Tuning the Blender Physics Engine via a Genetic Algorithm

CISC 7900X: RESEARCH PROJECT 1
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1 Abstract

Using a physics engine for robotic simulation provides fidelity with the added benefit of lower research costs, minimal space requirements, and even less time as the physical simulation can be run at faster than real-time speeds [13]. However, physics engines have numerous parameters to tune such as friction coefficients, rigid-body constraints, body mass, gravitational acceleration, material elasticity, collision shapes, etcetera [3][2]. Tuning these either programmatically or as in the case of *Blender*[1]–via the graphical user interface–is a daunting task considering the multidimensional state space. Simulation fidelity is compromised as some parameters are perfected while others are now maladjusted. Adjusting some parameters only to malign others leads a to a "herding cats" type of effect. This ultimately results in a "reality gap" between the simulated environment and the physical environment. However, by using a genetic algorithm to optimize or rather fine tune the physics-engine parameters, the hypothesis is that the physics engine will produce a robot motion model more closely reassembling that of the real-world robot kinematics.

2 Introduction

Utilizing a physics engine for robotic simulation allows for rapid trial runs with minimal overhead. By using a physics engine, one can maintain a high fidelity simulation of the real world. However, there are some caveats such as numerical errors, missed collisions, and timing issues ultimately resulting in some compromises. Compromises include time, scale, and intricacy. With so many parameters to configure, setting the initial state of the physics engine is a daunting task.

The Blender/Bullet physics engine is rigid and soft body based with approximately 57 individual parameter settings which include gravitational acceleration, physics steps, friction, anisotropic friction, elasticity, dampening, rigid-body constraints, material force-field, mass, radius, form-factor, collision bounds, collision margin, obstacle radius, servo control, force, torque, linear velocity, and angular velocity. There are even more parameters for the non-real-time rendering engine, however, this project will only focus on the real-time component of Blender known as the *Blender Game Engine* [1]. These parameters can be set either programmatically via the *Blender Python API* or through the graphical user interface.

To date, Blender's real-time physics engine has been used for many scientific simulation and visualization projects [8][7]. For this project, the Blender Game Engine will be used to produce a physics-based motion model (and ultimately a complete simulation) for the *Surveyor SRV-1 Blackfin* robots used in *HRTeam*'s multi-agent system [4][21]. As of right now, the Blender HRTeam 3D simulation—titled *BlenderSim*—uses a constant velocity motion model while only using the physics engine to test collisions between the robots and their environment also known as the *arena*. Moving forward, BlenderSim will use a probabilistic, data-mined motion model created by mining historical log data from previous real-world lab runs.

The goal of this research project is two fold. The first portion is to develop a methodology for heuristically searching—via a genetic algorithm (GA)—optimal physics-engine parameters in order to increase simulation fidelity. The second portion is to demonstrate this methodology by comparatively showing the differences and similarities between the produced, tuned-simulation setup and the real-world HRTeam, SRV-1 lab setup. As hypothesized, the methodology should demonstratively diminish

[1]Blender, released under the GNU General Public License, is a 3D creation suite allowing artists and programmers alike to produce immersive audio/visual works ranging from animation shorts to real-time 3D interactive games. Features include 3D modeling, 3D sculpting, texturing, sound editing, film editing, motion tracking, rigging, rendering, animation, physical simulation, a real-time 3D engine, and extensibility via the integrated Python API [12].

the differences while at the time increase the similarities between the simulated robot motion and the physical robot motion.

Creating the methodology involves three stages of research and development. The first stage involves exposing patterns—via data-mining—in the motion recorded during previous physical lab runs. The second stage involves a cycle of fitness testing the generational outcomes of the GA by comparatively evaluating the motion produced by the tuned physics engine with that of the motion patterns mined from the previous stage. Lastly, the third stage involves evaluating the effectiveness of stage one and two by comparing results collected in the tuned, simulated world with the results collected in the physical world. The hypothesis is that as the GA produces more and more generations, the physics-based motion model will converge with the probabilistic, data-mined motion model and ultimately closely converge with the physical robot motion.

If the hypothesis is supported, then future physics based simulations can be rapidly tuned to produce a high fidelity with that of the simulated object's real-world counterpart—in this case the SRV-1s. By having a high fidelity physics based motion model, simulated runs will provide stochastic results as is the case with real-world lab runs. Furthermore, this highly tuned physics engine will provide realistic movement adding to the quality of observation for any given simulated experiment.

The motivation for the research project is to develop a system to automatically tune a physics engine resulting in high fidelity without having to understand or even care about how the parameters were derived. Interestingly, by borrowing from naturalistic processes, an optimal solution can be found to a problem by seemingly random occurrences.

3 Background

3.1 Previous Work

This research project is mainly inspired by the work accomplished building BlenderSim during my *Research for Undergraduates Fellowship* and by the mentorship of Dr. Elizabeth Sklar and Dr. Simon Parsons. Over the course of three months, a Blender based 3D simulation was developed for HRTeam. Initially, BlenderSim was wholly physics based but soon proved to be problematic on three fronts: time, scale, and intricacy.

Initial problems arose when the treads of the SRV-1 were recreated in the simulation. Even after numerous hours adjusting physics parameters and rigid-body configurations, the treads would consistently behave in erratic fashions. See *Figure 1.*

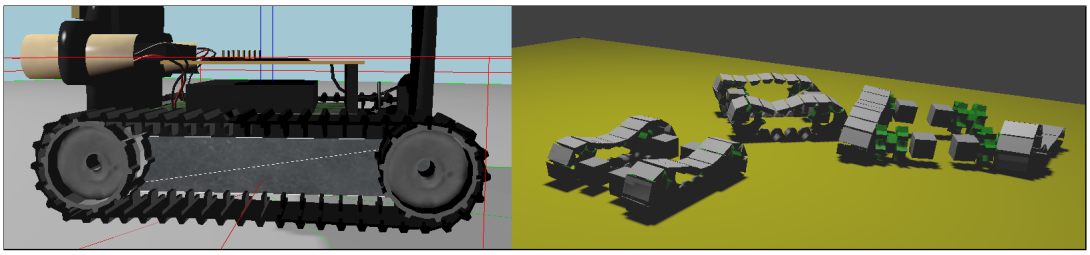

Figure 1: Here you see the to-scale treads modeled after the physical SRV-1 robot on the left and the physics-based rigid-body tracks in motion on the right.

Scale was problematic as the Blender/Bullet physics engine has difficulty with collisions of objects outside of its intended range of .05 to 10 meters [6]. Non-moving objects smaller than .05 (5cm) Blender/Bullet units in any given dimension erratically bounce when they should be still as no Newtonian force is being applied. For instance, the wheels on the 3D SRV-1 model which are 2.11cm x 2.45cm x 2.52cm.

To rectify these issues, the physics engine was largely abandoned—in terms of providing the motion model—and was only kept to keep the robots from running through each other and the arena. In its place, a constant linear and angular velocity motion model was developed of which only moves the 3D robot as if it was a single point body. See *Figure 2* and *Figure 3.*

To increase the fidelity of BlenderSim, a probabilistic motion model was discussed. The probabilistic motion model would be generated by data-mining previous physical experiments where robot locations were logged over time. Once in place, the probabilistic motion model would be used in the GA's fitness function. Here each generational offspring of a simulated physics-based robot's movements would

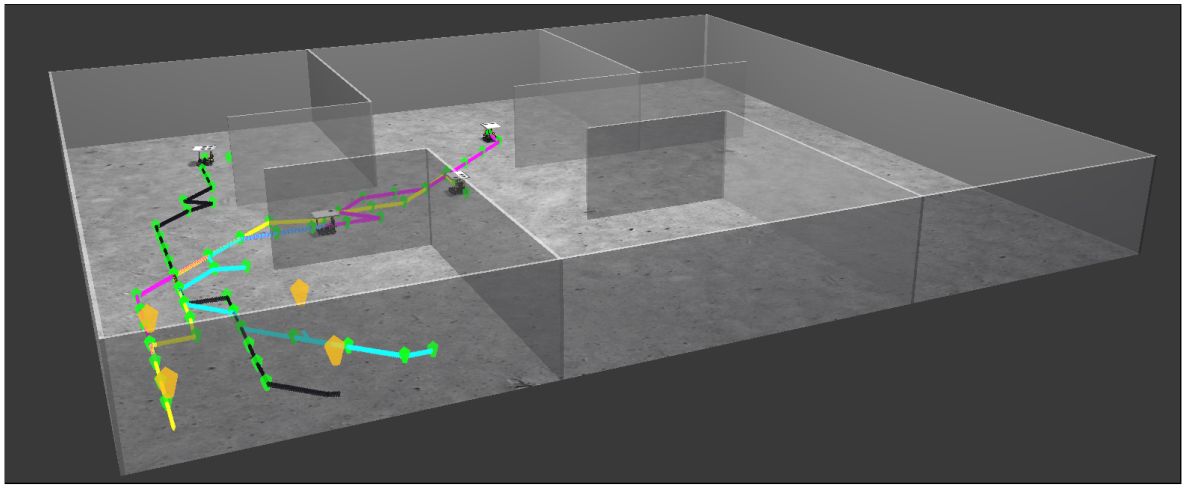

Figure 2: Here you see the constant velocity motion model at work in BlenderSim with four robots traversing their respective paths of which consist of way-points scrapped from a previously recorded physical lab experiment.

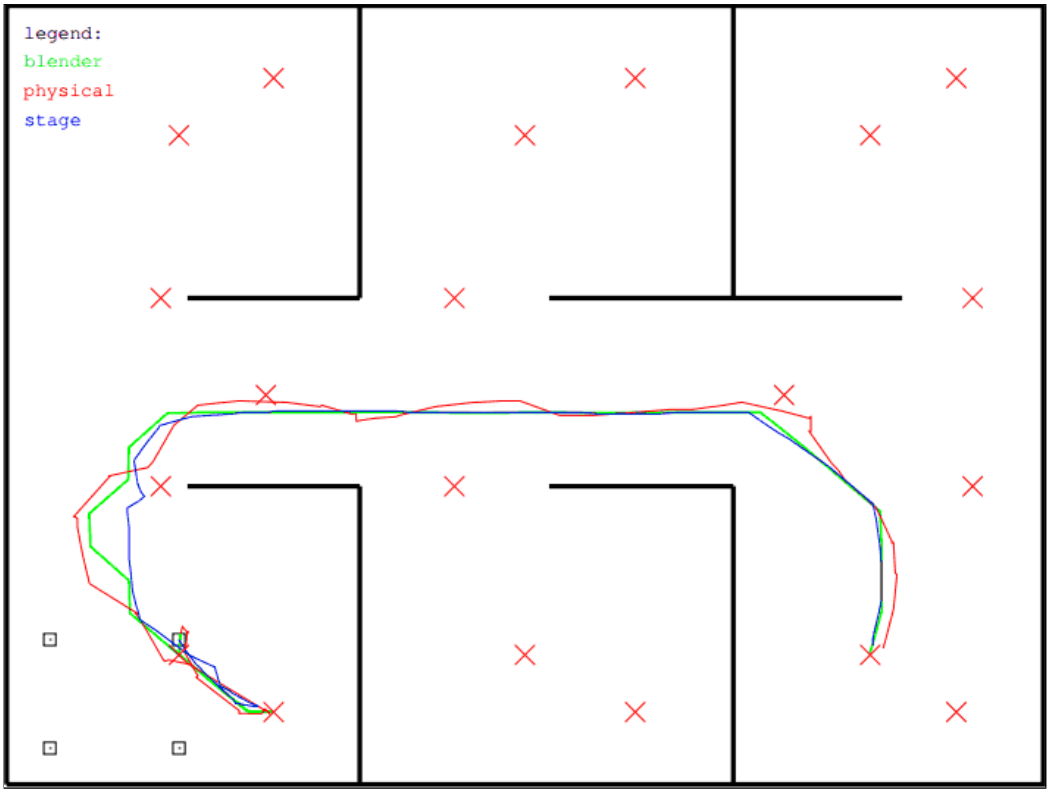

Figure 3: Here you see the path plots–as plotted by Dr. Elizabeth Sklar–of the BlenderSim robot, the physical robot, and the *Stage* (a 2D robot simulator already in use by HRTeam)[5] robot plotted in comparison.

be compared with that of a simulated probabilistic-based robot's movements given some time, initial orientation, and some location both robots must reach.

3.2 Readings of Related Work

Other inspirations for the project were the readings of [19], [9], [16], [14], [17], [20], [11], [10], [18], [22], and [15]. These related works have been separated into three distinct categories below. Category one deals with work concerning a wide range of uses for genetic and evolutionary algorithms. Category two

covers the comparison of simulated and physical environments by analyzing their respective "reality gaps". Lastly, category three covers specific work related to automatically tuning physics-engine parameters in order to increase simulation fidelity.

3.2.1 Genetic and Evolutionary Algorithm Parameter Tuning

In [19], simulated objects composed of 3D parts, sensors, neural networks, and effectors are generated via a genetic algorithm. These "creatures" are selected and "bred" towards some desired behavior such as swimming, walking, jumping, or following. The genotype of these creatures are represented as directed graphs of which are mutated and recombined to produce new generations. Each node in the graph represents some 3D part and within each node is a nested directed graph representing the control of the part. For each desired behavior scenario, each generation offspring is fitness tested which ultimately determines its survival rate into the next generation.

In [9], Mixed Integer Linear Program (MILP) solvers are the target for automatic software parameter optimization although the authors claim their approach could be applied to any algorithm/software where critical parameters with "good" values show improved performance. Utilizing software testing and machine learning paradigms, the authors develop *Selection Tool for Optimization Parameters* (STOP). STOP's framework is comprised of five phases. Phase one is the initial selection of the MILP solver's parameters and their settings. Phase two runs the solver, with phase one's selection, for evaluation. Phase three utilizes regression trees or a neural network to select additional solver parameters and their settings. Phase four reruns the solver with phase three's additional selection and evaluates again. Finally, phase five outputs the best solver parameters and their settings observed based on solver completion times. Phase one's selection uses one of three approaches: random selection, pairwise coverage, and a greedy heuristic. The authors concluded that out of the three phase-one selection methods, no method dominated yet pairwise coverage was often associated with the best parameter settings observed. Ultimately, STOP outperformed the default solver parameters and their settings even when STOP performed at its worst.

In [16], a general synopsis of genetic algorithms is given along with specific examples of their use in various fields of research such as the *Baldwin effect*, *Echo* dynamics, and classifier systems. Lastly, the authors give ideas for future research and additional readings concern genetic algorithms. The text describes how researchers used a GA model to capture the Baldwin effect where an entity's individually learning behavior populates through successive generations. Other notable portions of the text include how researchers modeled dynamic bug colonies, immune systems, and rat classifier systems all with genetic algorithms.

In [14], background is given on genetic algorithms, genetic programming, and co-evolution where the evolution of one population acts as the environment for another evolving population and vice versa. Prominent works mentioned in the text are the "artificial ant" where a genetic algorithm is used "to discover a finite state automaton enabling the 'artificial ant' to traverse [an irregular] trail" and the development of a *differential pursuer-evader game* where a "genetic programming paradigm can be used to solve the differential game of simple pursuit by genetically evolving a population of strategies for the pursuing individuals over a number of generations." Concerning co-evolution, the authors describe a co-evolution algorithm to simultaneously evolve two players' strategies. "This mutually bootstrapping process found the minimax strategies for both players without using knowledge of the minimax strategy (i.e. any *a priori* knowledge of the game) for either player."

In [17], the authors document their beginning research on how the role of crossover and *fitness landscape* characteristics improve genetic algorithms' performance. The text demonstrates how fitness landscape features of hierarchy, isolation, and conflicts affect genetic algorithm performance of finding global optimums to their class of *Royal Road* functions. Interestingly, they discover that intermediate-order solutions can be detrimental to the genetic algorithm's performance. They had hypothesized that the intermediate solutions were beneficial as they provided "stepping stones" to the optimum but this was not the case in their findings. Here the issue is premature convergence where the population loses useful solutions once one, of two disjointed useful solutions, is found. They did note however, that for larger problems (then the ones analyzed in the text), the intermediate solutions or *schemas* could be beneficial.

3.2.2 Comparing Physical versus Simulated Environments

In [20], the authors' physical HRTeam lab setup is compared to their simulated Stage lab setup. Comparisons are drawn between physical and simulated experiments with standardized setups across both the

simulator and physical environment. These comparisons tested their hypothesis that metrics produced in their simulation can predict the real-world performance in their physical lab. After experimentation, the authors discovered "encouraging agreement at the qualitative level between the results obtained in simulation and those obtained with physical robots." They noted though that this does not necessarily apply to all simulated versus physical comparisons. Their concluding analysis showed that the resulting metrics produced (in both simulated and physical environments) scaled in relative terms but not completely in absolute terms.

In [11], issues are identified with simulation prediction of multi-robot systems. Predictive models described in the text were statistical-based models and model-based packages such as Stage, *USARSim*, and *Webots*. The authors carried out comparative analysis of four scenarios—simulated, real, dataset, and a combination thereof—with each having an identical setup. Key issues identified were the modeling of sensor noise, position latency, message latency, environment dynamics, communication interference, and communication bandwidth. Since the text concerns multi-robot systems, the authors focused on communication interference and message latency. They found that unmodeled communication interference effects the predictive performance of a simulation especially for outdoor simulated environments. For message latency, they found that the variance in latency—between high message volume areas and low message volume areas—is much larger in real environments than in simulation. Ultimately, the authors found that simulation is still valid means for verification but discuss future work to model physical interference between multi-robot interactions.

In [10], the pertinent portion of the text is section four which documents the ongoing validation of USARSim's models. These models include robot geometry and kinematics, sensors, environments, and robot interactions. The authors describe previous works by other researchers who sought out to validate USARSim as a viable candidate for simulation. In all validation attempts described, the research showed close agreements between the simulated and real-world scenarios. As listed in the text, USARSim was tested on its simulated laser-range-finder sensor, human-robot interaction controls, task times under various environmental conditions, and its simulated camera.

In [18], the authors created two types of robots in USARSim modeled after two real robots. The two simulated robots created were given the equivalent dimensions and masses of the real robots in order to determine USARSim's prediction accuracy of simulated robot motion. After having the simulated and real robots traverse steps and trenches, performance analysis concluded that "USARSim exhibited a performance similar to that of the real robots," indicating that, "the simulated robots can be used for training for the environments with simple obstacles."

3.2.3 Physics Engine Tuning

In [22], the Bullet physics engine is selected for use in a comparison between a simulated robot arm pushing tangram pieces across a table and a physical robot arm pushing tangram pieces across a table. They identify nine physics-engine parameters as having significant impact on the stability of the simulation. Seven of those parameters were selected for optimization. The optimization was done via a simplex algorithm and differential evolution. The resulting optimization reduced the error rate between simulated and physical to less than half when compared with the default parameter settings.

In [15], the authors describe an evolutionary algorithmic approach to tuning *SimRobot*'s physics-engine parameters in order to close the "reality gap". "Notice that rather than finding the real parameters like e. g. the real friction between the robot's legs and the carpet, the aim in this work is to find parameters that overall result in a similar behavior of the simulated robot." The simulator, SimRobot, utilizes the *Open Dynamics Engine* (ODE) for its physics engine. For the experiment, an *AIBO* was chosen and modeled in SimRobot and recorded data from a real AIBO was used in the fitness function of their evolutionary algorithm. Local and global parameters of the physics engine were optimized in stages. The first stage involved learning the *PID controllers* of the AIBO. Here, "the fitness which is a measure for the quality of the matching, is evaluated by summing up the squared differences between the sensor curve of the real robot's movement and the sensor curve of the simulated robot." The second stage involved learning the servo-motor torques needed for realistic movement by running various fitness cycles of AIBO walks and soccer routines. Lastly, with stage one and two completed, the authors set out for an overall convergent, physics-based robot motion model of the simulated AIBO to that of the real AIBO. A set of 60 walks were recorded of the real AIBO for use in fitness testing the evolutionary outcomes (the physics-engine-parameter settings generated) of the simulated AIBO. These 60 walks were broken down into two groups, A and B, where 40 of walks were put in A for optimization and 20 of the walks were put in B as a control. Group B serves as a control to demonstrate that group A's learned

parameters are not performance specific only to A. Experimentation results included an 80 generation convergent rate in stage 1, a 200 generation convergent rate in stage 2, a clear reduction in the maximum and standard deviations of group A, and significant closeness to the real walks recorded in group B. Additional experimentation by the authors included comparing their tuned simulator of the AIBO to that of the simulated AIBO in Webots. While their initial settings in SimRobot were outperformed by Webots, after learning the SimRobot physics-engine parameters, their simulated AIBO significantly outperformed the simulated AIBO in Webots for both sets of walks in A and B.

4 Project Description

This research project will center around Blender's physics engine and the BlenderSim software developed during my Research for Undergraduates Fellowship. The hypothesis is that by using using a genetic algorithm to tune the starting state parameters of the Blender/Bullet physics engine, the physics-based motion model of the simulated SRV-1 robot will more closely converge to its real-world counterpart's observable motion.

The fitness function to calculate the fitness of each generational outcome will utilize a probabilistic motion model derived from historical physical lab runs where the real-world robots' movements were recorded over time. Given a task point, orientation, and time duration, the simulated physics-based robot will be run in comparison to the simulated probabilistic-based robot. Robot path routes will be compared and the simulated physics-based robots' respective physics-engine-parameters genotypes—with the highest achievement—will be selected for recombination and mutation to produce another generation. It is hypothesized, that after many successive generations, fitness will increase.

Software developed for the project will augment the BlenderSim software developed over my Research for Undergraduates Fellowship. Python will be the language of choice as this is the language utilized by the Blender API.

5 Experimentation and Results

Experimentation will center around the parameters of the genetic algorithm as well as the methodology of heuristically searching optimum physics-engine parameters in order to increase simulation fidelity. Experimental variables include initial population size, selection of physics-engine parameters to represent, chromosome representation of physics-engine parameters chosen, mutation probability rate, recombination probability rate, elitism, fitness analysis method, fitness threshold criteria, and termination criteria.

Results will include the error rates of the Blender physics engine given the parameters of the genetic algorithm, the parameters of the physics engine as selected for tuning by the genetic algorithm, the task point of the robot, and the starting orientation of the robot. The mean error rates will be plotted against the successive generations. The convergence rate of the simulated physics-based robot-motion-model with that of the physical robot motion will be analyzed to determine the success of the genetic algorithm.

6 Research Plan and Schedule

The practical outcomes of this research project will be a master's thesis proposal (with the aim of completing the thesis in Summer 2014) and the software infrastructure (BlenderSim) capable of carrying out the experimentation as outlined here and for the experiments proposed in the forthcoming master's thesis.

6.1 Fall 2013

Week 1-4	Literature review.
Week 5-8	Development of the software infrastructure setup to carry out the experimental design.
Week 9-11	Hypothesis investigation and experimental evaluation.
Week 12-13	Master's thesis proposal write-up and submission.
Week 14-15	Term paper write-up.

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