Morphology Evolution of a 3D Passive Dynamic Running Machine

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Abstract

Robust pedal machines present the potential to aid humans with increasingly difficult tasks, improve quality of life for the disabled, and allow for the creation of more realistic humanoid robots. For these reasons pedal locomotion continues to be an active research area in robotics laboratories worldwide. In bipedal robots, several different strategies have been employed in attempts to mimic the human gait. However, even the most popular of which, ‘Zero Moment Point’, always tends to produce robots that fall short in terms of robustness to disturbance, versatility, efficiency, and overall performance; features which are of critical importance in terms of creating useful pedal machines. A different approach, ‘Limit Cycle Walking’, has more recently been gaining traction as it addresses some of these issues. Passive Dynamic Walkers are the fundamental sub-group of Limit Cycle Walkers on which many of the robots are based. Passive Dynamic Walkers use no active control and acquire all the energy needed for walking motion through decent down a slope. Stability control is implicit in the mechanical design and is therefore said to be computed morphologically. Because of the groundwork laid by research in PDW, Limit Cycle walkers have already begun to deliver on robots with unparalleled efficiency and computational simplicity. In this research the effectiveness of an Evolutionary Robotics approach is analyzed with regard to the development of a simulated 3-dimensional passive dynamic walker morphology. The design constraints are chosen to be similar to that of previous research which suggests that such a model may be capable of walking and running. The hope is that this work will lead to better tools for engineering this type of system, increased understanding of the underlying mechanisms, and ultimately the creation of better limit cycle walkers. This paper reports on progress of the simulation as, for practical purposes, the work is at this stage incomplete.

I. INTRODUCTION

Robust walking mechanisms could greatly expand the potential usefulness of future robots. While wheeled robots have been be dominant in terms of simplicity and efficiency, their inability to adapt to changes in terrain and other environmental factors limits their practicality in a number of applications. Human walking is highly dynamic, efficient, and adaptable, yet bipedal robots have yet to inherit these characteristics[1]. Pedal robots could conceivably replace humans performing tasks in hazardous areas, or provide a means for disabled persons to lead a more normal lifestyle. The development of such a mechanism is also a crucial stepping stone if humanoid robots are to ever have a serious role interacting with humans in society

There have been many attempts to create bipedal robots dating back to the 1960s[2]however, even many of the modern state of the art attempts take an approach which severely limits performance in order to ensure stability. 'Zero Moment Point', as employed by Honda's ASIMO, requires the stance foot to be in flat contact with the floor at all times in order to ensure dynamic equilibrium is maintained. This approach, while demonstrated to be functional, restricts the robots to relatively slow unnatural looking gaits. Furthermore these gaits are quite inefficient as they require rigid control of all joints at all times. These robots employ high feedback gains for dynamic stability and disturbance mitigation, which only contributes to the overall inefficiency. [3]. Since it was initially characterized by McGeer in 1990 [4], there has been much exploration into the field of passive dynamic locomotion, [5],[6],[7],[8], that is, the ability of carefully designed robots to 'walk' down a slope without the use of sensors, actuators, or any other type of external power supply. This area offers much promise in the field of robot walking as it aims to provide a method through which the computational task involved with maintaining a stable walking cycle is offloaded onto the mechanical structure [5]. Limit Cycle walkers have since been designed to utilize such morphological computation, resulting in robots that rival humans in efficiency, require relatively simple controllers, have very natural looking gaits, and are able to maintain dynamic stability through low or zero feedback gains . Fig. 1 shows Denise and the Cornell biped, two state of the art LC walkers, and Honda's ZMP controlled ASIMO robot .

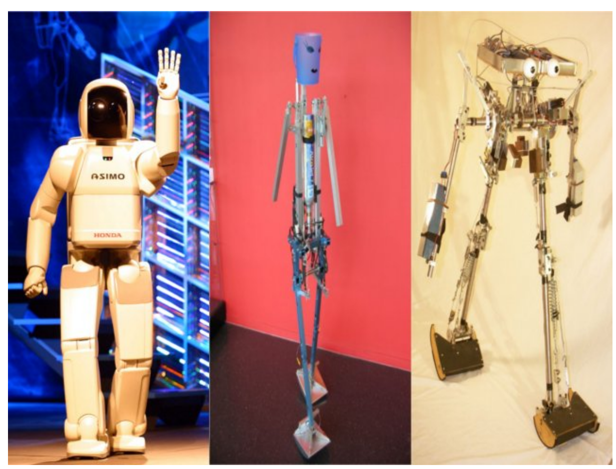

Fig. 1. From right to left: the Cornell Biped, Denise, and ASIMO

A key difference between LC and ZMP walkers is, as they have their origins in passive robots, LC walkers utilize underactuation; *i.e.* there are more degrees of freedom than are actuated. For this reason the natural dynamics of the body structure in an LC are of paramount importance, as they play a larger role in governing the overall behavior of the device. ZMP walkers must have tight control over all DoF in order to precisely control leg trajectory. LC walkers do not constrain leg trajectory or foot positioning, they only require that locomotion falls within a periodic limit cycle as shown in Fig. 2 [3].

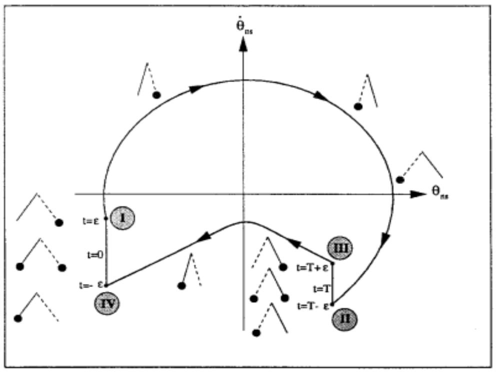

Fig. 2. Figure originally posted in [8]. This shows the Limit Cycle (aka. Phase Portrait) diagram for a compass model passive dynamic walker. θ represents the angle between the legs. The dashed leg is the swing leg, and the leg with the dot is the support leg.

II. Background and Related Research

In previous work Owaki et al. demonstrated the potential for running in a passive dynamic robot [6], [5]. In these experiments a 2-dimensional robot is constructed (in simulation) with springs and masses located at the leg and hip positions, as shown in Fig. 3. In this research the mechanically implicit feedback structure was modeled and a set of parameters and initial conditions were found which allowed the robot to walk down a slope at a given angle, and switch to a running gait (requiring a flight phase) when the incline angle was increased past a certain point. There have been numerous other experiments which demonstrate physical and simulated Passive Dynamic Locomotion in two and three dimensions[7].

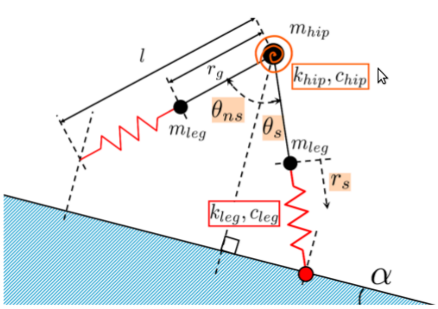

Fig. 3. 2 Dimensional passive dynamic running model, Owaki et al. [5]

Evolutionary Robotics (ER) is an approach to the design of control and/or morphology of robots which utilizes elements of Artificial Intelligence to locate solutions existing within potentially expansive search spaces. It can be useful in circumstances where the task is simple, but the dynamics of the system are complex or not entirely understood. Eventually the complexity of the systems that humans are able to design will be limited by the effectiveness of the mathematical tools we can create to decompose them. ER provides an alternative method by which machine intelligence methods, namely Genetic Algorithms (GA), Genetic Programming (GP), and Artificial Neural Networks(ANN), are used to craft these solutions. This can take place either in simulation or in an embodied environment[9].

In Vaughan et al. a 3-dimensional powered limit cycle walker is evolved in simulation. This research simulates a 10 DoF 3D legged walker and utilizes a tailored fitness genetic algorithm to evolve its 17 body parameters, as well as the weights in a Continuous Time Neural Network (CTNN) with a Central Pattern Generator (CPG) to control active walking. With this approach, the researchers were able to develop a simulated robot which maintained its passive characteristics and evolved for optimal active walking ability, efficiency , and disturbance rejection. This ER methodology proved to be exceptionally effective in creating a walker capable of meeting performance specifications, despite the minimal amount of *a priori* knowledge regarding the dynamics of the system. Another noteworthy feature of this research is that both external disturbances, representing random forces on the body and internal disturbances, representing mistakes in body's construction, are taken into account. The Sussex researchers claim that this resulted in the evolution of dynamic mechanisms within the robot which allowed it to adapt to the noise. Such an approach promises a greater chance for success if the simulated body is to be transferred to a physical model[1].

Passive dynamic Walkers have been called the gliders of bipedal robotic locomotion[10]. If 3D powered Limit Cycle running is possible, it would seem sensible to first demonstrate this with a 3D passive model on an incline. This research is an attempt to combine the Evolutionary Robotics approach to pedal locomotion demonstrated by Harvey et al., with a morphology similar to that shown by Owaki et al., to evolve a 3D passive dynamic walker with the versatility to walk as well as run.

III. Simulation

The body of the simulated model was made to be as similar as possible to the robot simulated in [5] (shown in fig. 3), with changes made to allow it to be suitable for a 3D environment, and something that could be physically constructed .

As shown in Fig. 4, the body was made up of a rectangular box at the hip which joined two legs connected by an angular spring and damper. The legs each consisted of an upper and lower capsule shaped segment, connected by a compressional spring dampener system. Arms were added to the model and rigidly attached to the opposing leg in order to balance torque from the leg swing. In some experiments spherical surface model feet were also used (this is not pictured) which

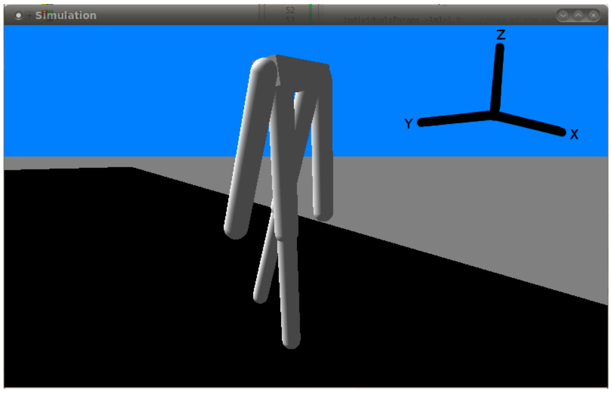

Fig. 4. Simulation body shown on incline

were rigidly connected to the feet at parameterized x and z distances. The Open Dynamics Engine was chosen as it is a proven and well supported open source physics engine suited for this type of numerical simulation [11]. A list of the parameters encoded into the genome is shown in table I, parameter ranges were roughly based on findings from the 2D model [5].

TABLE I
PARAMETERS EVOLVED IN SIMULATION

Parameter	Unit	Vale
r_{ini}	degree	initial body angle about roll axis
p_{ini}	degree	initial body angle about pitch axis
θ_{ini}	degree	initial angle between legs
m_h	kg	mass at the hip
m_{l1}	kg	upper leg mass
m_{l2}	kg	lower leg mass
m_{foot}	kg	foot mass
r_{l1}	m	upper leg radius
r_{l2}	m	lower leg/cylinder cap radius
r_{foot}	m	radius of foot surface sphere
l_{l1}	m	upper leg length
l_{l2}	m	lower leg length
hip_{len}	m	separation between legs
k_{leg}	N m^{-1}	leg spring constant
c_{leg}	N s m^{-1}	leg dampening constant
κ_{hip}	N m degree^{-1}	torsional hip spring constant
C_{hip}	kg m^2 degree^{-1} s^{-1}	torsional hip dampening constant
WH_{torso}	m	torso width/height
h_{foot}	m	z axis distance from foot to leg
$foot_x$	m	x axis foot offset from leg center

IV. The Genetic Algorithm and Evolution Process

This section will briefly cover the basics of GA, and describe the procedural details as they pertain to this experiment.

As mentioned , Genetic Algorithms are particularly effective when it comes to locating solutions within a large search space. In a GA a population of P items (in this case passive bodies) are created and initialized to random values within a predefined range. Each body is, in turn, tested and its effectiveness is evaluated according to a fitness function. The choice of fitness function is of critical importance to the GA, as it defines the type of solution to select for. Much work has gone into the study and design of suitable fitness functions and a thorough review of the different types and their experimentally proven effectiveness is given in [9]. In this experiment the 'test' consisted of placing the body on an incline in accordance with the initial conditions encoded in the genome, and allowing it to move freely afterwards. A variety of different fitness functions and incline angles were tested. After each member of the population is evaluated, they are ordered by fitness and selected for crossover (analogous to breeding in a real population). In this experiment $P/2$ members of the population are selected for crossover, and the members that are not selected 'die' and are removed from the population. Stochastic Universal Sampling (SUS) was was chosen as the method for selection as an individuals likelihood of selection is fitness proportionate and the selection algorithm exhibits no bias and minimal spread. As shown in Fig. 5 the net population fitness can be visualized as a bar, with sections sized according to the corresponding body's fitness. Here one random number, between 0 and F/N , is chosen to define the initial position. From this point the body is selected according to the position reached when incremented by F/N. Unless the fitness of the top individual sufficiently dwarfs that of other members, this method does not guarantee that the top individual will be selected, just that it has the best chance of being selected. Here, this method is superior to simply seletcing the top 50% (Elitist Selection) as it allows unique genes, which may not offer immediate fitness reward, to integrate into and diversify the population. This helps the GA to find the globally optimal solution, instead of fixing on a local maxima [12],[13].

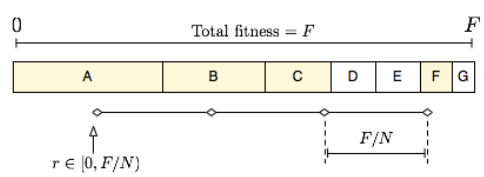

Fig. 5. Stochastic Universal Sampling. Here $N = P/2$ In this example A, B, C, and F would be selected.

Crossover between selected members of the population is configured at random. Each mating pair produces two offspring and is allowed to remain in the population during the next trial. The parameters of the offspring begin as identical replicas of the parents but are then swapped with one another at a fixed crossover rate (p_c) . Mutation then takes place on each parameter at a fixed mutation rate (p_m), meaning that each parameter has a p_m chance of being mutated. When mutation does take place on a parameter the amount mutated is equal to $\pm M\%$ of the parameter's original value. Values for the GA parameters are shown in II (Note: values for P and G are typical, and were varied in some experiments). This process is typically allowed to repeat until a sufficiently adequate population is evolved or fitness reaches an upper bound.

P was kept a 256 bodies for most of the experiments to

TABLE II
PARAMETERS USED IN GA

Parameter	Value	Name
p_c	.7	Crossover Rate
p_m	.25	Mutation Rate
M	.10	Mutation Amount
P	256*	Population Size
G	100*	Generations of Evolution

provide a sufficiently large amount of diversity considering the large number of parameters in the genome. A comparison between large and small population size evolutionary trials can be found in the following section.

In this experiment the evolutionary test consisted of placing each body on an incline according to the parameterized initial conditions, and then allowing the natural dynamics to take over. No external forces were added after the body was configured and placed on the ramp. Bodies 'live' until their arm, upper leg, or hip touches the slope, a leg rises higher than the torso, or a evolution timer runs out. The evolution timer was set to be sufficiently large that it was rarely encountered, and it mostly served as a failsafe against unexpected overly stable static body configurations. Steps were only counted after a foot touches the incline plane, is passed by the opposing foot, the opposing foot touches the incline plane, and is finally passed again by the original foot. This must occur in the order described and as shown in Fig. 6. While this criterion actually may be considered a 'double step, it ensures that if a robot's fitness is to be rewarded for completing a step, it must display features of a desirable gait. A number of different functions were tested for overall fitness, usually involving some or all of the following values from simulation:

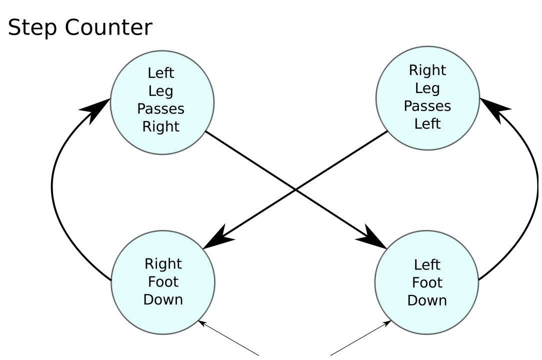

Fig. 6. State machine used for step counting. There must be four transitions in the order shown in order for a 'step' to be rewarded.

- S : Number of steps the walker was able to take before death. This is computed by the state machine shown in Fig. 6.
- d: Total distance (in the x direction) traveled by the torso.
- t: Amount of time the body lived for.
- avg_{hip}: Average position of the hip with respect to the feet at each time step.
- avg_{roll} : Average roll experienced by the hip about the x axis at each time step.
- F_r : Froude number, a dimensionless value that can quantitatively distinguish between walking and running gaits [6].

An example of one of the fitness functions that proved effective in evolving a robot capable of taking several walking steps is shown in eq. 2

$$fitness = d(S+\varepsilon)(1/avg_{hip})\ln(1+1/avg_{roll})\ln(1+t) \quad (1)$$

This fitness function selects for walkers that are long lived, take many steps, and spend the least amount of time falling over forward or to the side. The ε term was added to allow the walkers to evolve stability even if they are not able to make any steps.

In trials for running an additional

$$\ln(1+1/|F_r - F_{r0}|) \quad (2)$$

term was factored in to give runners a decaying reward as F_r approaches F_{r0}. Here F_{r0} is an approximated optimal Froude number. These and other similar fitness functions resulted in robots that were able to take several steps, but not maintain stable walking/running. This is discussed in more detail in the following section.

Should the ideal combination of incline angle, fitness function, and body constraint configuration have been found, this procedure would ideally continue in the following way:

Both the populations for walking and running bodies would be evolved to the extent that all members of the population are able to stabily decend down the incline. At this point, the incline angle would be encoded in the genome, and all body parameters would be removed, so that only initial conditions remain. The fitness functions used on the two populations would be adjusted, so the bodies evolved for running would evolve for walking, and the bodies evolved for walking would evolve for running. At this stage the genetic algorithm would be navigating the search space for robots that have the versatility to walk as well as run, only depending on the initial conditions and incline angle.

V. RESULTS

While simulation bodies evolved using the method described above have yet to produce stable walking/running, the Genetic Algorythm's ability to locate increasingly superior body configurations was verified. Figure 7 shows a histogram view of the fitness values achieved with respect to generation. The dots that appear above the average marker show newly discovered high ranking solutions that, over time, pull up the average fitness of the population. This demonstrates the GA's ability to come up with new solutions during the course of evolution. The more sporadic dots shown below and around the average marker show the effect of crossover/mutation allowing the GA to check remote parts of the fitness scape which have little or negative benefit to the body's fitness.

As implied by [12] and [9], a large population size is more effective when there is a large number of parameters being

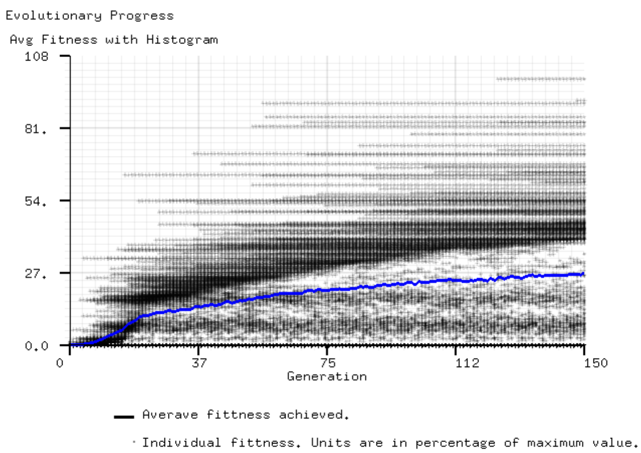

Fig. 7. Histogram view showing the density of fitness values achieved in each generation. For reference, average fitness is also shown. Units are in percentage of maximum.

evolved. Here the results of a population of 256 undergoing 150 generations of evolution are compared with that of a population of 32 evolving for 1200 generations. These values were chosen to constrain the number of bodies tested to a constant value. Shown in Figs. 8 and 9 both trials were able to evolve runners capable of taking several steps in the course of their evolution. In both cases the bodies evolved to e able to take the first step early on in the evolutionary cycle, and were able to develope two-step walkers shortly after that. The large flat sections on both graphs at 3 steps suggests that there is a local maxima at that point which the GA struggles to overcome. In the smaller population it seems that the more frequent crossover and mutation may in fact have provide a short-term advantage in terms of exploring distant areas of the fitness plane. However, as shown by the dip around generation 300, this can also be destructive. In both populations the average step count seems to be able to quickly follow the average to a first step, then grow slowly afer that. While the results from these to trials are largely similar, additional tests are needed before anything can be concluded from this.

VI. Conclusion

In this research a population of passive mechanical bodies was evolved via Genetic Algorithm in an attempt to achieve stable walking/running.

As mentioned above, even in the best experimental trials, evolutionary progress tapered off after creating a robot morphology that was only capable of taking a few steps. The following sections will break down possible reasons for this, and propose experiments which could prove beneficial in future work.

A. Walking/running is simply not possible with the given body configuration.

This possibility was considered, and, as mentioned above, parameterized spherical surface model feet were added to the body for a number of tests. This actually proved to be a hindrance to the robots ability to walk down the incline. However, this does not discount the potential for other types of modification to the body structure to be beneficial. The addition of differently shaped feet, knees, ankles or other features would indeed be interesting in future research.

B. The incline angles tested were inappropriate for the task at hand.

In this research a variety of different incline angles were tested, ranging from 4° to 30°, and it was found that the most successful evolution took place around 25°. This is interesting as it is substantially higher than that used in the 2D model [6],[5]. It would also be interesting to see the results of evolutionary trials where the incline angle is encoded in the genome.

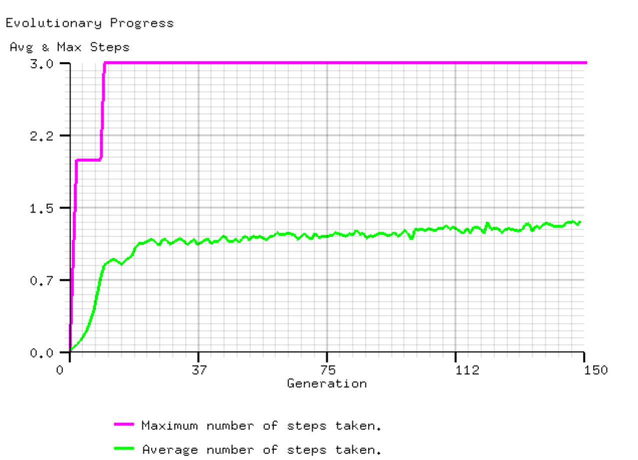

Fig. 8. Graph of maximum and average number of steps taken over 150 generations of at a population size of 256.

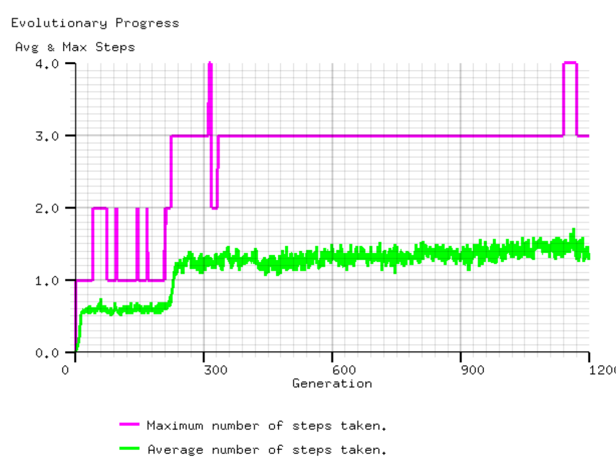

Fig. 9. Grap of maximum and average number of steps taken over 1200 generations at a population size of 32.

C. The bodies should have been given more generations to evolve.

These tests were conducted on a system using an AMD Athlon(tm) 64 3500+ processor running at 2.2GHz. On this machine 100 generations of evolution at a population size of 256 takes approximately 6.5 hours. While it is entirely possible that more generations of evolution could have produced walkers capable of taking more steps, the amount of time involved made extensive testing for a large number of generations quite challenging. Some effort did go into code optimization, however, it is still believed there is room for improvement. Additionally, due to the nature of the Genetic Algorithm procedure, it is well suited for parallelization and could largely benefit from the increasing number of cores becoming standard in desktop machines. Parallelization techniques were not a focus of this research, however it could be an important area for future exploration.

D. The search space is simply too vast.

As stressed in [9] , the GA's ability to develop new and unique solutions to the problem at hand largely depends on a minimal amount of *a priori* knowledge being applied in the program. To try to minimize the *a priori* knowledge in this experiment, a large number of parameters were encoded into the genome. Unfortunately, this also has the effect of creating a very large search space, thus requiring a large population size to ensure sufficient diversity. In this experiment a population size of 256 was generally chosen. However due to the sheer expansiveness of the search space, in many of the trials the robot's fitness honed in on what is believed to be a local maxima. The population was still not sufficiently diverse to locate higher level areas on the fitness scape during the time allotted for evolution. To improve on this efforts should be made to strike a better balance between a priori knowledge in the system and search space size. This would be done by intelligently limiting the number and range of values encoded in the genome. Increasing the population size is an alternative solution, but for reasons described above, a P value of 256 is already on the borderline of practicality.

E. The fitness function used prevents better solutions from being found.

While a number of different modifications to the fitness function were tested, it is difficult to quantitatively rate their effectiveness without a control experiment. [9]. It is entirely possible that a fitness function more clever than the one shown in eq. 2 could allow the GA to locate better solutions in fewer generations. One possibility for an improved fitness rating would include recognition of the limit cycle. While the fitness functions tested supported the existence of a limit cycle, they did directly test for nor analyze it. A fitness function which thoroughly analyzed and and rewarded walkers who most closely adhered to an existing limit cycle could be quite effective. This would also present a an interesting and challenging computational challenge as it would require:

- Determination of which state variables' periodicity (with respect to which other state variables') are most important to the walking function
- Continuous recording the values of these state variables
- Analysis and determination of periodicity in the cycle
- Detection of period doubling, quadrupling or 2^n bifurcation, adaptation of the above methods to analyze and reward fitness accordingly

This research has demonstrated the effectiveness of a Genetic Algorithm in the development of Passive Dynamic Walker morphology. While the ability of the walkers evolved in this experiment is limited, there are many areas that exhibit the potential for improvement and warrant future investigation.

Acknowledgements

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