Terrestrial and Aquatic Locomotion Parameter Tuning of Alli-bot: Experiments and Numerical Simulations

M.Tech Project Report submitted

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in

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by

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under the guidance of

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Certificate

This is to certify that the work contained in this thesis titled "Terrestrial and Aquatic Locomotion Parameter Tuning of Alli-bot: Experiments and Numerical Simulations" is a bonafide research work of Mr. Krishna Agrawal, carried out in the Department of Mechanical Engineering, Indian Institute of Technology Patna, under my supervision and that it has not been submitted elsewhere for a degree.

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Date

Place

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Name of the Student(s): Krishna Agrawal

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This is to certify that Mr Krishna Agrawal.

1. has/have sincerely worked on their project,
2. has/have contacted me regularly to update on the progress of the assigned project,
3. has/have received my comments on the preliminary version of the report and presentation and will address those prior to final submission/presentation,
4. may be allowed to present/defend the project before the department.

Remarks (if any):

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Dr. Atul Thakur

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Dedicated to

my Parents and my beloved ones.

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Nomenclature

$\boldsymbol{A_B}$	amplitude for head, torso, tail joints (1 and 2)
$\boldsymbol{A_H}$	amplitude for hip joint
$\boldsymbol{A_K}$	amplitude for knee joint
$\Delta\boldsymbol{\varphi}$	phase lag between body joint actuators
$\boldsymbol{e}$	error angle between robot orientation and goal
$\boldsymbol{\gamma_B}$	body offset parameter
$\boldsymbol{\gamma_L}$	leg offset parameter
$\boldsymbol{h}$	objective function
$\boldsymbol{K_A}$	acquisition function
$\boldsymbol{K_D}$	stochastic behaviour of objective function
$\boldsymbol{K_E}$	maximum objective evaluation
$\boldsymbol{K_S}$	number of seed points in cost function
$\boldsymbol{N}$	number of active joints in the body
$\boldsymbol{p}$	gait parameter of robot$p \in \mathbb{R}^3 \mid p = [A_H, A_B, T]^T$
$\boldsymbol{\varphi}$	angle between goal and robot centroid
$\boldsymbol{r}$	radius of acceptance
$\boldsymbol{S}$	average speed of the robot in cm/s
$\boldsymbol{T}$	time period in the gait cycle
$\boldsymbol{T_{tr}}$	time to travel from start to goal location
$\boldsymbol{\theta}$	control action $\theta \in \mathbb{R}^{12} \mid \theta = \left[\theta_{B_i}, \theta_{H_i}, \theta_{K_i}\right]^T$, i = 1 to 4.
$\boldsymbol{\theta_{B_i}}$	commanded angle for i^{th} body joint actuator, i = 1 to 4.
$\boldsymbol{\theta_{H_i}}$	commanded angle for i^{th} hip joint actuator, i = 1 to 4.
$\boldsymbol{\theta_{K_i}}$	commanded angle for i^{th} knee joint actuator, i = 1 to 4
$\boldsymbol{\bar{\theta}}$	robot orientation
$\boldsymbol{x}$	state space vector $x \in \mathbb{R}^4 \mid x = \left[x_{c,1},\ x_{c,2},\ \dot{x}_{c,1}, \dot{x}_{c,2}\right]^T$
$\boldsymbol{x_a}$	position coordinated of red colour marker($x_a \in \mathbb{R}^2$)
$\boldsymbol{x_b}$	position coordinated of green colour marker($x_b \in \mathbb{R}^2$)
$\boldsymbol{x_c}$	centroid of the robot ($x_c \in \mathbb{R}^2$)
$\boldsymbol{x_g}$	goal point ($x_g \in \mathbb{R}^2$)
$\boldsymbol{x_o}$	start point ($x_o \in \mathbb{R}^2$)

Acronyms

BO	≡	Bayesian Optimization.
LOS	≡	Line of Sight.

Abstract

Locomotion parameter tuning of legged robot is a challenging problem, many simulators based approaches have been developed so far, however the problem of reality gap limits the applications of such techniques. Performing parameter tuning directly on the experimental platform leads to parameters that can be directly used. However, the main challenge is the wear and tear of the platform during the experimentation. This thesis reports a Bayesian optimization based parameter tuning approach for in-house developed 12 DOF Alligator inspired robot namely Alli-bot, the developed approach ensures that the locomotion parameters tune to yield maximum mean robot speed while at the same time the no. of required experimental trial is minimized. We obtained an improvement of mean robot speed by a factor of 3.85 times for terrestrial locomotion (trot gait) and by a factor of 6.38 times for aquatic locomotion (anguilliform gait). We observed that the near optimal parameters can be obtained by performing not more than 15 experiments.

The thesis presents the details of formulation of locomotion parameter tuning as an optimization problem and Bayesian optimization based solution approach. We believed that the developed approach can be extended for other more complex robotic platform.

Key words: Amphibious, Alligator inspired, Gait smoothening, Control, Automatic Parameter tuning, Bayesian Optimization.

Chapter 1

Introduction

1.1 Background

Stability and manoeuvrability are two key issues, which impart a significant role in the performance of Legged Robot [1]. Various gait patterns such as trot and creep used by the quadruped animals are imitated in their robotic counterparts [2]. Legged reptiles use body undulation during terrestrial legged locomotion to improve their balance in the sagittal plane as well as to improve the energy-efficiency [3]. Amphibians use slow, large amplitude undulations down the length of their bodies for their terrestrial locomotion in contrast to high frequency, small amplitude undulations in water. In order to obtain the best energy efficiency, the quadruped robots should have flexible spine motion [4].

The design of the robot is inspired by legged reptiles, and thus it exploits the body undulation during terrestrial locomotion. While swimming, the legged reptiles mostly use their body undulation while tuck their legs in to minimize the resistance due to drag. Likewise, the robotic counterpart also utilizes only body undulation for swimming. This thesis reports a Bayesian optimization-based approach to tune the gait parameters of both leg oscillation and body undulation in order to maximize the average robot speed for different terrain conditions as well as for swimming. A combination of physical experiments and numerical simulations are used

Figure 1-1 American Alligator , Source www.endangered.org/animal/american-alligator/

1.2 Motivation

Alligator is one of the strongest living creatures with a highly stable gait. These are evolutionarily very successful both in terrestrial and aquatic environment. From a robotics point of view, it will be very attractive to develop an amphibious robot capable of swimming, crawling, and walking. This type of Robot can have proven to be an important machine in the defence for our country such as surveillance, surveying. The capability of such robots can be explored by research for autonomous navigation, motion planning, controlling, and machine learning.

1.3 Research Objective

Thus, the objectives of this thesis are

a) Implement a parameterized cycloidal trot gait on the Alligator-inspired robot named as ‘Alli-bot'’ in order to smooth the locomotion pattern.

b) Design the Control strategy in Alli-bot in order to navigate it in an effective way.

c) Develop a surrogate Gaussian Process model that captures the dynamics of ‘Alli-bot’ performance.

d) Application of Bayesian Optimization schemes to tune the locomotion parameters for obtaining the maximum speed for different terrain and swimming.

1.4 Scope

a) Amphibious creature like Alligator is one of the strongest in nature. It can survive in both terrestrial as well as an aquatic region. So it is a good research platform for researchers to develop a machine which can mimic the same behaviour and highly utilized in defence and aquatic surveillance.

b) Gaits are selected depending on the locomotion requirements, energy expenditure being an important parameter [5] [6] [7]. Roy et al proposed tuning of gait parameters for a wave gait of a six-legged robot for energy minimization during robot turning [8]. Alexander et al. (1985) hypothesized that additional energy storage mechanism in galloping is economical only above a certain range of speed. Similar conclusions can be drawn for an alligator with a high walking and swimming.

c) Manoeuvrability of such a Robot depends on many factors such as Energy consumption, Speed, turning Radius, etc. The study of these factors can improve the performance of Robot.

d) Automated parameter tuning is to be done with the help of Bayesian optimization technique in order to know the highest speed and effect of parameter tuning in obtaining the highest speed in different terrain.

1.5 Summary

Due to massive strength, flexibility and stability alligators can adapt any environment from land to rocky mountain and from water to mud in a most stable way. These enormous features inspire us to develop such a machine, which can be adapted by any environment with such a good stability. Such a machine can contribute mainly towards defence and aquatic research with surveillance and surveying. Nature created these creatures in such a way so that for every motion pattern optimal energy and maximum performance can be achieved. So we plan to develop an alligator inspired robot, which can walk in different terrain and swim with the highest possible speed in order to study the effect of different parameters in the behaviour of the robot.

Chapter 2

Literature Review

2.1 Quadruped Locomotion

Amphibious animals can survive both in land and water hence they have great locomotion capabilities in both terrestrial as well as the aquatic region. There are the large varieties of species within the class amphibian, and each species has accordingly different kinds of locomotion pattern. Alligators one of the strongest creatures known for their swimming ability, which uses their tail however, role of the tail is still debated in their terrestrial motion.

Wheel-based vehicles are limited to the structured terrain, but for unstructured terrain or varying conditions like aquatic and bumpy land these robots are unable to perform well. There are various quadrupedal animals, which have greater flexibility, stability and manoeuvrability in different uneven terrestrial terrain and marshy lands. We can inspire from these animals to provide better stability and manoeuvrability by improving designed and control in legged quadrupedal robot. Taking inspiration from these animals' bio-inspired robot can be designed, which can operate in both terrestrial and aquatic region and are particularly useful in surveillance, reconnaissance and environment monitoring in natural varying conditions.

Walking Gait

Commonly called as an inverted pendulum gait, it corresponds to slow walking and is characterized by a pendulum-like exchange between kinetic energy and potential energy of the centre of mass of the body [9].

Bouncing Gait

At higher speeds, legged animals use bouncing gaits like trotting, galloping, hopping and running. The legs behave like a compliant spring which causes the centre of mass to reach its lowest point in the middle of the stance phase [1].

These gaits are characterized by

For walking robots, both static and dynamic stability [11] as well as both active and passive walking have been extensively researched [12]. Recent advancements have provided a significant boost to the bio inspired robotics, especially terrestrial quadruped locomotion. Among amphibians, we have the Salamander robot [13], Amphi-Hex 1 [14] and the amphibious robot with flexible flipper legs [15], whereas when we talk of reptiles, the alligator inspired modular robot [16] is a notable citation. The highest number of such robots are, however, depicting mammalian locomotion. Be it the cheetah-cub [7], or the MIT Cheetah [17], there have been numerous robots developed by leading research institutes. Other than the broad animal families also, there have been famous quadruped like the TITAN-VIII [18] or the SCOUT [19].

Figure 2-1 Salamandar Robotica [2]**.**

2.2 Related Works

Apart from the design robustness and optimization, control of such robots has also seen considerable improvement over the years. Maleki, [20] talks about control and gait design with an active spine for energy efficiency A feed forward and feedback dynamic trot gait control systems that combined the 3D sway compensation trajectory, and the adaptive body position and swing leg motion control were implemented on the Titan-VIII [21] robot by Kurazume [22] [23]. The sway compensation trajectory enables keeping ZMP on the diagonal line of the support legs more efficiently with less energy consumption. A set of control algorithms based on SLIP (Spring's loaded inverse pendulum) model was given by [24] to regulate the forward and lateral running speed, hopping height and body attitude.

The Matsuoka model, as a neuron model of the Central Pattern generator was proposed [3] and implemented on an amphibious multilink mobile robot.

Alligator exhibits a peculiar type of reptilian locomotion. It is generally considered as an intermediate step in the evolutionary paradigm of vertebrate locomotion [26] [27] [28]. Their limbs are held laterally to their body. M.F.Silva [29], studied periodic gaits of quadruped locomotion systems to determine the best set of gait and locomotion variables during walking through average energy consumption and the hip trajectory errors during forward straight-line walking at different velocities [2] proposed the maximum speeds at which vertebrates are capable of running by studying the mechanics of the mostly used inverted pendulum model. Similarly, Cavagna, [10] worked on finding the determinants of the step frequency in running, trotting and hopping in man and vertebrates.

At the same time, very few robotic researches to have focused on the issue of gait optimization specifically for the alligator crawling gait. Xianbao, [4] proposed that critical trotting speed of the quadruped robot exists and can be used to decide the gait parameters. From the point of alligator motion, these studies seem to be missing an important aspect of the alligator motion, their lateral undulation.

Using body undulations for robot locomotion is not entirely a new concept. Loc et al., proposed a way wherein the robot's body was systematically adjusted to maximizing the reachability of the next swing leg in order to improve the traverseability of the robot and to navigate rough terrains [5]. However, similar studies are very rare in case of terrestrial quadruped alligator-inspired robotic locomotion. The following figure explains the notion of lateral undulation in alligators.

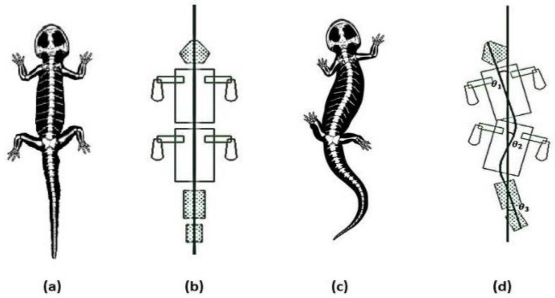


Figure 2-2 . (a) Schematic of an alligator moving without undulations (b) Alli-bot mimicking the motion without undulations (c) Schematic of an alligator moving with undulations (d) Alli-bot mimicking the undulatory motions.

Alligator exhibits different types of gait of which trot. The high walking gait is used for drier and hard terrains with a duty factor in the range of 0.73 to 0.83 and speed range of 0.16±0.01 m/s [30]. They have an uncanny reptilian locomotion which is considered as a next step in the evolution of vertebrate locomotion [26] [4]. Their tail accounts for nearly 28% of body weight due to which hind limbs to support an increased percentage of weight when a quadruped is working against a drag [31]. Coming to its amphibious capabilities when comparing to fish swimming, alligators have sharp amplitude variations (identified as a major thrust generator) from head to tail, the mean amplitudes of which are 0.07 and 0.1 times the body length respectively [32]. Tails of the mammalians play an important role in the dynamic stability and manoeuvrability as well as on its speed. The robotics have not investigated the effect of the tail on the speed of the robot.

Gait optimization is an active topic of research for a long time of about 20-25 years. A lot of researchers all around the world are trying to improve the behaviour of the robot by using different methods. Considerable success is achieved in the past for gait optimization with reinforcement learning and evolutionary methods like Saggar et al. 2007 [33] optimized both gait speed and stability for a quadruped, Mustafa and Kemal, 2007 [34] uses reinforcement learning to optimize the gait stability at a given speed for a hexapod robot and also tests it for the abnormal case of deficiency in one of the rear-legs. Thomas Roofer [35] used evolutionary algorithm to optimize the gait parameters for a quadruped in the Sony Four-Legged Robot League. Sonia Chernova, and Manuela Veloso 2004 [36] used an evolutionary approach based on genetic algorithms to optimize the speed over a physical quadruped. Weingarten, J.D. et al. 2004 [37] used

Nelder-Mead algorithm to optimize the gait speed for a hexapod. Nate Kohl and Peter stone 2004 [38] made a comparison of the different optimization algorithm Hill climbing, Amoeba (Nelder-Mead algorithm), genetic algorithm and policy gradient reinforcement learning, to improve forward speed over a quadruped in an offline setting.

Over the last few 6-7 years, Bayesian optimization has emerged for optimizing the gait parameters as it learns the properties of the value functions or policies with as few samples as possible. Several researchers successfully applied this approach for robotic gait optimization as can be seen in [33] [39] for quadruped and snake robots, [40] evaluates a new acquisition function to select the best prior for a 5-DOF planar arm. [36] uses simulation as a prior aid. For gathering more data about the system and improve the training on a physical platform. In on-line algorithms, robot gathers the data by experiencing it from the real world instead of a simulator and obtains information gradually with time. Whereas in off-line algorithms where simulations are used, the values for simulation environment variables are assumed to be known so the learning phases of these algorithms are not used on the real physical system. However, here is the catch, (1) Off-line algorithms have the advantage of not requiring costly runs of the system with sub-optimal policies and (2) trial runs of the real-world system are way too expensive. To overcome this issue for our Alli-bot we have combined both the online and offline procedure, first we are running the Bayesian Optimization algorithm in numerical simulations to determine the values of hyper-parameters for our algorithm and then using those hyper-parameters to get the optimized gait parameters by running it on the real physical robot.

2.3 Research Gap

Based on literature review we find

a) The role of spine movement during terrestrial locomotion in Alligator is totally a research object. So we have decided to perform an experiment on terrestrial locomotion of Robot in order to find the speed and study the role of undulation locomotion. In the robotics community, very few robotic platforms exist that have done the experimental analysis of the robot as a function of body and tail undulations.

b) The gait optimization is not a new research area but very few robotic platforms exist, which uses both trot gait and body undulation at the same time. And can operate both in the terrestrial and aquatic region. The studies have to the certain extent missed the connection of lateral undulation of the robot with its speed. We thus aim to bridge this research gap and try to study the importance of various parameters on the performance of robot locomotion.
c) Many researchers have done work in the application of Bayesian optimization in different robotics platform. However, very few have validated it in physical platform. Our work depicted the validation of this technique in complex systems like our robot.

2.4 Summary

On reviewing the literature on last 10 years in the field of Quadrupedal Bio Inspired Robotics and Amphibious Robots. We have come to following conclusion.

a) Use of tail and spine motion in the aquatic region is known but for the terrestrial, region still exists a conflict.
b) Robots which are amphibious in nature, i.e., can operate in terrestrial and aquatic regions are very few.
c) Due to the absence of theoretical model and lack of experimental evidence very less work has done in the field of gait parameter tuning using optimization technique such as Bayesian. Most work has been done in simulation only [41]. However, the experimental validation has been done so rarely to validate these techniques.

Chapter-3

Problem Statement and Approach Overview

3.1 Problem Statement

Let,

$\boldsymbol{S}$ be the average speed of the robot in cm/s,

$\boldsymbol{A_K}$ be the amplitude for knee joint of robot in the gait cycle,

$\boldsymbol{A_B}$be the amplitude for head, torso, tail1 and tail2 joints of robot in the gait cycle,

$\boldsymbol{T}$ be the time period for the knees and body movement in the gait cycle,

Where $\boldsymbol{A_K}$, $\boldsymbol{A_B}$, $\boldsymbol{T}$ be the gait parameters and $\boldsymbol{S}$ is the performance indie

The problem statement can be divided into two parts:

To compute, for a given terrain and a given gait pattern, an empirical model that can relate the amplitudes of different body parts of the alligator with the performance indices. The model developed will take the gait parameters as input to predict the forward speed of robot. This model can then be qualitatively studied and analysed to understand the role of body and tail undulations in the locomotion of an alligator inspired robot. Develop a model that maps the gait parameters into the performance indie.

$$\boldsymbol{S} = (\boldsymbol{A_B}, \boldsymbol{A_K}, \boldsymbol{T}) \tag{1}$$

To obtain the gait parameters $\boldsymbol{x}*$ = (A_B* , $\boldsymbol{Ak}*$,$\boldsymbol{T}*$) which maximizes the speed of the robot with minimal number of robot runs by optimizing an objective function h(x) i.e. the speed of the robot. x* is the set of parameters which maximize the objective function.

$$\boldsymbol{x} = \boldsymbol{w}*\boldsymbol{S} \tag{2}$$

$$\boldsymbol{x}* = (\boldsymbol{h}(\boldsymbol{x})) \tag{3}$$

By using an optimizer g (Bayesian Optimizer) in our case which will give us the optimal parameters for a given objective function. D is the set of function data set for each evaluation i.e. D = {x, h(x)} where x are the parameters and h(x) are the corresponding function evaluation of x.

3.2 Approach Overview

The major challenges while solving such a problem is that there still isn't a dynamic model that can explain the dynamics of such a motion while also validating the results. So we used the approach of surrogate modelling and conducted the experiments on 'Alli-bot' Alligator inspired robot to find the maximum speed in least no. of experiments in different terrain.

We have used the Bayesian optimization technique but for experiments, we need to fix the hyper-parameter so first we develop the simulator, i.e. computational model in Vrep and then apply Bayesian optimization technique with different hyper-parameter and compare the result and select the hyper-parameter which provides the best forward speed in least no. of iteration and fix that hyper-parameter for our experimental setup and optimize a physical parameter.

The approach followed may be explained through some of the key points:

a) Simulator Development.
b) Experimental Setup.
c) Bayesian Optimization Parameter tuning using simulator.
d) Locomotion Parameter tuning using physical robot.
e) Experimental Validation.

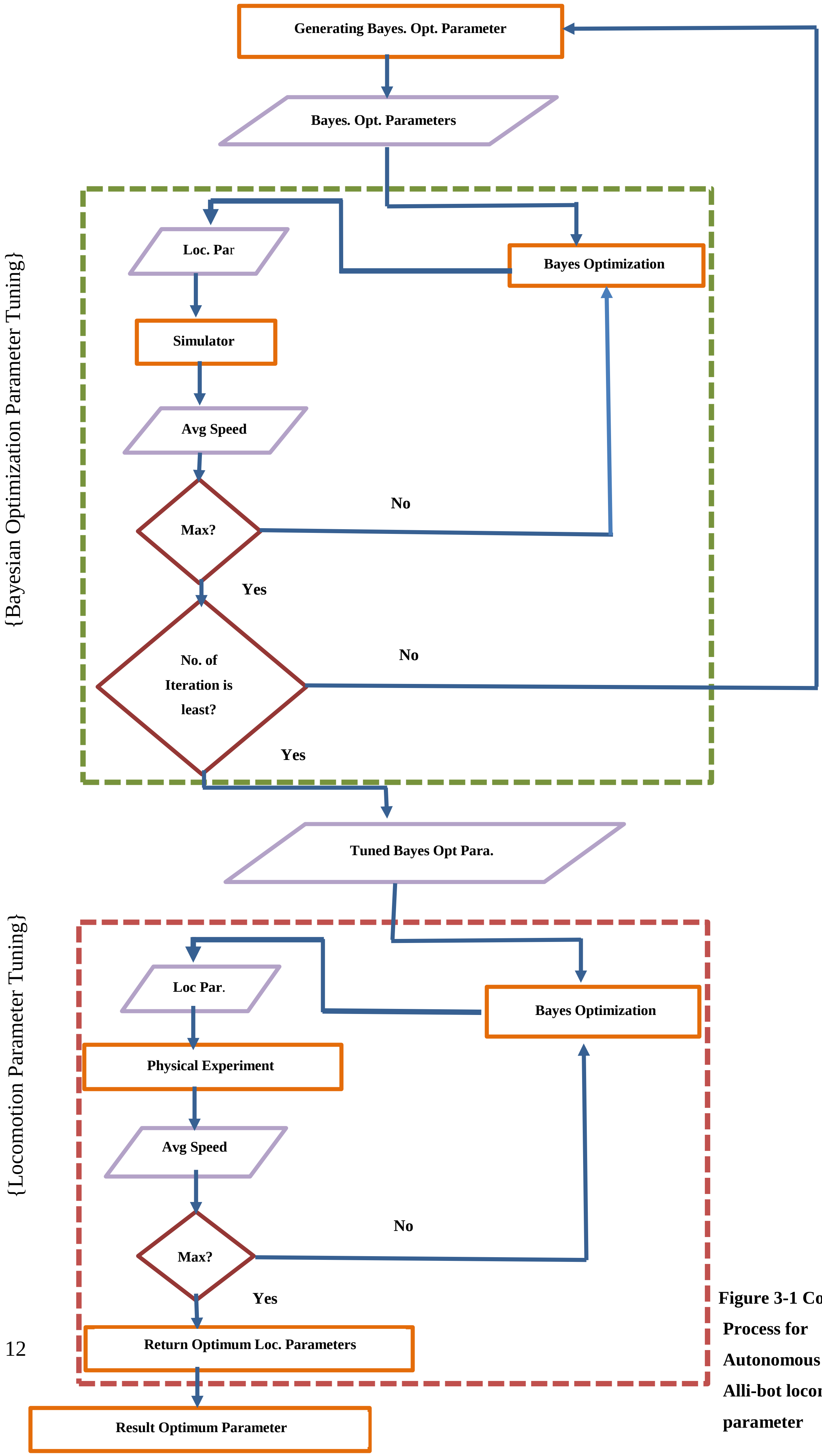


Figure 3-1 Complete Process for Autonomous tuning of Alli-bot locomotion parameter

Chapter-4

Simulator Development

Simulation plays a vital role for the development of any complex system. It is an impossible for real system to iterate multiple times to know the effect of various parameters in the performance of system [42] Through simulation; we can search in complete possible range of parametric space, and the best parameter can be validated in the real system. Every new algorithm can be tested in simulation in order to know its performance on the behaviour of system and also can reduce the chances of loss in form of wear and tear. Every algorithm we designed is first tested in simulated environment after successful implementation in simulated environment it is implemented in physical. For simulator development, we use Vrep environment.

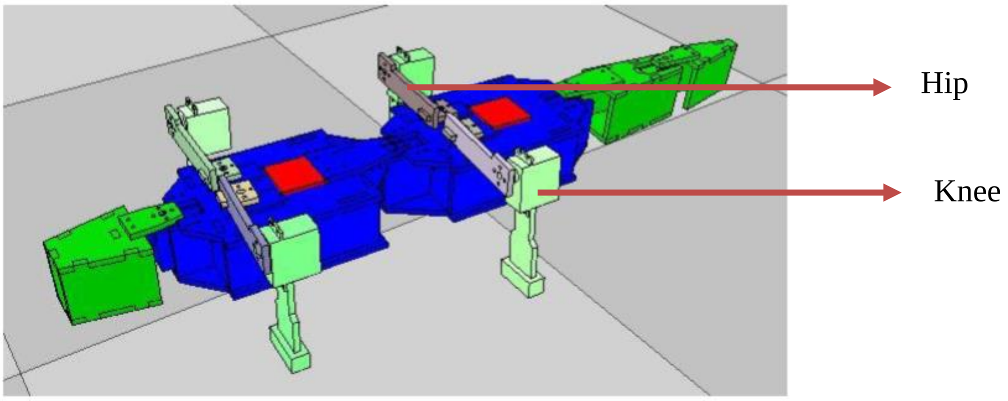


Figure 4-1 Simulated Model of Alli-bot developed in V-rep [4]**.**

Different steps for Simulator development are as follows

a) Modelling and Calibration:
b) Parameter Selection:
c) Validation of Simulation:
d) Matlab Interfacing:
e) Summary

4.1 Modelling and Calibration

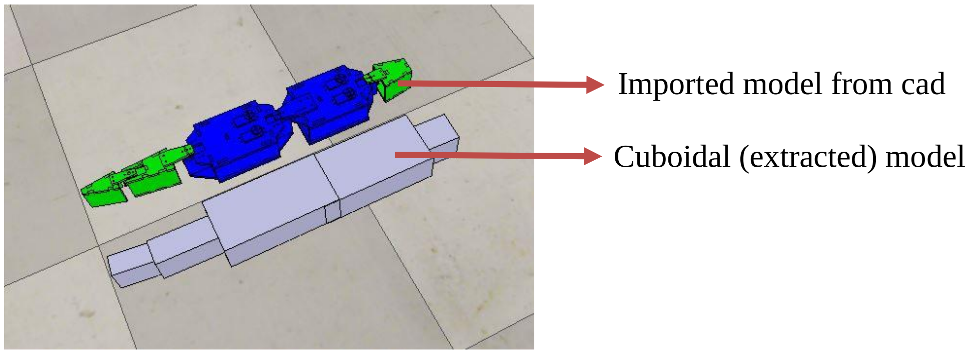


Figure 4-2 True shape (cuboidal shape) extraction in V-rep.

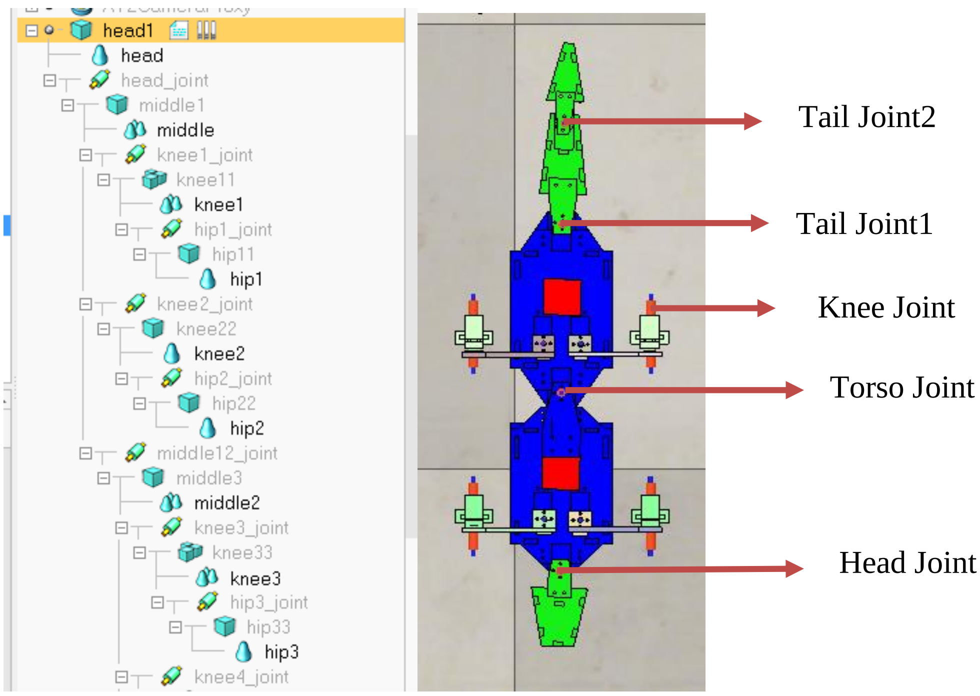


Figure 4-3 a) Tree structure to set relative joint b) Twelve revolute joint to provide 12 DOF.

Add twelve revolute axis in place of the twelve actuator. And formed a tree structure to maintain the relative motion between these joints. Add mass to each object as per the Alli-bot mass and make the object dynamic enabled and respondable. Enable collision detection, spectacular properties and provide frictional properties.

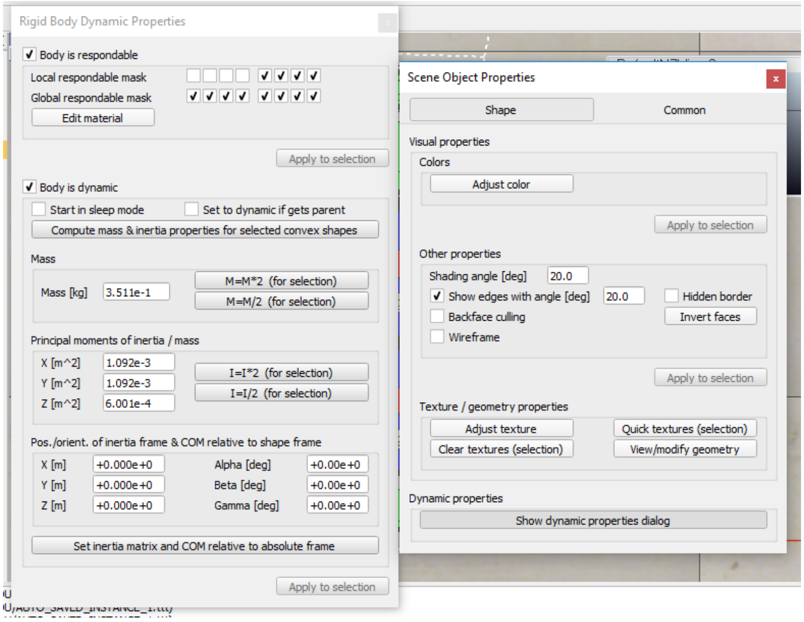


Figure 4-4 Dynamic properties in Simulated Alli-bot.

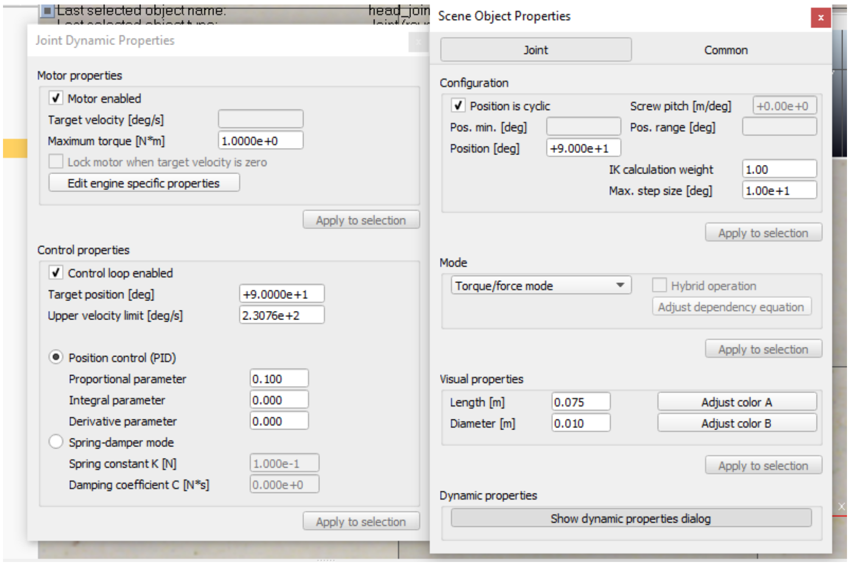


Figure 4-5 Revolute joint specification.

Enable dynamic engine properties for each revolute joint axis and fixed the control parameter through manual tuning. Set the initial joint angle 90^0 to each revolute joint and set maximum torque as per the specification of the servo actuator.

4.2 Parameter Selection

Create each revolute joint as an object in non-threaded script and write a control and gait parameterization algorithm as shown in fig 5-13. Control algorithms have designed such that from the overhead camera, centroid of the marker can be detected with the help of colour detection technique, and robot's centroidal position and goal position can be estimated and compute the error angle. Error is send to controller and controller generate a control signal from that error angle via manual tuning of parameter (Kp, Kd). And add these signals to joint revolute angles and in a way navigate the robot to the goal by repeating the same algorithm.

4.3 Validation of Simulation

In order to validate the simulator with the physical robot, we have performed similar experiment in the simulator as well as in the physical robot and compare the different result. Although our simulations internal parameter such as friction, damping, restitution, stiffness, etc. is not similar with the physical robot so the magnitude of a result is totally differed from the physical experiments result,

But the nature of variations in different experimental results is similar and these results validate that our simulation is correct with the dynamics of our physical robot. The result for simulation and Experimental results is shown in fig 4-6 and fig 4-7.

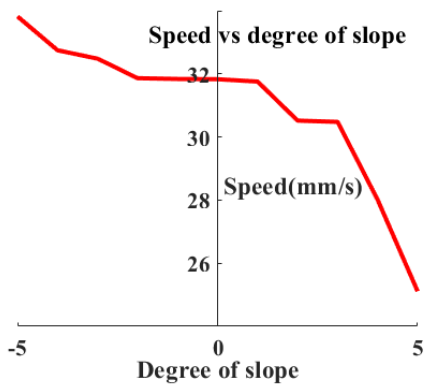


Figure 4-6 Average speed vs slope inclination in simulated enviorment.

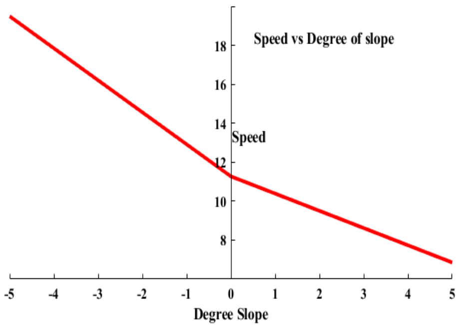


Figure 4-7 Average speed vs slope inclination (different terrain) in physical

From the figure, we can see that for simulation, we have done optimization from -5^0 slope to $+5^0$ slope and for physical experiment, we have done the experiment for $-5^{0,}$ 0^0 and $+5^0$ slope. We can see from fig that in both case's variation in average speed is of similar nature concerning the inclination of slope, i.e., for -5^0 speed is highest and for 5^0 slope, speed is lowest and also according to physics when a robot moves downwards gravitative pull support it and if a robot moves upwards gravitative pull against it, and it will decrease the speed, and these facts validate that our simulation's dynamics is correct although internal parameter tuning is required with the physical robot so that nearby results can be achieved.

4.4 Matlab Interfacing

To decide the feasible hyper parameter for our physical experiment different experiments, need to be done in simulator. In each experiment first fix the hyper parameter and after fixing it, experiment (simulated environment) is carried out for different locomotion parameter to obtain the highest possible speed in different no. of iteration. For different hyper parameters, number of experiments has to be done and the experiments which gave the highest speed with least no. of iteration is decided and from that experiment, hyper parameter is decided for physical experiment.

For deciding the hyper parameter first fix some hyper parameter, the bayesopt tool box generates locomotion parameters, which send to Vrep computational model and run that model in a controlled way to reach goal position. The calculated average speed is sent to matlab again so that bayesopt tool box again generates the new parameters, and process keeps repeated. Every time bayesopt toolbox checks the negative of speed to be minimum (i.e., highest possible speed) after a definite number of iteration this toolbox gives the nearby global speed with its parameters as shown in fig 4-8. Different experiment has done with different hyper parameter and hyper parameter which gives nearby maximum speed in least no. of iterations is selected.

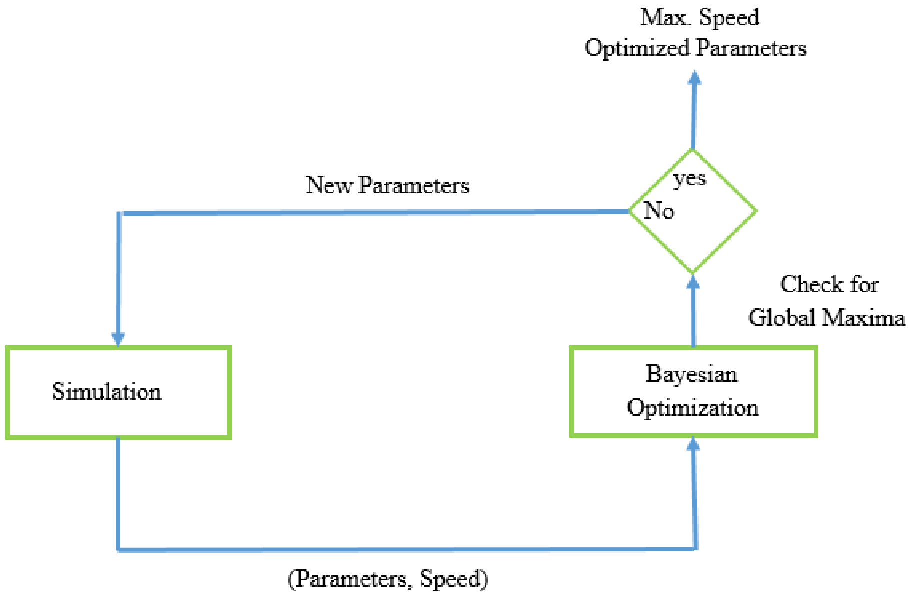


Figure 4-8 Matlab-Vrep Interface for Applying Bayesian Optimization.

4.5 Summary

From the simulation, we are able to decide the best hyper-parameters for our physical experiments. The results we get from simulation and experimental plate form have been compared and observe that the nature of variation of optimized speed with respect to different terrain is similar. Although the magnitude is not similar due to many factors such as friction, damping, restitution, etc. In the future after tuning these parameters, it will be possible to match the results exactly.

Chapter-5

Development in Experimental Platform

Alli-bot is an alligator inspired robot with 12 degrees of freedom (DOF) which uses its limbs and body undulations to move through a terrestrial environment. Each of its limb has 2 DOF and 4 DOF in the body for undulation. The proximal and distal joint in the limb of an alligator is referred to as hip and knee joint in the alli-bot respectively. While walking the entire body of the alli-bot is supported by its limbs. The body of the robot is divided into five parts connected by 4 servomotors; head joint connects the head and torso's 1st half; torso joint connects the two halves of the torso's and then tail joint 2 connect the third link with the posterior half of the torso and lastly the tail joint 1 which connects the two tail sections. We fabricated all the links using laser cutting, and more details of the same can be found in [43] [44]. We used 12 HK15328D servomotors with maximum torque capacity of 12 kg-cm for actuating the robot joints.

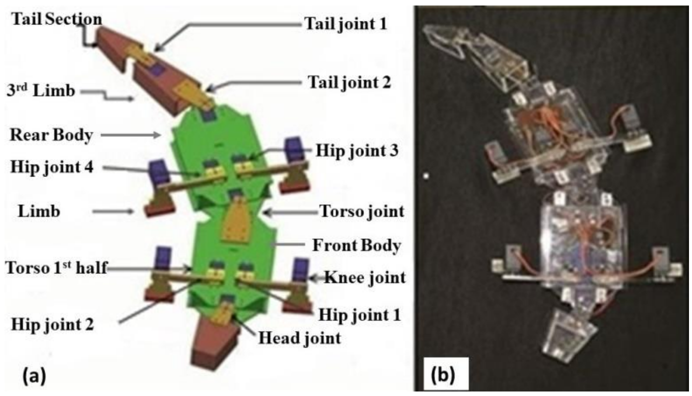


Figure 5-1 (a) Different parts of Alli-bot. (b) Fabricated Alli-bot.

The Alli-bot has developed and fabricated in MICL Lab IIT Patna before. However, for my experiment setup, there are some practical constraints for which we need to modify the design as well as electronic circuits:

The constraints are as follows:

a) Every time robots try to move laterally in spite longitudinally.

b) Robot's legs have no sufficient friction to produce enough traction, and it tries to slide and consumes a lot of energy.

c) Earlier robot was designed for untether situation, which used battery, and it deteriorates very quickly and due to deterioration of power, we cannot compare the result of different experiments, so we need a constant power supply source.

5.1 Improvement in Mechanical Design

Reptile such as snake, alligator has a certain type of pattern in their lower body parts, which help to restrict the lateral motion and provide them forward thrust [45]. This nature is known as an-isotropic friction which helps the animal to restrict the lateral motion due to high friction in lateral direction and move forward due to low longitudinal friction.

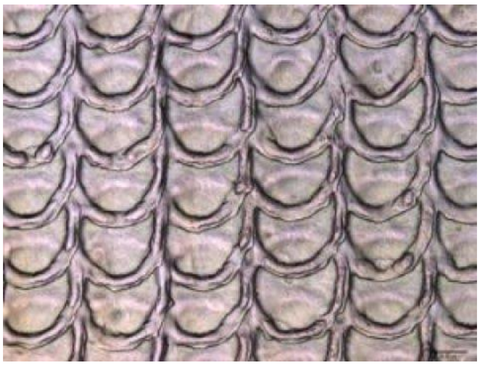


Figure 5-2 Pattern in skin help snake to restrct lateral motion [46].

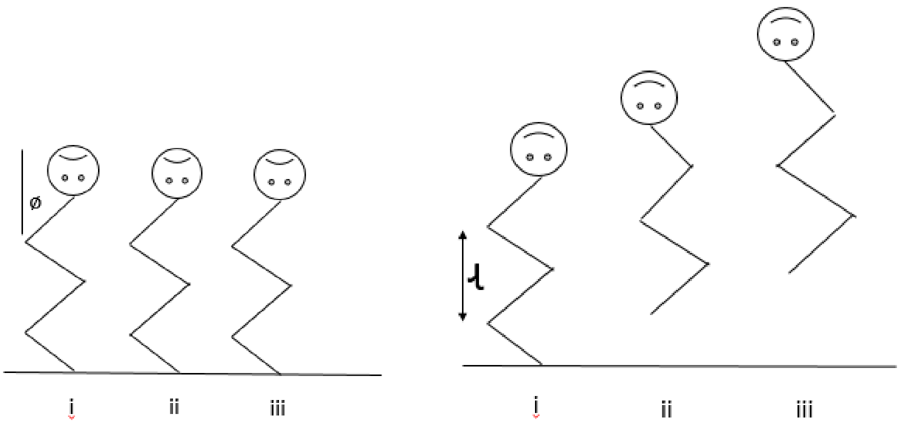


Figure 5-3 (a) No forward thrust only move laterally (b) Move longitudinally as well as laterally [5].

5.1.1 Introduction of Passive Wheel for Isochronous Friction Properties

Inspired from reptilian an-isotropic friction properties, we have used a passive wheel in our robot, which has designed to restricts the lateral motion due to high friction in lateral direction and move Alli-bot forword due to very less friction in longitudinal direction [46].

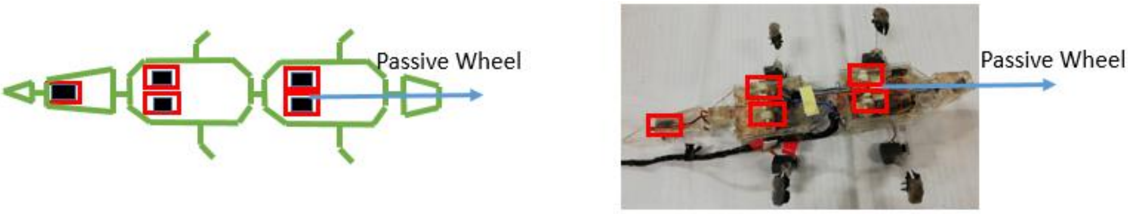


Figure 5-4 a) Schematic of passive wheel placement b) Fabricated wheel placed in Alli-bot.

5.1.2 Improvement in Friction of Legs

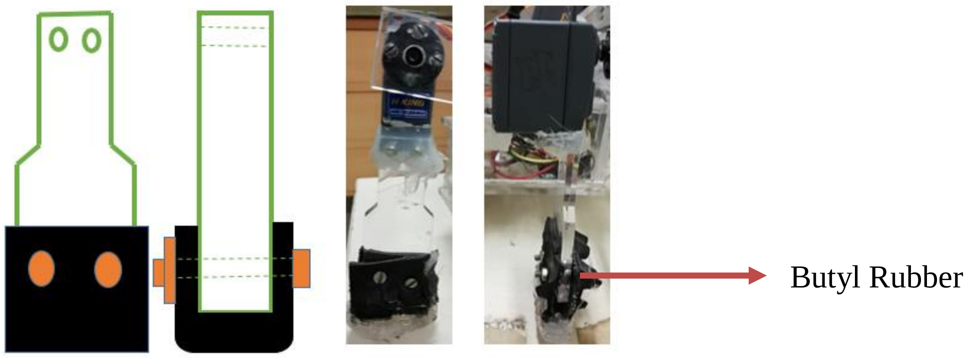


Figure 5-5 a) Represents schematic of frictional leg, b) Represents the real implementation in Alli-bot.

Friction plays an important role in moving the animal forward. So to move robot forward we use butyl rubber used in cycle tire and placed in feet of the robot as shown in fig 5-5 in such a way so that more traction with the ground can be produced and robot moves forward. Below the butyl rubber thermoplastic adhesive has attached to produce more friction.

5.2 Improvement in Electronic Circuit

Robots like Alli-bot always work untethered in war fields but for our experiment, the robot requires constant power supply. So that we can compare the performance of the robot in different experiment. For this, we need to manipulate the design of circuit.

The components in new circuit are as follows

a) DC-DC step down Buck-Converter (LM 8596): This device is used to convert 33 v (DC power supply) to 6v (max 3 amp) as per servo specification.

b) Arduino Nano (AT Mega-256): It is small and takes very less space and accommodates all 12 servo actuators and few sensors.

c) This device is used for the communication of computer to our microcontroller (Arduino Nano) with the help of radio signals.

d) Servo (HK 15328D): These are the positional control servo and water resistant, which runs in 6v max potential and 0.9-amp max current. All the joints have one actuator respectively in order to provide one degree of freedom to each joint and in a way robot has 12 DOF with the use of 12 actuators.

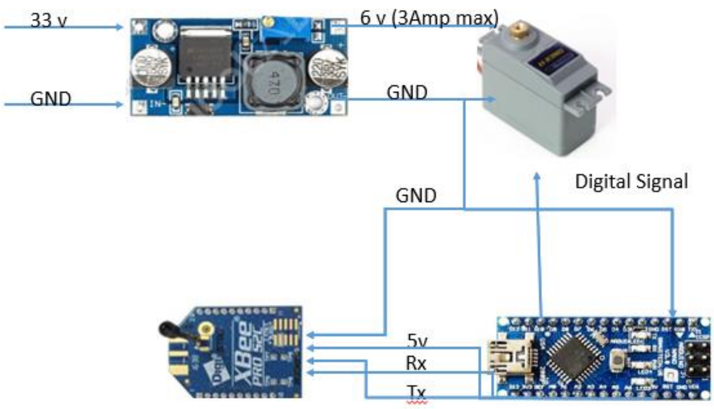


Figure 5-6 Electronic circuit assembled in Alli-bot.

The voltage from DC power supply has converted from 33v to 6 v with the help of LM 8596 and given to every servo actuator. It is impossible for one LM8596 to fulfil current required for 12 actuators, so we used two LM 8596 taking parallel connection from main power supply. The lower voltage (GND) has made common to every device in order to set same reference voltage. The digital pin of micro controller is connected to Servo signal pin so that digital signal can be given to change the servo position. The zigbee transmitter pin is connected to Arduino Nano transmitter pin and receiver pin to Arduino Nano receiver pin so that automatic signal can be given to the controller to change the state of the robot in a controlled way.

5.2.1 Architecture of Electronic Circuit

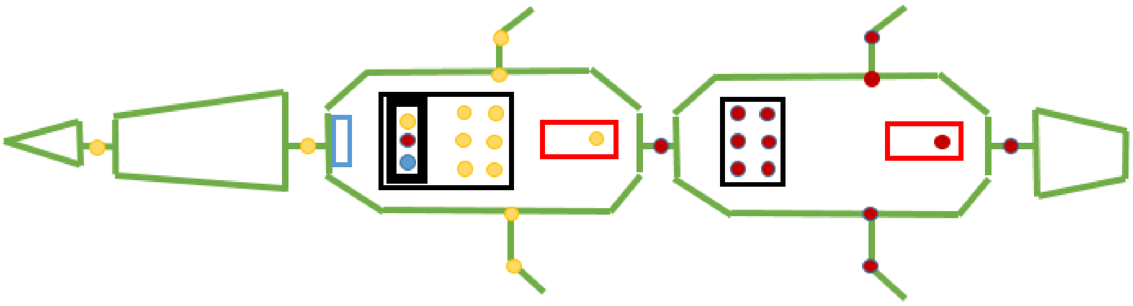
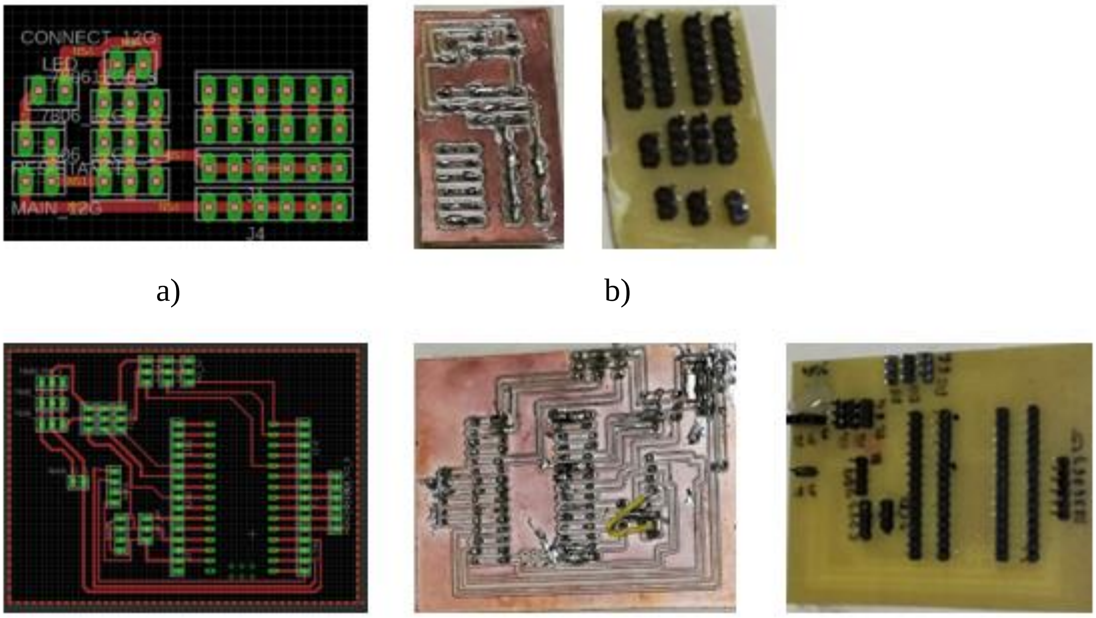


Figure 5-7 Overview of electronic circuit in Alli-bot.

In Fig:5-7 LM 8596 (buck converter) is used to convert higher voltage of power source to 6 volts according to motor specification Red colour represents first buck converter, which can power 6 servo motors of red colour, yellow colour represents second buck converter, which can power another six servo motor of yellow colour and blue colour represents the zigbee for communication, the bold black box represents Arduino Nano (micro controller) which is used to provide the signal to all 12 servo motors and zigbee. The grounds of all 12 motor, zigbee and buck-converters are common.

5.2.2 Fabrication of Electronic Circuit



a) b)

Figure 5-8 a) Schematic of circuit designed in eagle and b) Fabricated circuit used in Alli-bot.

The schematic described above is assembled in the form of the electronic circuit in two modules. First module holds the connection of first six servo motors, and second module holds the connection of other six servo motors, zigbee and Arduino Nano. Circuit is designed in eagle and then fabricated in PCB prototyping machine.

5.3 Gait Smoothing Using Cycloidal and Sinusoidal Function

When animal moves footprint pattern changes with time in order to change the state of the body. The rhythmic change in a footprint pattern with time is known as Gait pattern. However, the transition in footprint pattern should not be sudden. So that no thrust can be produced in joints, and joints can work longer. From this inspiration, we have smoothened our gait pattern by using cycloidal and sinusoidal functions so that no sudden thrust can be produced in actuators, and actuators can run longer without any failure.

We have used trot gait as our robot is inspired from quadrupedal animal, and these animals used trot gait while running [22]. The robot leg has two parts one is hip and another is knee portion. So to smooth the gait we have designed Knee Function and Hip

Function. Our robot also uses spine and tail motion in order to increase stability and speed [20]. In order to move spine and tail smoothly we have used sinusoidal functions as Body Function [47].

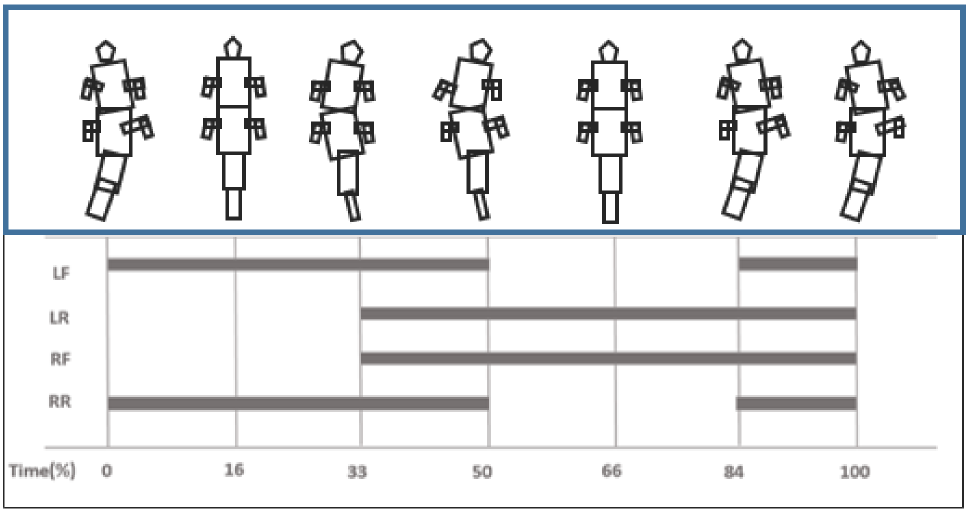


Figure 5-9 Trot Gait Pattern used in Alli-bot.

Hip Function

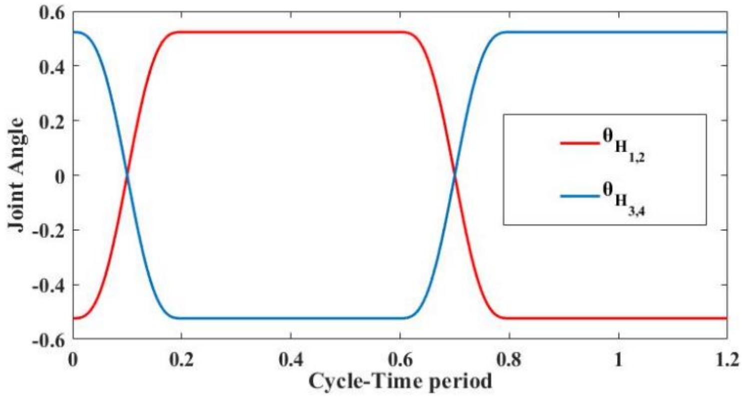


Figure 5-10 Hip function smoothens the variation of hip joint angle with cycle-time period.

$$\theta_{H_{1,2}} = \begin{cases} 2\mathrm{A_H}(\alpha) - \mathrm{A_H} + \gamma_L & 0 \le t < \frac{T}{6} \\ \mathrm{A_H} + \gamma_L & \frac{T}{6} \le t < \frac{T}{2} \\ 2\mathrm{A_H}(1 - \beta) - \mathrm{A_H} + \gamma_L & \frac{T}{2} \le t < \frac{2T}{3} \\ -\mathrm{A_H} + \gamma_L & \frac{2T}{3} \le t < T \end{cases} \tag{4}$$

$$\theta_{H_{3,4}} = \begin{cases} 2\mathrm{A_H}(1 - \alpha) - \mathrm{A_H} + \gamma_L & 0 \le t < \frac{T}{6} \\ -\mathrm{A_H} + \gamma_L & \frac{T}{6} \le t < \frac{T}{2} \\ 2\mathrm{A_H}(\beta) - \mathrm{A_H} + \gamma_L & \frac{T}{2} \le t < \frac{2T}{3} \\ \mathrm{A_H} + \gamma_L & \frac{2T}{3} \le t < T \end{cases}$$

Where $\alpha_1 = \frac{6\mathrm{t}}{T} - \frac{\pi}{2}\sin\left(\frac{12\pi\mathrm{t}}{T}\right)$, $\beta_1 = \frac{6\left(\mathrm{t}-\frac{\mathrm{T}}{2}\right)}{T} - \frac{\pi}{2}\sin\left(\frac{12\pi(\mathrm{t}-\frac{\mathrm{T}}{2})}{T}\right)$ and t is the running time of the current experiment.

Body Function:

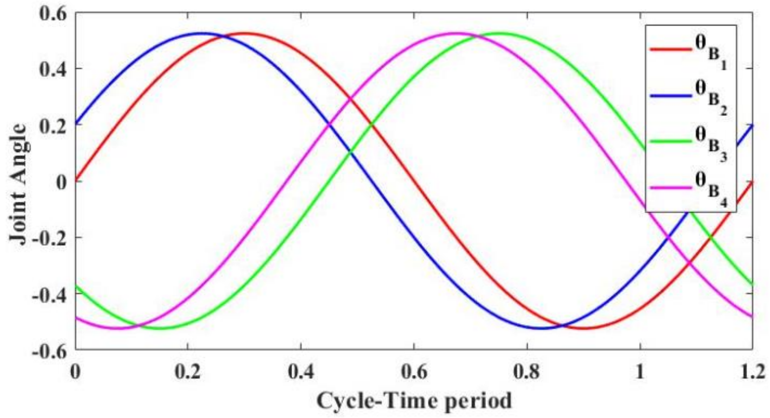


Figure 5-11 Body function which smoothens the variation of torso joint angle with cycle-time period.

$$\theta_{B_i} = \mathrm{A_B}\sin(2\pi\, t/T + 2\pi\cdot\Delta\varphi\cdot(i-1)) + \gamma_B \tag{5}$$

N•Δφ is the total phase lag between head and tail. N is the number of active joints in the body of the robot which is 4 in our case. An undulation with N.Δφ = 1.0 correspond to an undulation in which the body makes a complete wave [48].

Knee Function

$$\theta_{K_1} = \begin{cases} 0 & 0 \le t < \frac{T}{4} \\ \mathrm{A_K}(\alpha_2) & \frac{T}{4} \le t < \frac{5T}{12} \\ \mathrm{A_K} & \frac{5T}{12} \le t < \frac{3T}{4} \\ \mathrm{A_K}(1-\beta_2) & \frac{3T}{4} \le t < \frac{11T}{12} \\ 0 & \frac{11T}{12} \le t < T \end{cases} \tag{6}$$

$$\theta_{K_2} = \begin{cases} -\mathrm{A_K} & 0 \le t < \frac{T}{4} \\ -\mathrm{A_K}(1-\ \alpha_2) & \frac{T}{4} \le t < \frac{5T}{12} \\ 0 & \frac{5T}{12} \le t < \frac{3T}{4} \\ -\mathrm{A_K}(\beta_2) & \frac{3T}{4} \le t < \frac{11T}{12} \\ -\mathrm{A_K} & \frac{11T}{12} \le t < T \end{cases}$$

$$\theta_{K_3} = \begin{cases} \mathrm{A_K} & 0 \le t < \frac{T}{4} \\ \mathrm{A_K}(1-\ \alpha_2) & \frac{T}{4} \le t < \frac{5T}{12} \\ 0 & \frac{5T}{12} \le t < \frac{3T}{4} \\ \mathrm{A_K}(\beta_2) & \frac{3T}{4} \le t < \frac{11T}{12} \\ \mathrm{A_K} & \frac{11T}{12} \le t < T \end{cases}$$

$$\theta_{K_4} = \begin{cases} 0 & 0 \le t < \frac{T}{4} \\ -\mathrm{A_K}(\alpha_2) & \frac{T}{4} \le t < \frac{5T}{12} \\ -\mathrm{A_K} & \frac{5T}{12} \le t < \frac{3T}{4} \\ -\mathrm{A_K}(1-\ \beta_2) & \frac{3T}{4} \le t < \frac{11T}{12} \\ 0 & \frac{11T}{12} \le t < T \end{cases}$$

Where $\alpha_2 = \frac{6(\mathrm{t}-\frac{\mathrm{T}}{2})}{T} - \frac{\pi}{2}\sin\left(\frac{12\pi\left(\mathrm{t}-\frac{\mathrm{T}}{4}\right)}{T}\right), \beta_2 = \frac{6\left(\mathrm{t}-\frac{3\mathrm{T}}{4}\right)}{T} - \frac{\pi}{2}\sin\left(\frac{12\pi\left(\mathrm{t}-\frac{\mathrm{T}}{4}\right)}{T}\right)$

5.4 Gait Parameterization

Parameterization plays a vital role in improving the performance of any system. However, we need to account for all parameters which can affect the system performance. In Alli-bot locomotion, we need to know the different parameters which impact the robot's speed and manoeuvrability. In our robot basically, two types of gait are implemented i.e., trot and eil. For trot gait, leg is used, each leg has two joints one is hip and another is knee. The eil gait uses four body joint of Alli-bot. The knee's motion, hips motion and body motion can change the locomotion pattern. So our selected parameters are Hip amplitude($\mathbf{A_H}$) , Knee amplitude($\mathbf{A_K}$) Body amplitude($\mathbf{A_B}$) and Time(T).

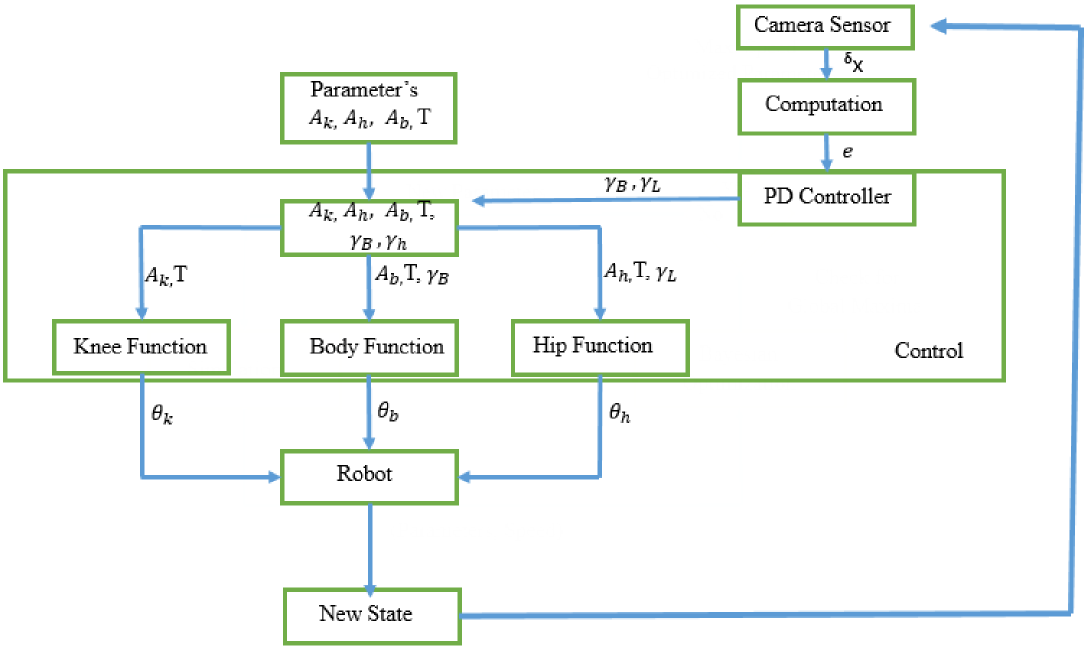


Figure 5-12 Gait parametrization Algorithm.

5.5 Control Strategy

Earlier robot works on the open-loop system mean it will not take any feedback. However, for our experiments, we need to navigate the robot equal distance in each iteration of experiments. For that we need to introduce a control system which takes input in the form of error angle computed from robot's centroid and goal and gave to the controller of the robot. Controller takes this error as input and gives signals to the servo actuators as an output. Sometimes due to practical constraint large error value input to the controller and causes the servo to take exceptionally large angle and robot's leg collide with the body. To avoid such a scenario we have to map the output control signal to certain definite range using sigmoid function and constraint the fluctuation to definite range in order to prevent the collision with the body of robot. Here we use two controllers one is to control the locomotion of the knee joint, and another is to control the locomotion of the body joint. We used sigmoid function in order to constraint the range of fluctuations.

$$\gamma_B = K_{P_B}.(e) + K_{D_B}.(\dot{e}) \quad (7)$$

$$\gamma_L = K_{P_L}.(e) + K_{D_L}.(\dot{e}) \quad (8)$$

$$\gamma_B = (\mathbf{A}_{\mathbf{B}(\max)} - \mathbf{A}_{\mathbf{B}}).\ ((1/(1+\mathbf{e}^{(-0.1.\gamma_B)-0.5}))) \quad (9)$$

$$\gamma_L = (\mathbf{A}_{\mathbf{K}(\max)} - \mathbf{A}_{\mathbf{K}}).\ ((1/(1+\mathbf{e}^{(-0.1.\gamma_L)-0.5}))) \quad (10)$$

Here $\mathbf{A}_{\mathbf{B}(\max)}$, $\mathbf{A}_{\mathbf{K}(\max)}$ are the maximum possible amplitude without collision and $\mathbf{A}_{\mathbf{K}}$, $\mathbf{A}_{\mathbf{B}}$ are the physical parameters respectively.

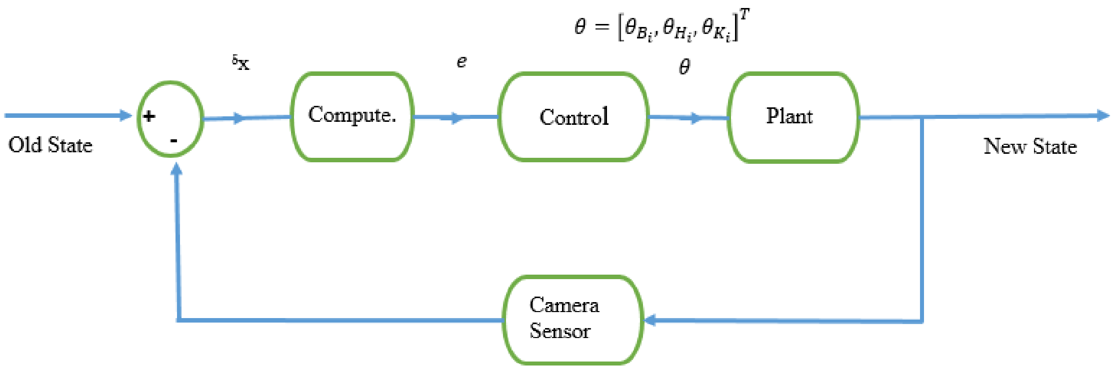


Figure 5-13 Control scheme used in Alli-bot.

5.6 Error Computation

We employed a vision-based localization system in the experimental setup described in this thesis. The whole setup is summarized in Fig 5-14. The vision based localization system comprises of an overhead camera (see Fig.5-17) which is connected to a desktop host computer and used for acquiring images at 30fps. The acquired images are processed to detect two-colour markers situated on the front body and the rear body using a colour based threshold scheme. The locations of the detected markers are used for determining the instantaneous position and orientation of the robot.

We utilize the line of sight (LOS) based guidance law to determine the error angle (e) between the specified goal and robot. The error is computed on the host desktop and then transmitted to on board Arduino mounted on the robot via ZigBee. Fig 5-14 shows the view from the overhead camera.

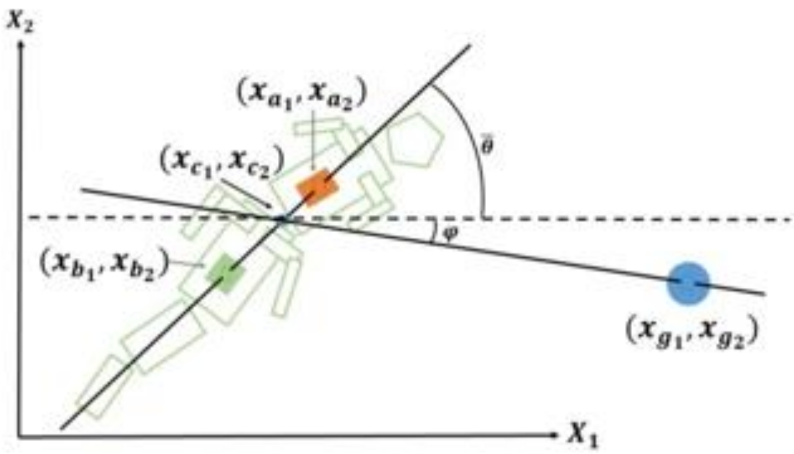


Figure 5-14 Calculation of error angle in laboratory frame of reference.

$$\boldsymbol{e} = \boldsymbol{\varphi} + \overline{\boldsymbol{\theta}} \qquad (11)$$

Where $\bar{\theta}$ is the robot orientation vector which is calculated by $\bar{\theta} = \tan^{-1}(\frac{x_{a,2}-x_{b,2}}{x_{a,1}-x_{b,1}})$ and $\varphi = \tan^{-1}(\frac{x_{g,2}-x_{c,2}}{x_{g,1}-x_{c,1}})$, x_c is the centroid of the robot which is calculated by $x_{c,1} = \frac{x_{a,1}+x_{b,1}}{2}$ and $x_{c,2} = \frac{x_{a,2} + x_{b,2}}{2}$. x_a and x_b are determined using the overhead camera.

5.7 Water-proofing for Swimming Capability

As robot is fitted with water proof servo and all electronics components are placed outside the water. There is no problem to operate robot on water but due to unsymmetrical design robot faced a lot of frictional drag while swimming which reduces a forward speed. So to reduce drag we have developed a water proof skin by making a hollow pipe like structure made of PVC (Poly vinyl chloride) a form of latex. And cover the Alli-bot with the pipe like structure. Seal the robots front and back opening with silicon rubber and provide extra material near each body joint so that joints can move freely.

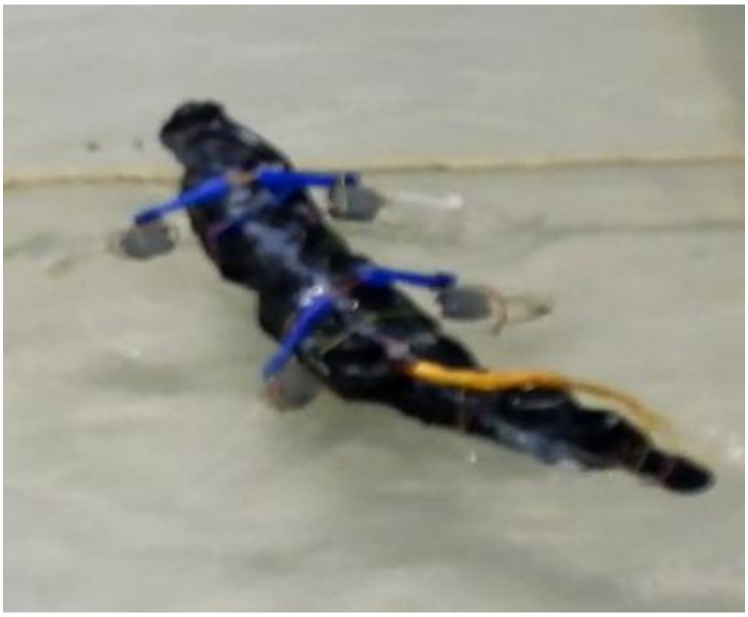


Figure 5-16 Testing of Alli-bot on water surface .

5.8 Experimental Setup

Error angle is computed in Linux Host-PC with the help of colour detection technique using overhead camera shown in Fig 5-15, and computed error angle is sent to the robot's controller with the help of Zigbee, and controller gives signals to the servo actuator, and robot comes to new state and same process repeats.

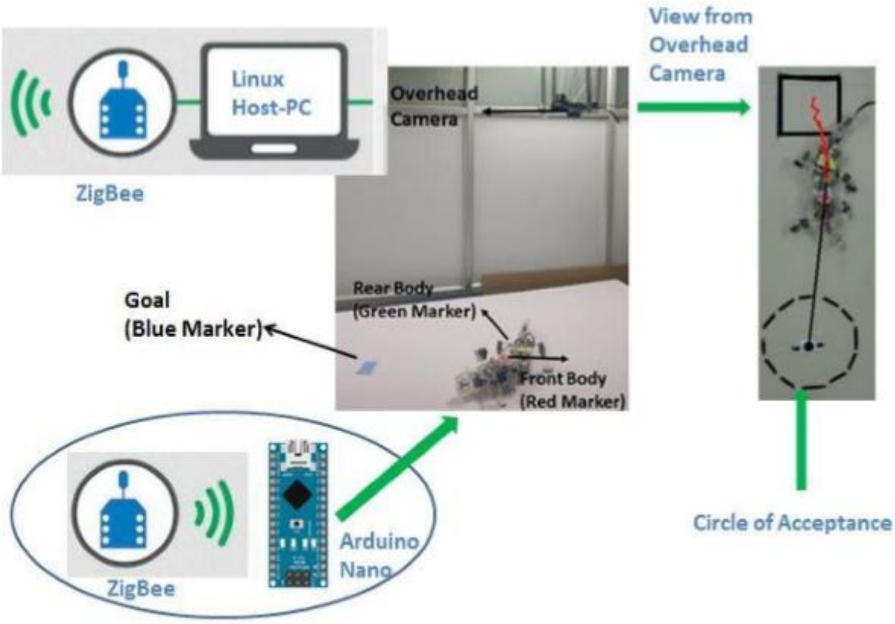


Figure 5-17 Experimental Setup

Chapter 6

Automated Parameter Tuning

6.1 Automated Parameter Tuning

Our robot dynamics is so complex it is very difficult to obtain a mathematical model also every iteration is costly in terms of time, wear and tear. We needed a model which can account for stochastic in points along with being free from calculation of gradients (as it takes lots of runs and subject to local minima) and be a global optimizer. Bayesian optimization is beneficial in experiments involving complex dynamics models where the only method to test a set of control parameters is to evaluate the parameters on the real robot. However, each trial takes the large amount of time while experimenting with the physical system.

Bayesian optimization with Gaussian process regression (GPR) as a surrogate model seems to be good solution for that. It works on exploration and exploitation. First for few iterations, it explores the parameters, and after it exploits the parameter to find the optimum parameter. It works sequentially first provide a parameter to the robot then robot run to the goal and calculate the speed then speed is given to the optimization algorithm either it exists if global optimizer, or it explores or exploits and again gives the parameter to robot and in the same way within a few iterations, this algorithm gives an optimal parameter with the best possible speed of the robot.

We have given the range of each parameter ($\mathbf{A_K}$ {15,30}, $\mathbf{A_B}${15,30},T{3,6}) to the Bayesian Optimization and then GPR initialize some random points and these random parameters given to robot and run robot multiple times (three times) to know the mean and variance of average speed. The mean of these speeds is given to Bayesian Optimization to acquire the new point to sample on the robot, and in the same way after multiple iterations arrive at an optimal value of the parameter.

In this thesis we focus on alligator inspired robot where we developed a set of parameterize equation to control our robot. Before this, we are hand tuning the robot parameter to get the suboptimal solution. We use the Bayesian Optimization to tune the gait parameter such that we can improve the effectiveness (here average speed) of these gaits and thereby enhance the capabilities of the robot. Furthermore, we wish to optimize these gaits on different terrain so that we can study the role of the different parameters on robot performance.

6.2 Bayesian Optimization

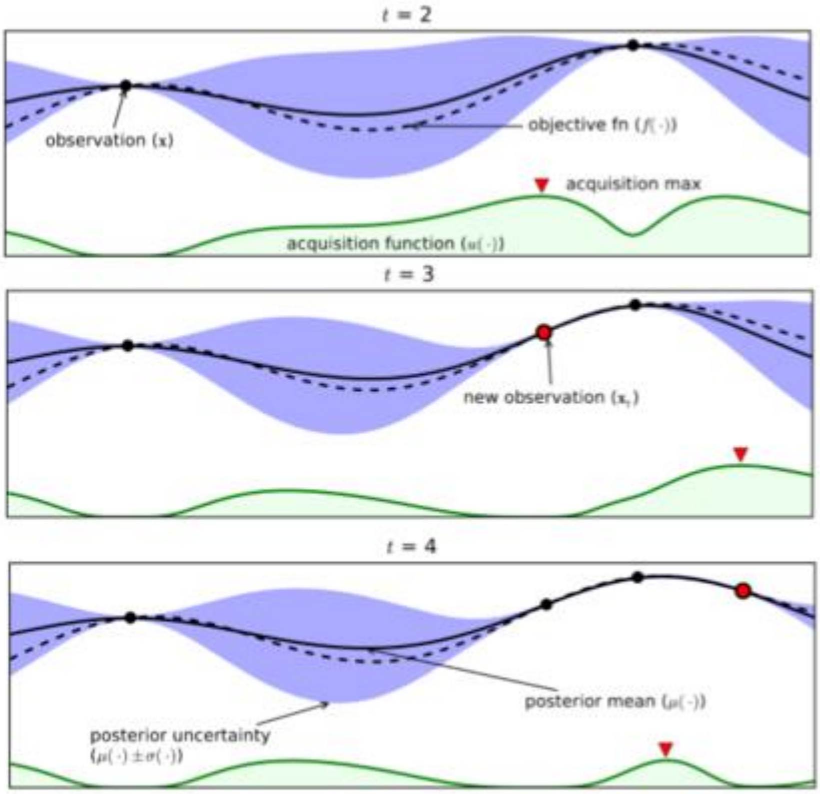


Figure 6-1 Bayesian Optimization in running for the 2nd and 3rd iteration [6]**.**

The basic skeleton of Bayesian Optimization algorithm as follows:

a) Gaussian process regression is used to fit a curve to sample data points. Then maximize the likelihood over randomly sampled points, which are locally optimized in hyper-parameter space.
b) Next point is found in space by using ‘expected improvement plus’ acquisition function over the previous curve.
c) Run the robot n times in this points we found from Bayesian to get the mean estimate.
d) Repeat.

In our system, each gait parameter takes the considerable amount of time, and each experiment is costly in terms of wear and tear, which limits the no. of experiments. Due to stochastic nature of our platform, we need an optimizer which considers of stochastic and in the same time optimizes globally. Gradient methods are prone to local optima. Grid search and Evolutionary Algorithms require a huge number of function evaluation, which are not good for our system.

D is the set of function data set for each evaluation, i.e. D = {x, f(x)} were x are the parameters and f(x) are the corresponding function evaluation of x. The data set D builds a model f(.):x f(x) the response surface so as to map the parameters x to the corresponding function evaluations. GPR tries to find the model that represents the data best, and we use the model as our objective function to get the optimal next point in the parameter's space.

6.3 Optimization Scheme

We defined the objective function for optimization as follows.

$$h\ (p; xo, xg) : \mathbb{R}3 \rightarrow \mathbb{R}1 \tag{12}$$

where h is the objective function which returns the maximum speed by the robot to go from the initial location xo to a specified goal location xg with p as gait parameter.

The dynamics of the robot motion can be specified by the following equation:

$$\dot{x} = f(x, u) \tag{13}$$

Where f is the dynamical model of the robot, x = [xc,1, xc,2, $\dot{x}c$,1, $\dot{x}c$,2] T is the state vector, (xc,1,xc,2) is the coordinate and ($\dot{x}c$,1,$\dot{x}c$,2) is the velocity of the robot centroid expressed in the laboratory frame of reference.

The term u represents the control functional defined as:

$$\theta = u(e;p) \tag{14}$$

Here the error angle e is determined using a line-of-sight guidance law $e = \varphi - \bar{\theta}$ which is explained in the previous section, xo = (xo,1, xo,2) and xg = (xg,1, xg,2) are the initial and the goal locations of the robot centroid respectively. The parameter p is a 3-tuple p = [A H, AB, T] T and control signal is defined as 12-tuple θ = [θBi, θHi, θKi] T where θHi are the hip joint angles, θKi are the knee joint angles, and θBi are the body joint angles.

The objective function is defined as $h = -\|xo-xg\|/\ Ttr$, Ttr is the travelling time required for the robot to go from xo to xg. The traveling time Tt is computed by solving the following equation:

$$\int_{x_o}^{x_g} dx \;=\; \int_0^{T_{tr}} f(x,u)\, dt \qquad (15)$$

A closed form solution for Equation 16 cannot be determined and hence we have used experimental evaluation on real and simulated platforms to evaluate Ttr. We can now define the optimization problem as

$$p* = argminp \text{ h } (p;\, xo,\, xg) \qquad (16)$$

To solve the aforementioned problem, we use Bayesian Optimization BO (h (p; xo, xg); K) where K is the hyper-parameter of the Bayesian optimization function. We are using the Bayesian Optimization implementation of Matlab™ in the Statistics and Machine Learning toolbox, namely bayesopt. Here the objective function works on minimization of negative speed which is equivalent to maximizing of speed.

The hyper-parameters from bayesopt include the following:

a) Acquisition function KA,

b) Stochastic behaviour of the objective function KD, which appears in Matlab as Is Objective Deterministic.

c) Maximum number of objective evaluations KE, and

d) Seed points KS.

Gaussian process regression is used to fit a curve to sample data points. Then maximize the likelihood over randomly sampled points, which are locally optimized in We have used the acquisition function expected-improvement plus (EI-plus). Tesch et al., [47] shows that EI converges faster as compared to other acquisition functions. The Matlab™ function bayesopt shows the facility for having a trade-off between exploration and exploitation. EI-plus in bayesopt has the propensity to explore, and also it escapes a local objective function minimum by avoiding overexploiting an area. Furthermore, we set the objective function as stochastic by setting the option KD as false in order to account for the actuation uncertainties and the sensor noise. Further, we selected the value of $KSas$ 3.

6.4 Simulation Results

To decide the hyper-parameter for physical experiment, experiment has done on simulation with different hyper-parameters and results has compared for different experiments. An experiment whose speed is about to maximum compared to other experiments but the number objective evaluation is least. The hyper parameter of that experiments is selected.

For KA, EI-plus in bayesopt has the propensity to explore, and also it escapes a local objective function minimum by avoiding overexploiting an area. Also, we set the objective function as stochastic by setting the option KD as false in order to account for the actuation uncertainties and the sensor noise. Further, we selected the value of K_S as 3.

We performed simulations to determine the minimum number of objective evaluations K_E. In order to determine the suitable value of K_E, we performed a binary search. For that, we ran the BO over the simulations with K_E values 10, 20, 30, 40, and 50.

We found that K_E values of 10 and 20 yielded a significant reduction in the objective values as compared to the other intervals. We then searched K_E using the same approach in the range 10 to 20. Based on the aforementioned search, we selected

K_E=15 for the experiments. From the simulations, we observed that 30, 40 and 50 values for K_E tend to give nearly an improvement of 18 mm/s.

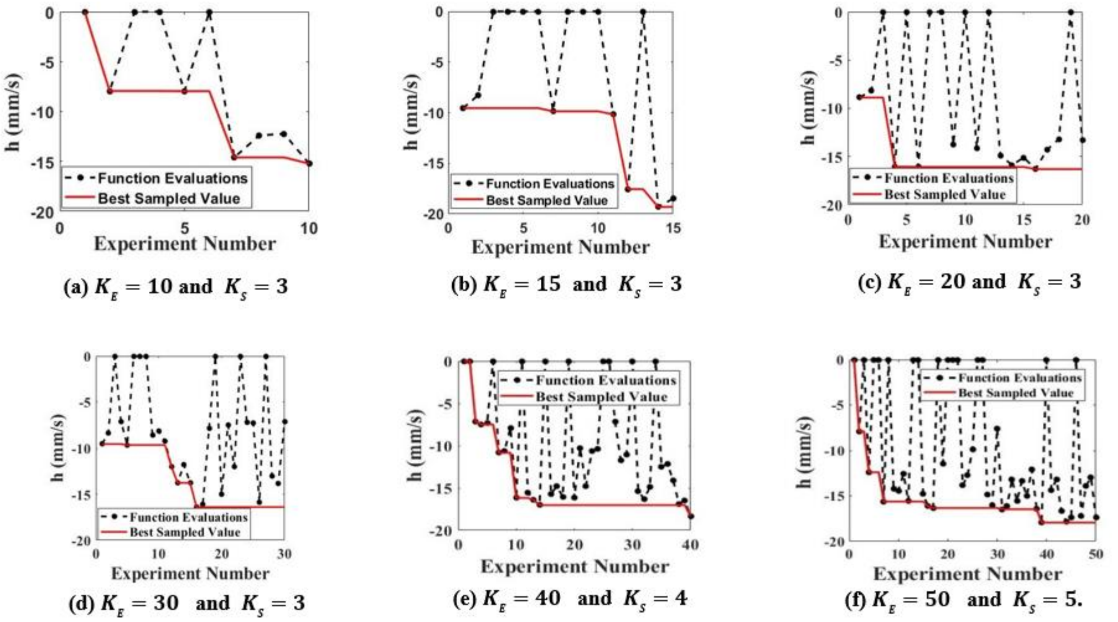


Figure 6-2 Optimization of robot speed in simulation with (a) KE = 10 and KS = 3 (b) KE = 15 and KS = 3 (c) KE = 20 and KS = 3 (d) KE = 30 and KS = 3 (e) KE = 40 and KS = 4 (f) KE = 50 and KS = 5.

Using the hyper-parameter values, thus determined, $K_A = EI - plus$, $K_D = false$, $K_E = 15$, and $K_S = 3$ we obtained optimized parameters from the simulation which are $A_K = 23°$, $A_B = 28°$, $T = 3.1\ s$.

Further in order to validate the simulation, we have simulated the computational model in different terrain, which is less smooth and has high friction with different slope inclination. And compare the pattern of results to experimental results.

The Results are as follows

Table 1 : Representing different parameters and speed in simulated environment.

Slope	A_K	A_B	T	Speed(mm/s)
-5^0	30	15	3.0005	33.81
-4^0	30	15	3.0341	32.74
-3^0	30	16	3.0041	32.48
-2^0	30	15	3.0740	31.86
-1^0	30	15	3.0046	31.83
0^0	30	15	3.0074	31.83
1^0	30	15	3.0055	31.75
2^0	30	15	3.0019	30.51
3^0	30	15	3.0084	30.47
4^0	30	15	3.0080	28.01
5^0	30	15	3.0066	25.10

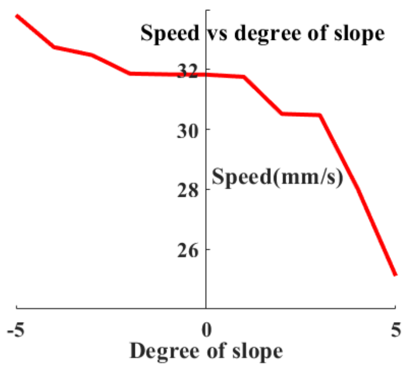


Figure 6-3 Mean speed vs slope inclination in simulated enviorment.

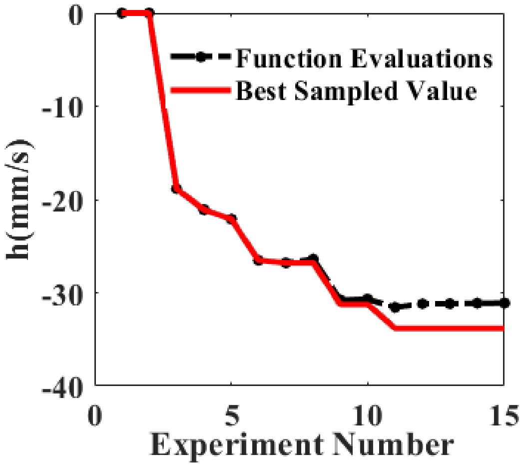


Figure 6-4 Optimization for slope with an inclination of -5^0 (number of iterations used are 15 and seed points 3)

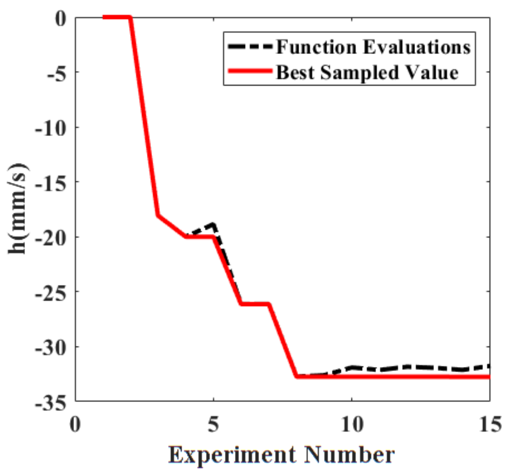


Figure 6-5 Optimization for slope with an inclination of -4^0 (number of iterations used are 15 and seed points 3)

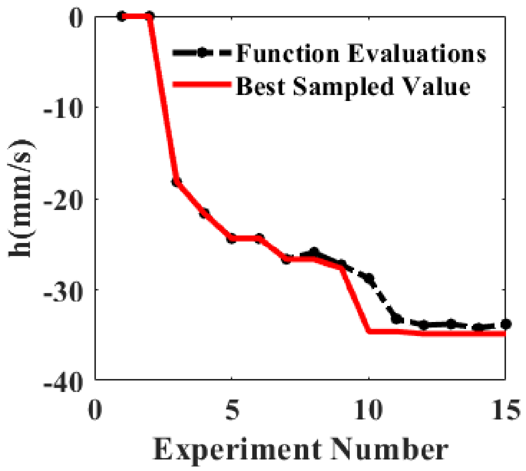


Figure 6-6 Optimization for slope with an inclination of -3^0 (number of iterations used are 15 and seed points 3)

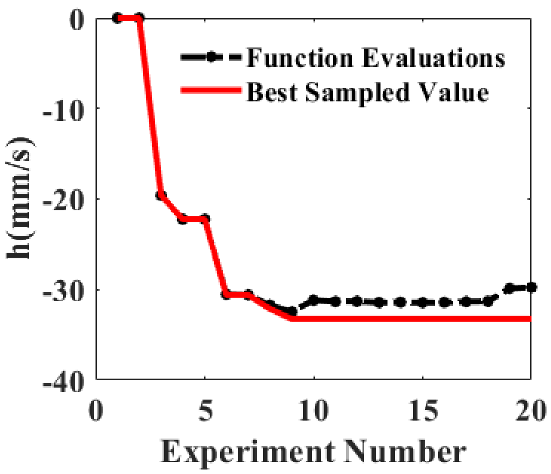


Figure 6-7 Optimization for slope with an inclination of -2^0 (number of iterations used are 15 and seed points 3)

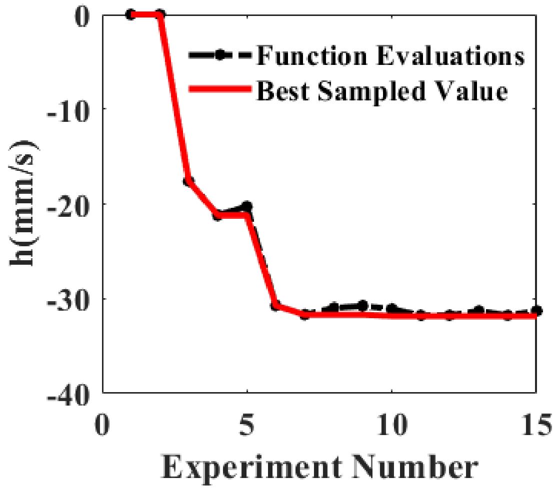


Figure 6-8 Optimization for slope with an inclination of -1^0 (number of iterations used are 15 and seed points 3)

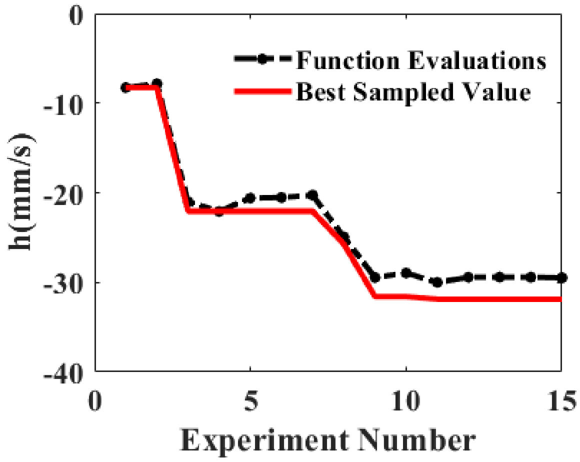


Figure 6-9 Optimization for slope with an inclination of 0^0 (number of iterations used are 15 and seed points 3)

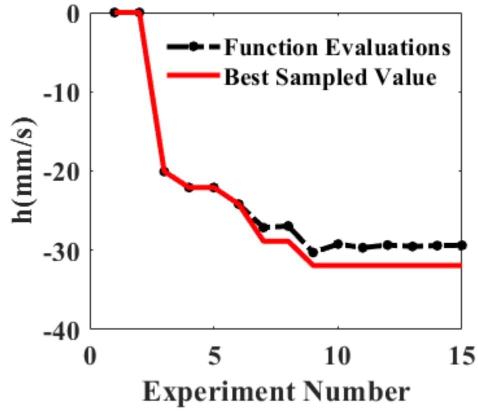


Figure 6-10 Optimization for slope with an inclination of 1^0 (number of iterations used are 15 and seed points 3)

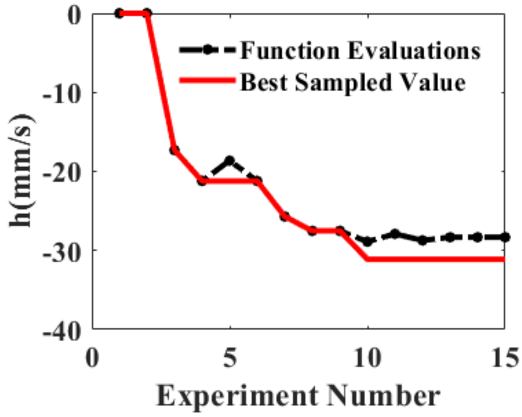


Figure 6-11 Optimization for slope with an inclination of 2^0 (number of iterations used are 15 and seed points 3)

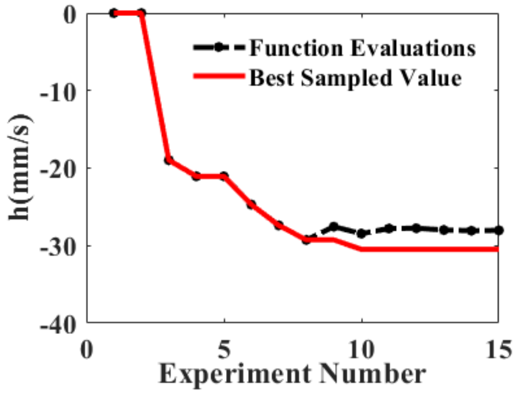


Figure 6-12 Optimization for slope with an inclination of 3^0 (number of iterations used are 15 and seed points 3)

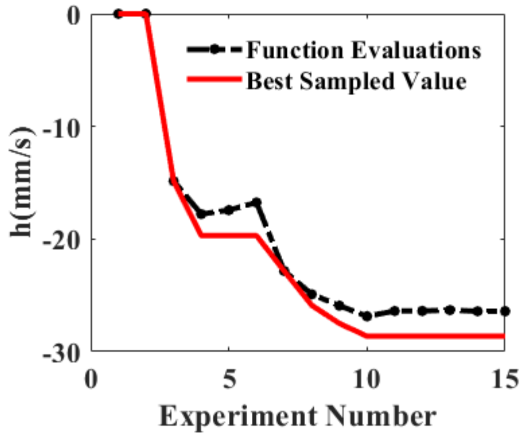


Figure 6-13 Optimization for slope with an inclination of 4^0 (number of iterations used are 15 and seed points 3)

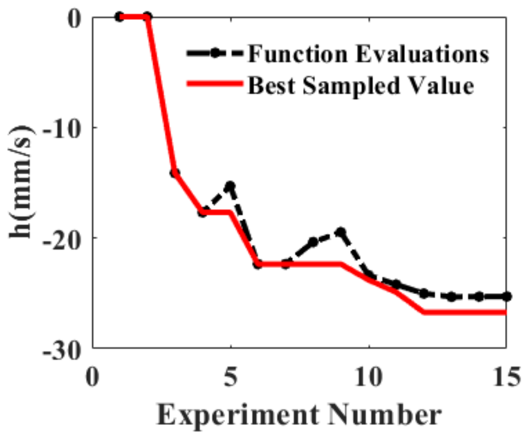


Figure 6-14 Optimization for slope with an inclination of 5^0 (number of iterations used are 15 and seed points 3)

6.5 Experimental Results

Experiment is an expensive process it takes a great effort and cost in terms of wear and tear. So it is impossible to do an experiment in all terrain as simulation does. However, in order to validate our results, we have done experiments in four terrestrial terrains flat terrain (tile slippery surface), flat terrain (rough surface), 5^0 slope (rough surface), -5^0 slope (rough surface) and on water surface while swimming. We have found that for slippery surface, best speed is 1.74cm/s but for rough surface due to more friction, best speed is 11.27(cm/s) for flat terrain, 6.85 cm/s in $+5^0$ slope and 11.27 cm/s in -5^0 slope. For swimming best speed is 15.43 cm/sec.

For flat surface with slip improvement in speed is about 47% for rough surface it is about 76% for 5^0 slope about 3.85 times, i.e. from 1.786cm/s to 6.85 cm/s for -5^0 slope about 1.85 times, i.e. 10.13 cm/s to 19.49 cm/s. For swimming improvement in speed is about 6.38 times i.e., from 2.415 cm/sec to 15.43 cm/sec.

The details are given in the given table below

Table 2 Represents the different physical parameter and mean speed in different terrain.

Surface	Slope	A_K	A_B	T	Mean Speed(cm/s)
Slip	0^0	22	30	5.60	1.74
Rough	0^0	29	22	3.06	11.27
Rough	5^0	30	15	3.07	6.85
Rough	-5^0	29	27	3.55	19.49

Table 3 Represents the locomotion parameter and mean speed while swimming in water.

Surface	A_B	T	Mean Speed(cm/s)
water	29	5.92	15.43

In water Alligator swim with body undulation and do not use legs as legs produce drag .So only 2 parameters is used i.e. A_B and T.

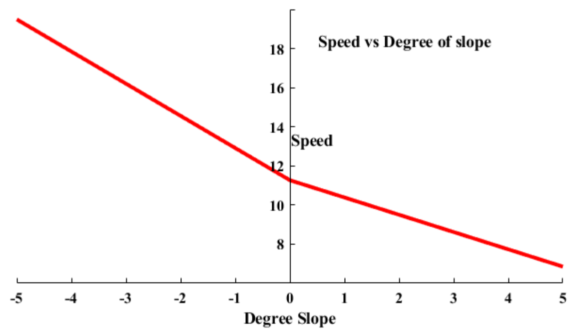


Figure 6-15 Mean speed vs slope inclination (different terrain) in physical platform.

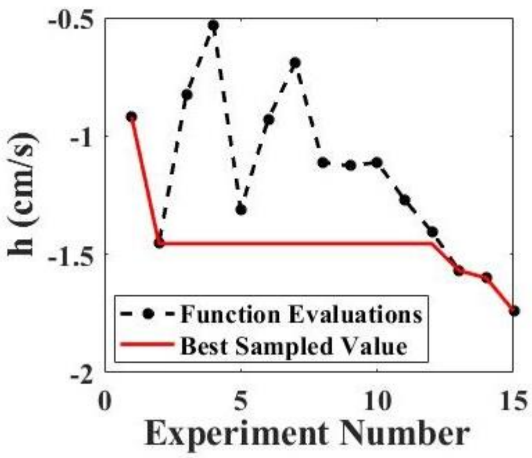


Figure 6-16 Optimization for slope with an inclination of 0^0 (number of iterations used are 15 and seed points 3) physical

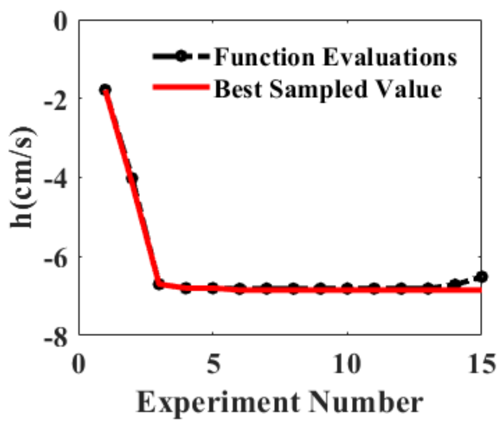


Figure 6-17 Optimization for slope with an inclination of 5^0 (number of iterations used are 15 and seed points 3) physical

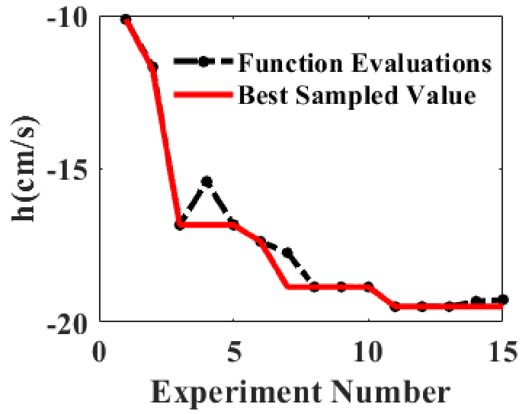


Figure 6-18 Optimization for slope with an inclination of -5^0 (number of iterations used are 15 and seed points 3) physical

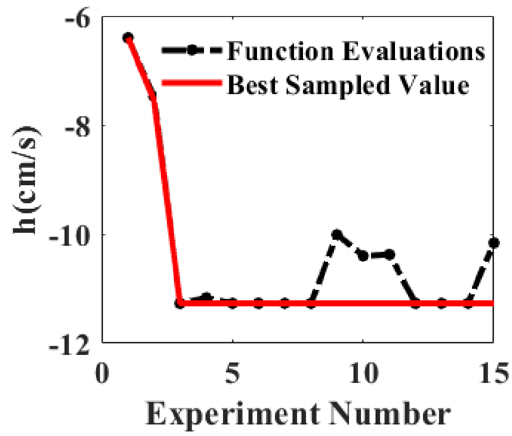


Figure 6-19 Optimization for slope with an inclination of 0^0 (number of iterations used are 15 and seed points 3) physical

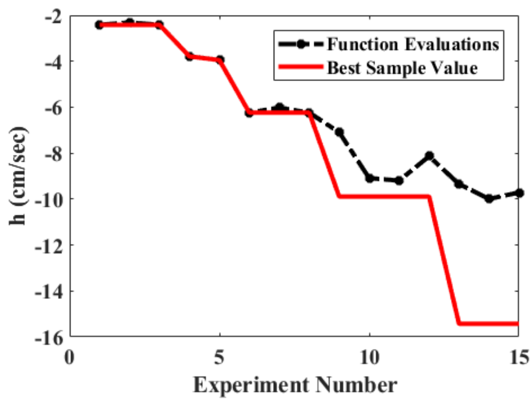


Figure 6-20 Optimization with swimming in water (number of iterations used are 15 and seed points 3) physical

Chapter-7

Conclusion

7.1 Contributions

This thesis proposes a surrogate modelling based approach for gait optimization of Alli-bot, an alligator inspired robot. We use Bayesian optimization technique to automate tuning the locomotion parameter of the robot. This technique explains the effect of lateral undulation and cycle time period on the locomotion performance. This technique helps to find the best possible speed for different terrains and swimming.

The usual trot and eil gait were modified by using cycloidal and sinusoidal function according to the needs of the mechanical robot. So that motion of Alli-robot smoothens and accurate. The effect of lateral undulations is also clear on the forward speed of the robot. The forward speed increases without any exceptions with increasing amplitude. The parameterization technique helps in deciding the physical parameters which effecting Alli-bot performance. The control helps in the repetition of an experiment a more unified way. The simulation played a major role in deciding the hyper-parameter for physical experiments.

The technique for doing experiments on water is also new we used polyvinyl chloride (PVC) which is inspired from animal skin and keep the Alli-bot on water for the no. of experiments. The results of experiments show a significant improve in the speed of robot in different terrain and swimming.

7.2 Anticipated Benefits

For flat surface with slip improve 47% in speed for rough surface speed improvement is about 76% for $+5^0$ slope improvement in speed is about 3.85 times i.e. from 1.786cm/s to 6.85 cm/s for -5^0 slope improvement in speed is about 1.85 times i.e. 10.13 cm/s to 19.49 cm/s. For swimming improvement in speed is about 6.38 times i.e., from 2.415 cm/sec to 15.43 cm/sec.

The results show a significant improve in speed which validate that this technique can be implemented in such a complex system with no prior model.

7.3 Future Directions

a) Incorporate specific energy consumption into the objective function and thereby optimize the both speed and energy simultaneously.
b) Collecting data on various terrain and features like position and orientation from terrains to make it learn and adapt with the optimum speed and energy consumption.
c) Alli-bot are designed to move in land as well as shallow water. It can also work in deep water with optimum energy and speed in a different aquatic medium such as mud, lime water, etc.
d) By tuning the simulators internal parameter's simulated robot speed can be similar to physical robot's speed. And then various new algorithms can be tested and validated on this platform

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