The Evolutionary Locomotion of Tripedal and Quadrupedal Biomorphic Robots*

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Evolutionary robots can achieve certain goals via evolutionary algorithms without specifying all the detailed actions. The robot interacts with the environment and receives natural feedback as the fitness of its goal. In this paper, we study two biomorphic robots and observe how the behavior can evolve with least computation resources and test the possibility of self-adjustment on an unexpected motor failure of one robot leg. The feedback is collected via a supersonic sensor and the evolutionary algorithm is a modified low cost genetic algorithm. In order to minimize the cost of evolution, we control the number of the population of each generation to a very low number. We find that the biomorphic robots can move faster with the motion sequence generated by the evolutionary algorithm than with the motion sequence assigned by human programmers. The structures of robots, in this case, and the number of legs might affect the speed of convergence. Our experiment result shows that the robot can adjust itself with this online evolving approach to deal with an unexpected motor fault. That is, evolutionary robot can overcome an unexpected situation without human intervention.

Keywords: evolutionary robotics, biomorphic robot, evolutionary algorithm, adoptive robot, tripedal robot

1. INTRODUCTION

Evolution in Multi-Modular Robotics (ER) is a promising research topic. ER consists of robots interacting with the environment and accomplishing a specific task within that environment [1]. Specifically, this research focuses on evolution and learning. Evolution is the adaptation of robot behavior or even structure to the environment. Multi-Modular Robotics requires the ability of evolution to control the robot in various mechanisms. Here learning is a task-oriented process whereby the robot gains the ability to achieve a given goal in the environment. Various evolutionary and learning algorithms, such as genetic algorithms or neural networks, have been tested in previous works. A key issue on the research is the methodology on how to design different feedback mechanisms for different tasks, which serves as the fitness function for evolutionary algorithms.

The design of the structure and movement are very different for ER compared to traditional robotics. Biomorphic robots are more adaptive to the environment than wheel-based robots for many such tasks as climbing up stairs or rough slopes. In previous works, there have been many biomorphic robots with a structure similar to insects, insofar as having six legs, a more stable structure than a bipedal humanoid [2]. A four legged robot can be controlled by genetic programming [3]. Compare to the off-line evolutionary robot controllers, the online evolutionary robot can adjust itself to the environment as quickly as possible [4]. And an autonomous robot must adapt behavior in a drastic...
In this study, we tested a novel structure, a tripedal robot, and a traditionally quadrupedal biomorphic robot in order to compare the different results between the different structures. And we will test the locomotion of a quadrupedal biomorphic robot when one of its legs is removed. The evolutionary mechanism is online and onboard, so that we can see the evolution changing the behavior of the robot on-the-fly.

Fig. 1 shows the scheme of the evolutionary robotics research. There are four important components in the research: (1) the robot and an embedded evolutionary algorithm; (2) the environment with which the robot might interact and the location of the task; (3) a fitness feedback mechanism that can tell whether the robot performed well or poorly with regard to a specific task; (4) the task assigned to the robot. The robot must get fitness from sensors and try to evolve to better achieve the goal.

(1) **Evolutionary Robots:** Evolutionary robotics consists of a robot and an evolutionary algorithm which can guide the robot to evolve new actions that are able to better fit their environment; the results of the robot movements will be decided by the interaction between the robot and environment. The structure of the robot and the initial knowledge are not the most important issues as with most robotics [6]. In evolutionary robotics, both the structure and behavior should be evolvable [7], and there is no limitation to the structure of the robot; it should be arbitrary. The evolution algorithm is also unlimited. In this study, we chose the Genetic Algorithm (GA). The GA is based on selection, crossover, and mutation of the chromosomes of populations [8]; these have been used in numerous applications.

(2) **Environment:** According to the literature, the environment will greatly affect the result of evolutionary robots. Most researchers keep the experimental environment fixed during the experiment in order to get consistent results of the evolution experiments.

(3) **Fitness:** Fitness must be associated with the task in experiments. For an autonomous evolutionary robot, the fitness is only related to the information source insofar as changing itself to fit the environment; fitness must be well designed [9]. In our experiment, robots detected moving speed as the fitness via a supersonic distance measurement sensor and an embedded clock.

(4) **Task:** There are many different tasks for testing evolutionary robots in the literature, such as: locomotion, object finding and object following.

In our experiment, we tested the locomotion task on our tripedal and quadrupedal biomorphic robots, as shown in Fig. 2. They were tested in a flat 82cm × 20cm box, as
shown in Fig. 3. We also test on whether the robot can adjust itself to deal with an unexpected motor fault with this onboard and online learning approach by removing one leg from the quadrupedal robot.

Fig. 2. The tripedal robot and quadrupedal robot used in our experiments.

Fig. 3. The experiment environment.

Table 1. The task, evolutionary algorithm, and fitness in previous works.

<table>
<thead>
<tr>
<th>Task evolved/Learned</th>
<th>Evolved controller type/Algorithm</th>
<th>Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Object pushing</td>
<td>Neural network</td>
<td>$f = \text{mean}(v_1,v_2)(1 - S_o)$</td>
</tr>
<tr>
<td>Gait evolution</td>
<td>Evolvable state lookup tables</td>
<td>$f = \text{mean}(v_1,v_t)(1 - (v_1,v_t)^2)(1 - S_o)$</td>
</tr>
<tr>
<td>Locomotion</td>
<td>Neural network</td>
<td>$f = v$</td>
</tr>
<tr>
<td>Locomotion with object avoidance</td>
<td>Evolvable sensor-to-motor</td>
<td>$f = d$</td>
</tr>
<tr>
<td></td>
<td>excitation mapping</td>
<td></td>
</tr>
<tr>
<td>Flying lift generation</td>
<td>Genetic programming</td>
<td>$f = d_{max} - d^2$</td>
</tr>
<tr>
<td>Locomotion with wall avoidance</td>
<td>Neural network</td>
<td>$f = v$</td>
</tr>
<tr>
<td>Gait evolution</td>
<td>Gait parameter set</td>
<td>$f = d / t$</td>
</tr>
</tbody>
</table>

In Table 1, we list the tasks, evolutionary algorithm and fitness that have been tested on robots according to the survey in [9]. The basic goals are locomotion, locomotion with object avoidance, and gait evolution. These tasks can be tested on various biomorphic robots. There are some researches focusing on higher level goals with the wheel-based robots, which is out of our scope.
The rest of the paper is organized as follows. In section 2, the method of our system is described. The experiments are described in detail in section 3. In section 4, we make some discussion on the current and future works. In the final section, a conclusion is given.

2. METHODS

2.1 Behavior and Action

The structure of the robot usually limits its behavior. However, from a biomorphic point of view, living creatures in the real world consistently adapt themselves to fit the environment and change behavior patterns by creating new actions or a new sequence of actions.

Our goal was to understand how well the evolutionary idea could be developed in the context of biomorphic robots. We tried a no kinematic analysis approach for the locomotion of a robot with arbitrary structure, for example, a human infant using four legs and gradually learning how to move with only two legs. The possibility of requiring three limbs to ambulate remained. We explored the possibility of evolution to three legs. This task could be treated as a backup program for a quadrupedal robot whose original design has four legs but has lost one due to an accident and has become a tripedal robot.

2.2 Applying GA on the Biomorphic Robots

The essence of GA can be understood through three steps: generate a new population through crossover or mutation, select the better ones according to the fitness as the seed for the next generation and repeat the process many times. There are some successful cases in the literature showing GA to have helped autonomous robots to fit the environment and finish various tasks [10-13].

In the following section, we will discuss how to model the action sequence of our biomorphic robots into a GA. We first defined the chromosome of a population as a sequence of action that the robot will perform; the first generation of population was generated randomly. The selection was based on the fitness feedback, in this case, the speed of the robot, which was calculated according to the return value of a supersonic distance measurement sensor, with the following formula:

\[
S_n = \frac{D_n}{\Delta t_n},
\]

\[
Fitness = S_n - S_0. \tag{2}
\]

where \(D_n\) is the distance between two measurements, \(\Delta t_n\) is the time between two measurements, \(S_0\) is the output speed and \(n\) is the index of iteration. In our experiment, the number of iterations was set to be 10.

We first defined the chromosome of a population as a sequence of actions which the robot would perform. Since the robot we used was composed by several servo motors, we wanted it to move iteratively. We represented it as Cyclic Genetic Algorithm [6]. That is, we defined a sequence of numbers that represent the angles of each servo motor as an action, and a sequence of actions becomes a behavior. Each chromosome is a sequence of behaviors and a robot with that chromosome repeats the same sequence of
behaviors as a way to achieve a goal.

Table 2 shows the possible angles of each of the servo motors. There are six motors and 256 different possible angles for each motor. Therefore, it requires eight bits to represent one motor and 48 bits to represent one pose. Suppose we define a behavior as consisting of a sequence of 10 actions; it then requires 480 bits to represent one behavior of a population, as shown in Figs. 4 and 5.

Table 2. Possible value angles for each motor of the tripedal robot.

<table>
<thead>
<tr>
<th></th>
<th>$m_0$</th>
<th>$m_1$</th>
<th>$m_2$</th>
<th>$m_3$</th>
<th>$m_4$</th>
<th>$m_5$</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>0-255</td>
<td>0-255</td>
<td>0-255</td>
<td>0-255</td>
<td>0-255</td>
<td>0-255</td>
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2.3 Tripedal and Quadrupedal Biomorphic Robots

Different tasks require different methods of measuring fitness, and each requires different sensors, which makes a comparison between different tasks uninformative. In this paper, we report a comparison between two robots with similar but significantly different structures. The tripedal robots can be viewed as a quadrupedal robot with a deficient leg. As the environment will provide feedback for it, the robot with only three legs will try to modify its behavior and move. Note that the possible angle of each motor for the quadrupedal unit is unlimited from 0 to 255. However, due to the mechanism, the possible angles of each motor for the tripedal robot are limited and are listed in Table 3.

Table 3. The limited angels of each motor of the tripedal robot.

<table>
<thead>
<tr>
<th></th>
<th>$m_0$</th>
<th>$m_1$</th>
<th>$m_2$</th>
<th>$m_3$</th>
<th>$m_4$</th>
<th>$m_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>190-215</td>
<td>72-91</td>
<td>86-91</td>
<td>0-255</td>
<td>0-255</td>
<td>0-255</td>
</tr>
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3. EXPERIMENTS

The flowchart of the experiments is shown in Fig. 6. A standard GA was implemented in our robot. The iteration was fully automatic; however, if the robot behavior was too poor, human intervention would terminate the experiment.

3.1 Task and Fitness Design

Locomotion of a robot is the basic starting task. However, its fitness design is not straightforward. Due to the limitation of hardware, we found that 30 cm to −20 cm was the best distance range for our experiment. Therefore, we designed the robot to calculate its speed as the fitness feedback after moving 30 cm or −20 cm.

3.2 Crossover and Mutation

In our experiments, the crossover point was always at the center of a chromosome to ensure that the new generation would differ from the parents. The mutation took place once every forty trials. A mutation randomly changed one motor’s angle, which was eight bit in the corresponding chromosome. Since there were 48 (because tripedal robots...
Fig. 4. Two example poses and the corresponding angle value of each motor.

<table>
<thead>
<tr>
<th>$m_0$</th>
<th>$m_1$</th>
<th>$m_2$</th>
<th>$m_3$</th>
<th>$m_4$</th>
<th>$m_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>190</td>
<td>91</td>
<td>86</td>
<td>15</td>
<td>13</td>
<td>15</td>
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</tbody>
</table>

Fig. 5. The sequence 10 random poses. A behavior is the repetition of this sequence.

<table>
<thead>
<tr>
<th>$m_0$</th>
<th>$m_1$</th>
<th>$m_2$</th>
<th>$m_3$</th>
<th>$m_4$</th>
<th>$m_5$</th>
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<tbody>
<tr>
<td>213</td>
<td>91</td>
<td>86</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>
have six motors) bits for one chromosome, the mutation rate was about \(\frac{8}{48 \times 10} = \frac{8}{480} = 0.0167\). The quadrupedal robot chromosome had 64 bits (because quadrupedal robots have eight motors), so the mutation rate was about \(\frac{8}{64 \times 10} = \frac{8}{640} = 0.0125\).

### 3.3 Experiment 1: Test on a Quadrupedal Robot

The robot is shown on the right hand side of Fig. 2, and it was placed in a box, as shown in Fig. 3. The speed of the quadrupedal robot with the behavior design by the vendor company was 2.0 cm/sec. The experiment was designed to see whether or not the robot could evolve a new behavior that can move forward faster than 2.0 cm/sec.

Two GA settings were tested, and the fitness of each generation is shown in Fig. 7 (a). We repeated the experiments ten times with the same setting. The final fitness of each experiment is shown in Fig. 7 (b). Since the population of each generation is different, it is not fair to compare the fitness result according to the number of the generation. We defined a new x-axis cost, which is the product of population and generation.

The initial setting was: population = 5, generation = 8. The average fitness is shown in Fig. 8 (a). We found that the speed increased gradually, but never exceeded 2.0 cm/sec. We then changed the settings to: population = 4, generation = 10. Note that the two settings took the same computation time. The average fitness is shown in Fig. 8 (b). Note that the speeds exceeded 2.0 cm/sec after 16 trials, which corresponded to the fourth generation. This was outside of our expectation since the speed of the robot never exceeded 2.0 cm/sec for the initial setting. We cannot conclude that the number of the population will affect the result of evolutionary behavior in a particular way, but it certainly is unstable in our experiment.
Fig. 7. Fitness of quadrupedal.

(a) Average fitness.

(b) best final fitness.

Fig. 8. Average fitness of quadrupedal robot (a) population: 5 (b) populations: 4.
3.4 Experiment 2: Test on a Tripedal Robot

In the second experiment, we tested the same task on a tripedal robot. The tripedal mechanism does not exist in the natural world; the only exceptions are injured animals. However, we wanted to test how much time it takes for a tripedal robot to evolve a reasonable speed in moving forward.

The robot is shown on the left hand side of Fig. 2; it was placed in a box, as shown in Fig. 3. The speed of the tripedal robot with the behavior design by the vendor company, robobuilder\(^1\), was 2.5 cm/sec. Our goal was to evolve a new behavior that could move forward faster than 2.5 cm/sec.

The initial GA setting was: population = 5 and generation = 8. The result is shown in Fig. 9 (a). We found that the convergence of GA was slow and the fitness far lower than 2.5 cm/sec.

To achieve the target goal, we increased the number of generations from 8 to 40. The results are shown in Fig. 9 (b). We found that the fitness exceeded 2.5 cm/sec on the 125th trial, which corresponded to the 21st generation. For a tripedal robot, it takes about eight times more trial than the quadrupedal robot to evolve a behavior that can beat the one given by the vendor company.

3.5 Experiment 3: Test on a Wounded Quadrupedal Robot with One Leg Removed

The ability of how a robot adopts to the change due to certain incident such as the damage of some parts is an interesting property of an evolutionary robot. In this experiment, one leg was removed from a quadrupedal robot to test whether the evolutionary robot could adjust itself and keep on moving.

The initial population was the sequence of actions designed for four legs. At the beginning of the experiment, the robot could not move forward with the remaining three legs with the action sequence design for four legs. Then the online evolution started to adjust the action sequence by genetic algorithm and the robot started to move forward. In order to reduce the cost of evolution time, we minimized the size of population as small as possible. We tested three different sizes of population for each generation, which were 2, 3 and 4; the corresponding numbers of generations were 30, 20, and 15 respectively. Therefore, the max cost of each setting was the same. The experiment repeated 4 times and the average result was reported.

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\(^1\) http://www.robobuilder.net/eng/
In the following figures we show the tendency of the growth of fitness values for three different experimental settings. In all the three cases, shown in Figs. 10 (a)-(c), the average speeds of the robot improve gradually as expected. The X-axis is the cost and the Y-axis is the average speed of the robot. Fig. 10 (a) shows that the highest speed for the population 2 setting is 1.2 cm/sec. Fig. 10 (c) shows that the highest speed for the population 4 setting is 0.7 cm/sec. The highest speed is shown in Fig. 10 (b), where the number of population of each generation is 3, the average speed of the robot reaches 1.57 cm/sec, which means the robot can move at an 80% speed even if it loses one leg. Although the motion of the robot is quite jolty, the robot can move at a speed 2.01 cm/sec in one case, which is the same as the speed of the human program.

3.6 Experiment 4: Comparing GA, and PSO on a Wounded Quadrupedal Robot

To understand more on the evolutionary robotics, we adopt PSO algorithm on the same wounded robot to compare the converging speeds and final finesses of GA. In this experiment, the population was set to 3 and the maximum generation was set to 25. Fig. 11 shows the results, GA converges faster than the PSO does, but later the PSO gets better fitness. We cannot conclude that the final fitness is the fastest possible moving speed of the wounded robot, but the result shows that the robot can evolve fast within a very short time to overcome an unexpended damage in this case.

4. DISCUSSION AND FUTURE WORKS

Early biomorphic robots were hexapod or quadrupedal, which mimicked the mechanisms of insects or animals. In the future, we shall try other possible mechanisms which might not exist in the natural world. The kinematic analysis of such robots is much more difficult than the traditional mechanisms; the importance of the automatically evolutionary ability of the robot behaviors is in urgent need. In a real world environment, where different obstacles may appear in front of the robots, the robots should be endowed with an ability to overcome difficulties in order to accomplish various tasks.

The evolutionary time required for the robot was quite short in our experimental results. It took about 30 trials for the robot to get to a speed that was quite comparative to the speed designed by human. Each trial took about 10 seconds in our experiment; therefore, it took about 5 minutes for the robot to evolve to move efficiently.

![Figure 10](image.png)

Fig. 10. (a) population: 2, generation: 30.
In this paper, genetic algorithm and PSO are tested for the locomotion task. Other evolutionary algorithms may be used on different levels of intelligence. For example, a differential evolution [14], which works just like GA and generally converges fast, can be a way to improve our system.

Evolution takes place not only within one robot to generate new behavior, it can also be a strategy to coordinate a multi-robot system using many robots. The ant colony optimization is based on the ideas that ants forage through pheromone communication to form paths, and it can be implemented in a multi-robot system [15]. Particle swarm op-
timization is based on the ideas of animal flocking behaviors [16]. This can be used as a way to achieve object-finding tasks by robots.

5. CONCLUSION

In this paper, we report our experimental results on how evolutionary locomotion can be achieved by using both quadrupedal and tripedal biomorphic robots with least computation resources. We also test on a wounded robot to show the robot’s potential for self-adjustment on an unexpected damage.

Our experimental results show that the robots can move faster with an evolutionary behavior than a pre-programmed behavior provided by the vendor company. We also find that the robotic mechanism affects the cost in evolving a good behavior. Since the convergence of the GA was not steady, we repeated each experimental setting ten times to get a more conclusive result. The result of the experiment on a wounded quadrupedal robot whose one leg was removed shows that the evolutionary robot can adapt itself to move quickly in an unstable gait. The result shows that online evolutionary robot can overcome an unexpected motor fault while no one can offer repairs.

REFERENCES


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