proposed. For a legged robot, one can compare covered distance (i.e. compare the fitness values), trajectory of the center of mass at each time-step, angular positions of each joint for each time-step, contact of the legs with the ground, ... At any rates, the best similarity measure highly depends on the task and on the simulator.

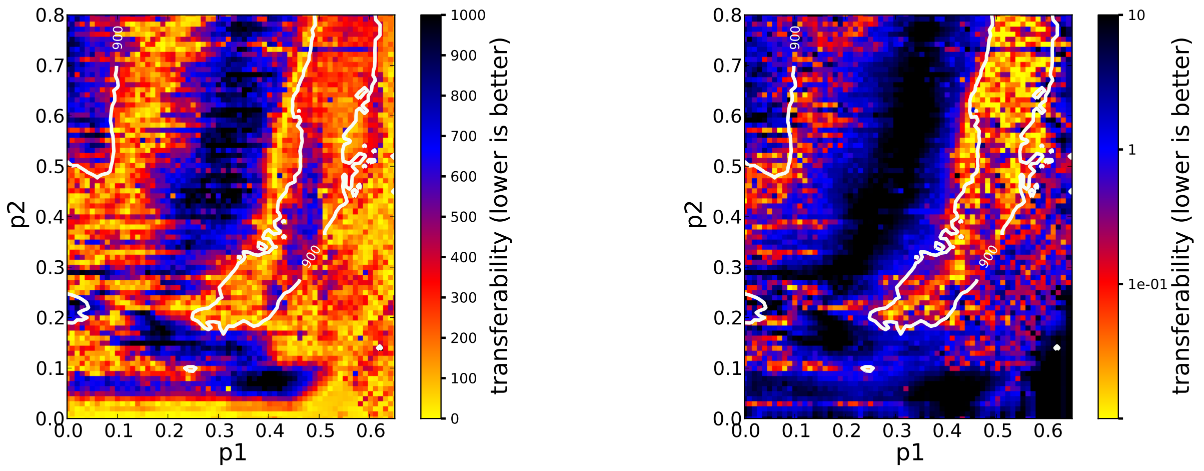


Figure 4: (left) Transferability function based on the difference of fitness values. (right) Transferability function based on the difference of trajectories. In both maps, the contour line denotes the zones for which the simulation leads to high fitness values (greater than 900mm).

The most intuitive input space for the transferability function is the genotype space. However, the maps from genotype to transferability may be very non-linear because the relationship between genotypes and behaviors is often complex in evolutionary robotics. Many genotypes (e.g. neural networks or development programs) are also hard to put as the input of functions. An alternative is to use the behavior in simulation, which is easy to obtain. The transferability function then answers the question: "given this behavior in simulation, should we expect a similar behavior in reality?". For instance, in many dynamic simulations we observe robots that unrealistically jump above the ground when they hit it. If the 3D-trajectory of the center of mass is used as an input space, then the transferability function will easily detect that if the z-coordinate is above a threshold, then the corresponding behavior is not transferable at all.

For the considered quadruped robot, we computed two transferability functions:

- input space: genotype; similarity measure:difference in covered distance (fitness) (Fig.4(a));
- input space: genotype; similarity measure: sum of the squared Euclidean distance between each point of the 3D trajectories of the geometrical center of the robot (Fig.4(b)).

In both cases we observe that the high-fitness zone of the simulation in the top left corner is not transferable but a large part of the solutions from the other high fitness zone appears transferable.

Learning the Transferability Function

For evolutionary robotics, it is obviously unfeasible to compute the transferability score for each solution of the search space – as we did it in these simple experiments – because this would require to test every point of the search space on the real robot. To avoid this issue, *the main proposition of the transferability approach is to automatically learn the transferability function using supervised learning techniques*. Using a few tests on the real system and a few evaluations in simulation, we propose to use a regression technique (e.g. a neural network or a support vector machine) to predict how well simulation and reality will match for any solution of the search space. This predictor will thus estimate the transferability of each potential solution. Put differently, the transferability approach proposes to learn the limits of the simulation.

It may seem counter-intuitive and inefficient to approximate the transferability instead of the fitness (i.e. using a surrogate model of the fitness), but working with the transferability function is promising for at least two reasons. First, approximating the fitness function for a dynamic system (e.g. a robot) means using a few tests on the real robot to build the whole fitness landscape. In the same way as simulators will never be perfect, this approximation will not be perfect, therefore we will likely face reality gap issues. Second, learning the fitness function is likely to be harder than learning the transferability function. Indeed, using a machine learning technique to learn the fitness function of a robot is equivalent to automatically design a simulator for a complex robot: the function has to predict a description of the behavior (the fitness) from a description of the solution (the genotype). Such a simulator would therefore need to include the laws of articulated rigid body dynamics, but these laws are unlikely to be correctly discovered using a few trajectories of a robot. On the contrary, predicting that a solution will not be transferable can often be done using a few

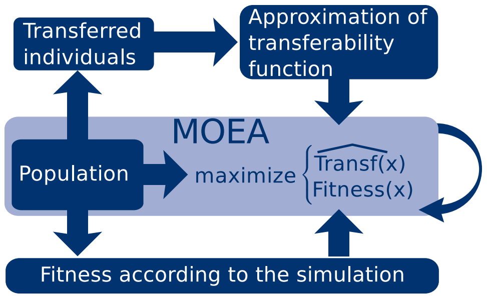

Transferred individuals
Approximation of transferability function
MOEA
Population
maximize
$\widehat{\text{Transf}}(x)$
Fitness(x)
Fitness according to the simulation

Figure 5: Principle of the multi-objective optimization of both the fitness and the transferability. Individuals from the population are periodically transfered on the robot to improve the approximation of the transferability function.

simple criteria that a machine learning algorithm can find. For instance, a classification algorithm could easily predict that high-frequency gaits are not transferable by applying a threshold on a frequency parameter (the ease of prediction depends on the input space of the predictor). In summary, learning the transferability *complements* a state-of-the art simulator instead of reinventing or improving it.

Finding Efficient and Transferable Solutions

Using a simulator to find solutions that perform well in reality can be restated as a two-objective optimization problem, where the objectives are (1) the performance in simulation and (2) the accuracy of the simulation for the tested solution. Optimal solutions for this problem will be perfectly simulated and perfectly efficient in simulation. However, there is no reason to believe that the best solutions in simulation will correspond to the best solutions in reality. On the contrary, the best solutions in simulation are often highly dynamic behaviors that strongly rely on unrealistic effects; the best solutions in reality will also be probably highly tuned behaviors instead of simpler, more robust behaviors.

We therefore expect to see a trade-off between transferability and fitness in simulation. Multi-objective evolutionary algorithms (MOEA, see Deb (2001)) are well suited methods for this two-objective optimization:

$$\text{maximize} \begin{cases} \text{fitness}(x) \\ \text{approximated transferability}(x) \end{cases}$$

Nonetheless, we are essentially optimizing the fitness under the constraint of the transferability. While MOEAs are recognized tools to apply soft constraints (Fonseca and Fleming, 1998), other constrained optimization algorithms could also be employed.

We chose to use the Inverse Distance Weighting (IDW) method to approximate the transferability function because it's simple and efficient enough. This method can be substituted with any other regression/interpolation method.

An interesting question is *when* to improve the approximation, that is when to transfer an individual to evaluate it in reality. A first option is to transfer solutions before launching the optimization, build the approximation and do not modify it during the optimization. Another option is to transfer a few individuals before the first generation, in order to initiate the process, and then periodically update the approximation by transferring one of the candidate solution of the population. The second option has the advantage of focusing the approximation on useful candidate solutions because the population will move towards peaks of high fitness. While the first option is simpler, we chose the second one in our current implementation: every 20 generations, the individual from the population that is the most different from the others is tested on the real robot. At the end of the optimization, we select the solution with the best fitness and above a user-defined value for the transferability.

Figure 5 summarizes this process. Our source code is available on EvoRob_db (`http://www.isir.fr/evorob_db`).

Experimental Results

The two objectives are optimized with the NSGA-II algorithm because it's a classic and versatile MOEA. The size of the population is 40 and the algorithm is stopped after 200 generations. The transferability function takes as input three behavior descriptors, computed using the dynamic simulator: (1) the distance covered during the experiment, (2) the average height of the center of the robot and (3) the heading of the robot at the end of the experiment. The similarity measure is the difference between the trajectories in reality and in simulation (Fig. 4(b)).

We chose a budget of about 10 evaluations on the real robot (depending on the treatment). While this number may appear very small, it is realistic if real experiments are not automated. Additionally, the problem is simple: only two parameters have to be optimized and many high-fitness solutions exist.

We compared the transferability approach to four different treatments, described belows.

Direct optimization on the robot. We used a population of 4 individuals and 5 generations. This leads to 20 tests on the real robot.

Optimization in simulation then transfer to the robot. We expect to observe a reality gap.

Optimization in simulation, transfer to the robot and local search. Parameters of the solutions are modified using 10 steps of a stochastic gradient descent, on the real robot.

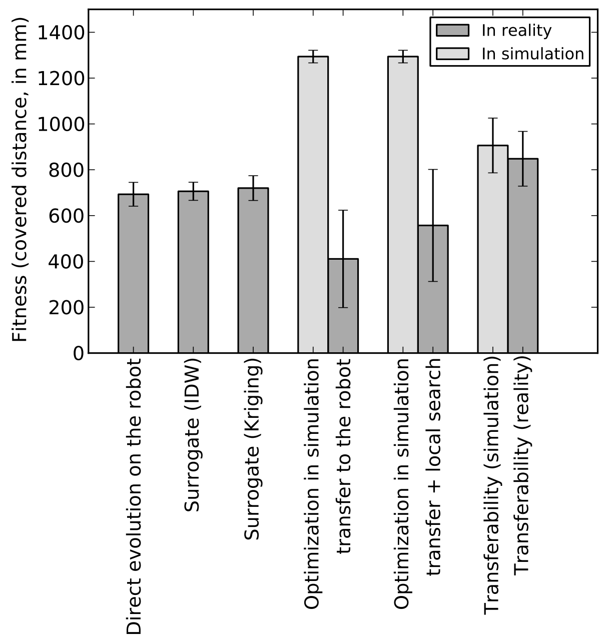


Figure 6: Average distance covered with each of the tested treatment (at least 10 runs for each treatment). The transferability approach obtains the best fitness in reality (Welsh's t-test, $p \leq 6 \cdot 10^{-3}$). Error bars indicate one unit of standard deviation.

Surrogate model of the fitness function. We tested IDW (Shepard, 1968) and the Kriging method (Jin, 2005).

Results (Fig.6) show that solutions found with the transferability approach have a very similar fitness value in reality and in simulation, whereas we observe a large reality gap when the optimization occurs only in simulation. These solutions are also the ones that work the best on the real robot. It must be emphasized that the transferability approach did not find the optimal behavior in simulation (about 1500) nor in reality (about 1500 too). The algorithm instead found good solutions that work similarly well in simulation and in reality.

The surrogate models worked better than the optimization in simulation but it did not significantly improve the result of the direct optimization on the robot. The addition of a local search stage after the transfer from simulation to reality significantly improved the result but final solutions are much worse than those found with the transferability approach.

We obtained similar results with a second experiment, inspired by Jakobi's T-maze (Koos et al., 2012).

Conclusion

The experimental results validate the relevance of automatically learning the limits of the simulation to cross the reality gap. The current implementation relies on several arbitrary choices and many variants can be designed. More specifically, the choice of the approximation model and the update strategy need more investigations.

The transferability approach essentially connects a "slow but accurate" evaluation process (the reality) and a second evaluation process that is "fast but partially accurate" (the simulation). The exact same idea can be used to improve the generalization and the robustness of optimized controllers in robotics: the reality corresponds to the evaluation of the controller in many contexts, whereas the simulation corresponds to its evaluation in a few contexts. We recently obtained promising results based on this idea (Pinville et al., 2011).

Last, we also found that learning the transferability function allows the design of a fast on-line adaptation algorithm that deports most of the optimization in a simulation of a self-model (Koos and Mouret, 2011).

References

Boeing, A. and Bräunl, T. (2007). Evaluation of real-time physics simulation systems. In *Proceedings of the 5th international conference on Computer graphics and interactive techniques in Australia and Southeast Asia*, pages 281–288. ACM New York, NY, USA.

Bongard, J., Zykov, V., and Lipson, H. (2006). Resilient Machines Through Continuous Self-Modeling. *Science*, 314(5802):1118–1121.

Deb, K. (2001). *Multi-objectives optimization using evolutionnary algorithms*. Wiley.

Doncieux, S., Mouret, J.-B., Bredeche, N., and Padois, V. (2011). *Evolutionary Robotics: Exploring New Horizons*, pages 3–25. Springer.

Fonseca, C. M. and Fleming, P. J. (1998). Multiobjective optimization and multiple constraint handling with evolutionary algorithms. i. a unified formulation. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 28(1):26–37.

Heidrich-Meisner, V. and Igel, C. (2008). Evolution strategies for direct policy search. In *Proceedings of PPSN X*, pages 428–437. Springer (LNCS 5199).

Jakobi, N. (1997). Evolutionary robotics and the radical envelope-of-noise hypothesis. *Adaptive behavior*, 6(2):325.

Jin, Y. (2005). A comprehensive survey of fitness approximation in evolutionary computation. *Soft Computing-A Fusion of Foundations, Methodologies and Applications*, 9(1):3–12.

Koos, S. and Mouret, J.-B. (2011). Online Discovery of Locomotion Modes for Wheel-Legged Hybrid Robots: a Transferability-based Approach. In *Proceedings of CLAWAR*. World Scientific Publishing Co.

Koos, S., Mouret, J.-B., and Doncieux, S. (2012). The Transferability Approach: Crossing the Reality Gap in Evolutionary Robotics. *IEEE Transaction on Evolutionary Computation*.

Lehman, J. and Stanley, K. O. (2011). Abandoning Objectives: Evolution through the Search for Novelty Alone. *Evolutionary Computation*, 19(2):189–223.

Lipson, H. and Pollack, J. B. (2000). Automatic design and manufacture of robotic lifeforms. *Nature*, 406:974–978.

Lohn, J. and Hornby, G. (2006). Evolvable hardware: using evolutionary computation to design and optimize hardware systems. *Computational Intelligence Magazine, IEEE*, 1(1):19–27.

Mouret, J.-B. and Doncieux, S. (2012). Encouraging behavioral diversity in evolutionary robotics: An empirical study. *Evolutionary Computation*, 20(1):91–133.

Nelson, A., Barlow, G., and Doitsidis, L. (2009). Fitness functions in evolutionary robotics: A survey and analysis. *Robotics and Autonomous Systems*, 57(4):345–370.

Pfeifer, R. and Bongard, J. (2006). *How the Body Shapes the Way we Think*. MIT Press.

Pinville, T., Koos, S., Mouret, J.-B., and Doncieux, S. (2011). How to Promote Generalisation in Evolutionary Robotics: the ProGAb Approach. In *Proc. of GECCO*, pages 259–266.

Shepard, D. (1968). A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference*, pages 517–524. ACM.

Whiteson, S. and Stone, P. (2006). Evolutionary function approximation for reinforcement learning. *The Journal of Machine Learning Research*, 7:877–917.

Zagal, J. and Ruiz-Del-Solar, J. (2007). Combining simulation and reality in evolutionary robotics. *Journal of Intelligent and Robotic Systems*, 50(1):19–39.