Imperial College of London

Research Project Report

Learning walking skills for Modular Robots

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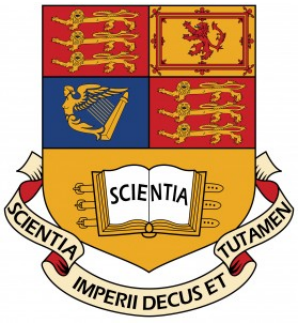

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Abstract

Department of Computing

Master of Advanced Computing

Learning Walking Skills and Laws of Command for Modular Robots

by Clement JAMBOU

In their designs Modular Robots present many advantages when facing a task in a difficult environment. Among these advantages the way they could potentially adapt to this environment and reconfigure themselves when facing different tasks makes them the favourite candidate for many applications, such as space exploration. However controlling the swarm of robots from high-level commands remains a tricky problem, especially since this problem is non-linear and contains many degrees of freedom. Therefore it is resistant to classical approaches used in automation when dealing with Robotics motion control.

The goal of this project is to present a survey of different control models and learning algorithms that proved to be efficient on similar problems. To compare these methods, we introduce a benchmark simulation built on the ODE Simulator and publicly available on Github. In this project we also apply for the first time Liquid State Machines to this particular problem of modular Robot locomotion.

Note : The first part of the project focused on bulding the simulation and the Central Pattern Generator: (Chapter 2 $\rightarrow$ 3.2) and the second part focused on compairing different models with different learning algorithms that were implemented (Chapter $1, 3.2 \rightarrow 6$).

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Chapter 1

Related Work

1.1 Overview

For over two decades, motion learning for complex structure has been a research focus. There has been many different approach to this problem, but it usually involves a simulated environment, where the creature can experiment with and get feedback from. The general problem is for this creature to learn by itself how to move in this environment in order to maximise a certain quantity such as its speed or distance with a certain amount of energy. The creature can have different ways of controlling its body using actuators to control the angle of its joints, (or even simulated muscles) and eventually some sensors to get feedback from the world. The goal being to generate the control function $\alpha_i(t, state)$ for each actuator's degree of freedom, that link time t and eventually the state of the creature to a command that can be send to the actuator (an angle for a servomotor, or command to a motor, an electrical signal to a simulated muscle ...). A widely used approach so far, which makes sense from a biological perspective is to implement smart actuators that can be linked directly to a sensor and modify the command with a low-level control. One of the examples of this behaviour is the muscle elasticity, which will alter the consequence of a specific command depending on the state of the muscle. Another example is the Proportional-Integral-Derivative controller (PID) of a servomotor. It is then possible to build a model that behaves as an open-loop from a high level perspective, but which actually shows robustness due to this low-level control loops. Under this assumption, we have the function $\alpha_i(t)$ that are only depending on parameter t. Finding the set of these functions remains an optimisation problem in an

infinite dimensional space. Therefore it is useful to make another assumption, which is that these functions are periodic. This make sense when we observe the movements of animals in the nature. In fact we can even consider the paradigm of oscillation based movements in the nature and apply it to the $\alpha_i(t)$ functions and write them using Fourier decomposition.

$$\alpha_i(t) = \sum_{k=1}^{N} b_{ki} * sin(kt) + \sum_{k=1}^{N} b_{-ki} * cos(kt) + b_{0i}$$

. With this decomposition, we transform our infinite dimensional research space (of functions) to a finite one containing the b_{ki} $(-N <= k <= N)$ coefficients. The parameter N is a restriction over the harmonics and can be seen as a precision parameter that determines how near we can get from any periodic function. This space of research remains big and does not reflects in its structure any of the physical interaction that can exist between two actuators (symmetry, graph structure) of the creature. Therefore, some of the following related works use different techniques to reduce the dimension of the space and also different learning techniques to obtain a solution.

1.2 Karl Sims Creatures

The first remarkable examples of modular robotics learning to evolve in a 3D simulated world is due to Karl Sims Creature in 1994 [1]. In his work, the structure of the creature evolves at the same time as the control system. One way of reducing the search space of Fourier coefficients is to create a graph that generate oscillations (much like the brain of animals does). The neural network used in Karl's creature takes as input a set of values from different sensors and each node can perform a specific function such as sums, products, logical and trigonometric functions to generate the oscillations of the structure. The physical shape of the creature, is built from a genotype and information to grow the creature.

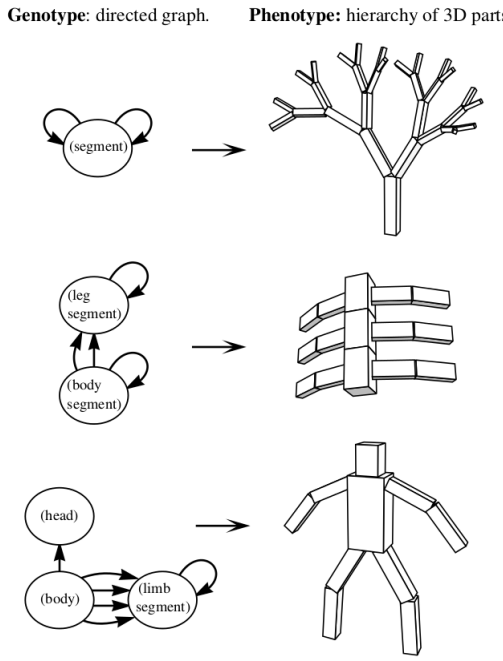

FIGURE 1.1: Designed examples of genotype graphs and correspond- ing creature morphologies.

Karl Sims uses Genetic Algorithms (cf Learning Methods section) in order to optimise all the parameters of the control graph and the structure. The mutation and cross-over steps of the Genetic Algorithm have been implemented for updating the population of genotypes. At each evaluation step, creatures are grown from a genotype and compared for a specific task (walking, jumping, swimming).

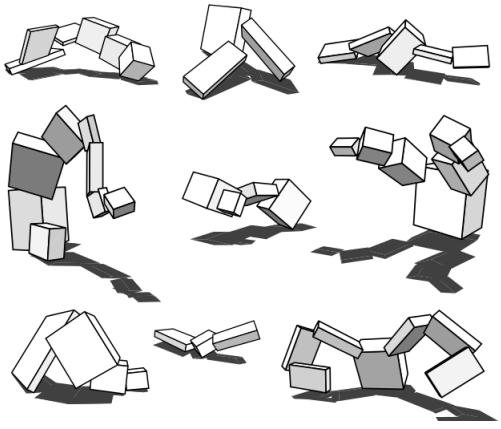

FIGURE 1.2: Karl Sims Creatures evolved for walking

1.3 Bio-Robotics lab at EPFL

In the last ten years, the bio-robotics lab of Ecole Polytechnique lauzanne (EPFL) has led breakthrough in modular Robotics, both in the Mechanical design and the control software. Central Pattern Generators are a widely use model to create oscillation for problems such as modular Robotics locomotion. In their work Sproewitz et al [2] focus on online learning parameters from a Central Pattern Generator (CPG). A CPG is a graph that relates directly to the physical structure in order to generate oscillation (see description in Learning Models). They use a gradient-free downhill method: Powell's method, to learn the parameters of the CPG. In their design CPGs follow the same concept introduced by Karl Sims, where the physical shape is used to produce a similar graph for control purposes. However, for CPGs the neurons are only oscillators.

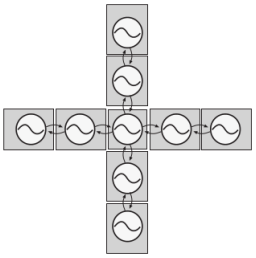

FIGURE 1.3: Central Pattern Generator Architecture

The Bio-Robotics lab also implemented physical blocs in order to build a swarm of modular Robots. The lab produced different prototypes to achieve this goal such as the YaMoR (Yet another Modular Robot) or Roombots module

FIGURE 1.4: Modular Robots implementation

1.4 Flexible Muscle-Based Locomotion for bipedal creatures

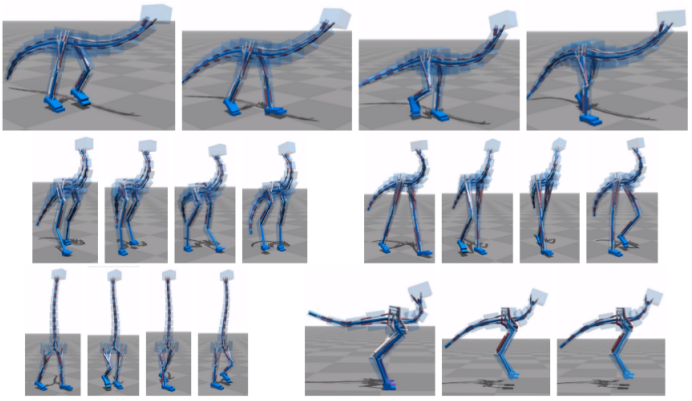

FIGURE 1.5: Synthesised walking for a bipedal creature

More recently, the progress of computational power and the growing interest of building humanoid robots for different tasks in non-friendly environment, such as the initiative from Virginia Tech to build a disaster response robots, or the growing demand of the animation movie and video games industry led to new results. Geijtenbeek et al [3] used muscle-based actuators and optimise at the same time the routing of the muscles and the control of the muscle activation from a musculoskeletal model. Though this approach is for graphic purposes (SIGGRAPH Conference) and it uses a musculoskeletal model, they follow the same method : a specific control model (simulation of the physical response and interaction of muscles) and a learning algorithm. In this paper, they use co-variance matrix adaptation as a the optimisation method [4]. This method updates a population of solutions by building new generations at each step based on a normal distribution, which mean and co-variance are estimated from the evaluation of the previous generation. Their results showed robust locomotion for different speed, target directions and small ground variations in terrain.

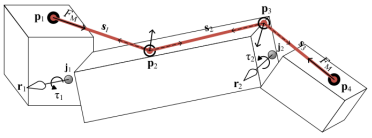

FIGURE 1.6: Example of Muscle Path

Chapter 2

Simulation Environment

The first task of my project was to build a simulator to be able to get feedback from a simulated world. The goal of the simulator is to provide an environment which is governed by physics laws. In this project such physics laws are gravity, friction and collisions. Combining these phenomena on complex structures can lead to situations that are difficult to predict, especially since it has a chaotic behaviour. Two movements of a structure in such a physical world, though they differ just a little, can lead to very different outcomes.

2.1 Physics Engine

In order to simulate the behaviour of complex shapes and bodies in a simulated world, a physical engine is required. This kind of physical engine is used in a lot of different areas, for instance the film and video games industry, to simulate destruction or complex situations where placing all bodies by hand would be too difficult. I tested two different libraries that provide tools to simulate these complex situations : `bullet` and `ODE` (`Open Dynamics Engine` [5]). The first part was to simulate the static part of the world, which is the ground. For now, I used a plane, with a friction coefficient, but we can imagine testing the creatures on different surfaces, (not necessarily plans)to test there reaction to a difficult environment. Also, in order to simplify the creature, so that the modules are simple shapes, all the robots are only composed of cubes (like the MIT project [6], linked by different type of joints. The idea behind this is to make

the creature depending on a really simple implementation of these modules, that can benefit from a chain manufacturing. ODE and bullet also provide tools to simulate joints (adding constraint on the relative movements of different bodies) and also to animate them simulating motors. I choose ODE for its simplicity to control different joints using this motors. In order to simulate a servomotor properly, it is for instance possible to set a maximum torque, boundaries within the degrees of freedom of the joint, and give a command to the motor.

All the calculation of the physics interaction is computed periodically by setting the time to wait between two calculations. Setting this parameter can be tricky : if we set it value that is too small, then the simulation will slow and it will take time to compute a 10 seconds simulation of the world. On the contrary, a large value for this parameter can lead to errors in the movement of the simulated bodies, especially if there are bodies with a high velocity in the simulation.

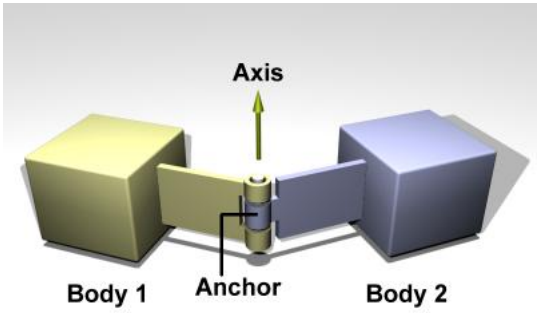

FIGURE 2.1: A 3D representation of a Hinge Constrain

2.1.1 Parameters settings

Many parameters requires to be set through to reduce the non-natural behavior of the simulation. Most of these parameters have been set using trials and error using a direct visual feedback of what seemed to be natural as well as a metric test(see Simulation Consitency in Results.). Among these parameters : the gravity, the friction coeffiscients, the timestep between 2 calculation physics calculation, the size of the cubical shapes.

2.2 Visual rendering

A good thing about the physical engine is that it is completely separated from the rendering part. That way, we can run all the simulation without watching the results which would reacquire additional computation and slow down the learning process. But it is also necessary to see the result, especially for the purpose of debugging the simulator. Carnegie Mellon University develops a framework called panda3d ([7]), that integrate both a rendering library using OpenGl and different physics engines (ODE and bullet). All these tools are developed in C/C++ with binding for python, which makes it an easy tool to create animation movie, games or simulations. They provide very useful tutorial to get started using these tools on their website.

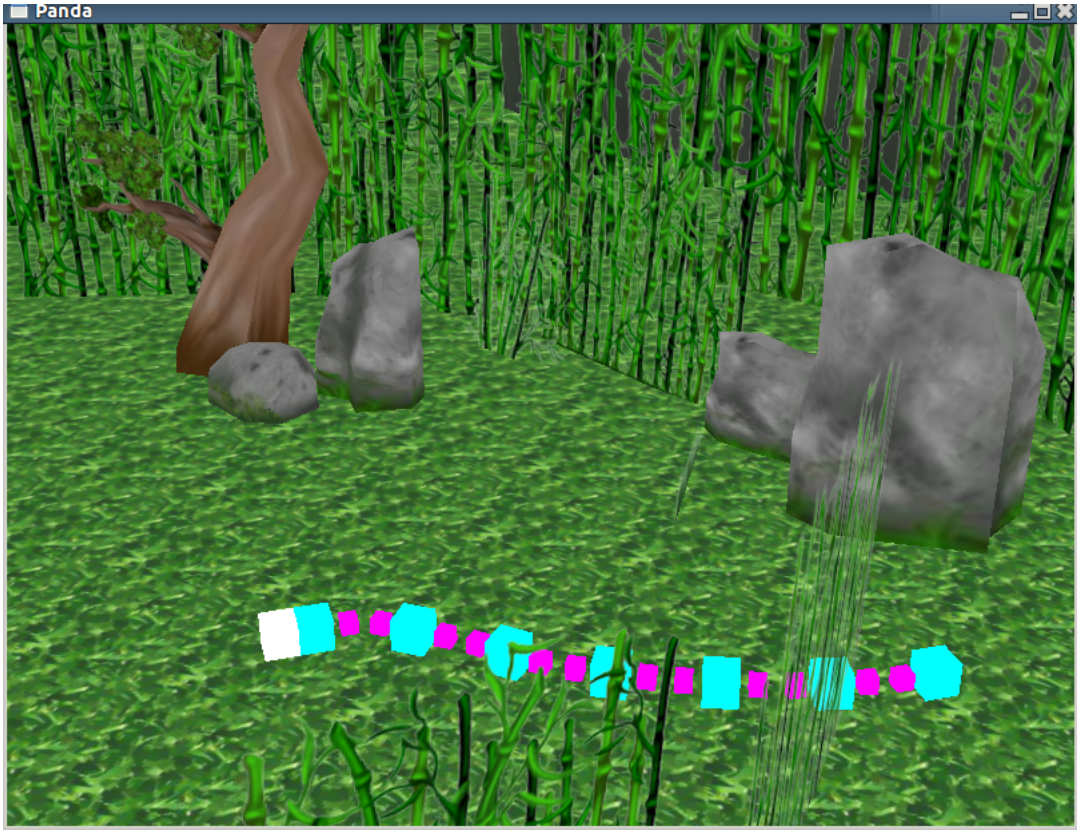

FIGURE 2.2: 3D Rendering of a snake in the environment

2.2.1 The coordinate system

In order to represent all the objects that we manipulate in the simulation (physics and rendering), panda3d, as most of 3D software, uses a system of global/local coordinate

and a tree architecture. Each element of the tree is represented in the coordinates of the father. In order to keep a coherence with this architecture, it is natural to use a graph to represent the modular structure of the Robots in this project. Panda3d also uses 4-by-4 matrices to represent the transformation of a node to its one of its children. These transformation are classical in 3D representation. They combine the benefits of 3 by 3 matrices that represent functions ($\mathbb{R}^3 \to \mathbb{R}^3$) that can be interpreted as the set of combined rotations and homotetia, where the matrix multiplication is the composition of such transformations. But manipulating translations requires to use 4 by 4 matrices(multiplying any matrix by the vector $(0,0,0)^t$ will not change this vector) instead of 3 by 3 that way the properties of the product are kept, which makes it a very useful tool to manipulate 3d objects. These calculation can run on a GPU as this is the kind of calculation GPU are designed for. For instance, if the children of the node are translated of a vector $(1,0,0)$, then we can use a function on the object representing the Matrix (TransformState in panda3d) to change the matrix and add the translation. The same goes for giving a certain orientation to the object using quaternions to represent the 3D orientation and add this to the 4 by 4 matrix.

$$T = \begin{pmatrix} \cos\alpha\cos\beta & \cos\alpha\sin\beta\sin\gamma - \sin\alpha\cos\gamma & \cos\alpha\sin\beta\cos\gamma + \sin\alpha\sin\gamma & x_t \\ \sin\alpha\cos\beta & \sin\alpha\sin\beta\sin\gamma + \cos\alpha\cos\gamma & \sin\alpha\sin\beta\cos\gamma - \cos\alpha\sin\gamma & y_t \\ -\sin\beta & \cos\beta\sin\gamma & \cos\beta\cos\gamma & z_t \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

FIGURE 2.3: Transformation Matrix for 3D bodies

2.3 Structures of the Robots as a Graph

We can represent a Robot as a graph, where each node is a component of the robot. In this project there is four types of components :

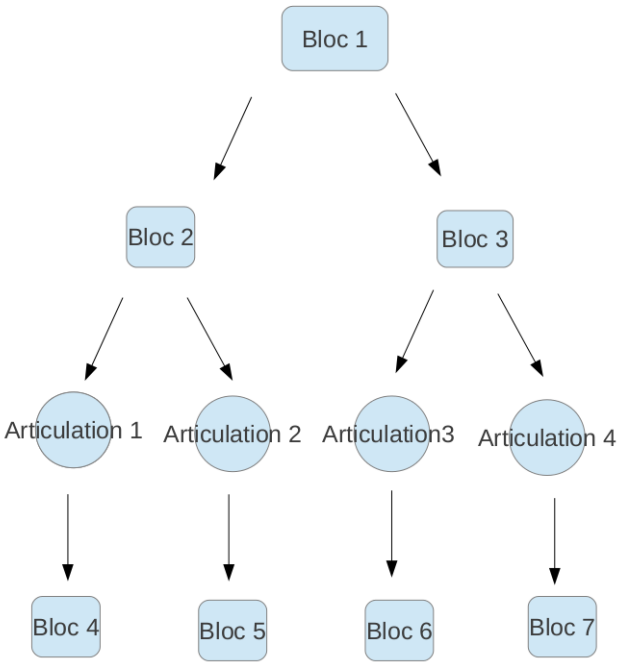

FIGURE 2.4: Structure described as a graph

- the head: which has a cube shapes and 6 sons (one for each faces), There is only one head per structure.
- a structural block: This is also a cube, also with 6 sons (or edges in the graph) for all faces.
- a hinge joint: The hinge is composed of two small cubes, separated by the joint with one degree of freedom.
- a vertebra : a vertebra is very much like a hinge but has two degrees of freedom (two angle directions) with smaller range, but bigger maximal torque.

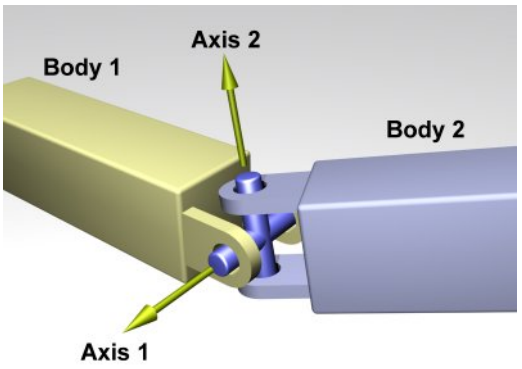

FIGURE 2.5: A 3D representation of a Vertebra Constrain

This Structure is represented in python with an object called MetaStructure, with very simple function to move within the graph and add components. This object is the key to describe a structure. It is then very simple to create a creature that we have in mind (or for possible later use to generate them automatically...). For instance, this is the code to create a snake with a given size : for the number of cell, we add a block and a joint.

```
def add_snake(m, size):
    #m is a Metastructure
    for i in range(size):
        m.add_block()
        m.follow_edge()
        m.add_joint()
        m.follow_edge()

    m.add_block()
```

Chapter 3

Control

Once the simulation is fully implemented, the goal is to use it as a test-bench for different ways of controlling the structure. The second part of the project was fully consecrated on this part. PID (Proportional-Integrate-Derivative) control loops have been implemented to make sure that the command is respected by the creatures. Three different model were implemented and tested to control the creature: Fourier Decomposition, Central Pattern Generators and Liquid State Machines. The goal of each of these models is to represent the $\alpha_i(t)$ functions that are the angle of the joints with a vector of finite size. The Fourier Decomposition model for example (see Introduction) represent the angle functions with their Fourier Decomposition.

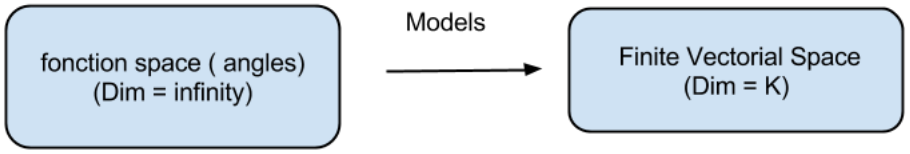

FIGURE 3.1: Learning Model

The two other models are described in this chapter.

3.1 PID Control of the joints

One of the problem to control accurately a joint is to adapt the command so that it can adapt to difficult situation. For instance, it is easier to walk in a swimming pool than on the ground and this is why people recovering after an injury do aquatic training. For a joint, it can be easy to do a movement in the air, but the same movement is more difficult when touching the ground. One way to avoid this problem is to implement PID (Proportional Integral Derivative) controller. This kind of controller is used in a lot of different situation in the world of automation to control degrees of freedom. In or case, servomotors often integrate such loops to account for these changes of use. In the simulation, at each step, the command of each degree of freedom of the structure is calculated using such a PID controller.

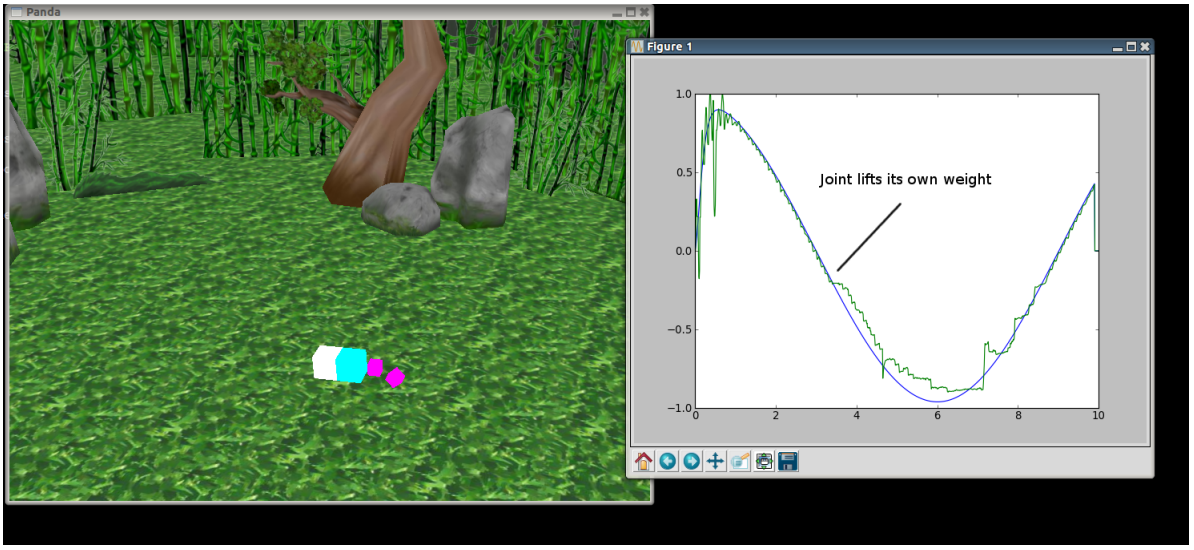

FIGURE 3.2: Answer of the joint to a sinusoidal command with PID Control

One of the problem with the control of the joints is the instability. On the simulation, as the angles have periodic values, if the joint has a high angle velocity, then between two steps, it can jump across the boundary and start turning faster and faster as the PID controller will not be able to work as well as if the degree of freedom were a linear parameter. The problem with this situation is that it can actually be seen as a good result for the learning algorithm, simply because the fitness function is the velocity of the creature. There are several things to prevent from this situation :

- reduce the time between two steps of computation for the physics engine and the PID
- reduce the maximum torque available per joint
- punish the creature if the joints are moving to slow
- change the fitness function to maximise parameter under a certain energy level

Another issue is more a biological concern. The main goal of this project is to find solutions that are biologically inspired instead of using a classical automation approach (even though we can compare the elasticity of or muscles as such controllers...). Therefore though the use of PID is necessary in many robotics applications, we will try to avoid using the in the second part of the project.

3.2 Central Pattern Generator

Central Pattern Generators (CPGs) are neural networks, that can generate oscillation for the control of the muscles of or body. They are the consequence and the cause of the paradigm of periodic movement in the locomotion of animals. Different models have been implemented to represent CPGs. We can represent them as a graph of coupled oscillator, where each node influence the behaviour of its neighbours. For a first implementation I choose to test the model of CPG followed at EPFL ([2]).

The CPG Neural Network in that case, is a graph that follow the physical architecture of the robot, setting one node for each joint (hinge or vertebra) on the structure. The dynamic of the CPG is determined by a coupling weight matrix w_{ij}, a phase bias matrix between nodes φ_{ij}, the frequency of the different oscillator ω_i and the desired amplitude and offset of the oscillation. We can compute the angle using the following system of equation and an integration method (I used the Runge-Kutta method in this project)

$$\dot{\phi_i} = \omega_i + \sum w_{ij} * r_j * sin(\phi_i - \phi_j - \varphi_{ij}) \tag{1}$$

$$\theta_i = x_i + r_i * cos(\phi_i) \tag{2}$$

This two equation gives the angle of the oscillator (θ_i) depending on the state variable of a node: x_i, r_i, ϕ_i, that can be described respectively as the offset, the amplitude and the phase of the oscillator.

$$\dot{r_i} = ar(\frac{a}{r}(R_i - r_i) - \dot{r_i}) \tag{3}$$

$$\dot{x_i} = ax(\frac{a}{x}(X_i - x_i) - \dot{x_i}) \tag{4}$$

Equations (3) and (4) describe the dynamic of the amplitude and offset (a second order dynamic that converge to the desired values). This trick is to ensure continuity in the oscillations, even if some of the parameters of the oscillator change. a_r and a_x are gains to control the dynamic ($a_r = a_x = 20rad/s$ [2]).

A modification of this model is possible to plug the measured value of the degrees of freedom. Instead of using the second order control loop on θ_i which is achieved with the PID, we can set this control on the phase. That way, if the joint has troubles achieving his movement, for instance when hitting the ground, the phase will be modified and the perturbation will have an impact on other joints through equation (1).

One way to do so is to add a term in the equation (1), with $\dot{\theta_{reali}}$ the measured angle velocity of the joint.

$$\dot{\phi_i} = \omega_i + \sum w_{ij} * r_j * sin(\phi_i - \phi_j - \varphi_{ij}) + a_\phi * \frac{\dot{\theta_{reali}} - \dot{\theta_i}}{r_i * sin(\phi_i)} \tag{1}$$

If we derive (2) we get:

$$\dot{\theta_i} = \dot{x_i} + \dot{r_i} * cos(\phi_i) + r_i * sin(\phi_i) * \dot{\phi_i} \tag{2'}$$

By making the assumption that the dynamic of the amplitude and the offset is slow compared to the phase, we get

$$\dot{\theta_i} = r_i * sin(\phi_i) * \dot{\phi_i} \tag{2"}$$

That way, if we consider small variation of the phase, we can deduce an error term on $\dot{\phi_i}$ from the error on $\dot{\theta_i}$ given by $\frac{\dot{\theta_{reali}} - \dot{\theta_i}}{r_i * sin(\phi_i)}$ that we can control with a gain (a_ϕ). For example

if the movement of a joint is made difficult because of the ground, then the measured velocity of this joint will be smaller that expected. The consequence will be to accelerate the movement for this joint (the derivative of the phase will be bigger), but also for the other joints that are linked to this one. We can interpret this as neural communication in our body within the central pattern generator, but also as the elasticity between joints. For instance if achieving a movement is too difficult for a joint, using elasticity, it is possible to get help from joints that are near.

3.2.1 Note on the implementation

- In the implementation of the CPG, we used a runge-kutta 4 integration method, with the same timestep as the simulation.
- The network was implemented so that it follows exactly the physical shape. However it could lead to interesting results to use networks with an architecture different from the physical shape, but inspired from it.
- The angles are scaled so that they initially fit in the range $[-\frac{\pi}{2}, \frac{\pi}{2}]$ and if during the learning process, they get bigger, then there is a saturation to prevent from impossible situations.
- All the other parameters in the implementation are inspired from [2]

3.3 Liquid State Machine

Liquid State Machine (LSM) and Echo State Network were independently and simultaneously introduced by Mass and al [8] and Jaeger and al. [9] and present a way of generating oscillations [10]. They were introduced as a way of using recurrent neural network for Machine learning purposes, as recurrent neural network are harder to train using the classical back-propagation algorithm. A LSM is created from a random recurrent neural network that contains N neurons and is called the reservoir. The state of the neurons in the reservoir are updated using the following equation:

$$X_{t+1} = f(W_r * X_t)$$

where W_r is the random weight matrix inside the reservoir and f is the activation function (in this project we used the hyperbolic tangent as the activation function)

Once this network is created, oscillations can be observed in the state of each neurons. A weight matrix is randomly initiated to produce linear combinations of these oscillations that can be plugged to control the joints angles of the creature.

$$\alpha_i(t) = \frac{\pi}{2} f(W_o * X_t)$$

where W_o is the output weights and f is also an activation function. We then multiply the results by $\frac{\pi}{2}$ to ensure that the angles are in an acceptable range for the control in any situation.

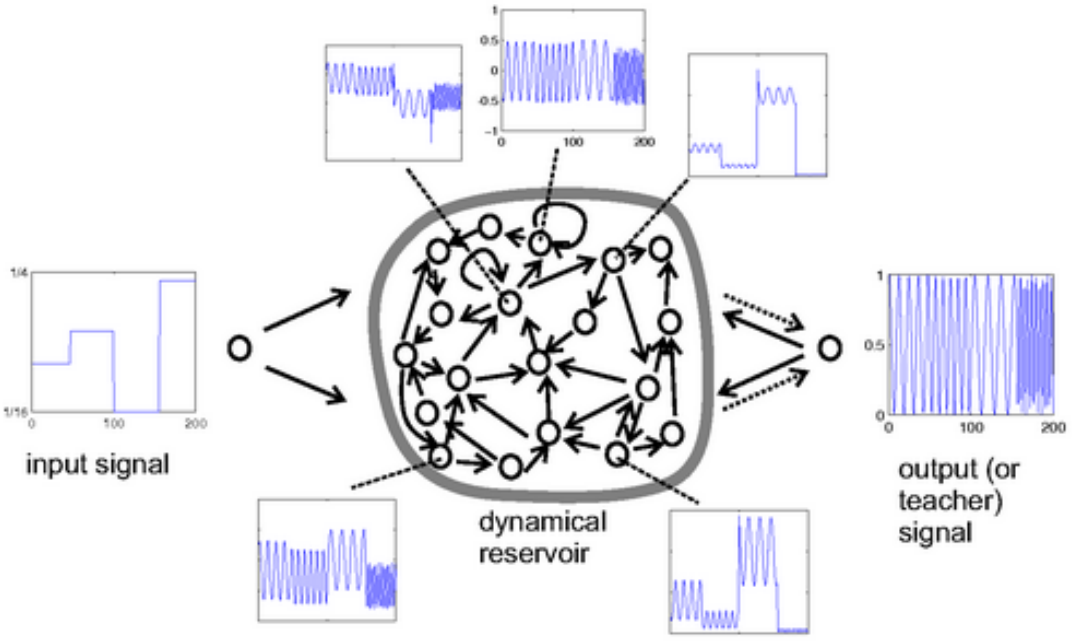

FIGURE 3.3: Liquid State Machine

The idea of the Liquid State Machine is to focus the learning parameters on the output weights. The reservoir of neurons can be big, and produce a large variety of periodic signals. By learning the W_o matrix (of size $N * K$ where N is the size of the reservoir and K the number of hinge) each hinge can select some features of these oscillations.

It is also possible to use a feedback loop in the network, by plugging the measured angles in the reservoir using the output weights. In this project we tested a different size of reservoir when generating random signals ($p \in 5, 20$). To be able to compare this model

with the other models, we used 5 neurons so that the total number of parameters to be learned for a 4 degrees of freedom creature is 20.

Chapter 4

Learning Methods

In this chapter we present different Learning Methods that have been tested and compared on this particular problem. All of these methods are optimisation algorithms to find a minimum (or a maximum) over a set of parameters. It is not possible to get a gradient or Hessian matrix for a problem involving a simulation as fitness function. Therefore none of these algorithms use the derivatives of the function as information to find optima (unlike Gradient Method or Broyden-Fletcher-Goldfarb-Shanno (BFGS)). The following sections present different algorithms that can perform such a task. We then compare their results on the simulation. For coherence in this chapter, we use the following notation:

- $X = \{X_p, p \in \{1, ..., q\}\}$ is a set of q elements (or vectors) of the parameter space ($\mathbf{R}^n$), where n is the dimension of this space. $X_{p,i}$ is a scalar, and represent the i-th coordinate of the p-th element of the population.
- $f(\mathbf{R}^n \to \mathbf{R})$ is the fitness function we want to minimise.
- $X^{(p)}$ the p first element of the ordered list of element from set X where the order relation is given by $X_i \leq X_j$ iff $f(X_i) \leq f(X_j)$
- iterators p, q are over the population, where i, j are over the coordinate of each element

Moreover, in this problem the fitness function is not likely to be convex, as taking the mean of two good solutions for the movement of a structure does not necessary

provide a good solution. The fitness function can also present some discontinuities or high variations because of collisions. Collisions are not continuous phenomena and even if the physics engine use smoothing techniques to simplify interactions. For instance there is a very small difference between a biped structure walking and a biped structure almost walking but with one leg that does not touch the ground, but the fitness function will give completely different results as one structure is moving and the other is not. Finally there is also the problem of consistency of a result, because two structures can behave differently for the same parameters, as the simulation can show chaotic behaviour as small variations can have a big impact on the movement. For all these reasons, it is difficult to use classical optimisation for the creatures to learn how to move in the simulated environment.

It is then possible to learn the parameters of the learning model (CPG, LSM, Fourier coefficients, see previous chapter) to optimise the movement of the structure.

4.1 Note on the Optimization Server

In order to implement and record the results of the different learning algorithms, an optimization server were implemented in python. The `Flask` package implement a very simple webserver interface, that can be used on a local network or over the internet. In the optimization process, we can distinguish, workers, which are processes running an instance of a simulation and the task manager, that assign different population of parameters X to be tested. In this case, one worker can communicate with the webserver using 2 different endpoints functionalities : getting parameters for evaluation and returning the results. The task manager, which is related to the specific learning algorithm can also communicate with the webserver for assigning parameters to be tested and checking if the results have been calculated and collect them. All the endpoints have specific URL that can be consulted using standard POST HTML request using the JSON format. Also, in order to record all the progress of an algorithm, all the parameters that have been tested are stored in a `MongoDB` database for its simplicity of use with python and `Flask` and flexibility when dealing with large datasets of small objects. The implementation of the optimization server is independant of the specific problem adressed in this report, it can be used for any optimization task, though no

information on the fitness function in the exception of testing specific values can be performed. Any number of workers on different machines with multiple processes can be used thatway, in order to compute results faster. The code for this optimization server is opensource and available on GitHub : `github.com/clement91190/optim_server`. For the specific use of the optimization server presented in this report, a special feature of the optimization server was implemented to compute the results of the fitness function 3 times for each set of Parameters and only keep the minimum of these 3 test samples. It is a way of ensuring that the parameters estimation will not be "lucky" (see Simulation Consistency.)

4.2 Genetic Algorithm

A Genetic Algorithm (GA) is an optimisation algorithm that replicates the process of natural selection. GAs were introduced in the 60s and early 70s and are inspired from biology. They consist of a loop of four steps until convergence (or a proper solution) is reached : evaluation, selection, cross-over, mutation. A population X of p elements is randomly generated to initialise the algorithm. The evaluation step is just running the fitness function f over the new elements. If the global structure of the genetic algorithm is fixed, the specific operations of selection, cross-over, mutation require to be adjusted to the specific problem, depending on the type of parameters (here vectors of float) and their complexity (dimension of the vectors, entropy of discrete reprentation...). In the following, we describe these operation used in this project.

4.2.1 Selection

The first step is a selection step. The goal is to keep only a part of the population and eliminate the rest. This is directly related to Natural Selection, where the "weakest" animals are less likely to survive. They are different ways of keeping "good elements". The first idea that comes to mind in performing such a step is to keep the q best elements, ie $X^{(q)}$. The problem with this solution is that it prevent the population from "exploring" as all the best elements will be kept, it is more likely for the population to get stuck into a local minima. A widely use alternative is the Tournament Selection. We randomly select two elements and keep only the best of the two. We repeat this

step until enough elements have been eliminated (usually half of the population). This alternative give a chance to all elements even if they are not in $X^{\{}q$ best.

Algorithm 1 Tournament Selection

```
p = 0
while p < q/2 do
  X_1 = randomelement(X)
  X_2 = randomelement(X)
  if f(X_1 ≤ X_2) then
    X.eliminate(X_2)
  else
    X.eliminate(X_1)
  end if
end while
```

4.2.2 Cross-Over

The cross-over is a step to repopulate after the selection. By taking two random elements of the set, we can compute new elements (usually 2) by performing a cross-over of the the two parents. This step is inspired from reproduction in biology. The idea behind it is that by taking two good solutions, we can create 2 new elements that are likely to be good solutions. Usually, this task is performed using a bit representation of the element of the population, when we deal with discrete representation of elements. In a way, using such a code is to represent the element is as if we manipulate the DNA of the elements. The Cross-Over to produce new element, is then just to exchange bits between the parents. When the elements are scalar vectors, a way of reproduce this phenomena is to use the barycenter of the two parents as described in the following procedure.

Algorithm 2 Cross-Over

```
for p ∈ [1 : q/2] do
  X_1 = randomelement(X)
  X_2 = randomelement(X)
  λ = randomfloat([0.5; 1.4])
  X.add(λ * X_1 + (1 − λ) * X_2)
  X.add(λ * X_2 + (1 − λ) * X_1)
end for
```

4.2.3 Mutation

Finally the mutation step is a way of exploring new solutions. We choose some elements to be mutated and modify them slightly. For this step also, if the parameters had a

binarry representation, it could be done by randomly picking some bits of the parameters to be modified. For scalar vector, one way of doing the equivalent operation is to use a Gaussian distribution which use the previous elements as a mean, and a co-variance matrix that depends of the population (for instance the co variance of p-nearest neighbours)

4.2.4 Note on some of the parameters

Many parameters needs to be set in order to use a genetic algorithm. These parameters depend on the fitness function (and therefore the learning model). The classical Rosenbrock function were used to set some of these parameters, as well as direct experiment with the fitness function.

- size of the population : The size of the population needs to be at least of size $n+1$, otherwise, because of the barycenter used in the cross-over, the population would be stuck on an hyperplane of the search space (except during mutation). Also in order to reduce the convergence time, if the population size is too small, then it is likely that over a space direction, the covariance matrix project poorly and make it then difficult for the algorithm to move along this axis. In the tests we choose to use the population size to be $4n$
- initialization : As the learning model is set to have all parameters within $[-1; 1]$ we use an uniform distribution to choose the elements for the first generation.
- contraction : in order to accelerate the convergence of the GA, we pick the λ value in the cros-over step within $[0.5, 1.4]$ using an uniform distribution. This as for an effect to contract globally the population over a large number of steps. However a wider value could be used to explorate the search space.

4.3 Nelder-Mead method

The Nelder Mead method [11] (or downhill simplex method) is a way of finding a local optimum, without knowing the gradient of the function in a given multidimensional space. We initialise a non-degenerated simplex in this space, then we follow the procedure described in the algorithm here-under:

Algorithm 3 Nelder-Mead Method

$p = 0$
repeat
  order the points of the simplex such that $f(x_0) >= f(x_1) >= f(x_2) \dot{>} = f(x_n)$
  compute the centre of gravity of all the points x_g
  compute the reflection of x_n in respect to x_g $(x_r = x_g + (x_g - x_n))$
  if $f(x_r) > f(x_{n-1})$ **then**
    compute the expansion point : $x_e = x_g + 2 * (x_g - x_n)$
    if $f(x_e) > f(x_r)$ **then**
      replace x_n with x_e
    else
      replace x_n with x_r
    end if
  else
    compute the contraction point : $x_c = x_g + 0.5 * (x_g - x_n)$
    if $f(x_c) >= f(x_n)$ **then**
      replace x_n with x_c
    else
      `homotetia`
      for all $x_i, 1 <= i < n$ **do**
        replace x_i with : $x_i = x_0 + 0.5 * (x_i - x_0)$
      end for
    end if
  end if
until convergence

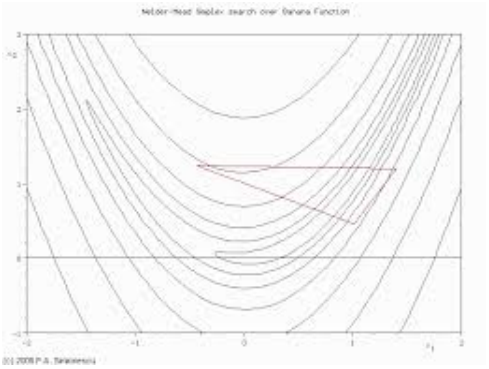

FIGURE 4.1: A simplex following the Nelder-Mead method

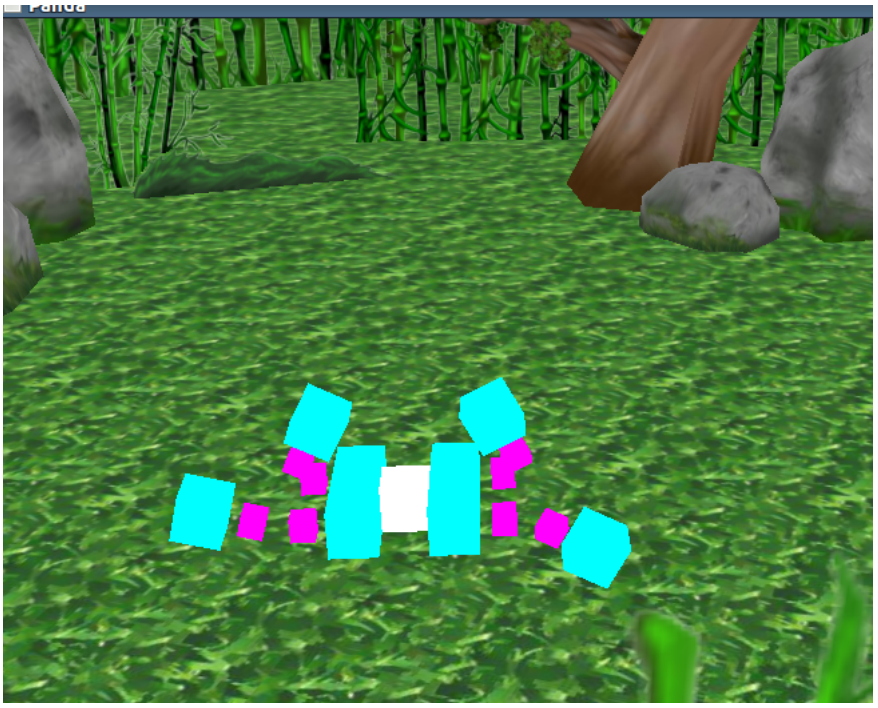

FIGURE 4.2: A structure with four legs learning

4.4 Random Search

A first very simple way of finding good solution is random search. We test a random set of parameters and keep the vector of parameters showing the best results. This has the benefit of being very simple to implement and provides a good test-bench for fixing issues with the simulation. A first problem observed was the consistency of the solution, testing the same parameters can lead to very different results. A first way to correct this was to take longer sample (about 20 sec of simulation). Even with this correction, online learning brought some issues, as it is possible that a good results is only good because of the initial configuration given by testing previous movement. A way to correct this is to set all angles to a default value and wait for the structure to have a null velocity. This also showed solutions using the first movement to jump as far as possible.

Chapter 5

Results

5.1 Simulation consistency

A large part of implementing a reliable simulation environment is to solve incoherences that can be problematic when used in a learning environment. Many parameters are to be set so that these "bugs" become a minor issue. These incoherences have two different sources : the float approximation, and the approximation of continuous phenomena with time steps. For instance when setting the parameters of a PID loop, the frequency of the loop is a crucial parameter : if it is two low, then the control can become unstable, and in a simulation it cannot be higher than the frequency of the simulation itself. Another example is the fact that collision are not continuous phenomena : in a simulation an object released to fall on the ground will be above the ground for one time step and "inside" the ground at the next time step. Physics simulation engines like ODE implement tricks to solve this problem, however with this phenomena and the limited float precision, we can understand that we see a chaotic behaviour : two estimations of the same parameters under the same initial condition can lead to different results and therefore two different estimations of the fitness function f. Therefore a large part of this project was to reduce the variance of the results of the fitness function on the same parameters for different trials. The graph here-under present these results with two different settings of the PID frequency.

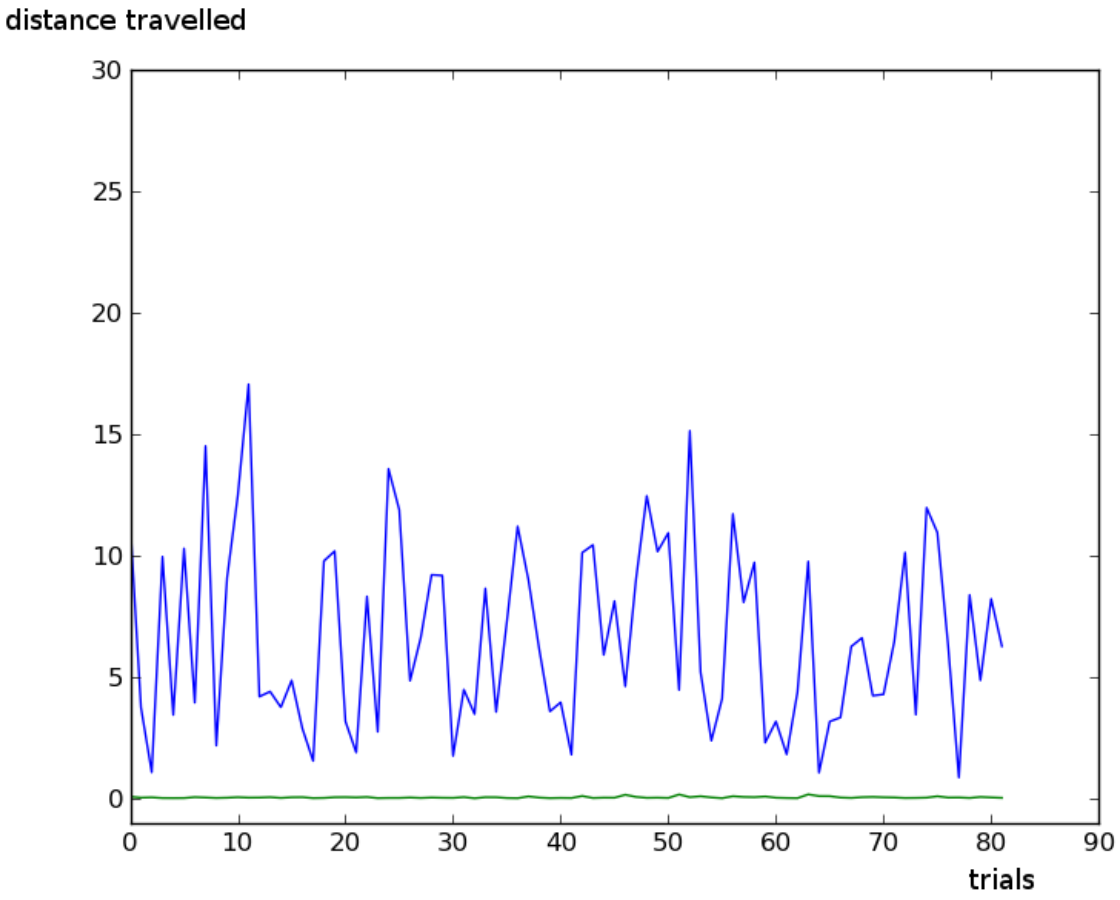

FIGURE 5.1: Variation of fitness function for a PID frequency of 30Hz(Blue) and 100Hz(Green)

5.2 Creatures taking advantages of simulation bugs

Another surprising behaviour in the simulation is the fact that the learning algorithm can take advantage of some of the existing bugs in the simulation. This results was also observed by Karl Sims [1]. In the simulation when starting another trial, the velocity and position used to be set to the starting situation. The problem is that using the approximation of ODE for collision using, some hidden parameters in the simulation were not reinitialised when moving the creature back to its starting position. Therefore, the creature could have some of its blocks under the ground, and was jumping in a really unrealistic way because of this bug. The learning algorithm learned to find the bug and all the best solution were using this bug to jump very far and have a high value for the fitness function.

5.3 Comparison

This section presents different curves obtained for the different learning methods and learning models. In each graph, we present the evolution of the evaluation of the fitness function which is the distance that a four-legged creature has walked during the learning period.

5.3.1 Fourier Decomposition Model

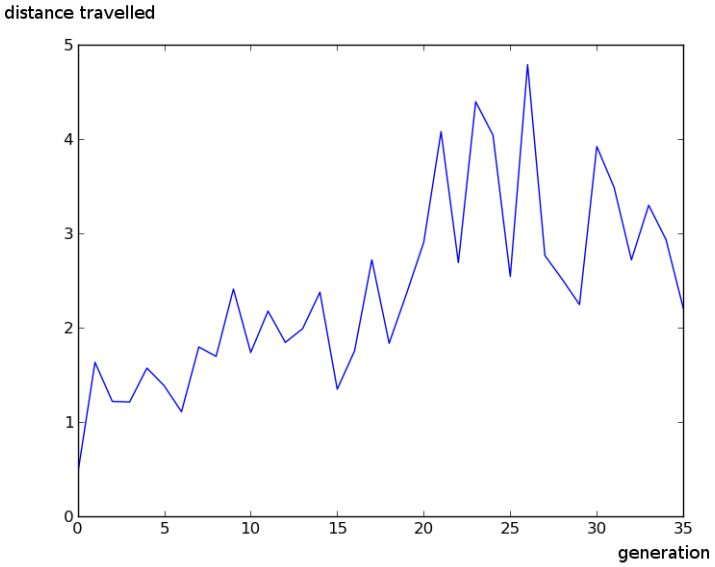

FIGURE 5.2: Learning Method : Simplex, Model : Fourier Decomposition

On these two learning curves, we can see that the Simplex method converge toward a value of 3 where the Genetic Algorithm converge to a value of 5. However it takes about 100 generations, which means 8000 (the population of a generation is $4 * n$, where n is the number of parameters, 20 for the Fourier Decomposition) parameters trials for the GA to converge, where the the Simplex method require 400 parameters trials.

5.3.2 Central Pattern Generator

For this model the Simplex method converges toward a value of 20 and the Genetic Algorithm toward a value of 30. The CPG model requires more calculation because of the integration of the model (compared to the other models, that are directly computed),

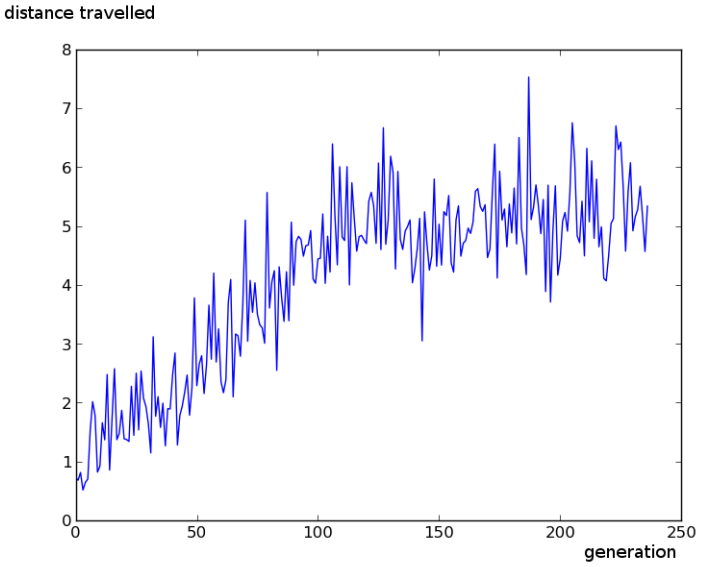

FIGURE 5.3: Learning Method : Genetic Algorithm, Model : Fourier Decomposition

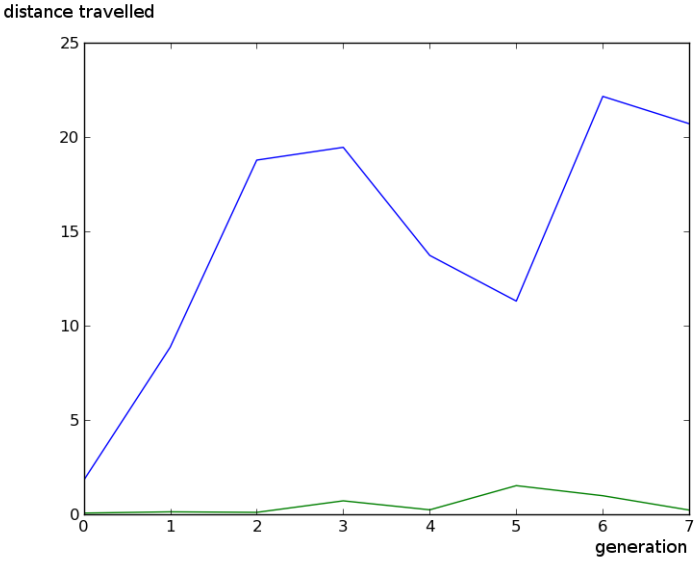

FIGURE 5.4: Learning Method : Simplex, Model : CPG

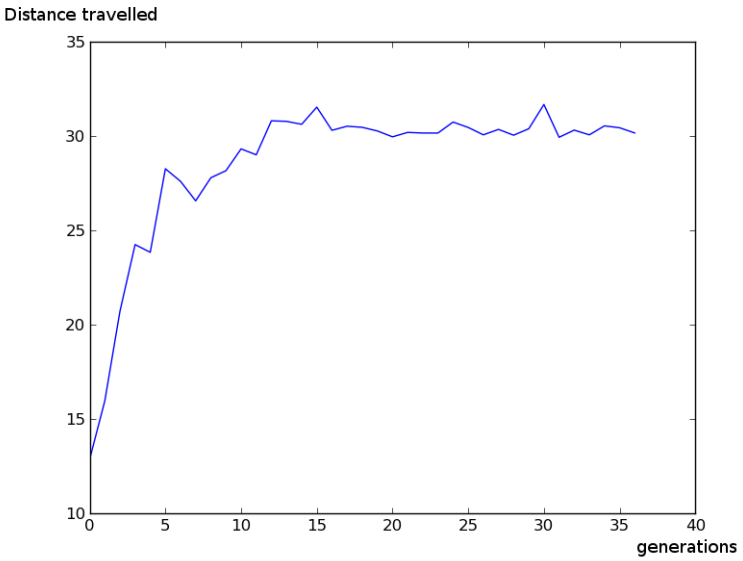

FIGURE 5.5: Learning Method : Genetic Algorithm, Model : CPG

therefore it is slower. It did require 20 generation for the genetic algorithm to converge, so 720 parameters estimations, as there is only 9 free parameters for this model. The 40 generation took 12 hours on a 8 processor machine.

5.3.3 Liquid State Machine

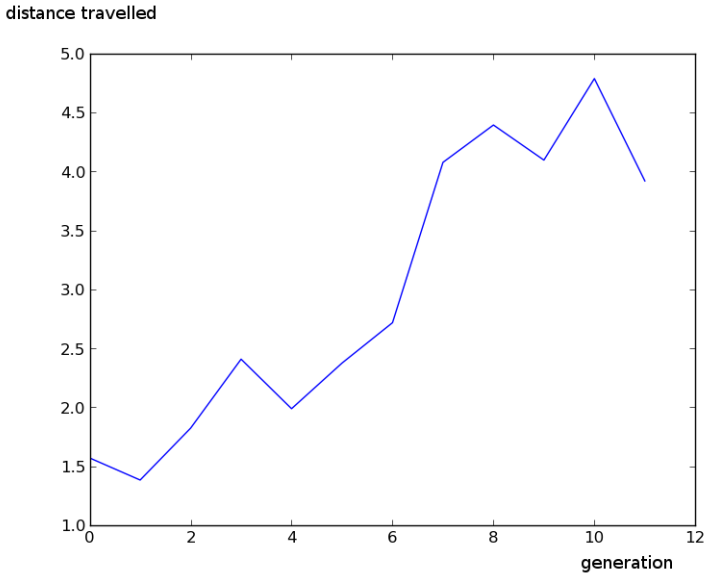

FIGURE 5.6: Learning Method : Simplex, Model : Liquid State Machine

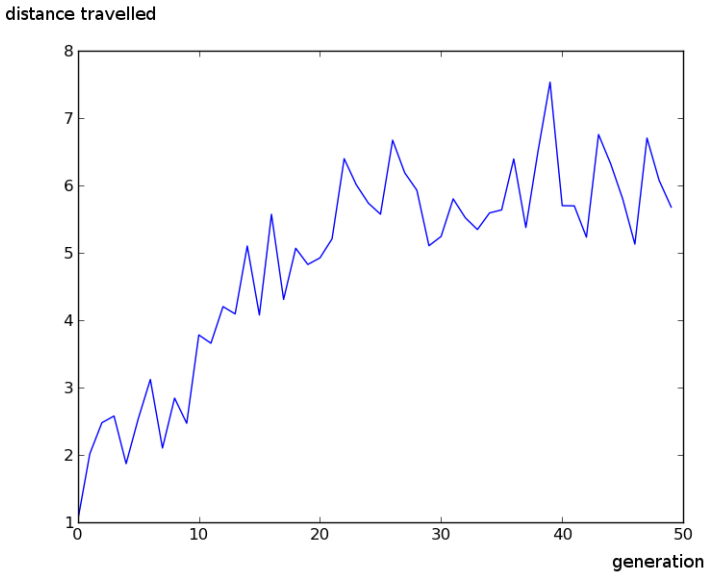

FIGURE 5.7: Learning Method : Genetic Algorithm, Model : Liquid State Machine

For the Liquid State Machine, we have similar results with the Fourier Decomposition Model with a convergence toward 4.0 after 10 generations for the Simplex method and 6.0 after 30 generation for the Genetic Algorithm. This results use a 5 neurons reservoir (so that we have the same number of parameters than the Fourier Decomposition model).

One of the feature that we can observe in comparing the genetic algorithm and the Nelder Mead method over the different models, is that the genetic algorithm is slower, however it converge towards a higher value. This is an expected behaviour as the simplex is a downhill method and therefore converge towards a local minimum. One of the example of the convergence of the Nelder-Mead method towards a local extrema that was encountered was a situation where the creature seems to have learn how to push on one leg only to move (Video).

The best results have been obtained using the CPG and the Genetic Algorithm (see learning curves). In their architecture, central pattern generator follow the physical shape of the creature, where the Fourier decomposition and the liquid state machine models are independent of it. Therefore, it is easier to train such a model, because it requires less parameters to produce the angles functions. However we could expect to have better results after a long training for the Fourier decomposition and the Liquid State Machine as well as they are more general models but it is not the case in these results : the learning algorithms are stuck in local minimum for these models.

Chapter 6

Conclusion

Because of its many applications in Space exploration, Medicine, Construction ... , Modular Robots is a very exciting area of Robotics. However, many problems still need to be solved in order to be able to use the advantages of Modular Robotics. In this project we tackled one aspect of the problem of robust locomotion using Machine Learning over a simulation. Different Control models and Learning method were tested and compared on a four-legged structure. On this particular structure, Central Pattern Generators present a good compromise between simplicity of the model (in the number of free parameters to train) and efficiency as the best results where obtained using Genetic Algorithms and this particular model. As we saw in this project, using the approach of having a system learn by itself how to behave in its environment can produce better results than hard-coding it and show unexpected natural behaviour. The simulation of these structure produced locomotion that seemed natural compared to what we usually see and think of in Robotics. With the computation power growth, it is likely that we will see more application of such an approach using a simulation, a model and a learning method.

The simulation is available on Github : `github.com/clement91190/rp` as well as an optimisation server allowing multiprocessing on different machines written in python with `Flask` and `mongodb` to store the results. The simulation can be used to produce and test locomotion on any structure composed of mechanical joints such as servomotors and cubical blocks.

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